Program + Abstracts

TSL Workshop 2019

7th INFORMS Transportation Science and Logistics Society Workshop

VIENNA, JULY 15-18 2019

Tuesday, July 16					
Registration					
Session	**Chair**	**09:00-09:30**			**Room**
1A: Crowdshipping	Jean-Francois Cordeau	**Crowdshipping with Stochastic Occasional Drivers and Time Windows** Fabian Alejandro Torres Duran, Walter Rei and Michel Gendreau	**The Role of Crowdshippers in an Integrated Item-sharing and Crowdshipping Setting** Moritz Behrend and Frank Meisel	**Crowdsourced Logistics: The Pickup and Delivery Problem with Transshipments and Occasional Drivers** Stefan Voigt and Heinrich Kuhn	Sky Lounge
1B: On-demand systems	Alexander Hübner	**Revenue management model for logistic on-demand systems** Shadi Sharif Azadeh, Benoit Montreuil and Yousef Maknoon	**Choice-based dynamic dial-a-ride problem for on-demand transportation** Bilge Atasoy, Shadi Sharif Azadeh, Yousef Maknoon, Michel Bierlaire and Moshe Ben-Akiva	**A Hierarchical Approach Enabling Supplier Choice in On-Demand Platforms** Jennifer Pazour and Seyed Shahab Mofidi	HS15
1C: Shared mobility	Fabien Tricoire	**Modeling Service Class Constraints in Autonomous Mobility-on-Demand Systems: A Data-Driven Approach for Dispatching and Rebalancing Vehicles** Breno Beirigo, Frederik Schulte and Rudy Negenborn	**Combining people and freight flows using a scheduled transportation line with stochastic passenger demands** Abood Mourad, Jakob Puchinger and Tom Van Woensel	**Routing Optimization for On-Demand Ridesharing: Formulation, Algorithm and Implication** Wei Zhang, Kai Wang and Shuaian Wang	HS16
Coffee break			**10:30-11:00**		Sky Lounge
Session	**Chair**	**09:00-09:30**	**09:30-10:00**	**10:30-11:00**	**Room**
2A: Routing games	Michel Gendreau	**Courteous or Crude? Understanding and Shaping User Behavior in Ride-hailing** Sasa Pekec, Yunke Mai, Bin Hu, Yuhao Hu and Zilong Zou	**Verifiable Stability in Collaborative Transport** Mathijs van Zon, Remy Spliet and Wilco van den Heuvel	**The Joint Network Vehicle Routing Game** Mathijs van Zon, Remy Spliet and Wilco Van Den Heuvel	Sky Lounge
2B: Carsharing & Ridesharing	Tal Raviv	**Station location and vehicle distribution for round-trip car sharing systems** Pieter Smet, Federico Mosquera, Emmanouil Thanos and Toni Wickert	**A Network Flow Approach to Relocating Vehicles and Assigning Operators for Large-Scale One-Way Carsharing Systems** Hanjun Fu, Chi Xie, Bo Zou and Peng Chen		HS15
2C: Ride-hailing	Michael Hewitt	**On the Analysis of Time-Space Flow Model Reformulation of Dial-A-Ride Problem for Autonomous Taxi System** Zhiheng Xu and Jee Eun Kang	**Control of Autonomous Electric Fleets for Ridehail Systems** Justin Goodson, Nicholas Kullman, Jorge E. Mendoza and Martin Cousineau	**A Learning Large Neighborhood Search for The Dynamic Electric Autonomous Dial-A-Ride Problem** Claudia Bongiovanni, Mor Kaspi, Jean-François Cordeau and Nikolas Geroliminis	HS16
Lunch		Restaurant Rebhuhn			
Excursion		13:30-21:00			

Wednesday, July 17					
Session		**09:00-09:30**	**09:30-10:00**	**10:00-10:30**	**Room**
3A: Platooning	Tom van Woensel	**A Network Design Approach for the Restricted Truck Platooning Problem** Szymon Albinski, Teodor Gabriel Crainic and Stefan Minner	**Service network design with mixed autonomous fleets and cooperative platooning** Yannick Oskar Scherr, Bruno Albert Neumann-Saavedra, Mike Hewitt and Dirk Christian Mattfeld	**Consideration of Platoons in Models of Vehicle Routing Problems** Jörn Schönberger	Sky Lounge
3B: Ridesharing	Justin Goodson	**Geographic Pricing in Ridesharing Services** Mehdi Behroozi	**Inferring commuter?s values of time in ride-sourcing service: a multi-stage deep learning approach** Yili Tang and Hai Yang	**Can ride-sharing alleviate traffic congestion?** Jintao Ke, Zhengfei Zheng and Hai Yang	HS15
3C: Bikes and parking lots	Sasa Pekec	**The Station Location Problem of Bike Sharing Systems** Vilde Graven Stokke, Vilde Schliekelmann Barth, Kjetil Fagerholt and Henrik Andersson	**Optimal Scheduling of Advance Reservations for Shared Parking Systems** Yun-Chu Hung and Chung-Cheng Lu	**Stable Exchange for Commute-Driven Sharing of Private Parking Lots** Minghui Lai, Xiaoqiang Cai and Qian Hu	HS16
Coffee break			**10:30-11:00**		Sky Lounge
Session	**Chair**	**11:00-11:30**	**11:30-12:00**	**12:00-12:30**	**Room**
4A: Parcel delivery	Stefan Minner	**Reliable Parcel Routing Policy in a Physical Internet** Tal Raviv and Ido Orenstein	**Sequence and Speed Optimization for Delivery Robots** Stefan Schaudt and Tolga Bektas	**Service Network Design with Scheduled Lines for City Logistics** Mike Hewitt, Tom van Woensel and Lucas Veelenturf	Sky Lounge
4B: Online order fulfillment	Jörn Schönberger	**Pricing for Goods Deliveries in the Sharing Economy** Luce Brotcorne, Anton Kleywegt and Youcef Magnouche	**A Continuous Solution Method for the Multi-Visit Drone Routing Problem** Adriano Masone, Stefan Poikonen and Bruce L. Golden	**Omni-channel grocery retailing: an approach for multi-depot order fulfillment** Alexander Hübner, Manuel Ostermeier and Christian Dethlefs	HS15
4C: Redistribution of goods	Jakob Puchinger	**A Branch and Price algorithm for the Pickup and Delivery Problem with Transfers** Cristián E. Cortés, Michel Gendreau, Cristiam Gil and Pablo A Rey	**The multi-attribute two-echelon location-routing problem with fleet synchronization at intermediate facilities** David Escobar Vargas, Claudio Contardo and Teodor Gabriel Crainic	**Optimizing routing and delivery patterns with multi-compartment vehicles** Manuel Ostermeier, Alexander Hübner, Markus Frank, Andreas Holzapfel and Heinrich Kuhn	HS16
Lunch		12:30-14:00	Restaurant Rebhuhn		

Session	Chair	14:00-14:30	14:30-15:00	15:00-15.30	Room
5A: Carsharing	Dominique Feillet	**Comparison of Different Carsharing Relocation Modes: Classification and Feature-Based Selection** Layla Martin, Stefan Minner and M. Grazia Speranza	**The Dynamic Relocation Problem for Electric Carsharing Services** Simen Hellem, Carl Andreas Julsvoll, Magnus Nyborg Moan, Henrik Andersson, Kjetil Fagerholt and Giovanni Pantuso		Sky Lounge
5B: Freight transportation	Anton Kleywegt	**Inland waterway efficiency through skipper collaboration and joint speed optimization** Julian Golak, Veerle Timmermans, Alexander Grigoriev and Christof Defryn	**Integrating drayage decisions in intermodal container routing** Hilde Heggen, Yves Molenbruch, An Caris and Kris Braekers	**Decomposition Methods for Dynamic Load Planning and Driver Management in LTL Trucking** Hugo Simao and Warren Powell	HS15
5C: Sharing of electric vehicles	Heinrich Kuhn	**Doubly-constrained rebalancing for one-way electric carsharing systems with capacitated charging stations** Theodoros Pantelidis, Li Li, Tai-Yu Ma, Joseph Chow and Saif Jabari	**Charging station placement in free-floating electric car sharing systems** Georg Brandstätter, Markus Leitner and Mario Ruthmair	**On the Range Anxiety for Electric Vehicles: An Empirical Investigation** Sang Won Kim, Ho-Yin Mak, Marcelo Olivares and Ying Rong	HS16
Coffee break			**10:30-11:00**		Sky Lounge
Session	**Chair**	**16:00-16:30**	**16:30-17:00**	**17:00-17:30**	**Room**
6A: Crowd-sourced logistics	Teodor Crainic	**Mobile Facility Location Problem in Crowd-shipping** Kianoush Mousavi, Merve Bodur and Matthew Roorda	**Integrated Matching and Routing for Crowd-Shipping systems** Tom van Woensel	**Workforce Scheduling for Service Routing with Crowdsourced Drivers** Marlin Ulmer and Martin Savelsbergh	Sky Lounge
6B: Carrier alliances	Claudius Steinhardt	**Cooperation of customers in traveling salesman problems with profits** Ondrej Osicka, Mario Guajardo and Kurt Jörnsten	**Multi-objective optimization framework for the integration of individual partner interests in a collaborative location-inventory model** Thomas Hacardiaux, Christof Defryn and Jean-Sébastien Tancrez		HS15
6C: Presentations of Vienna's FEAT project	Rudolf Vetschera	**Comparing Mechanisms for Request-Exchange Collaborative Transportation** Daniel Nicola	**The PDP with alternative locations and overlapping time windows** Alina-Gabriela Dragomir, Tom Van Woensel and Karl Doerner	**The two-region multi depot pickup and delivery problem** Adria Soriano, Margaretha Gansterer and Richard F. Hartl	HS16
Conference Dinner		19:00-Open end			Vienna City Hall

Thursday, July 18 2019						
Session	**Chair**	**09:00-9:30**	**09:30-10:00**	**10:00-10:30**	**10:30-11:00**	**Room**
7A: Collaborations	Frank Meisel	**Analyzing the impact of delays in an integrated mobility system** Yves Molenbruch and Kris Braekers	**Dynamic Prices as Incentives for Collaborative Transportation: Using Side Payments for Individually Rational and Stable Horizontal Cooperation** Bilge Atasoy, Eduardo Lalla-Ruiz, Frederik Schulte and Stefan Voß	**Analysis on Impacts and Characteristics of Collaborative Pickup Lockers** Necati Oguz Duman and Ozlem Ergun	**Experience with a Real-Time DSS for Cooperative Planning at an Express Carrier** Ulrich Derigs, Sascha Dahl and Stafan Ems	Sky Lounge
7B: Carsharing and -pooling	Markus Leitner	**How Scheduling Advances Affect Level of Service, Critical Mass, and Fleeting in Smartphone-Based Vanpooling** Donghui Li, Constantinos Antoniou, Hai Jiang, Wei Shen, Liang Zhang and Weijian Han	**The Value of Prepositioning in Smartphone-Based Vanpool Services Under Stochastic Requests and Time-Dependent Travel Times** Donghui Li, Constantinos Antoniou, Hai Jiang, Qianyan Xie, Wei Shen and Weijian Han	**A Globally Convergent Discrete Simulation-Based Optimization Algorithm for Complementing Transit Accessibility with Car-Sharing Service** Tianli Zhou and Carolina Osorio	**Predictive dynamic relocations in carsharing systems implementing journey reservations** Martin Repoux, Mor Kaspi, Burak Boyaci and Nikolas Geroliminis	HS15
Coffee break			**10:30-11:00**		Sky Lounge	
Lunch	12:30-13:30	Restaurant Rebhuhn				
Session	**Chair**	**13:30-14:00**	**14:00-14:30**	**14:30-15:00**		**Room**
8A: Sharing systems	Marlin Ulmer	**Collaborative Pickup and Delivery Problems with Time Windows and Heterogeneous Vehicles** Cornelius Rüther and Julia Rieck	**Modeling and solving the multimodal car- and ride-sharing problem** Miriam Enzi, Sophie N. Parragh, David Pisinger and Matthias Prandtstetter	**Stakeholder requirements to the design of a cooperatively used urban logistics hub** Sonja Maria Protic and Patrick Hirsch		Sky Lounge
Farewell Reception	15:30-20:00	Sky Lounge				

Data-driven approach to study the polygonalization of high-speed railway (HSR) train wheel-sets using field data of China's HSR train

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Abstract

The polygonalization of wheels is a serious threat to the safety and reliability of railway operation, as the failure of the wheel may lead to system failure and acceleration of degradation of other components[1][2][3][4]. The German inter-city express (ICE) had a derailment which was considered caused by wheel polygonalization[5]. Noise has been found closely correlated with wheel polygonalization in the Netherlands railway operation[6]. Over hundreds of examples of polygonalization have been found in China new high-speed train wheels[7].

Some studies have aimed at developing numerical techniques to predict the wheel–rail profile evolution[8][9]. Based on such physical models as the rail/wheel contact dynamics model, mechanism has been discussed. The speed of the train has been correlated with the formation of polygonalization, and the mechanism has been simplified using a mathematical model [10] [11]. Polygonalization can be related to both low-order harmonics and high-order harmonics[12]. Material of wheels and dynamic imbalance have been found correlated with low-order harmonics polygonalization[13]. High-order harmonics are more likely to be found in HSR trains because of their high speed [14][15]. There is a significant difference in the frequency of polygonalization for HSR trains and traditional trains[16][17].

With higher order harmonics come more noise, depending on the roughness of the wheel surface [18][19]. The octave band of locomotive wheels suffering from polygonal wear ranges from 160 to 315 mm [20].

Simulation systems also improve knowledge of polygonalization. A wear prediction programme has been developed to take into account other damage mechanisms [21]. A study has recently made use of these tools to include other considerations apart from wear, such as traction and braking [22]. It only considers a sample length of a track in service to reduce the computational cost. In fact, the exhaustive simulation of vehicle dynamics and of wear evolution on the entire railway network is computationally too expensive for practical purposes. Various methods have been proposed to reduce the computational cost of the simulation of the whole journey. One proposal is a statistical approach to the railway track description to study complex railway lines [23]. The length of curve can be also taken as a weighting factor [24].

However, the railway operating environment is complex and thus cannot satisfy the assumptions of many studies on polygonalization. Model-driven and data-driven models are more helpful when dealing with complex systems [25]. Field data are a valuable resource to reveal the pattern of polygonalization. In recent years, locomotive field data have been used to study reliability of locomotive wheels [26]. Bayesian analysis has been used to study degradation data collected from locomotive wheels [27]. The influence of the wheel's position, including bogie, axle and side, on degradation has been studied [28] and a corresponding maintenance schedule proposed.

We look at two possible factors in polygonalization: season and proximity to engines. Our analysis of field data shows the environmental factor has more impact on wheel polygonalization than the mechanical factor. A case study of China's HSR train wheels is conducted to confirm the finding. The case study shows the degree of polygonal wear is much more severe in summer than other seasons. The finding may give a totally new a research perspective on polygonalization of train wheels. We use Bayesian analysis because this method is useful for small and incomplete data sets. We propose three Bayesian data-driven models.

References

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The Airport Shuttle Problem

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The aviation industry is one of the most fast growing contributor to global economic growth and it helps the rise of globalisation by bringing people together. The industry has doubled in size every 15 years which increased the demand for more flights, more destinations as well as more aircrafts. The number of worldwide commercial fleet is about 25,000 aircrafts in 2018 and it is expected to be 35,000 in the next decade [1]. In order to increase their competitiveness, many airlines provide auxiliary services to their passengers, such as shuttle transfers to their customers. Transporting the small number of people without exceeding the capacity of shuttles between long time periods is quite easy. However, more the number of passenger demands, the number of vehicles increase, and the transfer time closes, more the problem becomes complex. This problem frequently faced in airport shuttle services which should be efficiently handled to increase the profit, service quality, and customer satisfaction.

This study introduces the airport shuttle problem (ASP) which is a variant of the vehicle routing problem (VRP). The ASP is related with several VRP variants defined in the literature such with pickup-and-delivery problems (PDPs) where nodes denote origins or destinations for the different entities to be transported. Many variants of PDPs have been intensively studied by many researchers in the last decades [2, 3]. In the context of the PDP, transportation of people is also studied [4]. One of the well-known variant of this problem is the dial-a-ride problem which is a combination of the VRP and scheduling problem and provides multi-occupancy, and door-to-door transport service for people [5]. Another similarity is with the VRP with backhauls where the customer set is partitioned into linehaul customers who require deliveries, and backhaul customers who require pickups [6]. The literature on optimization of airport shuttle services is scarce, however, several papers studied in different contexts. The door-to-door service of pickup and delivery of customers to the airport service provided by airline ticket sales agencies is studied [7]. This service picks up customer at desired position and at any time the customer preferred different than airport shuttles.

In the ASP, we transfer passengers from or to the airport and city center which must be completed in a specific time. The vehicle capacity is limited and it is renewed at airport or city center. It is not necessary to satisfy each demand by one vehicle. Because the demand is divisible, different vehicles that join the demand node can transfer an amount of the passengers. Furthermore, transportation of some customers can be rejected which brings no extra cost. Hence, the demand of some passengers cannot be satistified. Passengers are first assigned to vehicles and transferred to the destination. The service must be rendered to the passengers who are transferred to the city center from the airport in a specific time. After this transfer, we can assign new passengers to the vehicle or it can continue the trip with no passenger for the next service. The vehicle services are done or which has no service for a while, can wait in a location which was determined before. Each passenger transfer must begin within the time window. We may group passengers and assign them to the same vehicle. These passengers can be in different flights and are ready to transfer in different times. The passengers who are ready to transfer at the same time with shuttle are called as jobs. The jobs can be divided on the personal basis or the passengers in the specific jobs can be assigned to each vehicle. The fundamental reason of dividing jobs is to use the empty seat capacity more efficiently. We can assign passengers from different jobs to the same vehicles on the same routes. The objective of the ASP is to maximize the profit while satisfying the limited seat capacity, the predefined flight times, and the number of passengers constraints.

We first formulate the ASP as a mixed integer programming model, and we then develop a metaheuristic for its solution. The metaheuristic algorithm uses several effective methods such as passenger grouping mechanisms and route improvement procedures. Extensive computational experiments have shown that the metaheuristic is highly effective on the ASP.

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Dynamic repositioning strategy in a bike-sharing system; how to prioritize and how to rebalance a bike station?

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1 Introduction

Bike-sharing systems (BSS) are an increasingly part of today's cities transportation. The objective for the BSS operator is to propose a reliable service where users can easily find an available bike or an available dock to return a bike. For this purpose, the design of the BSS should be well conceived. This is a long-term issue for which the sizes of the stations, their location, or the number of available bikes have to be determined. However, even with a well-designed BSS, the risk of having full or empty stations cannot be completely avoided due to the stochasticity and the imbalance of bike arrivals and departures at a station. For instance, during peak morning hours, user flows are almost always one directional from residential areas to business areas.

One way to improve the quality of service without modifying the architecture of the BSS is to redistribute bikes among stations in order to provide a sufficient number of available bikes and empty docks at each station. For instance in Paris in 2017, the redistribution is done 24/7 by 23 trucks each with a capacity of 20 bikes and 2 buses each with a capacity of 62 bikes. The team in each truck is responsible of a given sector whereas the buses travel longer distances between large stations in front of train stations or universities. The buses follow predetermined routes which can be readjusted by the operator whereas the trucks' teams have more responsibilities in the choices made to redistribute the bikes in one sector. In both cases, the idea for the operator is to move bikes from maintenance inventory zones in the suburbs to a succession of bike stations in order to better balance the number of bikes per station.

The definition of a good redistribution policy is difficult to make for the agents and the operator. One of the reasons of this difficulty is the forecast of users' future movements. The forecasts are based on historical data and on external factors like the weather or the specific users' behavior due to a particular event. Yet, the stochastic aspect of the demand leads to important gaps between the forecasts and the realizations. Another difficulty lies in the limits of the interventions of the operator. In Paris, only 3000 bikes in average are moved per day by the operator over a total of 110 000 rented bikes per day in average. Hence, the ability of the operator to redistribute bikes is limited and priority choices have to be made.

To help the operator, we propose to develop an implementable decision-support tool to decide at any point of time (i) which station should be prioritized, and (ii) which number of bikes should be added or removed at each station. Our objective is to minimize the rate of arrival of unsatisfied users.

Alternatively to the existing studies, we propose to use a *Markov decision process* approach to derive a dynamic bike repositioning strategy. The value of Markov decision process approaches is that they can lead to exact optimal policies in the long-run in a stochastic context. In this sense, it seems to be the best tool to tackle the dynamic redistribution problem.

2 Problem Formulation

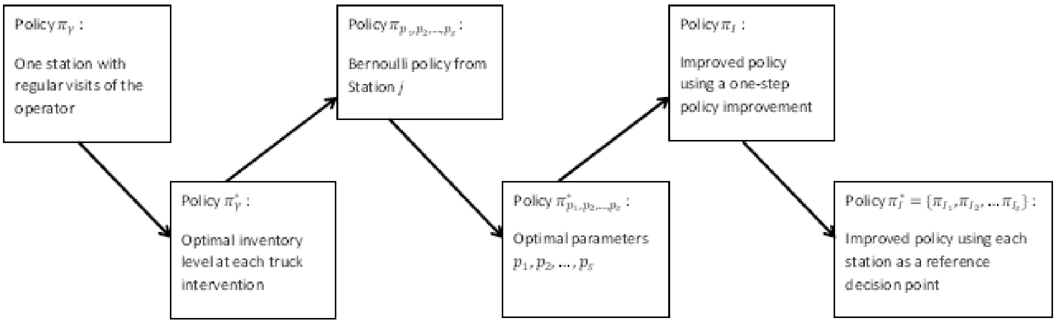
We consider a geographical area in a BSS modeled as a set of s independent stations each with capacity ci, for $1 \leq i \leq s$. At Station i, a bike departure is due to the arrival of a user in need of a bike. We assume that the arrival process of these users is a non-homogeneous Poisson process with rate $\mu i,t$, for $1 \leq i \leq s$ at a given time t, $t > 0$. A bike arrival is due to a user in need of returning a bike at a station. Again, we assume that the arrival process of these users at Station i is a non-homogeneous Poisson process with rate $\lambda i,t$, for $1 \leq i \leq s$ at a given time t, $t > 0$.

The operator's interventions in the area consist in sending a truck at a given station to add or remove bikes. The operator's ability to operate an intervention in a given Station i starting from another Station j is an important aspect of the repositioning problem. The time between two interventions is determined by the time spent at a given station, the driving time between these stations, the eventual necessity to go back to a maintenance inventory zone in the suburbs, and the intensity of the operator' activity in the intervention area. The time spent at a station is influenced by the number of bikes to add or remove and by unanticipated problems like bikes' breakdown which may force the truck to stay longer than expected at Station i to do on-site repairs. The driving time depends on the distance between the stations and on the tra c. The necessity to go back to the maintenance zone is determined by the working periods of the agents and by the need to add or remove bikes from the truck. The intensity of the operator' activity is conditioned by the limited fleet of trucks to operate repositioning in the intervention area. Hence, even if an intervention is desirable at Station j, the operator may decide to postpone the intervention and send the truck to a more urgent intervention area. The time to reset Station j starting from Station i is hence very complex to estimate. For the tractability of the analysis, we assume that this duration is exponentially distributed with rate $\gamma i,j$. We further assume that the truck has a su ciently large capacity which does not alter its ability to modify a station state. The objective for the system operator is to minimize the long-run overall rate of arrival of unsatisfied users.

We propose to employ a Markov decision process approach to determine the optimal number of bikes to add or remove in a given station and which station should be prioritized.The value function of the problem can be formulated as

$$\begin{aligned} V_{n+1}(\overline{x}) = & \sum_{i=1}^{s} \lambda_{i,y} \cdot (\mathbb{1}_{x_i < c_i} V_n(\overline{x} + \overline{e_i}) + \mathbb{1}_{x_i = c_i}(V_n(\overline{x}) + r_{2,i})) \\ & + \sum_{i=1}^{s} \mu_{i,y} \cdot (\mathbb{1}_{x_i > 0} V_n(\overline{x} - \overline{e_i}) + \mathbb{1}_{x_i = 0}(V_n(\overline{x}) + r_{1,i})) \\ & + \theta \cdot (\mathbb{1}_{1 \leq y < N} V_n(\overline{x} + \overline{e_{s+2}}) + \mathbb{1}_{y=N} V_n(\overline{x} - (N-1) \cdot \overline{e_{s+2}})) \\ & + \gamma_{j, \arg\min_{1 \leq i \leq s} \left(\min_{0 \leq m \leq c_i} (V_n(\overline{x} + (m - x_i)\overline{e_i} + (i-j)\overline{e_{s+1}})) \right)} \cdot \min_{1 \leq i \leq s} \left(\min_{0 \leq m \leq c_i} (V_n(\overline{x} + (m - x_i)\overline{e_i} + (i-j)\overline{e_{s+1}})) \right) \\ & + \left(1 - \sum_{i=1}^{s} \lambda_{i,y} - \sum_{i=1}^{s} \mu_{i,y} - \theta - \gamma_{j, \arg\min_{1 \leq i \leq s} \left(\min_{0 \leq m \leq c_i} (V_n(\overline{x} + (m - x_i)\overline{e_i} + (i-j)\overline{e_{s+1}})) \right)} \right) V_n(\overline{x}), \end{aligned} \tag{2}$$

The dimentionality of the problem together with the time dependency of the parameters do not allow to obtain the optimal policy. We instead develop a policy improvement approach as depicted below:

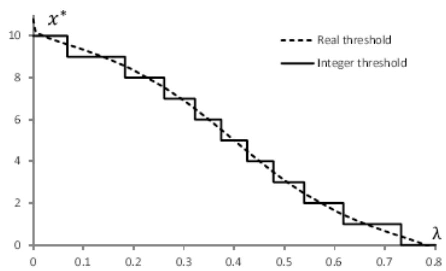


3 Optimal intervention at a bike station

We want to determine the optimal policy at each truck arrival for a single station under Policy $\pi\gamma$. More precisely, based on the station state, we want to optimize the number of bikes to add or to remove from the station. The main result of this section is that there exists an optimal station state that the operator should reach at each truck intervention. This result defines Policy $\pi\gamma$.

Theorem 1 In the long-run, for a given phase y ($1 \leq y \leq N$), there exists an optimal state

- If $x \leq xy$, the optimal action is to add $xy - x$ bikes to the station.
- If $x \geq xy$, the optimal action is to remove $x - xy$ bikes from the station. This minimum is the unique local minimum of the value function.



Obtained optimal state as a function of λ ($c = 10$, $\gamma = 0.2$, $\mu = 0.8 - \lambda$, $r_1 = r_2 = 0.1$)

A numerical analysis is developped to determine the case with non-constant parameters.

4 How to choose the next Station?

Algorithms 1 and 2 allow us to determine how a station should be prioritized. Next an evaluation of our method is performed using simulation.

Algorithm 1: Policy $\pi^*_{p_1,p_2,\cdots,p_s}$.

1. Initialization. Set $\epsilon > 0$ and $\vec{p}_0 = (p_{1,0}, p_{2,0}, \cdots, p_{s,0})$ with $p_{1,0} = 1$, and $p_{i,0} = 0$, for $1 < i \leq s$. Go to line 2.
2. Iterations. For $k > 0$, compute $\vec{p}_k = \underset{1 \leq i \leq s}{\text{argmin}} \left(\mathbb{1}_{\vec{p}_{k-1}+\epsilon\vec{e_i} \in [0,1]^s} g(\vec{p}_{k-1} + \epsilon\vec{e_i}) + \mathbb{1}_{\vec{p}_{k-1}+\epsilon\vec{e_i} \notin [0,1]^s} g(\vec{p}_{k-1}) \right)$ where $\vec{e_i}$ is a line vector with all coefficients equal to $-\frac{1}{s-1}$ except the ith coefficient which is chosen equal to 1. If $g(\vec{p}_k) < g(\vec{p}_{k-1})$, then go back to line 2. Otherwise go to line 3.
3. The vector $\vec{p}_k$ approximates the parameters of the optimal Bernoulli policy.

Algorithm 2: Policy π_{I_j}.

1. Assume that the truck is at Station j at phase y $(1 \le y \le N)$. Estimate the system parameters: $\lambda_{i,1}$, $\lambda_{i,2}$, ..., $\lambda_{i,N}$, $\mu_{i,1}$, $\mu_{i,2}$, ..., $\mu_{i,N}$, c_i, $\gamma_{j,i}$, θ and N, for $1 \le i \le s$. Go to line 2.

2. Determine the optimal Bernoulli policy, $\pi^*_{p_1,p_2,\cdots,p_s}$, with the optimal inventory levels at each station, x_i^*, and the related value function at Station i, $V_i(x_i, y)$, where $0 \le x_i \le c_i$ using the results of Section 4.2 and Algorithm 1. Go to line 3.

3. Choose the station to prioritize by improving the Bernoulli policy, $m = \underset{1 \le i \le s}{\operatorname{argmin}} V(x_1, x_2, \cdots, x_s, y) + V_i(x_i^*, y) - V_i(x_i, y)$.

Experience with a Real-Time DSS for Cooperative Planning at an Express Carrier Network

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During the last years, transportation firms are faced with increasing cost pressure and revenue erosion at the same time. Large transportation companies are able to realize a high utilization of their vehicles and acceptable operational cost by consolidating and combining orders to efficient roundtrips. Small carriers serving ad-hoc one-way shipping orders only are faced with the problem of low volume of shipments with less than truckload trips as well as dead-head trips due to an imbalance among locations. This leads to cost ineffective transportation plans and/or may result in non-competitive prices. Such small-sized companies may compensate their competitive disadvantage by allying with partners to a cooperation network to establish a more profitable portfolio of orders. In such a network each partner plans his orders and his vehicle fleet independently with the option to exchange orders with partners. Partners charge their own customers based on a specific price function. The carrier operating an order for a partner receives a monetary compensation, which has been specified in a generally agreed upon compensation schema.

For such a network to be successful and sustainable there are a number of critical factors: On the strategical level the choice of the right set of partners yielding enough consolidation potential as well as mutual trust is a cardinal point. On the operational level awareness is essential, i.e. existing potentials have to be detected and communicated, a task which calls for the establishment of a proper information and communication system supporting cooperative planning. Another success factor is the establishment of a compensation schema which puts incentives to both partners involved in exchanging orders and which is considered to be fair by all network partners.

In this talk we report on our experience with the development and maintenance of pool.tour, a distributed real-time internet-based collaborative Decision Support System (DSS) for a large express courier network. We analyze the impact of this system on the success factors awareness and fairness mentioned above.

The planning situation is as follows: Each partner is located at a specific depot and operates a set of vehicles. Each partner has acquired a set of orders which is defined by its pickup location , its delivery location , its capacity requirement and a time window which specifies the earliest time for pickup and latest time for delivery, respectively. Two different rates apply: a transportation price per km to be paid by the customer and an internal rate per km used for compensation if the order is transported by a partner. The revenue obtained from the customer after serving an order is calculated based on applying the transportation price per km to the distance between pick-up and delivery location plus an amount for picking up the order charging only the distance exceeding a certain threshold. Now a carrier has two options: to serve an order with his own fleet or to have it served by one of the partners. In the first case, contribution to profit is calculated as usual, reducing revenue by the marginal imputed cost. In the second case, if one of the partners serves the order, the compensation is determined according to a specific, rather complicated but contractually agreed upon compensation schema CS. The established cooperation mechanism is to exchange single orders after bilateral negotiation. Thus the autonomy of the partners does not allow a central authority which is able and legitimate to reallocate orders. Note, that each vehicle can transport more than one order at a time, as long as the total capacity is not exceeded, and that it is the task of the individual dispatching systems of the partners to combine orders to tours.

The dynamic of the business and the extremely short lead time between order entry and pickup time requires the installation of a Real-Time DSS which is capable to react to the changing environment instantly using fleet telematics while the fact that the partners are geographically spread partners over Europe requires to implement a Distributed DSS. Based on the requirements we have designed an interactive concept where the DSS integrates the decentralized databases of the partners' dispatching systems and uses a simple but fast and powerful on-line heuristic which is based on the current information on orders, planned tours and vehicle positions. The heuristic permanently generates proposals for inserting new orders into tours which are then communicated to the dispatchers in a pro-active manner.

The system had been in use for about two years, i.e. during their daily planning the dispatchers received proposals for order exchanges. Yet, the experience with the use of the system was not satisfactory, i.e. the reduction in deadheads and the increase in contribution to profit that materialized was far below expectation. A closer analysis revealed three problems: only a small fraction of the proposals concerned consolidations, the majority of the proposals were not implemented by the dispatchers, and, a large number of obviously promising exchanges was not proposed.

According to the comment of the partners the reason for the second failure is the fact that for exchanges which would result in a separate deadhead tour for the receiving partner the compensation to be paid by the acquiring partner is too high, i.e. all partners are aware of carriers outside the network who demand less compensation fee for such an order. Now, our hypothesis was that the specific compensation schema implemented is causing the other deficits, too, by disguising apparently cost-efficient exchange options by either setting the compensation fee too high for the acquiring partner or too low for the receiving partner.

Therefore we decided to propose and evaluate an alternative simple marginal cost-based schema compensation schema CSCB which observes the specific situation of the business at all partners explicitly and which is incentive compatible in the sense that whenever there is the potential for decreasing the total network-wide cost through an exchange then there is also a positive gain from it for each of the involved carriers.

The purpose of the study was not only to evaluate an alternative schema but also to analyze to which level the coordination potential is exploited. For that purpose we have simulated different organizational settings and scenarios: the collaborative planning approach supported by our DSS, a non-collaborative planning scenario where each carrier plans and operates his own orders only and a centralized approach imitating the situation that all resources and orders belong to one carrier. In all settings and scenarios we assume that the proposals generated by pool.tour are accepted and implemented by the partners.

For the simulation study we have used real data i.e. the orders over twelve weeks from our European-wide operating cooperative logistic network CLN consisting of about 50 carriers with a capacity of 8905 vehicles at the time of the study.

First, our simulations have shown that for the network as a whole collaborating using a proper compensation schema pays. While collaborative planning with the implemented compensation schema CS leads to a cost decrease of 4.23% compared to isolated planning, using the cost-based compensation schema CSCB cost can be reduced significantly to a cost level of 86.15%, i.e. the cost decrease is 13.85%. Also our simulation revealed that in the case of centralized planning cost can be reduced to a level of 85.93% only, i.e. the maximal cost decrease achievable by cooperating is 14.07%.

These results are rather significant. They support the experience of the partners that cooperation could only reduce cost marginally. They manifest that there is a substantial bottom line of cost resulting from inefficiencies caused by the imbalance of orders with respect to location and time which cannot be avoided even under centralized cooperative planning. Yet, most important, the results clearly demonstrate that the choice of the compensation schema is crucial for the economic success of the cooperation network. Collaborative planning with the simple, well understandable and easily applicable compensation schema CSCB leads to a significant decrease of network-wide total cost compared to CS. Yet, what is even more important is the result that by simply applying the cost-based compensation schema the network can exhaust nearly all cost saving potentials and reach the cost level of centralized planning.

In a second analysis we have measured the profit gains for the individual network partners resulting from their participation in the network. For that purpose we have calculated for every partner and for every week the gain with respect to contribution to profit. Here we could observe, that in the case of CS only a rather small number of network partners receive the bulk of the (relatively small) cooperation profit. On the other hand, using CSCB the (relatively larger) profit is distributed much more equally und thus more fairly among all network partners: The number of partners which gain a positive profit is significantly larger and the profit is distributed more evenly. Thus, with respect to the equality principle from the theory of distributive fairness the profit allocation resulting from CSCB is more fair than the one resulting from CS. Furthermore, the absolute profit each partner receives is larger than in CS, since the total amount to divide is larger.

A Multi-objective Approach for Pre-positioning Warehouses in Humanitarian Logistics

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1. Introduction

In the recent decade natural disasters start to be more on the public eye due to the increase in both the number and the impact of the disasters. The 2011 Tohoku Tsunami in Japan and the 2012 Sandy Hurricane in USA cost $223 and $52billion to the world economy, respectively. Observing more than 300 disasters per year is the norm nowadays since the millennium whereas that number was around 200 annually before [1]. By the year 2020, the world's population will be very close to eight billion people and unfortunately most of the people will be prone to the effects of the more frequent and more devastating disasters since they are living in states where fragility, conflict and violence is observed.

In collaboration with a research group from Georgia Institute of Technology, CARE investigate pre-positioning strategy for disaster relief items and completed the establishment of the Dubai, Panama and Cambodia warehouses by 2009 [2]. When disaster strikes, CARE provides emergency relief items such as food, supplies, water, sanitation and shelter to the affected people from its warehouses to provide fast and effective relief. But as stated above since the number of people to be affected by disasters are expected to be more in the near future and disasters trends are changing due global warming, how to expand such an established pre-positioning network calls for further academic research.

Bozkurt and Duran [3] work on analyzing the pre-positioning network of CARE International with the consideration of changing disaster trends and utilizing the historical disaster data between the years of 1977 and 2006 which are grouped into three decades. They show that Panama and Cambodia are robust locations when all three decades are considered but the location of the third warehouse changed from Italy to India in the second decade and settled at Dubai in the last decade ended by the year 2006.

In this study we improve the work of Bozkurt and Duran [3] in two ways. We use the most recent decade data (2007-2016) from the Emergency Events Database (EM-DAT) in our mathematical model and also apply a multi-objective approach to the expansion problem to obtain robust solution.

2. Method and Results

As explained in the previous works [2, 3] demand instances are created by grouping disasters occurred in two-week time periods in a region. With this assumption, 237 demand instances are obtained using the disaster data of the decade of 2007-2016. Although the model allows that an affected person in a region may require different combination of relief items according to the region of the world where she/he lives, since there is no evidence for discriminating the regions or disasters with respect to required relief items, we assume all of the affected people will demand the same combination of relief items when a disaster occurs. We assume that all of the affected people in a certain region will need the same demand package and all disaster events in the data set which is given for the years between 2007 and 2016 will occur in the future, at least for a reasonable strategic planning period, with the same frequency. Total inventory stored in the warehouses is assumed to be the average demand of 237 demand instances which is equal to 38,000,000 units.

With similar data collection methodology and mathematical modeling techniques to the previous works [2, 3], and considering maximum response time and maximum water delivery time as additional objectives to the average response time, we find 17 non-dominated solutions out of 402 solutions. When these non-dominated solutions are examined, the three-warehouse configuration of Honduras – Kenya – Hong Kong and the four-warehouse configuration of Honduras – Denmark – Kenya – Hong Kong are selected as most applicable ones.

Although Bozkurt and Duran [3] suggested the opening of a new warehouse in Kenya as the fourth pre-positioning warehouse and moving the half of the inventories in Dubai warehouse to Kenya with the usage of 2007-2010 data, when the complete 2007-2016 disaster data is utilized and additional objectives to the average response time is considered we cannot suggest the usage of Dubai warehouse anymore. CARE International should open the Kenya warehouse and pre-position 40-46% of all relief items other than tents to this location while starting to operate the Denmark warehouse instead of Dubai warehouse.

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Workforce Scheduling for Service Routing with Crowdsourced Drivers

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1 Introduction

We observe substantial changes in urban transportation service business models such as e-commerce delivery, passenger transportation, grocery delivery, or restaurant meal delivery [5]. The changes comprise both customer demand as well as the service workforce. Customers spontaneously request during the day and expect fast and reliable service within a short period of time. For service, many companies such as Amazon Flex, Uber, or Grubhub completely or partially rely on crowdsourced workforces [1]. Crowdsourced drivers are not controlled by the providers but opt in spontaneously to conduct services for an uncertain amount of time. Thus, service providers experience uncertainty in both customer demand and the available workforce. In this uncertain environment, companies struggle to satisfy customer demand cost-efficiently. Especially the volatility in crowdsourced driver availability impedes service quality and leads to customer dissatisfaction [3]. Recently, companies start hiring complementary controlled drivers to counterbalance the volatility of the crowdsourced drivers [6]. Controlled drivers are paid to work for a predefined shift in the day. The question arises how to schedule the controlled drivers to allow cost-efficient services while maintaining a high service quality for the customers.

In this work, we address the workforce scheduling problem with crowdsourced drivers (WSPCD). The WSPCD bases on an underlying operational dynamic service routing problem, where during a service period both controlled and crowdsourced drivers fulfill customer service requests. The customer requests and crowdsourced driver appearances are uncertain. In this work, we assume the underlying problem is the dynamic delivery of goods from a depot to customers within a delivery deadline. A solution for the WSPCD is a daily schedule of shifts for the controlled drivers. For each solution, we can measure the customer service quality. In our case, we measure the percentage of requesting customers we can offer service to. A feasible WSPCD-solution needs to satisfy a predefined service level. The objective is to find a feasible solution with minimal working hours for the controlled drivers.

Setting up a schedule of shifts for the controlled drivers is challenging. As for other workforce scheduling problems, for example for call centers, schedules need to consider uncertain customer demand. For the WSPCD, developing suitable solutions is even more challenging for two additional reasons. First, we observe uncertainty in the crowdsourced workforce. Second, there is potential for service consolidation. This consolidation manifests in both time and space. Customer services may be postponed, for example, as long as their deadline holds. Furthermore, adjacent customers may be served by the same driver at only limited additional driving time.

To derive effective schedules, we develop and combine methods of continuous routing approximation (CRA) and value function approximation (VFA). CRA approximates a function for the costs of serving a certain number of customers by capturing spatial consolidation effects [2]. We use CRA to determine an initial schedule based on the expected hourly workload and the expected crowdsourced drivers. To capture the temporal consolidation and the dynamism of the underlying problem, we apply VFA [4]. The VFA starts with the CRA-solution and uses simulations to learn the "value" of having a certain number of controlled drivers in an hour. One additional challenge in the VFA is the service level constraint. To address this, we introduce penalty functions based on the gap between promised and realized service quality.

We test our policy for 112 different instance settings with different delivery deadlines, customer orders, and behavior of the crowdsourced drivers. Figure 1 provides a short summary of the results. The x-axis shows four policies: our policy, CRA and VFA applied in isolation, as well as one exemplary benchmark policy, CallCenter. The benchmark policy schedules drivers relative to the expected number of orders and crowdsourced drivers. It ignores consolidation and temporal interdependencies. The y-axis shows the average working hours for the controlled drivers. The values of the bars indicate the average reduction in working hours of our policy. We see that our policy outperforms the benchmark policy substantially. While both CRA and VFA perform very well compared to the benchmark policy, our policy further improves the solution quality, thus, combining the respective strengths of the individual components.

We derive the following managerial insights:

- One controlled driver can replace between one and four crowdsourced drivers per hour. The value of controlled drivers is highly dependent on the underlying business model. For delivery companies with narrow deadlines, crowdsourced drivers have a high value. For business

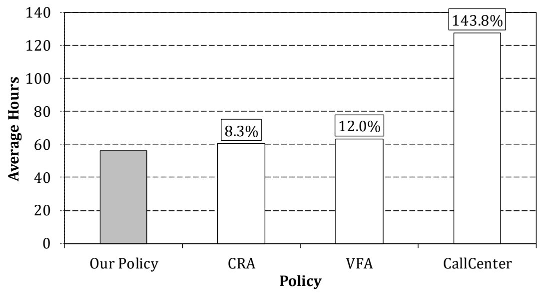

Figure 1: Summary of the Results

models with long deadlines, controlled drivers allow consolidated shipments when they start their shift. Short-time crowdsourced drivers add less benefit.

- It is valuable to keep crowdsourced drivers longer in the system to enable consolidation and to reduce potential setup times. There may therefore be value to incentivize drivers to stay in the system. Furthermore, volatility in the number of crowdsourced drivers per day causes additional costs. Companies should therefore also incentivize crowdsourced drivers to work on a daily basis.
- There is value in crowdsourced drivers pre-announcing their availability a certain time ahead. Again, this value depends on the underlying business model. For delivery companies with narrow deadlines, pre-announcements do not add significant value. For delivery companies with longer deadlines, pre-announcement is very valuable.

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The Joint Network Vehicle Routing Game

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1 Introduction

Collaborative transportation can significantly reduce transportation costs. However, allocating the remaining transportation cost to the collaborating companies remains difficult. We consider the cost-allocation problem which arises when companies, each with multiple delivery locations, collaborate by consolidating demand and combining delivery routes, effectively joining their distribution networks. We model the corresponding cost-allocation problem as a cooperative game: the joint network vehicle routing game (JNVRG). In this abstract, we refer to each company as a player and a group of companies as a coalition.

As is common in cooperative game theory, to allocate the costs we provide a method to identify a core allocation. A core allocation ensures that each coalition is worse off if they decide not to cooperate with all other players. The set of all such allocations is known as the core.

The vehicle routing game (VRG) is a game similar to the JNVRG, in which every player corresponds to a single delivery location instead. Numerical experiments are presented in [1] for instances with at most 25 delivery locations. In [2] the VRG with a heterogeneous fleet is considered and a single instance is solved consisting of 21 delivery locations.

Furthermore, in [3], [4] and [5] variants of the JNVRG are studied in which each player does correspond to multiple delivery locations. The former two consider a pick-up and delivery setting, while the latter a standard vehicle routing setting. In [3], transportation costs are determined heuristically, which allows instances to be solved consisting of 5 players and 50 pick-up and delivery requests. In [4], transportation costs are instead determined exactly, and instances are solved consisting of at most 5 players and 25 pick-up and delivery requests. For many instances, they report computation times in excess of 12 hours per instance. In [5], instances consisting of 4 players and 200 delivery locations are solved, while transportation costs are determined heuristically. Observe that the algorithms in [3] and [5] perform well for a large number of delivery locations, but we do not expect any existing algorithm to perform well for a large number of players.

We have developed a row generation method to identify a core allocation for games with a larger number of players. Using our algorithm we are able to solve instances ranging from 5 players and 79 delivery locations to 53 players and 53 delivery locations within 2 hours of computation time. Note that this implies good performance for the JNVRG but also in the special case of VRG. Also note that, as opposed to [3] and [5], we use exact transportation costs instead of heuristically determined costs.

2 The Joint Network Vehicle Routing Game

In order to formally introduce the JNVRG, we first define the CVRP. Consider a complete directed graph $G = (V, A)$. The vertex set V is defined as $\{0\} \cup V'$, where 0 represents the depot and V' represents the set of all delivery locations, also referred to as customers. With each arc $(v, w) \in A$, a travel cost $c_{vw} \geq 0$ is associated, which we assume to adhere to the triangle inequality. Furthermore, each customer $v \in V'$ has a demand $d_v > 0$. An unlimited number of vehicles with capacity Q is available at the depot to satisfy the demand by visiting customers along routes. A route is defined as a simple cycle, starting and ending at the depot, such that the total demand does not exceed the capacity. We assume that $d_v \leq Q$ for all $v \in V'$. The CVRP is the problem of constructing routes in such a way that the total cost is minimized and every customer is visited exactly once.

Next, we define the JNVRG. Let $N = \{1, 2, \ldots, n\}$ be the set of players. The set V' is the combined set of the customers of these players. In particular, $V'(i) \subset V'$ represents the customers of player i where $\bigcup_{i \in N} V'(i) = V'$ and $V'(i) \cap V'(j) = \emptyset$ for $i, j \in N$ with $i \neq j$. The cost $C(S)$ of coalition $S \subseteq N$ is the minimal cost of the CVRP on the subgraph $G(S)$ induced by $V'(S) \cup \{0\}$, where $V'(S) = \bigcup_{i \in S} V'(i)$ represents all customers of the players in coalition S. We define the JNVRG as an n-person cooperative game $\langle N, C \rangle$, where the aim is to allocate the cost $C(N)$ to the players.

3 Cost allocation method

We developed a row generation method to find a core allocation. We performed experiments to specifically find the EPM allocation ([6]), although the method could also be used to find other types of core allocations. The EPM is a cost allocation that can be found by solving a linear programming (LP) problem. It has an exponential number of constraints, required to describe the core. In the row generation algorithm, we initially relax most of these constraints and solve the relaxed LP problem. Next, we solve a row generation subproblem to identify a violated constraint. If one is identified, we add the constraint and iterate, otherwise the EPM allocation is found.

We model the row generation subproblem as a price collecting vehicle routing problem, in which a price is collected if all delivery locations of a single player are visited. We solve this problem using a branch-price-and-cut algorithm based on existing algorithms for vehicle routing problems.

To speed up the row generation algorithm we use the following techniques. First, we generate rows by relaxing the row generation subproblem, exploiting the tight LP bounds for our formulation of the row generation subproblem. This potentially results in the identification of constraints that are not violated, but this effect is generally offset by the increase in speed by which the row generation subproblem is solved. Secondly, we also solve the row generation subproblem heuristically and only solve it to optimality when the heuristic fails.

Our algorithm has been tested on instances of the JNVRG and VRG, which we have generated based on the the well-known A-instances and Solomon instances for the CVRP. They have been modified by selecting delivery locations to correspond to a single player, for various numbers of players. Experiments showed that in terms of computation time our row generation algorithm greatly outperforms a standard approach of trying to solve the LP problem as a whole. Furthermore, our proposed speed-up techniques help to reduce computation time even further.

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Verifiable Stability in Collaborative Transport

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1 Introduction

We consider a setting in which multiple companies collaborate in their transport operations. Each company has a set of delivery locations requiring a visit from a vehicle to satisfy demand. Although it is well-known that collaboration can lead to reduced transport costs, the remaining costs still need to be allocated to each company. A standard approach is to model this collaboration as a cooperative game, in which each company is referred to as a player and each set of players as a coalition. With each coalition a cost is associated, which represents the costs of transport operations. To allocate costs, it is standard to use a so-called core allocation, see e.g. [1], [2] and [3]. We provide a definition of the traditional core of a cooperative game and comment on the limitations of using a core allocation in practice. We introduce the concept of verifiable stability and provide an allocation method which is verifiably stable. We argue that our verifiably stable allocation method overcomes the limitations of a traditional core allocation, while in some sense upholding the concept of rationality on which core allocations are based. We will perform experiments to demonstrate the tractability of our approach and compare it to traditional core allocation methods.

2 The traditional core and its limitations

We define a cooperative game $\langle N, C\rangle$, where N is the set of players and C provides the costs, where we denote $C(S)$ as the cost of coalition $S \subseteq N$. In our application, the cost $C(S)$ results from solving a vehicle routing problem to make deliveries to all the delivery locations of the players in S. In practice, this typically involves all kind of problem specific features, such as capacity constraints, time windows, a heterogeneous fleet, multiple depots, time dependent travel time, etc. We will generically call the underlying optimization problem that needs to be solved to compute C, a rich vehicle routing problem (rich VRP).

The core of a game is defined as follows. Let y_i be the cost allocated to player i, for all $i \in N$, and $y(S) = \sum_{i \in S} y_i$ for all $S \subseteq N$. A cost allocation is said to be efficient if $y(N) = C(N)$. Furthermore, a cost allocation is said to be rational if it satisfies the rationality constraints $y(S) \leq C(S)$ for all coalitions $S \subset N$. The rationality constraints ensure that no coalition has an incentive not to cooperate. The set of rational and efficient cost allocations is known as the core [4] and is described as

$$\text{Core}(\langle N, C \rangle) = \{y : y(S) \leq C(S) \; \forall S \subset N, y(N) = C(N)\}. \tag{1}$$

Obviously, finding a core allocation poses challenges. Firstly, the number of rationality constraints grows exponentially in the number of players. Secondly, computing the costs $C(S)$ can be very difficult for rich VRPs. To deal with the exponential number of constraints, it has been proposed to find a core allocation by solving a linear programming problem, which includes these rationality constraints, by means of row generation techniques. This is for instance done in [1]. In a row generation algorithm, a row generation subproblem is repeatedly solved which answers the question: Does there exist a coalition for which the rationality constraint is violated? It seems that the row generation subproblem is at least as difficult as the rich VRG, which clearly limits the applicability. Secondly, to overcome the difficulty of computing $C(S)$, one might defer to heuristic methods instead of exact methods for the rich VRP, as is done in [3]. However, when $C(S)$ is defined based on a heuristic, it is not clear how to employ row generation, and as a result we suffer again from the exponential number of rationality constraints.

Furthermore, all previous studies on cooperative transport games, assume there is a single algorithm for solving all rich VRPs to determine costs. In practice, however, there might not be such a single algorithm. Different companies use different planning methods, ranging from manual planning to highly sophisticated planning software. Not every coalition of players will have the same planning methods at their disposal, which we believe should be taken into account when defining a game, core and allocation.

Setting aside for a moment the limitations of finding a core allocation, there is still the matter of players who need to accept the allocation. The concept of the core is in our view that a player accepts an allocation if it is not able to form a coalition (other than N) to achieve lower costs than allocated. This is not an easy task to verify. For a player to accept an allocation, it needs to answer the following verification question negatively: Does there exist a coalition that includes me for which the rationality constraint is violated? Observe that answering this question seems almost as difficult as solving the above mentioned row generation subproblem. Hence we argue that the same reasons that prevent us from finding a core allocation, also prevent a player from verifying (and thus accepting) such an allocation.

3 A practical game and verifiable stability

We propose a practical way to model a cooperative transportation game. We suppose each player has their own algorithm, and we define $C_i(S)$ as the cost of coalition S as computed using the algorithm of player $i \in N$, where we assume each player has access to all relevant information. Moreover, we assume that if a coalition cooperates, it has the algorithms of all players in that coalition at its disposal, so we define $C(S) = \min_{i \in S}\{C_i(S)\}$.

Furthermore, each player $i \in N$ has a verification algorithm V_i at its disposal. Given a cost allocation y, $V_i(y)$ provides a (potentially empty) set of coalitions that all include player i and for which the rationality constraints are violated. We wish to emphasize that V_i could be a heuristic algorithm, which might not identify all violated rationality constraints. This allows a representation of the current situation in many real world applications, in which the ability to perform this verification is often limited. For instance, a simple verification method could be to verify if the allocated cost is smaller than the stand-alone cost of a player. We will consider more advanced algorithms by generalising the rich VRP algorithms.

We call an allocation y verifiably stable, if $V_i(y) = \emptyset$ for all $i \in N$. This also provides us with a method to identify verifiably stable allocations. For LP based allocation methods, we can apply a standard row generation procedure in which we solve the row generation subproblem of identifying violated coalitions by applying V_i for all $i \in N$.

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Stable Exchange for Commute-Driven Sharing of Private Parking Lots

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1 Abstract

Downtown parking has been a major challenging issue in many large cities, because of the heavily imbalanced demand for parking and the short supply of parking spaces. Due to rapid urbanization, more and more people in China choose to commute by driving. However, the number of new parking lots is not increased significantly to match with the growing parking demand. As reported by CBNData & ETCP (2017), in 2016, the supply gap for the parking demand in the major cities of China is more than 50%. The parking problem is becoming critical for many commuters who do not have a reserved parking space around their workplaces. During the peak hours, they have to spend considerable time searching for an unoccupied parking space. The insufficiency of parking also becomes an important yet often ignored source of traffic congestion (Zou et al. 2015).

Although the excessive demand for parking exists, the average utilization rate of the existing parking spaces is merely 51.3%. One reason for the low utilization rate is that the parking demand

typically arises on a peak and off-peak schedule, and demonstrate complementary patterns. That is, during the working time in a day, "office parking lots" are generally full while "residential parking lots" are mostly empty. If an office parking lot and a residential parking lot are located near each other, a straightforward idea is to allow some commuters whose workplaces are nearby to park their cars using the unoccupied parking spaces in the residential parking lot.

During the daytime, a driving commuter may rent out his own private parking space at a residential housing estate while using the private parking space of another commuter near the workplace, i.e., *exchanging the rights of use*. This is an example of the emerging concept known as *shared parking*. With exchange, it not only helps commute drivers avoid the cruising-for-parking but also generates extra income for them, allowing for efficient and optimized use of existing parking infrastructures (Institute for Transportation & Development Policy 2014).

In China, shared parking by individuals is difficult, due to the complications in the ownership of parking spaces and administration. For example, cars without permits from the housing estate agency cannot enter a residential parking lot. The estate agencies address concerns about additional cost caused by managing outside car traffic and installing new equipments, while some other residents may also oppose with the reasons including security issues and potential inconvenience to their own parking need (Southcn.com 2017). Thus, the sharing of residential parking spaces generally requires the consent of a majority of residents and the assist of the estate agency. This is also true for sharing apartment parking spaces in some densely populated cities of other countries (Sansom 2014). In such cases, it is necessary to consider the commuters at the same housing estate as a group that make collective decisions. In practice, usually the agency of the housing estate is designated by the group of commuters to manage their parking spaces, and shares the revenues with the commuters. Individual commuters do not need to make any decisions in how to exchange their parking spaces.

With the revolution of communications technology and the latest rise of the internet of things (IoT), shared parking is generally organized by an e-platform, e.g., ParqEx (U.S.), JustPark (U.K.), and Airparking (China). Airparking is a Chinese startup founded in 2015, aimed to create a win-win solution for real estate companies, car owners, and property owners. To achieve this, for each fulfilled order, the estate agency gets $10\% \sim 20\%$ of the revenue, while 50% to the owner and the remaining $30\% \sim 40\%$ to Airparking (Sohu.com 2017). By the end of June 2017, Airparking has over 400,000 parking spaces signed up on the platform by contracting with many estate agencies in ten large cities of China (Sohu.com 2017). However, the platform allocates parking spaces to random demands generally on the first-come-first-serve basis, which may not optimize the use of parking spaces. Such mode of shared parking works very similarly to Ridesourcing; that is, the individual owners mainly benefit from the revenues. Due to the issues discussed as above, the attractiveness of revenues is rather limited, as the development of this market is slow. Clearly, new modes for shared parking should be investigated.

In this paper, we consider that commuters owning private parking spaces are grouped as a single entity and represented by the estate agency for each housing estate in the shared parking system operated by an e-platform. The e-platform decides how the private parking spaces are exchanged and the transfer prices among the agencies to optimize the use of private parking spaces. Specifically, the e-platform assigns to each agency a quota of parking spaces from every other agencies. Before leaving for work, the commuters of each agency book private parking spaces near their workplaces through the e-platform, and the number of successful bookings cannot exceed the given quota.

A distinctive feature of the commute-driven shared parking system is that the total parking spaces that an agency can share depends on the total quotas received from others. This is a *many-to-many exchange economy* with multi-unit valuation. Each estate agency's objective is to maximize the welfare of its own commuters, including the travel cost savings from buying and the profits from selling. To motivate agencies' participation, the e-platform must design a "stable" exchange scheme and fairly distribute the benefits. This is the central issue investigated in this paper. We extend the stability concept proposed by Ostrovsky et al. (2008) and Hatfield et al. (2013) to our setting and develop an algorithm based on the M-convex submodular network flow model proposed by Murota (1999) to search stable solutions.

Our paper studies a new sharing economy with multi-unit valuation and contributes to the literature in the following aspects. *First*, the shared parking problem in the multi-unit exchange case is more practicable especially in China but not studied yet. Our model can facilitate this sharing practice with a stable exchange scheme. *Second*, we extend the stability concept for the single-unit exchange economy to the multi-unit case, where agents can buy and sell multiple units of the same good with each other. Monetary transfer payments are necessary. *Third*, we develop an algorithm based on an M-convex submodular flow model to search stable solutions. We prove that the exchange scheme derived from the algorithm is stable, efficient, weakly budget balanced, and in the core when the transfer prices are non-discriminated for any realized exchanges. *Finally*, we show that the stable scheme is highly effective by conducting extensive computational experiments and also provide a variety of managerial insights for practice.

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Decomposition Methods for Dynamic Load Planning and Driver Management in LTL Trucking

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1 Introduction

We address the problem of dynamically managing the flows of shipments and drivers for a major LTL carrier using a parameterized lookahead policy that is tuned in a stochastic simulator. It involves simultaneously determining the least-cost paths for all shipments from origin to destination, through transfer terminals, *and* their consolidation in trailers moving between successive terminals in the paths. We consider constraints on the availability of company drivers *and* on the total amounts of freight that can be moved by rail and/or contracted drivers. A major challenge has been developing a solution strategy that is acceptable to the business, which required a solution approach that focused on incremental changes with a high level of transparency.

The optimization problem uses the framework of designing an operational policy that is effective and implementable. The core framework can be written as

$$\min_{\pi} \mathbb{E}\{\textstyle\sum_{t=0}^{T} C(S_t, X^{\pi}(S_t|\theta))\} \text{ where } S_{t+1} = S^M(S_t, X^{\pi}(S_t|\theta), W_{t+1})$$

and where exogenous inputs are described through $S_0, W_1, W_2, \dots, W_T$. This abstract focuses on the design of the policy $X^{\pi}(S_t|\theta)$ which is a parameterized lookahead model controlled by tunable parameters θ which manage issues such as dispatch of partial trailers or the savings before accepting a change in the base load plan.

Section 2 describes the model and section 3 summarizes the status of the implementation and estimated benefits.

2 The lookahead policy

Given a snapshot of the state of the system (shipments and drivers) at a certain time, the dynamic load planning problem, $X^{\pi}(S_t|\theta)$), is solved as a deterministic lookahead optimization problem over a time horizon H, starting at time $t = 0$. Usually too large to be solved in a single shot, the problem is decomposed into T sub-problems, each over a time period of length τ, so that $T \times \tau = H$. These sub-problems are solved consecutively and are linked to each other by an underlying simulation procedure.

For each optimization sub-problem spanning the time period $[t', t' + \tau)$, where $t' \in \{t, t + \tau, \dots, t + (T - 1)\tau\}$, let I be the set of shipments that need to be handled within that time period (we will omit time subscripts for the sake of clarity). Shipments can be actual ones already in the system at the snapshot time, or shipments forecasted to enter the system during the optimization horizon $[t, t + H)$.

Let $\mathcal{J}$ be the set of trailer *buckets*, with a given origin and destination, that shipments can be loaded onto. Each bucket will be composed by one or more trailers, loaded at the current location of the shipments and destined to their next load-to point. Besides the origin and destination, other distinguishing attributes of these buckets are the service network type (expedited or standard), the cargo type (hazardous or not), and the transportation mode (company drivers, rail, or contracted drivers). Let $\mathcal{K}$ be the set of different company driver types, each characterized by the driving time range of the dispatch legs in which the drivers primarily drive (for e.g., multi-day, single-day or half-day legs). Let $\mathcal{M}$ be the set of partitions of the dispatch legs, based on their directions (say, forward or back haul). Finally, let $\mathcal{N} = \{A, R + C, C\}$ be the set of three partitions of the transportation modes, where A represents the combination of all modes, $R + C$ represents the combination of rail and contracted drivers, and C represents contracted drivers only.

The optimization *decision variables* are: $\boldsymbol{x_{ij}}$, the 0/1 variable on whether shipment i will be assigned to bucket j; $\boldsymbol{y_j}$, the integer variable on the number of trailers closed in bucket j, with a given upper bound U_j; $\boldsymbol{z_{km}}$, the variable on the deficit of available duty hours of company drivers of type k, driving on dispatch legs in the direction m; and $\boldsymbol{v_n}$, the variable on the ton-mileage excess in transportation mode partition n. The slack variable in the capacity of bucket j ($\boldsymbol{s_j}$) can be computed from the previous variables in the appropriate constraint, but was explicitly included in the model for the sake of clarity.

The *cost parameters* in the minimization objective function are: $\boldsymbol{\bar{c}_{ij}}$, the estimated cost of moving shipment i from the destination of trailer j to the shipment's final destination (including mileage and/or transfer costs, and penalties for delivering the shipment late); and $\boldsymbol{\bar{p}_j}$, the estimated line-haul cost of moving one trailer in bucket j from its origin to destination.

The *constraints* ensure that: (1) each shipment is assigned to one bucket only; (2) the loading capacity of each bucket is not exceeded; (3) the available driver capacities are not exceeded; and (4) the maximum allowed ton-mileage percentages in rail and contracted drivers are not exceeded. The *operational parameters* in these constraints involve the calculated ton-mileage of shipment i in bucket j ($\boldsymbol{\bar{w}_{ij}}$) and the total ton-mileage capacity of bucket j ($\boldsymbol{\bar{B}_j}$); the estimated driver duty hours associated to trailer j in dispatch leg l ($\boldsymbol{\bar{h}_{jl}}$) and the available duty-hours of drivers of type k in legs in the direction m ($\boldsymbol{\bar{D}_{km}}$); and finally the calculated ton-mileage for shipment i in trailer j in mode partition n ($\boldsymbol{\bar{r}_{ijn}}$), the estimated maximum desired percentage of mode partition n during an optimization time period ($\boldsymbol{\bar{G}_n}$) and the estimated ton-mileage in mode partition n carried over from the previous time period ($\boldsymbol{\bar{Q}_n}$).

The optimization sub-problem can then be stated as the following MIP:

$$Min_{x,y,z,v} \sum_{i \in I} \sum_{j \in \mathcal{J}_i} \bar{c}_{ij} x_{ij} + \sum_{j \in \mathcal{J}} (\bar{p}_j y_j + P_1 s_j) + P_2 \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} z_{km} + P_3 \sum_{n \in \mathcal{N}} v_n$$

subject to:

$$\sum_{j \in \mathcal{J}_i} x_{ij} = 1 \qquad \forall i \in I \quad (1)$$

$$\sum_{i \in I_j} \bar{w}_{ij} x_{ij} + s_j = \bar{B}_j y_j \qquad \forall j \in \mathcal{J} \quad (2)$$

$$\sum_{j \in \mathcal{J}_{km}} \sum_{l \in L_{jkm}} \bar{h}_{jl} y_j - z_{km} \leq \bar{D}_{km} \qquad \forall k \in \mathcal{K};\ \forall m \in \mathcal{M} \quad (3)$$

$$\sum_{i \in I} \sum_{j \in \mathcal{J}_i} (\bar{r}_{ijn} - \bar{G}_n \bar{r}_{ijA}) x_{ij} - v_n \leq \bar{G}_n \bar{Q}_A - \bar{Q}_n \qquad \forall n \in \mathcal{N} - \{A\} \qquad (4)$$

$$x_{ij} = 0\ or\ 1; \quad 0 \leq y_j \leq U_j\ integer; \quad s_j, z_{km}, v_n \geq 0;$$

where P_1, P_2 and P_3 are "sufficiently large" penalties, and $\mathcal{J}_i, I_j, \mathcal{J}_{km}$ and $\mathcal{L}_{jkm}$ are appropriately defined subsets. If P_2 and P_3 are set to zero, constraints (3) and (4) are effectively relaxed.

3 Application to a large LTL carrier: cost saving estimates

We developed an application of the model for an LTL carrier in the USA with a network of 34 major sorting facilities and 264 smaller freight-handling terminals. It picks up about 40,000 new shipments per weekday and has about 4,500 drivers in the line-haul network.

In order to estimate the available duty hours of the drivers in the network, we also developed a driver dispatch simulation model that runs in tandem with the load planning model. In the operational setting where the model has been implemented, the application runs with an optimization time period length τ of six hours. For the model to run within the actual operational constraints *and* to increase the business acceptability of the results, the size of the feasible set of trailer buckets $\mathcal{J}$ had to be controlled. That set obviously has to include all the trailer buckets present in the existing static load plan. We implemented a set of carefully designed business rules to *augment* the static set with a limited but promising set of *load plan adjustments* (LPAs). This strategy resulted in an application that was initially accepted by the business and is currently in production. The expectation is that, as the business becomes more comfortable with the application, we will be able to incrementally increase the size of the set of feasible LPAs in the model.

To evaluate the macro benefits of the application, we ran a set of carefully designed simulations using eight-day historical shipment data from three months in 2018. These simulations show a potential to reduce the total number of shipments delivered late by 12% for the standard service network and 6% for the expedited one, and a potential to increase the total number of delivered shipments per week by 2%; all with an estimated reduction in the total annual cost of operation (line-haul movement plus transfer-handling) of over six million US dollars. All of these results have been developed in close consultation with the carrier, using recommendations that place a high priority on transparency and the ease of implementation. We anticipate that the benefits may increase as the carrier develops confidence in the recommendations.

A Hierarchical Approach Enabling Supplier Choice in On-Demand Platforms

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1 Motivation

On-demand platforms, exemplified by companies like Uber and Lyft, are a disruptive business model. Requests (e.g., a ride, a delivery) are fulfilled by matching independent suppliers (e.g., freelance logistics providers) with demand requests. Current centralized approaches to platform design excel at meeting demand commitments, but limit supplier autonomy. Decentralized approaches provide supplier autonomy, but sacrifice systematic performance and are time consuming. This research proposes a new hierarchical approach, recasting the platform's role as one providing personalized recommendations (i.e., a menu of multiple requests) to suppliers. Supplier choice can increase participation (capacity) and resource utilization when request fulfillment is combined with suppliers' original planned tasks. However, supplier choice also makes task allocation more complicated, requiring new methods to determine which requests and how many to recommend, as well as strategies to mitigate outcomes of supplier choice (e.g., rejections, duplicate selections).

As illustrated in Figure 1, we consider how to design and operate a platform that first must decide how multiple, simultaneous recommendations are made. The same request may be recommended to multiple suppliers to decrease the time to match and to hedge against suppliers' autonomy to decline recommendations. Then, suppliers have autonomy to select requests (if any) from the personalized recommendations. This results in some requests not selected and others with duplicate selections. The

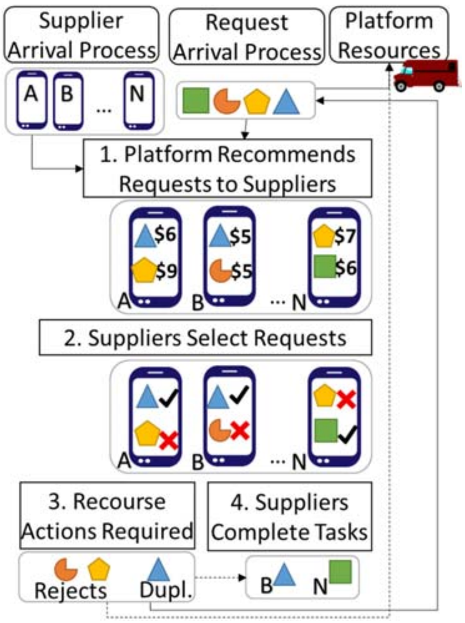

Figure 1: A hierarchical approach to matching requests to suppliers, in which suppliers choose from personalized recommendations.

platform determines recourse actions for these requests, which may be fulfilling rejected requests using platform resources or recommending them to another supplier.

2 Literature Review

Dynamic ride-sharing focuses on matching drivers with riders to share one-time trips [1]. For example, Stiglic et al. (2016) study the use of relay points for drivers to match with more than one rider [6]. Lee and Savelsbergh (2015) consider a dedicated fleet of drivers as a backup plan for serving requests not matched [4]. Wang et al. (2017) enforce dynamic ride-sharing matches to be stable when the platform and the drivers' preferences are known [8]. Other works capture drivers' willingness to participate and availabilities with additional constraints (i.e., limiting number of stops or detour distances but only if the information is provided by the drivers in advance [2,3]). However, all assume driver full compliance of the platform's decisions. None incorporate supplier choice decisions in the optimization model. Related is Powell et al. (2000), in which a platform recommends a single alternative to a single dispatcher who can accept or reject it [7]. Powell et al. (2000) neither incorporates discretion decisions into the optimization model nor considers dependencies in systematic performance due to multiple suppliers' decisions. In summary, none of the existing research for matching supply and demand in platforms considers hierarchical approaches modeling a set of suppliers with discretion in the optimization model.

3. Bilevel Optimization Framework

To guide design questions and to quantify the impact of supplier choice on platform efficiency, effectiveness, and equity, we create a bilevel optimization framework [5]. These models are novel as they capture the interdependent outcomes of supplier selections. By harnessing the problem's structure, we transform the computationally expensive mixed integer linear bilevel problem into an equivalent, single level problem by proposing logical expressions. Able to solve large problems reasonably quickly, we use this framework to answer the open research question: when is supplier choice beneficial? To determine when providing choices can improve a platform's performance, we simulate different scenarios using ride-sharing as a computational study. When a platform is uncertain about suppliers' selections, the hierarchical recommendation model outperforms existing centralized, many-to-many stable matching, and decentralized approaches. We measure how the recommendation or menu size impacts objectives. When supplier utility is known perfectly to the platform, we prove there is no advantage to the platform in offering multiple requests to the suppliers. However, when the platform does not have perfect knowledge of supplier behavior, choice can be useful. As the number of choices increases, suppliers have a higher chance to be recommended a request they are willing to select. This benefits the platform, up to a point. However, due to misalignment between the suppliers and the platform's utilities, larger menu sizes lead to suppliers selecting a request with lower platform benefit. Also, as the number of choices increases, less systematic coordination occurs, and the chance for rejected requests increases. Whether and how much choice is useful to the platform depends on (1) suppliers' willingness to participate in the platform's assignments; and (2) the variability in the suppliers' and the platform's utilities. We find that a platform's lack of knowledge over suppliers' selections can be compensated by providing more choices in environments with either inflexible suppliers or when suppliers' utilities have higher variance than the platform's utilities.

Building upon results of solving a single, snapshot, deterministic optimization problem in [5], on-going work captures multi-period and stochastic optimization problems. The multi-period recommendation problem captures requests and suppliers arriving dynamically in the system and determines policies regarding the recommendation of personalized menus, as well as policies concerning non-complying suppliers and suppliers that continuously get rejected due to consecutive selections that end up being duplicates. In this research, a two-stage multi-period optimization model is developed to explore recommendation policies, specifically whether an overlap of requests between these menus impacts the platform's performance and suppliers' participation. We also examine how to set policies on the time given to suppliers to make a selection. To account directly for the uncertainty in supplier utility, we consider a stochastic bi-level optimization approach. We develop a Sample Average Approximation method and show its computational efficiency.

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Locating a Biorefinery in Northern Spain Using Multi-stage Stochastic Optimization

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Abstract

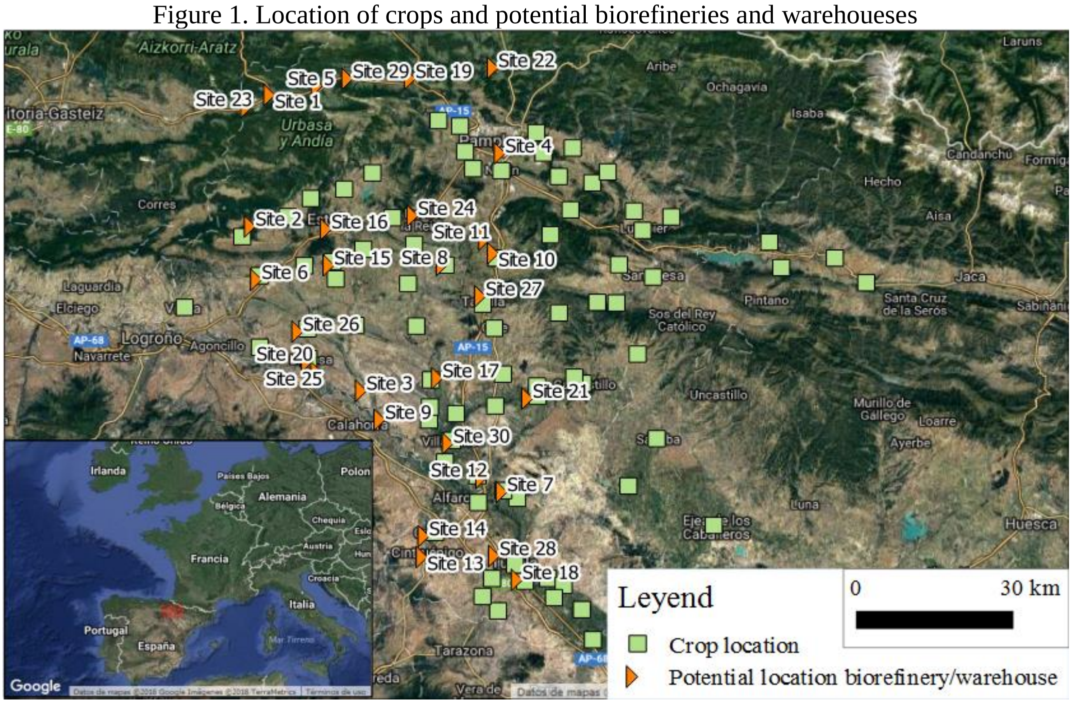
Risk-free decisions are uncommon in business environments. Uncertainties may come from supply and demand sides and they should be taken into account when assessing decision making. Moreover some of those decisions are extremely remarkable in the success of a particular project as the case of facility location decisions in industrial or commercial firms. Consequently, Facility Location Problems (FLP) have been widely studied from many perspectives due to their undoubtable impact on the profitability and survival of location-sensitive projects. In addition, location decisions are particularly risky as they hold resources for a very long time-horizon and influence on forthcoming tactical and operational decisions [1]. Therefore, consideration of uncertainty within the strategic decision of facility location is of utmost interest for stakeholders.

Moreover, energy sector is undertaking a revolution as a new economic and social context is being settled up. Firstly, the European Union (EU) is a major importer of energy resources, especially oil, thus EU countries are seeing oil dependences are threating their economic progress. Secondly, the increasing concern about environmental issues is focusing on transportation sector. Therefore, cleaner fuels and technologies are replacing traditional fossil-fuels vehicles as alternative-fuel vehicles are continuously increasing. In this sense, biofuels are a renewable alternative to fossil fuels in the EU's transportation sector, helping to reduce greenhouse gas emissions. Actually, 10% of transport fuel in EU is aimed to come from biofuels by 2020 [2].

In light of the above, EU countries are seeking to diversify their energy resources by producing alternative and renewable fuel such as biofuels. Therefore, construction of new biorefineries are spreading all around Europe as new and more efficient technologies for biorefining are being developed [3].

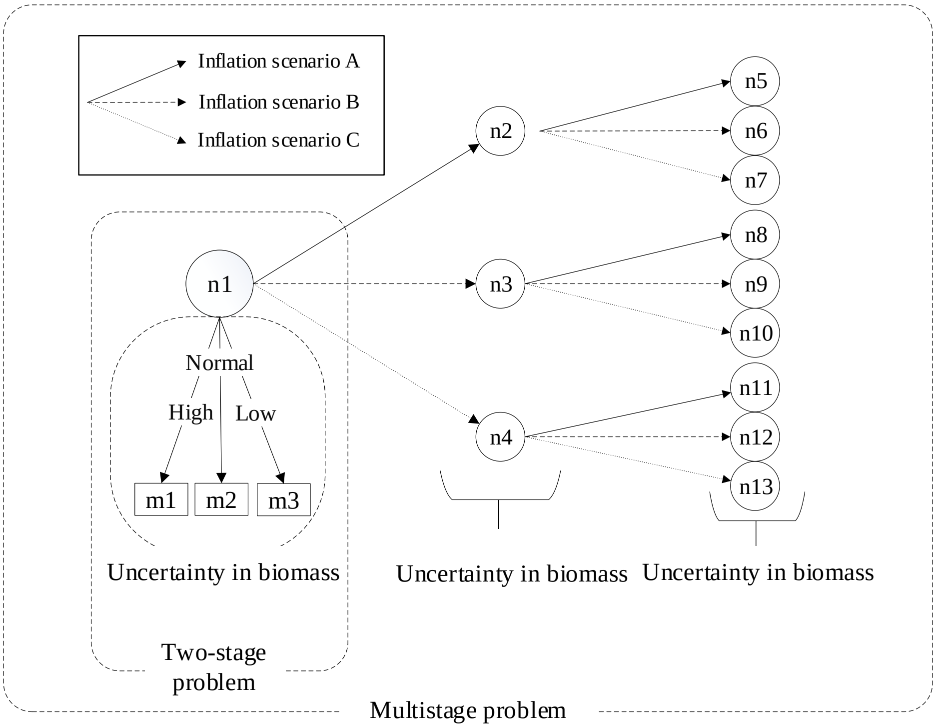
In this context, this paper proposes a methodology to locate a lignocellulosic biorefinery in northern Spain for the production of bioethanol [4]. Figure 1 shows the geographical scope of the problem and lists the selected potential locations for hosting the biorefinery and the warehouses as well as the location of the crop fields. Biorefinery facilities may last for up to 20 years and involve a huge investment. Consequently, a careful and robust analysis should be carried out to ensure the suitability of the location decision. Likewise, supply chain decisions must be also deeply analyzed when deciding infrastructure location, considering crop and biomass selection from the surrounding fields. Uncertainties in biorefinery location mainly come from two sources: the potential lack of biomass availability and the prices volatility. On the one hand, availability of resources for supplying a biorefinery is a critical issue because biomass is weather-dependent and heavily seasonal. In our work, a wide range of biomass with different physic-related attributes such as humidity and depreciation is considered. The outcome is a a model formulation with different scenarios which consider the most frequent uncertainties (prices changes, biomass availability, or use of biomass distribution fleets). Note also that biomass prices are determinant for selecting a biomass type. To this respect, real current prices based on agricultural surveys are employed. Official estimations of prices evolution are also considered within the biorefinery lifetime. Finally, warehousing policy is further analyzed as renting is allowed during the project execution.

Figure 1. Location of crops and potential biorefineries and warehoueses



The problem has strategic decisions about the location of the biorefinery infrastructure, tactical decisions about location and timing of warehouse infrastructures, and operational decisions on the available network during each time period. The uncertainty in the strategic and tactical side is represented in a multistage scenario tree, while the uncertainty in the operational side is represented in two-stage scenario trees which are rooted at the tactical nodes. The backbone of the proposed model is displayed in the Figure 2. On the one hand, we consider 13 strategic nodes (from n1 to n13) in the three-stage scenario tree accounting for 9 strategic scenarios based on the price evolution (inflation scenarios A to C). On the other hand, three operative scenarios are rooted on each tactical node describing the uncertainty on biomass availability (high- m1-, normal- m2-, and low- m3- disposal of biomass). This scheme is replicated in the rest of nodes accounting for 39 operative scenarios. Therefore, a robust multi-stage biorefinery location model is developed to cope with uncertainties based on biomass availability and prices. Thus, three kinds of decisions are taken into account: firstly, we consider the strategic decision of biorefinery plant location; secondly, the tactical decisions about intermediate warehouses time period-location and crop/biomass selections; and, finally operational decisions regarding fleet management.

Figure 2. The proposed multistage tree



Outstanding managerial implications are expected being the model able to provide a robust solution about biorefinery location based on biomass-related uncertainties. Furthermore, a detailed supply chain is also reported subject to the chosen robust optimal location.

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Pricing strategy of ridesharing service under travel time variability

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1 Introduction

Ride-sourcing refers to an emerging urban mobility service provided by transportation network companies (TNCs) from a for-hire private car owner pool. TNCs, such as Uber and Lyft in the U.S., Didi Chuxing in China, have greatly changed the transportation industry. These companies efficiently match the nearby supply and demand. They also encourage the ridesharing behavior by providing fast, convenient and cheap online matching platforms. With the development of TNCs, the ridesharing market has seen significant growth in recent years and the economy quickly becomes the new norm.

The implementation of ridesharing is an efficient way to ease congestion and reduce emissions by substantially increasing vehicle occupancy. To promote ridesharing, many studies are dedicated to the pricing strategy. Zha et al. [1] used time-expanded network to represent the work schedules of drivers and investigated the impact of surge pricing. Wang et al. [2] studied the driver-rider cost-sharing strategies and equilibria in a ridesharing program. Liu and Li [3] derived a time-varying compensation scheme to maintain ridesharing service at user equilibrium and discussed the departure orders in a morning commute problem.

However, few studies pay attention to travel time variability when analyzing shared mobility service, even though it has been recognized as a major obstacle for commuters to choose shared mobility service for work. The research of Rayle et al. [4] showed that most of the travelers choose shared mobility service for social/leisure purposes. Li et al. [5] addressed that people are willing to pay for improved travel time reliability. In the ride-sourcing market, travel time variability is a key factor for people to choose between solo-ride and ridesharing services, or convert to a public transit trip. Compared with a single-rider trip, a ridesharing trip makes multiple stops and detours to pick up different passengers, which increases both their travel time and travel time variability. As a compensation, ridesharing customers enjoy cheaper prices than non-sharing ones.

Recognizing the importance of travel time variability, this study makes the following contributions. The first contribution is that we develop an integrated framework for modeling ride-sourcing services, including both ridesharing and non-ridesharing ones under travel time uncertainty. The modeling framework captures the interaction between travel time variability, pricing strategy and demand under the competition of different modes. In this framework, the important factors influencing travelers' choice regarding to the ride-sourcing services are addressed, such as waiting time, detour time, in-vehicle time, travel time uncertainty, monetary cost and etc. The endogenous relationship between these factors will be analytically formulated. Such understanding will be helpful to propose or promote the ridesharing services. The second contribution is that we propose pricing strategies to achieve specific goals, which can be profit maximization from the perspective of ride-sourcing company, or to promote the ridesharing service and improve the social welfare from the perspective of the government.

2 Problem formulation

Consider a given number of N heterogeneous non-car owners who have different values of waiting time, in-vehicle time and travel time reliability. They commute through a corridor connecting a residential area and a workplace. It is assumed that there is a ride-sourcing company providing non-sharing (NS), i.e. solo-rider service and ridesharing service (RS) for travelers. The total fleet size of the company is fixed. Travelers have three available travel modes: NS, RS and public transportation (PT). For those who intend to join the ridesharing program but fail in matching, they can only use the NS service. For the NS and RS services, the travel times of travelers are assumed to be stochastic and the uncertainty of travel time can be characterized by its standard deviation. According to Fosgerau [6] , the variance of travel time generally increases with congestion level.

2.1 Mode choices of the heterogeneous travelers

The generalized cost of travelers can be categorized into (1) time-related cost, (2) monetary cost and (3) inconvenience cost. For the time-related cost, we define w_{ns} and w_{rs} as the expected waiting time for NS and RS services, respectively; μ_{ns} and μ_{rs} are the corresponding expected in-vehicle times; σ_{ns} and σ_{rs} represent the standard deviations of the in-vehicle times. For the monetary cost, τ_{ns} and τ_{rs} indicate the prices for the trips. The inconvenience cost is denoted as δ for RS service and is 0 for NS travelers. Set the cost of public transport to be a constant c. For a traveler with value of waiting time α, value of in-vehicle time β and value of reliability γ, the generalized cost of the three choices are listed as follows:

$$C_{ns}(\alpha,\beta,\gamma)=\alpha w_{ns}+\beta\mu_{ns}+\gamma\sigma_{ns}+\tau_{ns} \tag{1}$$

$$C_{rs}(\alpha,\beta,\gamma)=\alpha w_{rs}+\beta\mu_{rs}+\gamma\sigma_{rs}+\tau_{rs}+\delta_{rs} \tag{2}$$

$$C_b=c \tag{3}$$

Generally, a solo-rider trip is more expensive than a ridesharing trip. So we assume $\tau_{ns}>\tau_{rs}$.

The mean and standard deviation of travel time are related to the congestion level ρ. When the congestion level is high, the mean detour time and the detour time variability increase.

$$\mu_i=f(\rho),\sigma_i=h(\rho)\quad i=ns,rs \tag{4}$$

The waiting time is associated with the demand N_i and supply S_i for each mode and the congestion level ρ:

$$w_i=l(N_i,S_i,\rho)\qquad i=ns,rs \tag{5}$$

Intuitively, we have $\partial w_i/\partial S_i<0$ and $\partial w_i/\partial\rho>0$ for both NS and RS modes. Separate discussion should be given to the influence of travel demand under different situations. For NS service, the waiting time increases with increasing demand: $\partial w_i/\partial N_i>0$; For RS service, in situations where the demand is much more than the supply, the waiting time increases with demand, i.e. $\partial w_i/\partial N_i>0$. Otherwise, the waiting time decreases with the demand since the probability of being matched increases with demand, i.e. $\partial w_i/\partial N_i<0$.

The in-vehicle time should be distinguished among different travel modes. For RS service, the in-vehicle time is longer than that of NS service with additional detour time. The travel time variability will influence not only the in-vehicle travel time, but also the detour time. We introduce d to denote the expected detour time to pick up other travelers. Then the mean value and standard deviation of NS in-vehicle time and RS in-vehicle time have the following relationship:

$$\mu_{rs} = \mu_{ns} + d, \sigma_{rs} = \sigma_{ns} + \sigma_d \tag{6}$$

Besides the congestion level on the road, the detour time is also related to the number of successful matching travelers and can be derived as:

$$d_{rs} = d(M_{rs}, \rho) \tag{7}$$

where M_{rs} is the actual number of ridesharing travelers.

As the deployment strategy of the NS and RS services is not considered in the current stage, the supply of the two services are assumed to be deterministic. The relationship between successfully matched travelers and the number of intended travelers can be derived as:

$$m = M(N_{rs}), \frac{\partial M}{\partial N_{rs}} > 0, 0 < M(N_{rs}) < N_{rs} \tag{8}$$

$$p_{rs}(N_{rs}) = \frac{M(N_{rs})}{N_{rs}}, \frac{\partial p_{rs}(N_{rs})}{\partial N_{rs}} > 0 \tag{9}$$

where m is the number of successfully matched ridesharing travelers and p_{rs} is the matching probability. The matching probability increases with the number of intended RS customers.

2.2 Pricing strategy of ride-sourcing company

In this section we will investigate the optimal pricing strategy for the ride-sourcing company. In view of the risk of unsuccessful matching, the maximum profit of the company under different pricing strategies should be studied. Concerning which side will bear the risk, two pricing strategies are proposed.

(1) The passenger chooses ridesharing and pays the price of non-ridesharing if unsuccessfully matched, i.e. the passenger bears the risk of unsuccessful matching

$$C_{rs} = p_{rs}C_{rs} + (1 - p_{rs})C_{ns} \tag{10}$$

(2) The passenger chooses ridesharing and still pays the price of ridesharing if unsuccessfully matched, i.e. the company bears the risk of unsuccessful matching

$$C_{rs} = p_{rs}C_{rs} + (1 - p_{rs})(C_{ns} - \tau_{ns} + \tau_{rs}) \tag{11}$$

To explore the profit-maximizing scheme for the ride-sourcing companies, suppose the cost of operating a car is fixed. Therefore, the operation cost is fixed due to the deterministic fleet size. The revenue of the company is determined by the actual number of travelers using NS and RS services, which are N_{ns} and N_{rs} respectively. Therefore, the objective function is

$$\max_{\tau_{ns}, \tau_{rs}} Z = \tau_{ns} N_{ns} + \tau_{rs} N_{rs} \tag{12}$$

2.3 Discussion

This paper is dedicated to addressing the following questions. First, we investigate the mode choice behavior under travel time uncertainty. Second, the pricing strategies of the ride-sourcing company are analyzed. The model can be relaxed by introducing elastic fleet size, labor-supply relationship and dynamic congestion level.

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Crowdsourced Logistics: The Pickup and Delivery Problem with Transshipments and Occasional Drivers

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Extended Abstract

The growth in online sales during the last decades combined with consumers expectation for a fast, cheap and on time delivery service, leads to the necessity of developing new and more cost-efficient delivery concepts. The global share of e-commerce in retail sales is predicted to more than double from 7.4 % in 2015 to 15.5 % in 2021 [11]. At the same time, consumers expectations rise. According to a study conducted by McKinsey on the future of last mile delivery, same-day delivery will grow up to 25 % of X2C volume. Nevertheless, only a fraction of customers is willing to pay an appropriate premium for this kind of service [7]. Traditional grocery retailers, recognize the growing importance of online sales and accepted the challenge on creating a fast and inexpensive delivery service for their customers, by amongst other measures, introducing crowdshipping [5], [6].

Crowdshipping applies the concept of crowdsourcing to logistics [9]. Crowdsourcing is a participative online activity in which individuals, institutions, non-profit organizations, or companies propose to a group of individuals, the voluntary undertaking of a task, via a flexible open call. The undertaking of the task always entails mutual benefit [4]. This definition of crowdsourcing implies several characteristics, which apply for crowdshipping to the same extent.

Crowdshipping is a participative online activity, therefore the platform has to be provided digitally and all participants need access to mobile technology. Participants are ordinary people who become couriers, so called occasional drivers (ODs). ODs can be commuters or travellers who are already travelling or dedicated, (un)professional drivers. In accordance with the definition of crowdsourcing, the undertaking of the delivery task is voluntary and flexible, which leads to challenges for the platform provider to sustain and guarantee a certain level of service quality. Finally, the task entails mutual benefit. The platform provider supposedly cuts costs at the same time offering a fast delivery service. In addition to the obvious benefit of monetary compensation for ODs, there exists a variety of possible incentives. Some ODs are motivated by social or moral considerations, some just want to pass the time, some need further economic incentives, like vouchers, discounts or bonuses [3]. The crowd consists of a group of individuals and is therefore diverse. The platform needs to consider this diversity by offering a certain flexibility in order to reach a critical mass of ODs. Flexibility regards compensation, allowance of detouring, number of pickups/drop-offs per trip and time windows. If the platform provider wants to allow multiple pickups and drop-offs in a single trip, the routing has to be considered, which makes the problem even more challenging [2].

There have been several publications regarding matching algorithms and models for variants of crowdshipping in the last years (see for example [1], [2], [8]). None of these consider the possibility of transshipments together with multiple pickup/drop-offs in a single trip, to further enhance the flexibility of the system.

We consider a setting, in which a distributor (e.g. a courier, express and parcel service provider or an omni-channel retailer) operates a fleet of vehicles with regular drivers (RDs) to ship parcels from pickup to delivery points, e.g. from retailer to online-customers or from one individual to another. Additionally, the distributor uses a platform where ODs offer their willingness to fulfil pickup/delivery tasks. To better integrate the ODs the distributor operates transshipment points. At these predetermined transshipment points ODs or RDs can hand over or take on, respectively, their freight. In this context, arise several planning problems. For example, the distributor has to determine the location and capacity of the transshipment points. This article however, deals with the daily planning of routes and assumes that the transshipment points are given. The distributor then has to decide which tasks are assigned to RDs, which to ODs, in which sequence the drivers attain to the customers and whether transshipment points are used. The distributor aims to minimize the overall costs, which arise from the distance travelled by RDs and the compensation paid to ODs. ODs get a compensation depending on the additional effort to fulfil their task(s), to be more specific, the compensation depends on the length of the respective detour and on the number of additional stops.

The problem at hand is modelled as mixed-integer programming model and called Pickup and Delivery Problem with Transshipments and Occasional Drivers (PDPTOD). We develop a specialized heuristic solution approach based on a Large Neighbourhood Search (LNS) in a Simulated

Annealing framework, which solves practical-size problem instances within reasonable computation time. The LNS uses several remove and insert operators known from [10] and specialized operators for ODs as well as transshipments. We conduct numerical experiments with our solution approach on well-known instances from the literature which we extend by occasional drivers and transshipment points. We conduct a case study together with a newspaper distributor to verify the practical applicability of our solution approach. We come to the conclusion that introducing transshipment points is an opportunity to reduce costs. However, the potential to achieve cost savings highly depends on the instance at hand and is sensitive to the assumed compensation scheme.

This article makes several contributions to the field of research. We introduce a new and challenging routing problem with RDs, ODs and transshipments which we term PDPTOD. Additionally, we develop a heuristic solution approach, which performs reasonable on the classical PDP, as well. Furthermore, we conduct extensive numerical experiments, providing insights on how the number and the location of transshipment points influence the cost-advantages achieved when occasional drivers are integrated in the delivery process. We show that the cost-advantages depend not only on the location and number of transshipment points but also on the compensation scheme and the interaction between the aforementioned aspects.

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Collaborative Pickup and Delivery Problems with Time Windows and Heterogeneous Vehicles

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1 Introduction

Due to the increasing pressure of pricing on transportation markets, small- and medium-sized freight forwarders or carriers have to develop solutions to keep their competitive ability. In order to stay in the market, a possible and clever strategy is to affiliate in coalitions to collaborate in transportation planning. In such coalitions, the participating carriers exchange unattractive transportation requests, aiming at maximizing their profit by reducing the total fulfillment costs. In order to organize the exchange process, a central procedure or a decentral collaboration framework (DCF) can be used. In the former approach, a central entity optimizes the transportation plans over all participants of the coalition through assigning the requests, which probably have primarily been acquired by another carrier, cost-efficiently to the coalition partners, and allocating the profit gain which results from the request exchange to the carriers. Hence, the full information about all requests must be known for central optimization. Since the request information is a sensitive property for a carrier, a DCF is a common approach for the request exchange in which each participant optimizes its transportation plan itself and decides which request shall be exchanged. In doing so, a carrier has to uncover as little information of its customer data as possible.

2 Decentral Collaboration Framework

A typical structure of a DCF has been introduced by Berger and Bierwirth in [1]; it is also used in our framework and consists of a 5-phases procedure:

(i) identification and release of the unattractive requests into an auction pool by each carrier

(ii) generation of favorable request bundles by an auctioneer which are supposed to be offered to the participating carriers

(iii) determination of bids for each offered request bundle by each carrier

(iv) Winner Determination Problem: optimal bundle assignment to the carriers based on their bids, which is consequently the solution of the corresponding Combinatorial Auction Problem

(v) allocation of the profit which has been gained through the combinatorial auction

To identify unattractive transportation requests in (i), we use evaluation techniques which, e. g., depend on generally known carrier data (cf. [4]) or the ratio of gross profit and request load. After releasing all improper requests and transferring them to an auction pool, a central entity called auctioneer has to generate favorable request bundles in phase (ii) on which the carriers have to bid in step (iii). If the auctioneer generates all bundles, there are $2^n - 1$ possibilities for an auction pool size of n. Since the bids $b_{m,B} = f(x') - f(x)$ for each carrier m are generated through calculating a solution x' for the underlying routing problem with bundle B and a solution x without bundle B, it is important to provide only a small number of sufficiently attractive request bundles to enhance performance (cf. [3]). Since the attractiveness of a bundle is indicated by the bid of a carrier, which is not known in advance, we use Simulation-Based Optimization techniques to solve the so-called Bundle Generation Problem. After the bidding process is done, we use a Combinatorial Auction to tackle the Winner Determination Problem (cf. [1]) and solve it to optimality by using ILOG Cplex. This auction is modelled as a Vickrey auction. In step (v), we have implemented several profit sharing variants which make use of, e. g., the number or gross profit of the exchanged transportation requests to allocate the profit gained out of the auction. Finally, no carrier should be worse off by the resulting solution with re-allocated requests than by the initial solution.

3 The Underlying Routing Problem

As we know from Gansterer and Hartl [2], collaboration in transportation planning has been studied regarding to many routing problems. In this contribution, we consider medium-sized less-than-truckload carriers that may have different vehicle capacities. These vehicles must be routed such that a set of transportation requests with positive quantities are transported from origins to destinations. Each route starts and ends at an assigned depot and ensures pairing as well as precedence constraints for requests. Additionally, time windows respect the time at which pickup and delivery locations must be visited. Such a problem can be modelled as a Pickup and Delivery Problem with Time Windows and Heterogeneous Vehicles (PDPTWHV), which, to the best of our knowledge, has not been considered for collaborative vehicle routing yet.

To solve the PDPTWHV, we apply several insertion heuristics depending on, e. g., the increase of route length or the loss of shifting flexibility regarding to the start time of service at a customer. The procedure is embedded in a multistart environment to generate multiple solutions. The obtained solutions provide sufficient variability and can therefore be applied to a Genetic Algorithm

(GA) as an initial population. The basic idea of our GA is based on the Grouping Genetic Algorithm (GGA) introduced for PDPTW in [6]. Here, the representation of a solution only depends on the requests served by one vehicle and not on the ordering within the corresponding route due to the bigger impact of the clustering problem on solution quality in PDPTW problems. In this way, it is ensured that pickup and delivery nodes cannot be split while using crossover operators in order to create offsprings. As a consequence, the routing of a candidate solution will be executed by a separate embedded heuristic as soon as decoding of the representation. All solutions in a population are measured by a fitness function. The method is constructed in such a way that on average each new population tends to be better than the previous one.

4 Computational Study and Conclusion

We have presented a DCF in which the routing has been done heuristically by a GGA, whereas the winner determination for the combinatorial Vickrey auction has been solved exactly. To analyze the results, we have used the well-known PDPTW datasets provided by Lim and Li [5]. Furthermore, the data sets were extended by heterogeneous vehicle capacities, fixed costs, gross profits etc. For evaluation, we compared the solutions of the DCF to the ones of the individually generated routing. Using the latter as an upper bound, we have shown that no carrier is worse off by collaboration.

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Choice-based dynamic dial-a-ride problem for on-demand transportation

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1 Introduction

Transportation systems are moving towards user-centric solutions in the context of both passenger and freight with the help of advances in information and communication technology (ICT). The users and operators can interact through smart-phone apps and real-time information is available. Furthermore, the demand is becoming increasingly time-sensitive, e.g., shipments are requested to be delivered within tight time windows. Therefore, on-demand services (e.g., [1]) are promising with potential improvements in user satisfaction and efficiency in operations. We present a choice-based dynamic dial-a-ride problem (DARP) that integrates user preferences into the optimization of on-demand transportation systems in order to achieve those improvements. The objective of this paper is to have a proof-of-concept for the proposed choice-based dynamic DARP.

In the considered on-demand system, the service provider has a homogeneous fleet of vehicles which can be used to offer both taxi and shared-taxi. Sequentially arriving users initiate their requests through a smart-phone app. The requests include information about origin, destination and preferred pick-up time. When a new user arrives, on-demand service provider needs to provide an optimized menu (assortment) of alternatives in order to maximize the expected profit. The alternatives have three dimensions: (i) service: taxi or shared-taxi, (ii) time-window: varying waiting times, (iii) price levels. The preference of users towards the alternatives in the menu are represented by a choice model. The user can choose one of the alternatives in the menu or opt-out. The expected profit depends both on the preferences of the new user and the operating cost of the system considering the existing users. Therefore, in order to optimize the menu to be offered, the choice-based assortment optimization and the DARP needs to be solved simultaneously.

2 Problem Description and Methodology

The problem is formulated as a mixed integer linear programming problem and is defined on a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ and $\mathcal{A}$ represent the nodes and arcs, respectively. Each user corresponds to a pair of nodes: pick-up and drop-off. An open VRP is considered such that the vehicles can start and end at any node in the network.

The objective function is expected profit and given by the expected revenue and the marginal cost upon new user arrival. The expected revenue is represented by the choice probability and the price of alternatives on the menu. The marginal cost considers both the routing and opportunity costs for the entire fleet (i.e., those that are already serving existing users and those that are considered to offer a menu to the new user). The opportunity cost represents the cost of losing future demand based on the load of vehicles, e.g., offering a shared-taxi has less opportunity cost compared to taxi, as it can accommodate more users on the vehicle in the future.

The constraints include typical routing constraints and they are linked to assortment optimization constraints so that the routing decisions are consistent with the offered assortment. Time related constraints maintain the time windows, the consistency of time across pick-up and drop-off nodes as well as a desirable total travel time for each user. Furthermore, load related constraints maintain the capacity limitations and define the opportunity cost of vehicles.

The formulation and solution of this problem bring together various methodologies. The problem is linearized through (tight) big M constraints. The set of assortments is pre-processed considering all combinations of alternatives and the size is reduced by defining efficient sets in order to increase the computational efficiency. As we have a dynamic context, we solve the problem every time a new user arrives. The proposed choice-based DARP determines the optimal menu to be presented to the new user. For our experiments, we simulate the user choice based on a logit mixture model. Depending on the simulated choice, the system updates the transportation plan. This process continues till the end of the planning horizon.

The main distinction of the paper is the choice-based dynamic DARP that is introduced for the first time in literature. Different than typical DARPs (e.g., [2]), as the choice of the user is not known when providing the offer, all potential routings and the associated costs need to be considered. In the literature, there are examples that introduce user preferences (e.g., [3]), however having a choice model explicitly in the model is new. Furthermore, the opportunity cost introduces a forward-looking characteristic to the model. Moreover, we consider different price levels for the alternatives and so have the notion of dynamic pricing based on user preferences.

3 Initial Results and Ongoing Work

Simulation experiments are carried out with 50 users and 2 vehicles under different scenarios based on (i) frequency of user arrival (ii) booking time (iii) level of the opportunity cost (i.e., weight of forward -looking characteristic) and (iv) choice model parameters. Table 1 focuses on the results for frequent vs infrequent arrival and low vs high opportunity cost. The outputs provide the number of served users (out of 50), profit per user, average and maximum users on-board. It is observed that, more users are served when arrival is less frequent as it can allocate the resources easier. However, the profit per user is higher under frequent arrival. When the opportunity cost is higher, shared-taxi is used more as the system reserves resources for potential future requests. Furthermore, shared-taxi can more easily be offered when arrival is frequent, as expected.

Ongoing work focuses on computational efficiency for meeting the real-time requirement of such an on-demand system. Future work includes incorporating stochasticity in the model.

Table 1: Experimental Results

	High opportunity cost		Low opportunity cost	
	Infreqent arr.	Freqent arr.	Infrequent arr.	Frequent arr.
Served users	49.20	42.50	47.4	34.8
Profit per user	9.95	11.36	10.32	10.74
Avg/Max users on-board	1.20/3.00	1.60/4.50	1.00/1.00	1.00/1.00

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Stable dispatch for shared autonomous vehicles

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1 Introduction

Among the many revolutionary uses for autonomous vehicles is the concept of large-scale mobility-on-demand replacing personal vehicle travel. Due to the lack of a driver, shared autonomous vehicles (SAVs) could provide point-to-point transportation at a cost similar to that of personal vehicles. Consequently, travelers may choose to rely on SAVs rather than personal vehicle ownership for their daily transportation needs. Previous studies [e.g. Fagnant et al., 2015] have constructed simulations of SAV interactions with travelers on city networks and found that SAVs could replace between 3 to 11 personal vehicles. However, results are highly dependent on the passenger-to-vehicle matching used. Since vehicle routing problems are in general NP-hard, most studies have used heuristics to dispatch SAVs to passengers. Other challenges include the additional congestion caused by SAV route patterns and empty travel [Levin et al., 2017]. The combined route choice and dispatch problem can be formulated as a linear program (for continuous SAV flows) [Levin, 2017], but requires future knowledge of travel demand.

The purpose of this paper is to address the SAV dispatch problem through the notion of stability from max-pressure control of traffic signals [Varaiya, 2013]. For traffic networks, stability occurs when the number of vehicles in the network remains bounded in expectation. Inefficient signal timings or sufficiently high demand prevent stability. For a system of SAVs, the number of vehicles in the network is constant (the fleet size), but the number of waiting travelers could grow arbitrarily large if the fleet is too small to serve them. Ideally, the dispatch strategy for SAVs would maintain stability for the largest set of demand possible. The contributions of this paper are as follows: we analytically derive the region of demands that could be stabilized for any SAV system, which may be used for determining the relationship between fleet size and demand. Furthermore, we investigate analytically a maximum-stability dispatch policy for SAVs. Simulations are conducted to connect the analytical policy to empirical results.

2 Formulation

2.1 Network model

Consider a traffic network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ with set of nodes $\mathcal{N}$ and set of links $\mathcal{A}$. SAVs travel through this network, interacting with passengers. Let $\mathcal{Z} \subset \mathcal{A}$ be the set of zones, which are a subset of the links because SAVs enter and exit zones to pick-up and drop-off travelers then proceed to their next assignment. Let $\mathcal{A}_o$ be the set of non-zone links. Each time step, SAVs can move forward through the network towards zones. Assume without loss of generality that each link has a travel time of one time step (longer links can be separated into segments). Let $x_j^{rs}(t)$ be the number of SAVs on link j traveling from $r \in \mathcal{Z}$ to $s \in \mathcal{Z}$ at time t. Let $y_{ij}^{rs}(t)$ be the number of SAVs going from r to s moving from link i to link j at time t. Then $x_j^{rs}(t)$ evolves via conservation:

$$x_j^{rs}(t+1) = x_j^{rs}(t) + \sum_{i \in \mathcal{A}} y_{ij}^{rs}(t) - \sum_{k \in \mathcal{A}} y_{jk}^{rs}(t) \tag{1}$$

The variables $y_{ij}^{rs}(t)$ determine the route choice. At zones, SAV interactions are slightly different. SAVs can change their origin and destination at zones. Let $p_r(t)$ be the number of SAVs parked at r at time t. Then

$$p_r(t+1) = p_r(t) + \sum_{i \in \mathcal{A}} \sum_{q \in \mathcal{Z}} y_{ir}^{qr}(t) - \sum_{j \in \mathcal{A}} \sum_{s \in \mathcal{Z}} y_{rj}^{rs}(t) \tag{2}$$

Exiting vehicles is constrained by the number of parked vehicles:

$$\sum_{j \in \mathcal{A}} \sum_{s \in \mathcal{Z}} y_{rj}^{rs}(t) \leq p_r(t) \tag{3}$$

Passengers have an origin $r \in \mathcal{Z}$ and a destination $s \in \mathcal{Z}$. Let $d^{rs}(t)$ be the demand (number of new passengers) at time t wishing to travel from r to s. $d^{rs}(t)$ are random independent identically distributed variables with mean $\bar{d}^{rs}$. We assume that passengers wait at their origin until being picked up. Let $w^{rs}(t)$ be the number of passengers waiting at r for travel to s. Passengers can only depart r after being picked up, so $w^{rs}(t)$ evolves as follows:

$$w^{rs}(t+1) = w^{rs}(t) + d^{rs}(t) - \min\left\{ \sum_{j \in \mathcal{A}} y_{rj}^{rs}(t), w^{rs}(t) \right\} \tag{4}$$

Notice in equation (4) that some SAVs may travel from r to s empty to rebalance SAVs in response to demand.

2.2 Stability

The variables $y_{ij}^{rs}(t)$, in particular SAV destination choice at zones, determine passenger movements. The objective is to achieve stability which occurs when the number of waiting passenger should remain bounded in expectation. Stability requires that there exists a $K < \infty$ such that

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{(r,s)\in\mathcal{Z}^2}\mathbb{E}\left[w^{rs}(t)\right] \leq K \tag{5}$$

If demand is sufficiently high, it cannot be stabilized by a given SAV fleet. Let $\bar{y}_{ij}^{rs}$ be the average SAV flows from i to j traveling from r to s. Any feasible average SAV flows must satisfy

$$\sum_{i\in\mathcal{A}}\bar{y}_{ij}^{rs} = \sum_{k\in\mathcal{A}}\bar{y}_{jk}^{rs} \qquad \forall j\in\mathcal{A}_{\mathrm{o}}, \forall(r,s)\in\mathcal{Z}^2 \tag{6}$$

$$\sum_{i\in\mathcal{A}}\sum_{q\in\mathcal{Z}}\bar{y}_{ir}^{qr} = \sum_{j\in\mathcal{A}}\sum_{s\in\mathcal{Z}}\bar{y}_{rj}^{rs} \qquad \forall r\in\mathcal{Z} \tag{7}$$

$$\sum_{(i,j)\in\mathcal{A}}\sum_{(r,s)\in\mathcal{Z}^2}\bar{y}_{ij}^{rs} \leq F \tag{8}$$

where F is the fleet size. Let $\mathcal{Y} = \{\bar{\mathbf{y}} : (6)\text{–}(8)\}$.

Proposition 2.1 *If for every $\bar{\mathbf{y}} \in \mathcal{Y}$ there exists an $(r,s) \in \mathcal{Z}^2$ such that $\bar{y}_{ij}^{rs} < \bar{d}^{rs}$ then $\bar{\mathbf{d}}$ cannot be stabilized.*

As with Varaiya [2013] we will present a policy that stabilizes demands in the interior of $\mathcal{D}$. (Demands on the boundary result in a null recurrent Markov chain.) This policy will therefore have maximum-stability for the SAV dispatch problem.

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An Iterative Combinatorial Auction Design for Fractional Ownership of Autonomous Vehicles

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1 Introduction

The current model of vehicle ownership is neither cheap nor efficient. According to the American Automobile Association, the average annual cost to own and operate a new vehicle was around \$8,849 in 2018. In 95% of time, however, cars are parked [1]. The recent trends of collaborative consumption in transportation, such as ride-sharing services and peer to peer car renting services, bring into the perspective new forms of vehicle ownership. Such a trend will expedite when fully autonomous vehicles (AVs) are introduced to consumer markets.

This study investigates a novel form of vehicle ownership, called *fractional ownership* of AVs, where an AV is co-leased by a group of individuals. With the steady advancements in AV technology, we believe that the key challenge in the fractional ownership of AVs will not be the technology, but rather a *market design*. A leasing company needs *mechanisms* to match customers for using a co-owned vehicle, allocate time slots for each customer and determine prices, while customers require easy to use tools to co-own the vehicle. Thus, the market design becomes essential for the successful application of fractional ownership of AVs.

We propose an iterative combinatorial auction, namely the Combinatorial Clock Auction (CCA), as a market design for fractional ownership of AVs. In the proposed market design, a dealer serves as the auctioneer offering several homogeneous AVs. Then interested customers bid iteratively online to co-lease an AV by submitting combinations of desired time slots, bidding prices and location information of their trips. The auction outcome determines both the matching groups and individual payments, thus allocating time slots based on the valuations of customers.

To the best knowledge of ours, this is the first study investigating the CCA as a market design for applications in transportation. Further, the proposed CCA for fractional ownership of AVs is

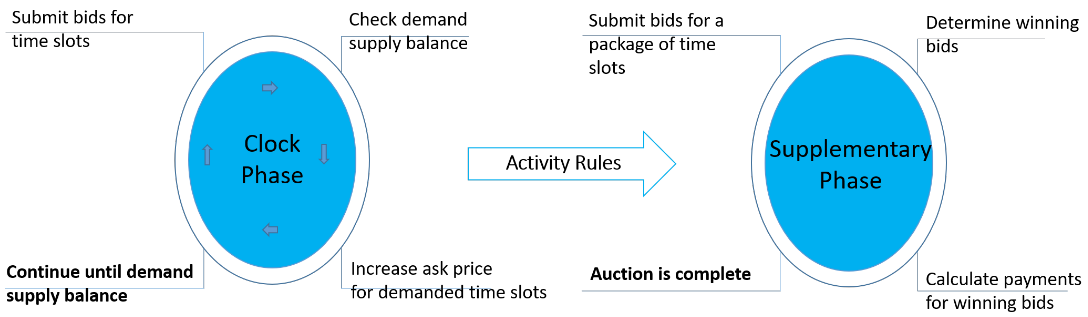


Figure 1: The auction structure for fractional ownership of AVs

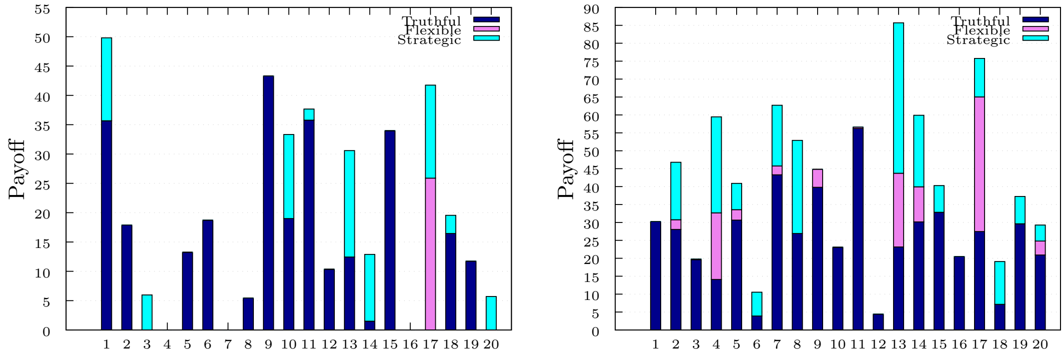
unique in its design. In particular, in the traditional CCA, items are discrete and defined by the auctioneer, while in the proposed auction items are continuous and defined by the bidders. We develop fast algorithms for determining ask prices in the first stage of the CCA and for solving the winner determination problems in the second stage. We also introduce user agents as optimization problems to support customers' decision-making within the auction. In computational studies, we demonstrate numerical analysis of the performance of the auction under various payment rules and bidding strategies and derive managerial insights.

2 The Auction Design

The proposed iterative combinatorial auction entails two main properties. The combinatorial nature of the auctions allows customers to submit bids as a combination of time slots. The distinct advantage of such design is evident in the case of complementary time slots [2]. Further, the iterative nature of auction helps to resolve the preference elicitation problem for customers [3]. Further, the auction design includes activity rules to suppress strategic behaviors of customers.

In general, the auctions consists of two stages. The goal of the *clock stage* is to provide insights for customers about the market value of time by submitting iterative bids with linear prices. In particular, in each round of clock stage, an auctioneer announces prices for time slots and customers respond with desired time slots. Ask prices increase for time slots with an excess demand. Thus, the *clock stage* serves as price discovery for customers [4]. In the *supplementary stage*, customers submit their final bids as packages of time slots taking into account the results of clock stage. Consequently, an auctioneer solves the Winner Determination Problem (WDP) considering bids both from clock and supplementary stages and calculates payments. Figure 2 summarizes the proposed auction design.

In order to aid customers with valuation problems, we propose user agents that offer different bidding strategies and automatic time slots combination generation capabilities. User agents solve



(a) Truthful Bidding

(b) Flexible Bidding

Figure 2: Bidding strategy effect on bidders' payoff

some optimization problems and analyze customer travel patterns.

3 Computational Experiments

Using our own algorithms for solving various optimization problems arising within the proposed CCA design, we build a simulation model to test the performance of the auction under various strategies of customers. For computational studies, we use the 2010–2012 California Household Travel Survey, which indicates the start and end time of trips as well as miles for 2,908 vehicles for one week. We test the effect of bidding strategy choice offered by user agents to a customer payoff, which is measured as the difference between a bid price and payment. Our experiments indicate, that wen all other bidders bid truthfully, bidding truthfully generates the highest payoff. Similarly, when everyone bids strategically, bidding truthfully generates the highest payoff indicating the effectiveness of activity rules as shown in Figure 2. Further, we test the choice of payment rules: Vickrey-Clarke-Groves (VCG) payments, core-selecting payments, and proxy payments on the revenue of an auctioneer and computational time. The performance of core-selecting payments turns out to be the most favorable.

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A Queueing Network Approach for Modeling Ride-Sourcing Systems

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1 Introduction

Ride-sourcing services have become increasingly important in meeting mobility needs in metropolitan areas. By requesting rides via a mobile application, customers are matched efficiently by a online platform with affiliated drivers nearby. Such on-demand e-hailing services significantly reduce search frictions in the ride-for-hire market and bring together riders and drivers with very low transaction costs [1,2]. While these services have enjoyed huge success, they have also created many controversies, such as unfair competition with regulated taxi services, congestion externalities of in-service vehicles, and surge pricing adopted by the platforms. Examining/resolving these controversial issues have attracted extensive research interests. See, e.g., [3–5] and references therein. In pursing these quests, a pressing need emerges, which is to establish a theoretical framework to capture operational characteristics of a ride-sourcing system. With the framework, properties of the system performance can be then discussed as well as controls and strategies to improve the performance. This study aims to address this need by using a queueing network approach. In building the model, we attempt to follow closely the operational mechanism of a ride-sourcing system. We then leverage the queueing network to examine and control the system in various market contexts.

The queueing network approach has been utilized in modeling shared-use mobility services to characterize the system stochasticity and quantify its level of service. For instance, a closed queueing network was formulated for the vehicle rental service to derive the asymptotic behavior of vehicle availability at rental stations, based on which a profit-maximizing optimization is proposed to cater the fleet-sizing problem in practice [6]. In addition, queueing-theoretic models have been constructed to investigate optimal control, such as pricing [7] and fleet dispatching [8] in centralized ride-hailing services. A recent study [9] incorporated road congestion in a queueing network model of ride-hailing systems and applied the model to approximate the aggregate system performance using real data from New York City. In contrast to the above endeavors, we attempt to establish a general framework that can support strategy designs and system optimization in various contexts. Our framework captures key interdependences among system states and will enable us to meticulously deploy different "controllers" to cope with the strategies implemented or under discussion by ride-sourcing platforms.

2 Preliminary Model

Consider a city consisting of N subregions, each representing a relatively isotropic area and being translated as a node in the queueing network. Supply of vehicles and demand of rides originate at node i according to Poisson processes respectively in rate λ_i and $\mu_i(n)$, where n denotes the service state on the node. Positive n represents the state of having n idle vehicles waiting, while the negative counterpart refers to the condition of having $-n$ passengers held to be served. As the conditional expression implies, the realized demand (i.e., the requests being served) is dependent on the availability of supply. For example, when there are $n(<0)$ passengers queueing, the information such as the expected waiting time will be broadcast to the coming requests. As a result, a part of the arriving requests will abandon the queue, giving rise to a reduced arrival rate. For simplicity, we specify $\mu_i(n)$ to satisfy the following relationship,

$$\mu_i(n) = \begin{cases} \mu, & n > -B_i \\ 0, & n \leqslant -B_i \end{cases}, \quad \forall i \in N$$

where B_i is the maximum number of passengers waiting at node i. We assume that the passengers who are already waiting in the system will not cancel service, i.e., they have infinite patient time. However, exponentially distributed patience can be easily incorporated into our model.

After being matched to drivers, passengers originating from node i go to node j with a probability p_{ij}, and $\sum_{j\in N} p_{ij} = 1$ for $i \in N$. The travel time from node i to node j denoted as T_{ij} can be random and follow an arbitrary distribution. Note that here j may be equal to i, implying an intrazonal travel. We further assume that each vehicle after dropping a customer at node i will leave the market with probability q_i. Clearly, if $\lambda_i = q_i = 0$ on all nodes, the network then replicates a closed system with a fixed number of vehicles in service.

The state of the system can be expanded as $\Omega = (n_i, i \in N; n_{ij}, (i,j) \in W)$, where n_i denotes the state of node i and n_{ij} is a nonnegative integer denoting the number of vehicles traversing from i to j, and W is the complete set of origin-destination pairs. Let α_i denote the overall vehicle arrival rate at node i. Then, α_i can be easily computed by the following traffic equations:

$$\alpha_i = \lambda_i + (1 - q_i) \sum_{j\in N} \alpha_j p_{ji}$$

Then, the steady state distribution of the system is guaranteed with a close-form solution:

Theorem 2.1 *The steady state distribution of the network is*

$$\pi(n) = C \prod_{i\in N} \pi_i(n_i) \prod_{(i,j)\in W} \pi_{ij}(n_{ij})$$

where $\pi_i(n_i) = \frac{\alpha_i^{n_i}}{\prod_{l=1}^{n_i} \mu_i(l)}$ *and* $\pi_{ij}(n_{ij}) = \frac{(\alpha_i p_{ij} T_{ij})^{n_{ij}}}{n_{ij}!}$.

3 Applications

The above queueing network will serve as a foundation for disentangling the complexity of spatial interactions in a ride-sourcing system. We plan to apply the model to examine the supply property of the system and investigate strategies to improve the system capacity and efficiency. Strategies to be investigated include:

- *Differentiated matching.* Differentiated matching sets different level of priority in matching for passengers of different origin-destination pairs. It is a form of demand rationing. The queueing framework can be easily coupled with optimization techniques to design a rationing scheme that maximizes the capacity.

- *Differentiated pricing.* Price differentiation of interest here is with respect to passengers' destination. We will apply the queueing model to examine the effectiveness of destination-based pricing in sustaining the supply circulation within the network.

- *Fleet dispatching.* The basic model can be further extended to consider multiple driver groups under different types of contracts. We are interested in investigating the potential of dispatching those dispatchable drivers in alleviating the spatial unbalance of supply and demand to further enhance the system performance.

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Consideration of Platoons in Models of Vehicle Routing Problems

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1 Introduction

Several trucks form a truck platoon if they move through a network in a convoy under a common control. Typically, the trucks in the platoon follow the same route and travel at a coordinated speed. One of these trucks serves as the leader and determines the travel speed(s) as well as the route of all platoon members. Control instructions for the trucks in the platoon are given by the driver of the leading truck of the platoon and are broadcasted and propagated immediately to all following trucks.

The incorporation of technological features like car-to-car communication as well as synchronized braking systems or distance-preservation-devices enables the reduction of the distance between consecutively driving vehicles down to a few meters without any safety impairment even if the convoy travels at high speed. The major benefit of the reduction of the space between adjacent trucks is the reduction of aerodynamic drag which leads to fuel savings. In addition, the reduced length of the technically coupled convoy lowers the needed space on crowded roads since a higher level of traffic coordination is achieved. This contribution reports mathematical models as well as model solving approaches for the combined route planning and platoon forming tasks that must be solved in order to exploit the overall fuel saving potential.

2 Truck platoon formation in VRP-contexts in the literature

We can distinguish two perspectives of platoon formation. From the micro-perspective (or local perspective) it is necessary to take care that vehicles traveling on the same road segment at the same time can perform the automatic docking so that they initiate a platoon. Here, travel speed coordination among the platoon candidates is the major challenge [1]. Similarly, the split up of platoon must be prepared.

In order to prepare a rendezvous of two or even more vehicles in a part of a network to initiate a platoon it is necessary to provide coupling opportunities. Often, vehicle routes have to deviate from individually optimal vehicle paths during the planning of the vehicle routes for the overall fleet through the road network. We call this the macro-perspective (or network view) of platooning. Here, the well-known but quite complex vehicle routing problem [2] must be merged with platoon building opportunities [3].

The major driver of platooning in the trucking industry seems to be the expected significant energy saving of trucks traveling in a platoon instead of traveling alone [4]. However, other researchers emphasize the opportunity to exploit the driving time savings of drivers in the non-leading vehicles within a platoon [5]. Finally, an improvement of the traffic flow is promised if traffic lights control a complete platoon instead controlling individual trucks [6].

Research on platoon formation in the context of vehicle routing is still in the early stages. The explicit compilation of routes together with the setup of platoons as objects of planning in one single planning model is not yet discussed. This paper contributes a concept for integrating platoon formation and vehicle routing in the macro-perspective context promoting the formation of beneficial platoons by coordinating vehicle routes. We present a mixed-integer linear model in which platoons are contained as explicitly considered variable objects.

3 Reported Contribution to the Enhancement of Truck Platoon Formation

The contribution of the here reported research to the truck platooning covers two issues. First, we propose a straightforward model extension of vehicle routing and scheduling models in order to consider platoons as variable planning objects. Second, we give insights into the results of the application of some algorithms especially developed for the simultaneous route compilation and platoon formation in truck dispatching. We explain the representation of the platoon formation task in a mixed-integer linear CVRP-model. Furthermore, the integration of platoons into vehicle routes and the evaluation of the resulting combined platoon-customer-node vehicle routes is addressed.

The integration of new planning objects like platoons in a CVRP-related decision task requires a re-design of existing algorithmic concepts. Beside the compilation of vehicle routes it is necessary to decide the setup of platoons. Furthermore, some nodes might be locations where a platoon can be initiated (like a parking lot or a motorway entry) while others like the representative of a customer location cannot do. We propose a framework of hybrid algorithms that consists of specialized heuristics that are able to commonly find convincing solutions of vehicle routing problems with platoons. For some realizations of this framework we provide insights into numerical results from computational experiments.

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A Disjunctive Graph Approach for the Channel Scheduling Problem

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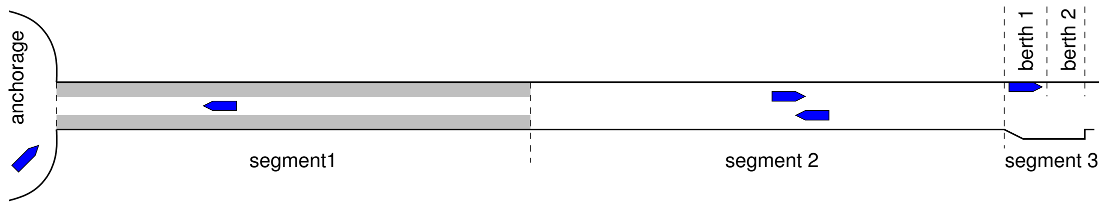
1 Introduction

This work builds on a previous paper [1] which introduced the Channel Scheduling Problem (ChSP) and integrated ChSP with the discrete Berth Allocation Problem (BAP) [2]. The problem considers a channel connecting an open sea anchorage with a set of berths for loading/unloading ships. A channel consists of a series of channel segments, which either allow or forbid passing of oncoming vessels. Following ships are permitted to concurrently occupy the same channel segment, but must observe a minimum separation time constraint on entry and exit to the segment. For a given set of berth allocations and berth sequences, the problem is to schedule movements of ships through the channel to minimise channel access delays at anchorage and prior to berth departure.



The figure illustrates a ChSP problem with 3 channel segments and 2 berths. The segment on entry/exit does not allow passing of opposing ships because it is narrow. Ships must maintain speed to avoid drifting into the walls of the channel. This is accounted for in ChSP by assuming that no-wait constraints exist between channel segments (although it is straight forward to relax this constraint if an inner anchorage is present).

A mixed-integer program (MIP) was proposed in [1], along with constructive heuristics to find solutions to ChSP and the Berth Allocation Problem with Channel Restrictions (BAP-CR), both of which were demonstrated to be computationally challenging. The current study extends the previous work by exploring the hybridisation of the constructive heuristic with meta-heuristics such as simulated annealing, along with an alternative disjunctive graph based formulation which allows for the development of additional solution approaches.

2 Disjunctive Graph Model

The constructive heuristic (CH) proposed in [1] produces feasible, active schedules, of reasonable quality. The current study has hybridised this constructive heuristic with simulated annealing, by perturbing the order of insertion to the schedule. Desktop analysis found that the CH-hybrid could not reproduce all possible active schedules, due to earliest departure time insertion strategy. Thus, the hybrid meta-heuristic searches a subset of active schedules, with no guarantee that the optimal schedule is contained within this subset. This discovery motivated exploration of other meta-heuristic implementations based on a disjunctive graph.

In order to build this ChSP graph framework, we consider a particular port configuration with single entry/exit point, linear channel (multiple segments) and single wharf-center (multiple berths). Most of the fundamental disjunctive graph modelling techniques we have adapted are described in [3]. It is proposed to construct a graph $G(V, E)$ with nodes V and arcs E, from which a ChSP schedule can be generated using a standard longest path algorithm. The set of nodes $V = \alpha \cup I \cup O$, where α is a dummy source node and I and O are sets of nodes representing inbound and outbound ship movements respectively. Each ship will have one node in I and one node in O. We are using an activity on arc implementation, and so nodes have zero weight.

The set of edges $E = \bigcup_{i=1}^{3} C_i \cup \bigcup_{i=1}^{4} D_i$, has three distinct sets of conjunctive arcs and four sets of disjunctive arcs. C_1 corresponds to release times, with $C_1 = \{(\alpha, u) : u \in I\}$ and weighted by ship release times. C_2 links the inbound and outbound movements of each ship, with $C_2 = \{(u, v) : u \in I, v \in O, ship_v = ship_u = j, j = 1, ..., n\}$, and the arc weight w_{uv} is equal to the sum of inbound channel transit (p_u) and berth handling time for ship j, i.e. $w_{uv} = p_u + b_j$. Finally, C_3 imposes the berth sequences which are assumed fixed, $C_3 = \{(u, v) : u \in O, v \in I, ship_u \prec ship_v\}$, with weighting $w_{uv} = \delta_1 - p_u$ where δ_1 is the minimum berth separation delay and p_u is the inbound travel time for movement u. This is a fairly standard application of a blocking arc since a ship cannot come onto berth whilst another is delayed on berth.

The first three sets of disjunctive arcs D_1, D_2, D_3 are constructed based on a desired sequence of movements σ passing the entry/exit point of the channel. D_4 is an additional set of disjunctive arcs required to determine how passing conflicts are to be resolved (which is not uniquely determined by σ). Without loss of generality, assume that nodes in V are indexed based on their position in sequence σ, so that nodes v and $v+1$ represent consecutive movements past the channel entry/exit. D_1 consists of arcs between consecutive inbound movements, with $D_1 = \{(v, v+1) : v, v+1 \in I\}$, and similarly $D_2 = \{(v, v+1) : v, v+1 \in O\}$ relates to consecutive outbound movements. Arcs in D_1 and D_2 have weight $w_{v,v+1} = \delta_2$ which is the minimum time separation between following ships.

Arcs in D_3 relate to outbound movements directly preceding inbound movements with $D_3 = \{(v, v+1) : v \in I, v+1 \in O\}$. The weight of arcs in D_3 is equal to the time required to complete the outbound movement ($w_{v,v+1} = p_v$). Arcs in D_4 related to the opposite case of inbound movements preceding outbound movements in σ (not necessarily direct precedence). In this situation, we require an additional decision of which channel segment c_{uv} movements $u \in I$ and $v \in O$ $(u < v)$ will sail past each other ($c_{uv} \geq 1$), or if v is to arrive at berth before u departs (we say $c_{uv} = 0$). We therefore further subdivide $D_3 = D_3' \cup D_3'' \cup D_3'''$. For the latter case described earlier ($c_{uv} = 0$), we define $D_3' = \{(u, v) : u \in I, v \in O, c_{uv} = 0\}$, with weight $w_{uv} = p_u$.

When $c_{uv} \geq 1$, two arcs are needed to ensure the passing of u and v occurs beyond the start of segment c_{uv} and before the end of the segment. This is achieved with the arcs $D_3'' = \{(u, v) : u \in I, v \in O, u < v, c_{uv} \geq 1\}$ and reverse arcs $D_3''' = \{(v, u) : (u, v) \in D_3''\}$. Arcs in these sets have weights $w_{uv} = P_{uc} - P_{v,c+1}$ and $w_{vu} = -(P_{u,c+1} - P_{vc})$, where P_{uc} is the portion of inbound travel time inbound from anchorage to the start of channel segment c, and similarly P_{vc} is the portion of travel time outbound from berth. This arrangement of arcs is a fairly standard implementation of perishability constraints from scheduling theory.

This disjunctive graph fromulation of ChSP forms the basis for meta-heuristics, a bespoke branch-and-bound algorithm and hybridisation variants. The advantage over this approach compared with the constructive heuristic hybridisation is that now the full set of active schedules is accessible to the meta-heuristic search.

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Revenue management model for logistic on-demand systems

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1 Motivation

With the increase of population in metropolitan areas, transport and logistics planners are seeking new resolutions to maximize the resource utilization for transport of goods inside the cities. There are a number of emerging technologies that can address this challenge. Especially, technology development has contributed in defining new solutions such as, flexible transport in relation to the on-demand service, internet-of-things and sharing services [4], [3], [5], [6]. The Physical Internet (PI) was defined as a global logistics system founded on physical, digital and operational interconnectivity through encapsulation, interfaces and protocols [7]. This system is based on standard and smart modular containers that are easily transported through all transport means (e.g. trucks, drones and private cars) [9], [8] [11]. Bringing these technologies close together can help to enable on-demand urban-logistics services [1], [2].

Multimodal forms of transportation are of interest to both customers and transportation operators to offer customized options from users' point of view and optimizing capacity usage from operators' perspective. Such system provides various levels of services to each user request. Customers are presented with a menu of choices from which they make a selection based on their preferences.

In this paper, we consider an on-demand logistic network of a single operator which uses cargo vans and drones for the last mile delivery in an urban area. We focus on the real-time operation of this system. Specifically, we focus on its capability to instantaneously receive and execute vehicle plans (such as, routes, pick up and delivery plans, fleet management and customer assignments). We present an optimization model that maximizes the profit of the operator. For each new user, this model simultaneously generates menu of choices while re-planning the existing routes, schedules, and customers assignments. Thereafter, we investigate the impact of demand forecasting accuracy on the revenue performance of the system.

2 Methodology and discussion

In this problem, we consider two transportation modes: drones and cargo vans. The transportation requests arrive in real time and the system has to generate options to fulfill this demand. We formulate the problem as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where $\mathcal{V}$ and $\mathcal{A}$ represent the vertexes and arcs, respectively. Each user corresponds to a pair of nodes: pick-up and drop-off while arcs denote the feasible travel between nodes.

We use multinomial logit to model the choice of users. Each choice is expressed based on the combination of pick-up and delivery time and price levels. Users make their request on an app then they are provided with a menu of options. Competition is modeled implicitly via an opt-out option inside the choice probably (multinomial logit). The problem is then formulated as a choice-based MILP with the objective of maximizing the expected marginal profit. The expected profit is represented by the choice probability and the price of alternatives on the menu. The marginal cost considers both the routing and the opportunity costs for the entire fleet (i.e., those that are already serving existing users and those that are considered to offer a menu to the new user). We assign a penalty to the empty capacity on board of the fleet (both vans and drones) to make sure the maximum capacity is used as much as possible.

The constraints include typical routing constraints and they are linked to assortment optimization constraints so that the routing decisions are consistent with the offered assortment. Time-related constraints maintain the time windows, the consistency of time across pick-up and drop-off nodes as well as desirable total travel time for each package. Furthermore, load related constraints maintain the capacity limitations.

The formulation and solution of this problem bring together various methodologies. The set of assortments is pre-processed considering all combinations of alternatives and the size is reduced by defining efficient sets in order to increase the computational efficiency. Several problem specific valid inequalities are added to reduce the computational time. Finally, we solve the model by using a tailored branch & bound strategy.

We test the performance of our algorithm over 12 scenarios. Each scenario is characterized based the request distribution, travel distance and rate of arrival. For each scenario, we solve the problem under three different situations: (1) myopic (2) using a heuristic that dynamically updates the opportunity cost and (3) perfect information. For each case, we show that the revenue performance can be dramatically improved by using a simple heuristic to incorporate future demand into the revenue management model.

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Integrating Dial-a-Ride with Mode Choice

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Over the past few decades, shared mobility services have been boosted due to high energy cost, limited parking and advanced internet technologies. Recently, dial-a-ride systems have regained popularity due to their potential to offer competitive travel solutions in terms of cost and convenience. Nevertheless, several modeling and computational challenges hinder the successful deployment of dial-a-ride solutions. Dial-a-ride is an on-demand transportation system that provides shared vehicle services to requests by travellers with specific origins, destinations and time windows. The standard dial-a-ride problem (DARP) aims at designing the minimum-cost routing that accommodates all requests, under a set of constraints [1]. The standard DARP has been studied extensively, and the current trend of research on DARP is to incorporate additional real-life characteristics to extend the original formulation [2].

In this work, we propose to incorporate travellers' mode choice decisions that within a rich DARP formulation. Specifically, we consider that two travel modes are available: a DARP service and a private travel option, and we integrate utility functions for each travel mode within a classic DARP formulation.

We follow and briefly recall the formulation of [1] for the classical part of the proposed DARP model. Let n be the number of travellers' travel requests. The classical DARP is defined on a complete directed graph $G = (V, A)$, where $N = P \cup D \cup \{0, 2n+1\}$. Subset $P = \{1, \ldots, n\}$ contains pick-up nodes and subset $D = \{n+1, \ldots, 2n\}$ contains drop-off nodes, while nodes 0 and

$2n+1$ represent the origin and destination depots, respectively. Each node pair $(i, n+i)$ represents a travel request from i to $n+i$. Let K be the set of shared mobility vehicles. Each vehicle $k \in K$ has a capacity Q_k and a maximal vehicle travel time T_k. Each request i has an associated load q_i and a service duration d_i. We assume that $q_0 = q_{2n+1} = d_0 = d_{2n+1} = 0$, and $q_i = -q_{n+i}$. The earliest and latest time that service may begin at node i is represented by the time window $[e_i, l_i]$. For each arc $(i,j) \in A$ in the network, c_{ij} represents its travel cost and t_{ij} represents its travel time. We denote L the maximum acceptable travel time of a traveller when using the shared mobility service. For each arc $(i,j) \in A$ and each vehicle $k \in K$, let x_{ij}^k be a binary decision variable equal to 1 if vehicle k is used from i to j. For each node $i \in N$, let B_i be the time at which node i is serviced and let Q_i^k be the load of vehicle k after visiting node i. We denote L_i as the travel time of user i using the shared mobility service.

Let ρ_i be the trip utility for user i expressed in monetary units, this utility is independent of the mode used to make the trip. Let ρ_T and ρ_W be parameters that convert travel time and waiting time into monetary units. For private travel, we assume that travel time is equal to $t_{i,n+i}$ and that waiting time is null. For the shared mobility service, travel time is represented by variable L_i which depends on the route taken by the vehicle servicing user i. Waiting time when using the shared mobility service is determined by the difference $B_i - e_i$ between the pick-up time of user i and the earliest possible pick-up time for user i. Let ρ_i^P and ρ_i^S be the travel costs in monetary units for private travel and the shared mobility service, respectively. The utility functions for the shared mobility service U_i and private travel and $\hat{U}_i$ are summarized below:

$$U_i = \rho_i - \rho_T L_i - \rho_W (B_i - e_i) - \rho_i^S \qquad \forall i \in P \tag{1}$$

$$\hat{U}_i = \rho_i - \rho_T t_{i,n+i} - \rho_i^P \qquad \forall i \in P \tag{2}$$

Observe that the utility of the shared mobility service depends on the collective choice of travellers whereas we assume that the utility of private travel is fixed. Assuming that travellers are rational and seek to maximize their trip utility, we introduce the following constraints:

$$\sum_{j \in D} \sum_{k \in K} x_{ij}^k = y_i \qquad \forall i \in P \tag{3}$$

$$(2y_i - 1)(U_i - \hat{U}_i) \geq 0 \qquad \forall i \in P \tag{4}$$

Constraint (3) links variable y_i to the variable x_{ij}^k enforcing that request i is serviced only if $y_i = 1$. Constraint (4) sets $y_i = 1$ if the utility of the shared mobility service is greater than that of the private travel option for user i and $y_i = 0$ otherwise. Incorporating utility functions (1) and (2) within constraint (4), we obtain the proposed DARP with mode choice formulation (5).

$$\min \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} c_{ij}x_{ij}^k \tag{5a}$$

subject to

$$\sum_{j\in D}\sum_{k\in K} x_{ij}^k = y_i \qquad \forall i \in P, \tag{5b}$$

$$\sum_{j\in D} x_{ij}^k - \sum_{j\in D} x_{n+i,j}^k = 0 \qquad \forall i \in P, k \in K, \tag{5c}$$

$$\sum_{j\in N} x_{0j}^k = 1, \sum_{i\in N} x_{i,2n+1}^k = 1 \qquad \forall k \in K, \tag{5d}$$

$$\sum_{j\in N} x_{ji}^k - \sum_{j\in N} x_{ij}^k = 0 \qquad \forall i \in P\cup D, k \in K, \tag{5e}$$

$$B_j \geq (B_0^k + d_0 + t_{0j})x_{0j}^k \qquad \forall j \in P\cup D, k\in K, \tag{5f}$$

$$B_j \geq (B_i + d_i + t_{ij})\sum_{k\in K} x_{ij}^k \qquad \forall i \in P\cup D, j \in P\cup D, \tag{5g}$$

$$B_{2n+1}^k \geq (B_i + d_i + t_{i,2n+1})x_{i,2n+1}^k \qquad \forall i \in P\cup D, k\in K, \tag{5h}$$

$$Q_j^k \geq (Q_i^k + q_j)x_{ij}^k \qquad \forall i \in N, j\in N, k\in K, \tag{5i}$$

$$L_i = B_{n+i} - (B_i + d_i) \qquad \forall i \in P, \tag{5j}$$

$$B_{2n+1}^k - B_0^k \leq T_k \qquad \forall k \in K, \tag{5k}$$

$$e_i \leq B_i \leq l_i \qquad \forall i \in P\cup D, \tag{5l}$$

$$t_{i,n+i} \leq L_i \leq L \qquad \forall i \in P, \tag{5m}$$

$$\max\{0, q_i\} \leq Q_i^k \leq \min\{Q, Q+q_i\} \qquad \forall i \in N, k\in K, \tag{5n}$$

$$(2y_i - 1)(\rho_T(t_{i,n+i} - L_i) - \rho_W(B_i - e_i) + \rho_i^P - \rho_i^S) \geq 0 \qquad \forall i \in P, \tag{5o}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall i \in N, j\in N, k\in K, \tag{5p}$$

$$y_i \in \{0,1\} \qquad \forall i \in P. \tag{5q}$$

The objective function (5a) minimizes the total routing cost. Constraint (5b) ensures that i is serviced only if $y_i = 1$. Constraints (5c)-(5n) are adopted from [1] to model pick-up and drop-off requirements, ensure flow conservation and, time and load consistency as well as route and user constraints. Constraint (5o) sets the value of variables y_i to model users' mode choice.

We explore the behavior of the proposed integrated DARP with mode choice constraints formulation (5) by conducting sensitivity analyses on the parameters of the utility functions (1) and (2) and present new solution algorithms for this rich DARP model.

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The Dynamic Relocation Problem for Electric Carsharing Services

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1 Introduction

Carsharing systems have gained popularity in recent years, and several carsharing companies provide these innovative services in many cities around the globe. Several of the planning problems faced by carsharing companies give rise to new and unexplored optimization problems and are consequently drawing the attention of the Operations Research (OR) community.

Carsharing services can be classified in *station-based* and *free-floating* services. Station-based services require that cars are picked up and returned at stations available in the perimeter of the city. Free-floating services allow users to pick up return cars at any available parking spot. Free-floating carsharing systems are prone to unbalanced distributions of rental cars due to uneven patterns in customer demand. Therefore, measures designed to prevent unfavorable distributions of the fleet, such as ad-hoc pricing schemes [1], are paramount for the profitability of such services. Among these measures, staff-based relocation [4], which is the focus of this talk, is inevitable.

This talk examines the problem of relocating a fleet of shared cars in a free-floating carsharing service using electric vehicles. We assume that relocation activities are undertaken in combination with charging activities. A mathematical model for the resulting *Dynamic Electric Vehicle Relocation Problem* (DE-VReP) is thus proposed. The goal of this operational problem is to maximize the demand served in a cost-effective way by strategically charging and relocating cars. A heuristic based on the Adaptive Large Neighborhood Search (ALNS) is thus proposed.

2 Problem Description

The DE-VReP is the operational problem, faced by carsharing companies, of deciding: a) an assignment of cars to charging stations or to different zones, b) an assignment of staff to relocation tasks and c) routes and schedules for the staff. The scope of the carsharing company is to maximize demand served in a cost-effective way. The costs involved in these activities include wear of the vehicles, tolls, electricity for the cars as well as the cost of the service employees. Therefore, a trade-off between demand satisfaction and relocation and recharging cost is sought. Consistently with a number of real-life carsharing operators, it is assumed that service employees move between cars using folding bicycles or public transportation. This assumption is also consistent with the previous work of [2] and [3].

Customer demand varies during the day. Similarly, the supply of vehicles (their location and charge) varies during the day as the result of customers usage. Cars with a remaining charge falling below a certain threshold, or in need of maintenance, are assumed to be unavailable to customers and must be relocated to an available charging station.

3 Solution Method Overview

The DE-VReP gives rise to a complex Mixed Integer Linear Programming problem which cannot be solved for instances of size compatible with real-life problems. Therefore, consistently with common practice in real-life carsharing companies, we propose a rolling-horizon approach which allows a decision maker to plan relocation and charging activities at several time points during the day as a result of updated system information (i.e., demand, position of cars and battery status). For the underlying static version of the DE-VReP we propose a metaheuristic based on the Adaptive Large Neighborhood Search [5]. The ALNS metaheuristic is divided into a Tabu Search (TS) component, and a Large Neighborhood (LNS) component. The workflow of the solution process can be sketched as follows:

- An initial solution is fed to the TS which locally searches for better solutions in a greedy manner.
- If no improvement is found for a certain number of iterations, the LNS component is activated.
- The LNS component destroys and repairs the current solution, guiding the search into a new area of the search space.
- The TS is reactivated in the new neighborhood.
- This process is repeated until either the time has expired or no improvement has been found after a certain number of iterations.

4 Preliminary Results

The solution method is tested on instances adapted from a real-life carsharing company. Preliminary results show that the ALNS metaheuristic can achieve satisfactory results for real-life-size instances of the DE-VReP. Particularly, the metaheuristic can find high-quality solutions for instances with up to 380 cars in less than 180 seconds. Furthermore, the metaheuristic is able to find the optimal solution for several small to medium size instances. For the instances with known optimal solution (i.e., those for which the corresponding MILP can be solved to optimality) the ALNS metaheuristic finds the optimal solution in less than 10 seconds. For the remaining large-scale instances, the ALNS metaheuristic shows great stability, with an average gap of 0.5% to the best-known solution.

Finally, based on our computational study, we provides operational insights for carsharing operators. As an example, preventive charging yields significant improvements in terms of long-term served demand.

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The Role of Crowdshippers in an Integrated Item-sharing and Crowdshipping Setting

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1 Motivation

An item-sharing platform provides its members a temporary access to items such as tools or leisure equipment so that the members can use the items for their own purposes, see e.g. [4, 5]. Accessing items for the time needed may allow for a more resource-efficient consumption as multiple members can sequentially use a same item instead of each buying it individually. The sharing of items does, however, necessitate a frequent peer-to-peer exchange that poses challenges from a transportation perspective. A delivery option is usually not offered and consumers need to pick up the requested items themselves.

To make item-sharing more attractive, we investigated in [3] the concept of an integrated item-sharing and crowdshipping platform in which the transportation of items can also be outsourced to private drivers. These so-called crowdshippers execute delivery jobs along their intended trips and receive financial incentives for that [1]. It has been shown that such an integration is a promising approach to enhance the profitability of a platform and to provide a higher level of service to its members as both item-sharing and crowdshipping are mutually beneficial. Item-sharing benefits from crowdshipping as it provides the opportunity to efficiently transfer single items between (distant) locations. Conversely, crowdshipping benefits from item-sharing as the delivery jobs are an outcome of a preceding assignment and therefore can be 'fitted' to the crowdshipping trips.

So far, we made a conservative assumption about crowdshippers' willingness to get involved in crowdshipping. A crowdshipper is expected to detour from his/her intended trip to pick up at most one item from a supply location and then either delivers it to the assigned request location or takes it to the destination of the trip. The goal of the latter option is to bring the item closer to the requesting location so that the designated recipient can pick it up more conveniently from there. The recent publication of [2] shows, however, that crowdshippers may also be willing to execute more than one delivery. This raises the question by how much an integrated platform would benefit from more engaged crowdshippers. Moreover, our proposed concept is a blueprint of a platform that does not yet exist in this form in practice, meaning that little is known about the longterm performance of such a system. To this end, we model a virtual platform and derive managerial insights by analyzing its performance in a dynamic setting. The two issues that are of particular interest in this context are the transport capacities of crowdshippers and the effects of a multi-period operations management of the considered platform.

2 Capacitated Crowdshipping

A capacity extension of crowdshippers in an integrated item-sharing and crowdshipping problem is a generalization of the problem described in [3]. It asks for a fundamentally different solution approach as the single-capacitated crowdshipping can be formulated as a three-dimensional assignment problem whereas assigning multiple deliveries to a crowdshipper requires solving a routing problem. After all, crowdshippers only accept to execute the assigned delivery jobs if the overall execution time does not exceed the travel time to get from their origin to their destination plus some additional time they are willing to spend on crowdshipping. We refer to this problem as *detour routing*, i.e. a routing of crowdshippers between two fixed locations within bounds, and we propose an exact solution approach that is based on a combination of label setting and set packing.

3 Crowdshipping in Multi-period Item-sharing

A typical dilemma of (online) sharing platforms is that the announcements to be matched enter into the system successively, i.e. the information that is relevant to the platform becomes available in the course of time. Although users of such a platform will request items at least a couple of days in advance and hold them for days or even weeks, the platform has to inform the users about the potential fulfilment of their requests as soon as possible. To support this and to account for the dynamics and uncertainties that are inherent to such a system, we also propose a rolling horizon framework. Previously developed static solution methods could be adapted here, but this would result in a myopic planning as only the announcements of the next period could be considered. Therefore, we propose a new mathematical model for the resulting multi-period assignment problem that takes into account submitted requests that refer to future planning periods. The model is solved using standard commercial solvers. Against this background, we re-evaluate the benefit that stems from crowdshipping as crowdshippers will most likely announce their trips on rather short notice.

4 Our Presentation

In our presentation, we describe in detail the concept of an integrated item-sharing and crowdshipping platform and its operational planning. We also explain the proposed methodological approaches. Eventually, essential findings from our numerical experiments are presented and discussed. The capacity-extended model is used to investigate the benefit that stems from the integration with crowdshipping, particularly when crowdshippers offer larger capacities or accept longer detours. In this context, we also investigate whether and how crowdshippers shall be motivated to get more involved. The multi-period extension is used to identify critical parameters to the profitability of an integrated platform in the long run. We compare different response strategies of the platform and we analyze to what extend crowdshipping supports the distribution of items, especially if trips are announced on short notice.

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A SUSTAINABLE CAPACITATED VEHICLE ROUTING PROBLEM UNDER DEMAND AND TRAVELING TIME VARIATIONS

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1. INTRODUCTION

Transport constitutes one of the sectors generating more externalities, including both social and environmental impacts. Given its strategic role in most countries, smart approaches for designing sustainable and robust routes are required. In this context, industrial needs have been changing over the last years. Currently, companies, customers and governments are increasingly concerned for social and environmental issues. Additionally, these processes frequently face unexpected changes in demand levels and urban conditions.

Generally speaking, logistic challenges are focused on pollution targets, achieving pollution reduction and collaboration strategies to lead the cities to a smart growth. Recently, World Bank affirmed that in developing countries the 60% of operation costs are referred to fuel bills, for that reason the sustainable initiatives are focused on emission and cost reduction, standing out the direct relation among environmental improvements and economic benefits on the social welfare. As a consequence multiple realistic and rich vehicle routing problems have been studied over the last few decades. Most studies focus on theoretical scenarios and evaluate emissions or fuel consumption without considering the social dimension.

To reduce the existing gap in the literature, this abstract presents a model that deals with all the dimensions of sustainability considering the capacitated vehicle routing problem (CVRP) under scenarios considering customers with a specific probability of presence and different traveling times. Then, in this abstract is tackled a sustainable capacitated vehicle routing problem under scenarios with different traveling times and demands. The objective is to minimize the distribution costs, which CO_2 emissions and fuel consumption (environmental dimension); accident risk (social dimension); and a driver cost and a fixed vehicle cost (economic dimension). An integer lineal programming model is proposed. Afterwards, a computational experiment is carried out to analyze the effect of road states and demand levels on the solutions.

2. MODEL APPROACH

The CVRP can be stated as follows. Let $G = (N, A)$ be a complete undirected graph where $N = 0 \cup N_C$ is the set of nodes. *0* corresponds to the depot and N_C the subset of customers. Each customer *i* may be present or absent. In the first case, it has a demand q_i. Three type of customers are defined: (i) fixed customers with a known demand; (ii) customers who regularly place orders with a known demand; and (iii) customers who place orders sporadically with random demands. A is the set of arcs that connect all nodes in N. Three paths, P, are defined for each arc (i, j) differing in the average length from the longest to the shortest path. Each path is characterized by a traveling distance d_{ij} and a traveling time t_{ij} that depends on the road state. Each route starts and ends at the depot, and all customers' demands must be satisfied.

An integer lineal programming formulation is developed. It uses the binary variable $X_{ij}^{\varphi p}$: $X_{ij}^{\varphi p} = 1$ if the path p of arc (i, j) is traversed by a vehicle in the scenario φ, and $X_{ij}^{\varphi p} = 0$ otherwise, where φ represent three scenarios: (1) Scenario 1 refers to the best distribution conditions on which the customers set and demand levels are known and traveling times represent a low-level congestion; (2) Scenario 2 represents the average scenario where there are medium congestion levels and a portion of customer demands are unknown. Finally, (3) Scenario 3 is the pessimistic situation by a high variation of demand levels, customers and a high level congestion. In this sense, three probable distribution scenarios are tackled to consider variation in customers' amount, demand levels and traffic conditions.

For a given solution (i.e., a set of routes), each arc has a cost C_{ij} that represents the impacts of traveling through it:

Economic dimension. It includes the traveling time which affects the amount paid for driver wages (DW) and vehicle fixed costs (FC), additionally the traveling distance is monetized relying on the oil price (C_f).

$$\sum_{\forall (i,j) \in A} X_{ij}^{\varphi p} \cdot (t_{ij} \cdot DW + FC) \qquad (1); \qquad \sum_{\forall (i,j) \in A} C_f \cdot f_{i,j} \cdot d_{ij} \cdot X_{ij}^{\varphi p} \qquad (2)$$

Environmental dimension. Kuo (2010) introduced a model that considers CO_2 emissions as a function of the fuel consumption [1]. Here, it is estimated the emissions (C_e) and the fuel consumption ($f_{i,j}$) as suggested in this work.

$$\sum_{\forall (i,j) \in A} C_e \cdot f_{i,j} \cdot X_{ij}^{\varphi p} \qquad (3)$$

Social dimension. Related indicators are very subjective, because most of the negative impacts generate intangible effects on people. These effects are difficult to measure and depend on the perspective analyzed, which leads to diverse results and practical implications. In this study is considered the approach of Delucchi and McCubbin in 2010, which monetizes the accident risk for pedestrians and vehicles by a given coefficient (a_{ij}) [2]. This risk depends on the distance and the vehicles loading on that arc (Q_{ij}).

$$\sum_{\forall (i,j) \in A} a_{ij} \cdot d_{ij} \cdot Q_{ij} \cdot X_{ij}^{\varphi p} \qquad (4)$$

Finally, the objective is defined as a multi-criteria function considering the total travelling time, total travelling distance, environmental cost, and social cost, respectively.

$$\sum_{\forall(i,j)\in A}(t_{ij}\cdot DW + FC + C_f\cdot f_{i,j}\cdot d_{ij} + C_e\cdot f_{i,j} + a_{ij}\cdot d_{ij}\cdot Q_{ij})\cdot X_{ij}^{\varphi p} \tag{5}$$

3. COMPUTATIONAL RESULTS

The results demonstrate that the traveling time of the solution does not depend on the presence of sporadic demands. In this pessimistic scenario, the model designs the routes minimizing the traveling time and, in turn, the fuel consumption and carbon emissions. Figure 2 illustrates the routes defined for Vehicle 1, while Table 1 shows the model performances for each scenario.

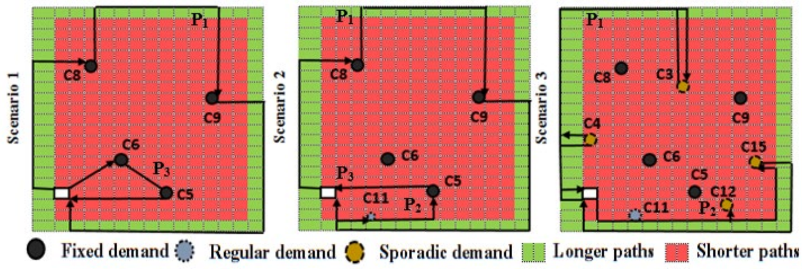

Figure 1 - Representation of a partial solution, including a single vehicle

Table 1 - Sustainability indicators for vehicle 1 routes

		Scenario 1	Scenario 2	Scenario 3
Vehicle 1	Traveling distance (km)	10.88	11.00	14.77
	Traveling time (Hours)	0.18	0.22	0.58
	Carbon Emissions (Dollars)	0.11	0.09	0.31
	Accident rate (Dollars)	0.24	0.33	0.58
	Fuel consumption (Dollars)	1.06	1.06	1.55
	Route cost (Dollars)	1.39	1.40	2.44
Demand (kg)		380	525	825

In addition, the model selects the appropriate path according to the demand levels and the speed variations. Indeed, it uses the longer paths which have associated a relatively faster traveling speed because of the traffic congestion. However, the increases in the distance and traveling time are not directly proportional; it allows to demonstrate that the negative impacts also have a relationship with the traveling times, besides being a sensitive indicator against any perturbation on roads.

4. CONCLUSIONS

This abstract presents the distribution process in urban zones from a dynamic perspective. A model has been proposed, which considers traffic conditions and different customers' behavior. It provides an optimal solution to distribution problems taking into account the three axis of sustainability as performance measures. Finally, this study demonstrates the need of not only developing structured but also flexible methods to consider the urban dynamics and the new operational trends, such as the collaboration strategies and the use of information and communication technologies into the decision-making process.

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Optimal Scheduling of Advance Reservations for Shared Parking Systems

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1 Introduction

This past few years witness the rise of various sharing transportation services, such as bike-sharing, scooter-sharing, car-sharing and shared parking. Shared parking is a type of parking management that aims to efficiently use parking spaces in big cities. This type of parking management takes advantage of the fact that most parking spaces are only used part time by a particular individual or group, and many parking facilities have a significant portion of unused spaces. Through shard parking, private parking owners such as companies, universities, hospitals and individuals can rent out their parking space at times they don't use it. This allows drivers to park their car at parking spaces that are so far not accessible for them, and hence may help drivers to avoid the long search and the circling around to find an empty parking space.

Recently, shared parking has been considered as an effective means of resolving parking problems in several urban areas around the world, such as Indianapolis in Indiana, Montgomery County in Maryland, Ann Arbor in Michigan, Beijing in China, and Taipei in Taiwan. A number of startups also develop mobile Apps that serve as platforms of shared parking (e.g., JustPark in UK, MobyPark in Europe, Pavemint in USA, Nokisaki Parking in Japan, Airparking in China, and USpace in Taiwan). These platforms are operated as online transaction mediums for private parking owners and individual parking requests. While private parking owners typically rent out parking spaces in advance, there are generally two categories of parking requests: current and advance. Current reservations are those in which users request parking spaces in less than a certain amount of time (e.q., 1h). Conversely, advance reservations are typically made a certain amount of time beforehand (eg., 1 day). The focus in this paper is on advance reservations.

One of important decisions for operating a shared parking system is how to assign advance reservations to available parking spaces and schedule those requests. However, to our best knowledge, there exists no previous research that focused on the scheduling problem of advance reservations for shared parking systems. To fill in this research gap, we formulate the scheduling problem as a mixed integer linear program (MILP) based on an innovative parking space-flow network. The objective of this model is to determine the optimal assignment and schedule of advance requests which maximizes the revenue (or profit) of the operator of a shared parking system while satisfying parking requests. Since the problem is formulated as an integer multi-commodity network flow problem, which is characterized as NP-hard, a simulated annealing (SA) algorithm is developed to efficient solve large-scale instances of the problem, although small- and medium-scale instances can be solved by the Gurobi Optimizer.

2 The parking space-flow network

The model is developed based on the parking space-flow network. As shown in Fig. 2, the status of a parking space at a certain time is either occupied or idle. For example, this parking space is occupied by vehicles A, B, C and D in the four periods: 9:00-11:00, 13:00-14:30, 15:00-16:00 and 17:00-18:00. We consider the four vehicles to "flow" through the parking space sequentially. The vehicle which can be serviced at that parking space are included in that parking space's network. From the system perspective, that parking space can be considered as being flowed through by the vehicles assigned to that parking space in the order of their scheduled arrival times. It is assumed that vehicles arrive as scheduled; stochastic vehicle arrival times should be addressed in future research.

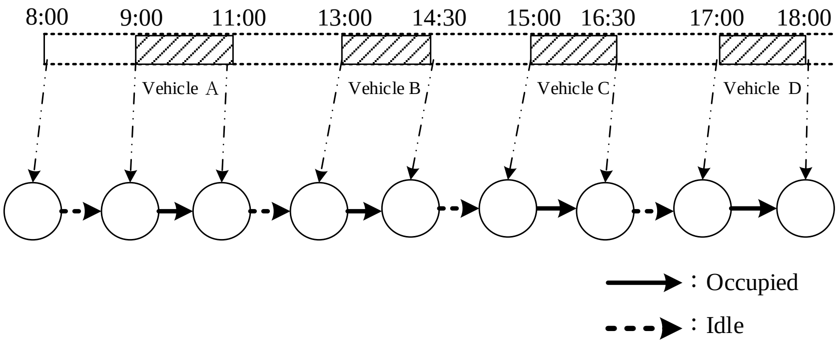

Fig. 2. An example of parking space usage

The proposed model is developed based on the multiple parking space-flow networks. As shown in Fig. 3, in each parking space network, there are four types of nodes:

(1) Starting node and ending node: representing the beginning and the end of the allocation of the parking space in the planning period, respectively.

(2) Arriving node and leaving node: representing the scheduled arrival and departure times of a vehicle associated with the parking space, respectively.

In addition, there are five types of arcs. The flow on each arc is either 1 or 0. The arc cost of each arc is 0, except for parking arcs. The arc cost of parking arcs is the revenue of serving vehicles.

(1) Staring arc: A starting arc connects the starting node to the arriving node.

(2) Ending arc: An ending arc connects a leaving node to the ending node.

(3) Parking arc: A parking arc connects the arriving node to its leaving node, and represents the association of that vehicle with the parking space.

(4) Connectible arc: A connectible arc connects the leaving node corresponding to one vehicle to the arriving node corresponding to another vehicle. A leaving node is connected to an arriving node by a connectible arc only if the time corresponding to that leaving node is earlier than the time corresponding to that arriving node. This type of arc represents the feasibility of assigning two vehicles sequentially to a parking space, that is, one vehicle is serviced by that parking space after another.

(5) Cycle arc: A cycle arc connects the ending node to the starting node to ensure the flow conversations at the starting and the ending node in the parking space-flow network.

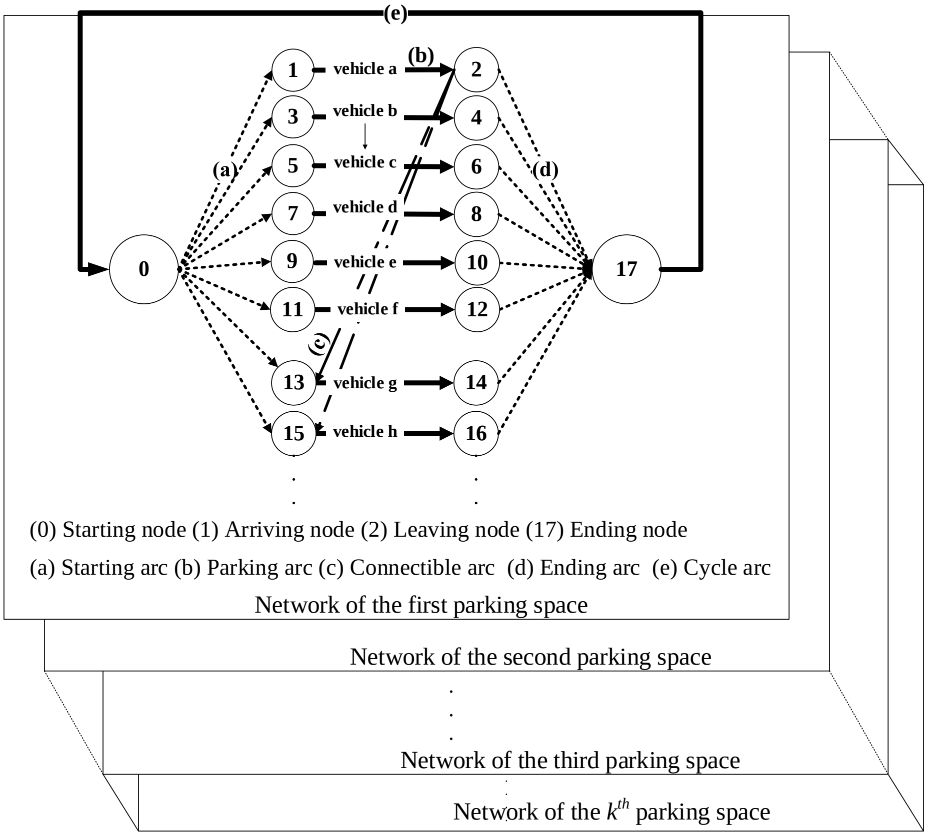

Fig. 3. Illustration of parking space-flow network

3 Model formulation

This study develops a new model for the optimal scheduling of advance reservations for shared parking systems. The model is formulated as an integer multi-commodity network flow problem, based on the parking space-flow networks described above. The notations used to present the model are listed as follows.

Sets

K : the set of sharing parking space available

D : the set of vehicles arriving in the scheduling planning

A^k : the set of arcs in the k^{th} parking space-flow network

R^k : the set of parking arcs in the k^{th} parking space-flow network

N^k : the set of nodes in the k^{th} parking space-flow network

U_i^k : the set of upstream nodes of node i in the k^{th} parking space-flow network

L_i^k : the set of downstream nodes of node i in the k^{th} parking space-flow network

V_υ^k : the set of parking arcs of the υ^{th} vehicle in the k^{th} parking space-flow network

Parameter

P_{ij}^k : the cost of arc (i,j) in the k^{th} parking space-flow network

Decision Variable

x_{ij}^k : the flow on arc (i,j) in the k^{th} parking space-flow network

Maximize $\sum_{k=1}^{K}\sum_{i,j\in R^k} P_{ij}^k x_{ij}^k$ (1)

Subject to $\sum_{k=1}^{k}\sum_{i,j\in V_v^k} x_{ij}^k = 1 \quad \forall v \in D$ (2)

$\sum_{j\in L_i^k} x_{ij}^k - \sum_{h\in U_i^k} x_{hi}^k = 0 \quad \forall i \in N^k,\ \forall k \in K$ (3)

$x_{ij}^k = 0$ or 1 (4)

The objective function, Eq. (1), maximizes the total revenue for the system operator. Constraint (2) ensures that every vehicle is assigned to one and only one parking space. Eq. (3) is the flow conservation constraint at every node in the parking space-flow networks. Constraint (4) indicates that all the decision variables are binary.

4 Numerical examples

In order to examine the model and the performance of the proposed algorithm, we conducted numerical experiments on a set of problem instances generated based on the real data provided by a shared parking system operator in Taipei, Taiwan. The instances were classified into three categories: small-, medium- and large-scale instances, with 50, 70 and 90 parking spaces, respectively. Different demand levels in terms of number of parking requests were considered for each category of instances. A C++ computer program was developed to code the model solved by the Gurobi Optimizer. The SA algorithm was also implemented using C++ computer programming language. The numerical results show that the proposed model and its solution algorithm are able to effectively and efficiently generate schedules of advanced parking requests. Conclusively, this study provides an effective means of obtaining optimal assignments and schedules of advanced reservations for shared parking systems.

Optimizing routing and delivery patterns with multi-compartment vehicles

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1 Problem Description

The vehicle routing problem discussed in this work is an extension of the classical capacitated vehicle routing problem (CVRP; [5]) and addresses a real-life problem for retailers in grocery distribution. The distribution of groceries is characterized by supplying stores from a central warehouse with products across various product categories ([1]; [2]). The distribution process involves multi-temperature logistics due to the different temperature requirements across products and therefore multi-compartment vehicles (MCV) are used to enable a joint distribution ([4]). MCVs can be characterized by the possibility to split the loading area into different compartments. The individual compartments can be adjusted to a given temperature requirement.

Grocery retail stores usually have a weekly demand pattern for the individual segments and therefore require the supply on multiple days of a week to ensure product availability. Typically, cyclical store-specific delivery patterns are used for each segment to supply the individual stores according to their needs. Delivery patterns (DP) constitute a defined combination of weekdays on which a delivery to the store for each product segment individually happens. DPs are usually designed according to the volume of sales and store sizes ([3], [6]). MCVs increase the flexibility for the supply of stores as they enable the combination of different product segments for deliveries. Thus they offer new possibilities for DP selection as DPs of individual segments can be aligned to achieve synergies, possibly resulting in higher delivery frequencies for certain segments.

This raises the question, how MCVs and as such the combination of the supply across multiple segments influence the definition of store-specific DPs for individual segments and how the changed DPs affect total logistics costs in warehousing, transport and stores.

2 Decision Problem

We present a Periodic Multi-Compartment Vehicle Routing Problem (PMCVRP) for the determination of DPs and the corresponding vehicle routing. The formulated PMCVRP considers both delivery pattern dependent costs and routing costs. Supplementary to existing literature, the applied research introduces the following characteristics:

- Extension of an MCVRP for multiple planning periods.
- Identification and incorporation of decision relevant costs for the use of MCVs and the selection of DPs (along the internal grocery supply chain consisting of DC, transportation, and store).
- Selection of store- and segment-specific DPs for the distribution of groceries, i.e., defining the delivery frequency for each store-segment pair.
- Definition of cost-efficient delivery tours based on the selected delivery patterns, i.e., considering the interdependence of routing with MCVs and DPs.

Our problem formulation considers i) heterogeneous products, and ii) their assignment to vehicles with multiple compartments and the corresponding compartment setting. We further decide on iii) the optimal DP for each store-segment combination while taking into account iv) the interdependence between DP and routing decisions. The problem is NP-hard since it is a generalization of the CVRP ([5]).

3 Solution Approach and Numerical Results

The complexity of the given PMCVRP asks for heuristic solution approaches to solve practical relevant problem sizes. We propose a holistic solution approach that iteratively solves the assignment and routing problem. More precisely, in the first stage of the search an ALNS framework is used to determine DPs for each customer-segment combination and hence to assign deliveries to each day of the planning horizon. We introduce specialized operators for the assignment of DPs that are tailored to the given problem specifics.

The assignment of DPs results in an multi-compartment vehicle routing problem for the daily planning. The daily MCVRP is solved by a lean LNS in the second stage of the search. The used LNS has been applied successfully to similar routing problems. Using the two different stages, the algorithm iteratively improves the interdependent decisions on delivery frequency (DPs) and routing.

We show the effectiveness of our solution approach by comparing it to the problem formulation of [3]. They consider the assignment of DPs for a standard VRP and therefore the split supply of different product segments. In further numerical studies we show the influence of MCVs on the definition of delivery patterns. Moreover, we analyze the impact of the cost relation between pattern dependent costs (e.g., store replenishment, picking) and transportation costs.

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Integrating drayage decisions in intermodal container routing

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1 Problem statement

Intermodal transportation involves multiple actors and decision makers, resulting in a more complex planning environment compared to unimodal transport. Ambra et al [1] emphasize the need for innovative integrated support systems with a focus on cost efficiency in order for intermodal transport to increase its competitiveness. One innovative, recent solution concerns synchromodality. In a synchromodal view, ideally, load units are routed through an interconnected network of hubs depending on the network capacity, where the sender is not concerned about the route of its packages [1]. This requires flexible and real-time planning, which poses a number of challenges for planners. In this context, adequate decision support and fast planning algorithms with real-life characteristics are needed to support this synchromodal vision.

When transport orders enter into the system, the intermodal operator assigns load units to an intermodal long-haul service to maximize the overall network capacity utilization, and local drayage routes must be established to transport load units between customer locations and the transhipment terminals for long-haul transport. Usually, these decisions are made in a sequential way. The integration of both interdependent problems may result in cost savings, but research efforts which simultaneously consider both decisions are still limited. Most related literature concerns dial-a-ride problems in which transfers to and from timetabled public transport are integrated into demand-responsive passenger transportation [2]. With respect to freight transportation, a first research effort has been performed very recently [3].

In our research, the local drayage problem with a heterogeneous truck fleet is combined with a long-haul routing problem with detailed capacity considerations into an integrated intermodal routing problem. A model formulation and heuristic algorithm are developed to compare a sequential and integrated approach, and quantify the potential savings.

2 Problem description

An intermodal operator considers a number of full-container requests which should be transported from their customer origin location to their customer destination location through an intermodal network. This network consists of a number of long-haul rail services between two large service regions, each with multiple intermodal terminals. Within each service region, local pre- and end-haul operations are performed.

In a sequential approach, the long-haul service for each request is selected in advance, resulting in one clearly defined drayage task in each region, i.e. one pickup and one delivery task. In our integrated approach, the long-haul service is not fixed in advance, which results in multiple potential drayage tasks per region, of which one per region has to be selected. While trucks start and end their route at a depot located at a terminal, they can be out for multiple days before returning to the depot. Therefore, a multi-day scheduling procedure is proposed, with a maximum daily active time and a minimum overnight's rest before or after the execution of a transport task. Furthermore, in practice, planning for a single time period is executed, while an initial planning for future time periods is composed. We pay attention to this dynamic nature of the problem by including information on past week's planning as well as the initial planning for the next week.

3 Solution methodology

A large neighborhood search algorithm is proposed to solve the intermodal routing problem. Both a sequential and an integrated version of the algorithm are presented. The sequential approach serves as a benchmark for the improvements that may be obtained by the integrated intermodal routing problem. The heuristic building blocks are similar for both approaches, but different parts of the solution are destroyed and repaired. Whereas operators in a sequential setting remove and reinsert individual, fixed drayage tasks (with predetermined terminals), an integrated setting removes and reinserts both the pre-haul and end-haul task of any request simultaneously, as well as the selected long-haul service. Moreover, removal operators which focus on the integrated aspect are proposed. As the goal of this research is to explore and quantify the differences between a sequential and our new, integrated approach, the heuristic parameter setting should allow a fair comparison of both approaches. Therefore, for each solution approach, a parameter setting is determined independently.

4 Computational results

A real-life service network with various demand characteristics is studied to compare both approaches. Customer locations are either random or clustered around intermodal terminals. Three demand levels are considered, varying between a relatively low and high capacity utilization, with the latter considered common in practice.

Results show a lower trucking cost per drayage task for clustered instances with a high capacity utilization. On the one hand, a cost reduction is obtained by providing more efficient truck routes. On the other hand, this effect is reinforced because of the fact that more load units are planned on a long-haul service which departs and arrives in the current planning cycle. This further decreases costs as this higher number of load units can also be planned more efficiently. The advantage is less clear for instances with random customer locations or a smaller capacity utilization. In a sequential approach, the closest terminal can always be selected if enough capacity is available, and no trade-offs are required. On the contrary, with a higher capacity utilization, a decision should be made based on the relationship between costs of truck routes and assigned services, and the closest terminal cannot always be selected. In all demand scenarios, the integrated approach postpones less load units to next week's services at a small additional truck cost.

To conclude, results of the integrated approach demonstrate that the largest savings are obtained for clustered instances with demand characteristics closest to real-life cases (i.e. high capacity utilization). In all cases, less load units are postponed, consistent with an improved capacity utilization. For these instances with high demand, trucking costs per drayage tasks are even reduced in the case of clustered instances. Using this integrated approach for real-life data, the heuristic algorithm is employed to analyze how operational transport costs are influenced by decisions at the tactical level.

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An enhanced lower bound for the Time-Dependent Traveling Salesman Problem

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1 Introduction

Vehicle routing is concerned with the design of routes for fleets of vehicles, in order to optimize a given objective (such as minimizing the travelled time), possibly subject to side constraints, such as vehicle capacity limitations or delivery time windows. In recent years there has been a flourishing of scholarly work in time-dependent routing. See Gendreau et al. (2015) for a review of the field. Given a graph $G = (V \cup \{0\}, A)$ (V is the set of vertices, A is the set of arcs and 0 is the vertex representing the depot) whose arc traversal times vary over time, the Time-Dependent Travelling Salesman Problem (TDTSP) amounts to find a Hamiltonian tour of least total duration. In this work we define a new lower bounding scheme whose parameters are determined by fitting the traffic data.

2 Problem definition and background

Let $[0, T]$ be the time horizon partitioned into H subintervals $[T_h, T_{h+1}]$ ($h = 0, \ldots, H-1$), where $T_0 = 0$ and $T_H = T$. The travel time $\tau_{ij}(t)$ functions are continuous piecewise linear with breakpoints T_h ($h = 0, \ldots, H$), and satisfy the *first-in-first-out* (FIFO) property (Gendreau et al. (2015)). Ghiani and Guerriero (2014) proved that this class of travel time functions can be generated from the model defined by Ichoua et al. (2003) (IGP model) in which the velocity of a vehicle is not constant over the entire arc, but varies when the boundary between two consecutive time periods is crossed. Under these hypotheses, the IGP speeds are nonnegative (Ghiani and Guerriero (2014)) and can be decomposed according to the following *speed factorization* (Cordeau et al., 2014):

$$v_{ijh} = u^0_{ij} b^0_h \delta^0_{ijh}, \qquad (i,j) \in A, h = 0, \ldots, H-1 \tag{1}$$

where u^0_{ij} is the maximum speed of arc $(i,j) \in A$ over $[0,T]$, i.e. $u^0_{ij} = \max_{h=0,\ldots,H-1} v_{ijh}$; $b^0_h \in [0,1]$ is the lightest congestion factor during interval $[T_h, T_{h+1}]$ on the entire graph, i.e. $b^0_h = \max_{(i,j)\in A} v_{ijh}/u^0_{ij}$; and $\delta^0_{ijh} = v_{ijh}/u^0_{ij}b^0_h \in [0,1]$ is the degradation of the congestion factor of arc (i,j) in interval $[T_h, T_{h+1}]$ w.r.t. the less congested arc in $[T_h, T_{h+1}]$.

A fundamental role is played by $\Delta^0 = \min_{\substack{(i,j)\in A \\ h=0,\ldots,H-1}} \delta^0_{ijh}$ which is the worst degradation of the congestion factor of any arc $(i,j) \in A$ over the entire planning horizon. If $\Delta^0 = 1$, then all arcs $(i,j) \in A$ have the same congestion factor b^0_h during interval $[T_h, T_{h+1}]$ $(h = 0, \ldots, H-1)$.

Cordeau et al. (2014) derived a first relaxation of the problem by removing δ_{ijh} for each arc (i,j) and each time period $h = 0, \ldots, H-1$. This amounts to solve a TDTSP w.r.t. speeds

$$v^0_{ijh} = b^0_h u^0_{ij}, \quad (i,j) \in A, h = 0, \ldots, H-1. \tag{2}$$

A second relaxation can be obtained by giving each arc its maximum speed over the time horizon. This amounts to solve an Asymmetric TSP (Applegate et al., 2011) w.r.t. (constant) speeds

$$\underline{\underline{v}}^0_{ijh} = u_{ij}, \quad (i,j) \in A, h = 0, \ldots, H-1. \tag{3}$$

We denote with $z(c,t)$, $\underline{z}(c,t)$, $\underline{\underline{z}}(c,t)$ the duration of a circuit c assuming that the vehicle leaves the depot at time t and speed laws (1), (2) or (3) hold, respectively.

We preliminary observe that the speed factorization (1) for arc $(i,j) \in A$ still holds if parameters b_h and δ_{ijh} $(h = 0, \ldots, H-1)$ are computed on the basis of a maximum speed u_{ij} greater than u^0_{ij}: i. e. $\quad u_{ij} \geq u^0_{ij} \quad (i,j) \in A,\ h = 0, \ldots, H-1$.

This is equivalent to add an additional time slot $h = H$ (in which the vehicle has already returned to the depot) with speed $u_{ij} = v_{ijH} \geq v_{ijh}$ $(h = 0, \ldots, H-1)$. Let $\mathbf{u}$ be the vector of u_{ij} associated to arcs $(i,j) \in A$. Then, the travel speeds can be expressed as

$$v_{ijh} = u_{ij} b_h(\mathbf{u}) \delta_{ijh}(\mathbf{u}), \tag{4}$$

where:

- $b_h(\mathbf{u}) \in [0,1]$ is the best congestion factor during interval $[T_h, T_{h+1}]$ w.r.t. $\mathbf{u}$, i.e.,

$$b_h(\mathbf{u}) = \max_{(i,j)\in A} \frac{v_{ijh}}{u_{ij}};$$

- $\delta_{ijh}(\mathbf{u}) = \dfrac{v_{ijh}}{b_h(\mathbf{u}) u_{ij}}$ belongs to $[0,1]$ and represents the degradation of the congestion factor of arc (i,j) in interval $[T_h, T_{h+1}]$ w.r.t. the least congested arc in $[T_h, T_{h+1}]$.

With each vector $\mathbf{u}$ are associated a lower bound $LB(\mathbf{u})$ and an upper bound $UB(\mathbf{u})$. In particular, let $\underline{\underline{c}}(\mathbf{u})$ be the optimal solution value of an Asymmetric TSP whereas arc (i,j) has a cost L_{ij}/u_{ij}.

The upper bound is simply $UB(\mathbf{u}) = z(\underline{c}(\mathbf{u}))$ while the lower bound $LB(\mathbf{u})$ is:

$$LB(\mathbf{u}) = \phi(\underline{z}(\underline{c}(\mathbf{u})), 0, \mathbf{b}(\mathbf{u})) \tag{5}$$

where, $\mathbf{b}$ is the vector of traffic factors b_h $(h = 0, \ldots, H-1)$ and $\phi(l, t, \mathbf{b})$ is the traversal time of a dummy arc of length l assuming it is traversed starting at instant t with speeds $\mathbf{b}$. It is worth noting that, by increasing the u_{ij} variables, $\underline{z}(\underline{c}(\mathbf{u}))$ decreases (or remains the same). At the same time, the traffic factors b_h decrease (or remain the same). Hence, the ϕ value increases or remains unchanged. As a result, LB($\mathbf{u}$) may increase, decrease or remain unchanged. In order to find the best (larger) lower bound, the following problem has to be solved:

$$\begin{aligned} & \max LB(\mathbf{u}) && (6) \\ s.t.\quad & u_{ij} \geq v_{ijh} \qquad && (i,j) \in A, h = 0, \ldots, H-1 \end{aligned}$$

Unfortunately, this problem is nonlinear nonconvex and non-differentiable. So there is little hope to solve it to optimality with a moderate computational effort. Instead, we aim at finding a good lower bound as follows. We first determine a $\mathbf{u}$ vector by fitting the traffic data (solving a linear programming model). More specifically, we determine $\mathbf{u}$ in such a way the average residual,

$$\overline{\delta} = \frac{1}{H|A|} \sum_{h=0,\ldots,H-1} \sum_{(i,j)\in A} \delta_{ijh}, \tag{7}$$

is as large as possible in the hope to get $\Delta(\mathbf{u}) = 1$, or, at least, improve on lower bound $LB(\mathbf{u}^0)$. Then, we solve the Asymmetric TSP w.r.t. costs L_{ij}/u_{ij} in order to compute the associated $LB(\mathbf{u})$. Computational results show that, when embedded into a branch-and-bound procedure, this lower bounding mechanism allows to solve to optimality a larger number of instances than state-of-the-art algorithms.

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A stochastic programming approach to emergency response planning for rail hazmat incidents

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Introduction: Hazardous materials (hazmat), aka dangerous goods, are referred to substances that can cause harm to people, property, and the environment [1]. In North America, a significant portion of hazmat shipments is transported over the railroad network. Besides pipeline capacity shortfall, favorable safety statistics have made rail a growing mode for hazmat transport. For instance, Canadian railroads carried over 44 million tons of hazmat in 2015, which shows a remarkable increase from 29 million tons in 2006 [2]. Although rail is one of the safest modes for hazmat transport, the risk of catastrophic events such as the tragic event in Lac Mégantic (Quebec, Canada) in 2013, does exist. In this study, we investigate emergency response planning as a risk management technique, aimed at alleviating the harmful consequences associated with rail hazmat incidents.

Timely response is crucial in keeping the incident consequences relatively low. While first responders are typically able to reduce damages to some extent, the presence of specialized response teams and equipment is necessary to effectively respond to hazmat emergencies. A potential hazmat incident scenario would be deemed covered if it could be reached from an emergency response station within a specified time. We characterize a given incident scenario by *location*, *hazmat class (type)*, and *release volume*; based on these scenario-specific paramters, a *composite risk measure* can be calculated to account for both incident probability and estimated cost associated with incidents that are not responded to in a timely manner.

Problem Description: This study deals with facility location and resource allocation at the strategic and the tactical levels, respectively. Planning for emergency response to highway hazmat shipments has been studied in the literature using a deterministic approach [3]. Also, in the maritime domain, the problem of location and capability of oil-spill response facilities has been investigated, taking into account the uncertain aspects of oil-spill events [4]. However, to the best of our knowledge, there is no study in the literature that incorporates the differentiating aspects of the rail hazmat transportation into planning for hazmat incident response. It is pertinent that the initiatives taken by railroad companies are not publicly available, and thus difficult to ascertain.

We propose an optimization-based framework that accounts for the uncertainties involved in this problem, e.g. incident location. We specifically provide answers to the following questions: *where to locate emergency response facilities*; *what types and how many equipment packages to stockpile at each facility*; and, *how they are going to be utilized and dispatched in response to hazmat incidents*.

Modeling Approach: Because of the uncertainty associated with location, class, and release volume of hazmat incidents, we decided to use two-stage stochastic programming with recourse, which is cited as a general-purpose technique to deal with uncertainty in model parameters. The first stage accounts for the strategic decisions i.e. facility location and equipment acquisition, and the second stage is related to the tactical/operational decisions i.e. resource allocation. The two stages can then be combined into a single integer programming problem, which we refer to as *Emergency Response Planning Problem (ERPP)*.

Solution Methodology: Due to the *combinatorial* nature of (ERPP), the computing time needed to find the optimal solution to realistic size problems could be extremely long. Consequently, we proposed a *heuristic* solution methodology, which combines a *Decomposition Method* with *Lagrangian Relaxation* to efficiently solve the problem. However, we are still working on developing alternative solution methods to more efficiently solve the problem in question. We hope to share all the computational details, steps of the solution methods, and the resulting insights at the workshop.

Case Study: We have recreated the railroad network in Ontario (Canada) using the available information from the two Class I railroad operators, i.e., *Canadian National (CN)* and *Canadian Pacific (CP)*, who account for approximately 95% of the annual rail ton-kilometers in Canada. The resulting network has 100 nodes and 103 arcs.

Class 2, 3, and 8 (i.e., *gases*, *flammable liquids*, and *corrosives*) account for almost 80% of the rail hazmat tonnage in Canada [5]. Our data extraction and analysis endeavor validates this statement and shows that the abovementioned three classes constitute the majority of hazmat transported by rail during the last decade, which also motivated us to focus on only these three classes.

The model input parameters are estimated via a dedicated data analysis technique, which is versatile enough to incorporate uncertainty if required. The model parameters are listed below for the reader's convenience. We hope to provide more details on parameter estimation at the workshop.

- Fixed costs to open emergency response facilities;
- Acquisition costs of equipment packages;
- Capacities of emergency response facilities;
- Hazmat incident scenarios;
- Hazmat incident probability by scenario;
- Total hazmat incident cost by scenario, which is made up of three components: population exposure, property loss, and environmental cleanup costs;
- Transport costs of specialized equipment packages and emergency response personnel;
- Operating costs of equipment packages; and,
- Minimum required coverage of the network for each hazmat class (relaxed in some cases).

Computational Results: We used CPLEX 12.7 to solve several variations of (ERPP) and conduct computational experiments. Additionally, we have been able to visualize the results using ArcGIS, to show where emergency response facilities need to be located, and which rail-links they would be able to cover in case of a hazmat incident. In addition to this information, each sample solution would also indicate the number and type of equipment packages required at each response facility, and the resulting network coverage.

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Omni-channel grocery retailing: an approach for multi-depot order fulfillment

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1 Motivation

We consider a multi-depot vehicle routing problem (MDVRP) for the order fulfillment in omni-channel retailing. The formulated problem extends the classic capacitated vehicle routing problem ([2]) and comprises a special problem variant that happens in grocery distribution.

The development of the retail market shows that the combination of offline and online concepts becomes ever more important to compete on the market. While in the past many grocery retailers merely focused on the offline fulfillment of customer demand, the development of a functioning omni-channel environment is one of the main challenges for retailers.

Grocery retailers with established offline sales channels often struggle to determine the best fulfillment concept when merging an existing online business model with their existing operations or when introducing a new digital offering. These retailers have build up their business over many years and have implemented a wide network of stores, warehouses, and distribution centers that are optimized for offline retail. When trying to succeed in the online world, it is crucial to develop a strategy in which online and offline operations work efficiently together. While some retailers decide to keep online and offline operations separate from each other, an integrated omni-channel business can generate benefits that pure one-channel retailers do not retrieve.

Due to the given challenges, the question arises how the existing structures can be used to serve both online and offline customers. Each retailer therefore has to assess its given structure and possibilities to evaluate suitable options. Consequently, an efficient fulfillment concept has to be chosen whilst ensuring a sustainable business model. Moreover, given an increasing pressure to act economically and ecologically efficient, mechanisms to create collaborations are on the rise. Both delivery services and retailers across industries need to learn how to manage and share available transport capacities. This goes also inline with collaborative transportation (e.g., among different retail and delivery partners) which can be efficiently implemented for such a purpose.

2 Problem description

The problem discussed in this work comprises a holistic view on the order fulfillment for omni-channel retailers. It therefore simultaneously considers (i) the order assignment to depots and (ii) the vehicle routing for each depot.

Order-Depot Assignment Today, most grocery retailers maintain central distribution centers (CDCs) or regional distribution centers (RDCs) from which they supply their offline store network [1]. Large distribution centers and local stores show significant differences. On the one hand, picking of orders and other process costs for the preparation of an order are usually more efficient and show lower cost in distribution centers. Here, a higher number of orders can be handled at the same time and existing structures can be used. On the other hand, transportation costs are lower and customer service better for local stores or smaller warehouses located in customer proximity. Local stores can utilize their advantage of lower distances to customers and deliver products faster, even on the same day. This leads to a trade-off between the different types of warehouses and therefore is an essential decision for the the order assignment. It is crucial to quantify all positive and negative effects in order to develop a comprehensive decision model that decides on the optimal fulfillment concept.

We consider depots of different sizes and locations, from large distribution centers, located far from customers, to local stores, located close to a customer. Our work focuses on the assignment of orders to a depot for fulfillment and therefore, the depot decision is the primary decision to make.

Vehicle Routing Problem Depending on the order assignment decision, orders have to be distributed from the corresponding warehouses to customer. The different depots offer varying possibilities and options for the delivery. These differences have to be taken into account for the vehicle routing decisions. Each depot holds its own fleet of vehicles for distribution. Usually, the fleet of each warehouse consists of homogeneous vehicles but the vehicles between different depots vary significantly. For instance, distribution centers use trucks with a high capacity for distribution while stores use alternative transportation means like small cars or bikes/scooters.

After orders have been assigned to warehouses, the vehicle routing problem has to be solved for each depot and the corresponding customers that are supplied. The order assignment therefore directly impacts the routing options and costs. Consequently, the interdependency between the order assignment and the vehicle routing problem have to be considered simultaneously to enable a cost efficient distribution and thus an optimal fulfillment concept for retailers. An overview of the problem is given in Figure 1.

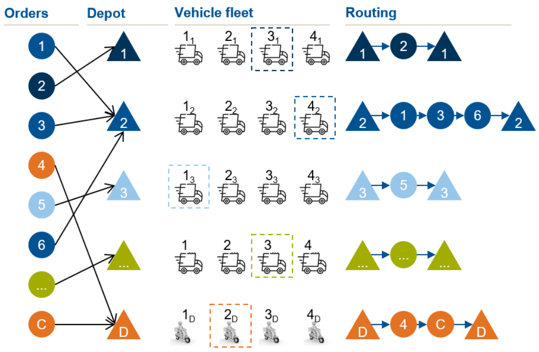

Figure 1: Problem overview

3 Model and Solution Approach

In order to address the described problem we present a model formulation for the corresponding special type of MDVRP. For this, we first assess the given relevant cost structures for the order processing. We therefore identify all decision relevant costs for the order assignment to the different depot types. Moreover, in a field study we examine the actual picking and packing costs of stores for the processing of online orders. The information generated within this field study is used as direct input to our model and solution approach.

In a next step, the model is evaluated using suitable solution approaches. This comprises an exact approach for the order assignment that estimates routing costs and a specialized heuristic for our problem formulation to solve the integrated assignment and routing problem.

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Optimization of deployment and dynamic repositioning of dock-less electric scooter sharing systems

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1 Introduction

Dock-less electric scooter sharing systems (DESSS) is a new type of transportation services. The optimization of dock-less sharing systems has rarely been studied in the literature. Few related studies focused on dock-less bikesharing systems. Because scooters are one of the major transportation modes in Taiwan, optimizing DESSS is expected to provide more benefits than optimizing bike-sharing systems. Thus, this paper optimizes the operations of DESSS focusing on the battery-swapping electric scooters. Moreover, the deployment and repositioning of electric scooters in DESSS are simultaneously optimized. That is, in addition to optimizing the deployment of scooters in the beginning of the day, the scooters are dynamic repositioned in response to user actions during the day. The simultaneous optimization of deployment and repositioning is a highly complicated logistics problem. The model is extended from vehicle routing problems with the side constraints of the factors such as origins, destinations, and departure times of users, locations of scooters, and battery power charging and consumption. The problem has never been studied in the past and thus this paper has clear methodological contributions.

2 Methodology

The problem of DESSS optimization can be described with two networks: the service flow and repositioning networks. The service flow network is modified from the generalized network formulation of One-to-One Pickup and Delivery Vehicle Routing Problem with Time Window (1-1 PDVRPTW) proposed by [1]. The network can be formulated on a graph G=(V,A) where V is the vertex set and A is the arc set. In set A, trip connection links represent the connection of destination nodes and origin nodes which belong to different OD pairs but closed enough to each other. Reposition links indicate the direction of repositioning, which indicate where the scooter is picked up and delivered. Reposition links might not be consistent with the true repositioning route, since these links are the most direct paths and the repositioning vehicle may takes other routes to perform repositioning. Figure 1 illustrates the network formulation of service flow network. The constraints associated with the model includes the ones in [1], power consumption, and thresholds of battery swapping.

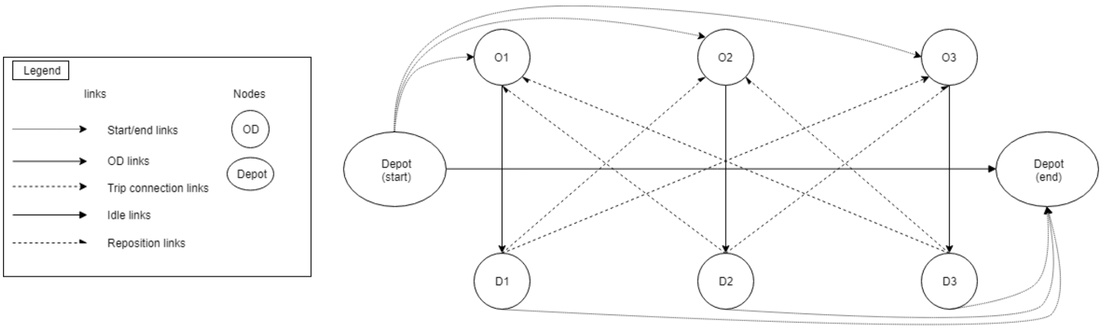

Figure 1. Network formulation of service flow network

The repositioning network, which describes the repositioning route, is extended from the Capacitated Vehicle Routing Problem with Time Window (CVRPTW) (see, for example, [2]). Since the vertex set of this network is the same vertex as the service flow network, the graph of this network is formulated as $G^{VRP}=(V,A^{VRP})$ where A^{VRP} is the set of repositioning links. Within set V, destination nodes are called pickup nodes since repositioning fleets can pick scooters up there after the trips end; on the other hand, origin nodes are called delivery nodes since the repositioning fleets can deliver scooters at there before the new trips start. In set A^{VRP} , nodes excluding dummy depot nodes connect each other. The constraints associated with the repositioning network include the constraints of a CVRPTW and the connections of flow and time between the service flow network and repositioning network.

The objective of the model is to serve the maximum number of users in DESSS efficiently. The objective function can be formulated as:

$$\text{Minimize Z} = \sum_{(i,j)\in A} \sum_{k\in K} C_{ijk}\, x_{ijk} + \sum_{(i,j)\in A^{VRP}} \sum_{f\in F} T_{ij}^{R} y_{ijf}$$

In the above function, C_{ijk} is the dissatisfaction cost of customer that served by different kind of modes. If the user cannot rent a scooter, there is a flow representing other transportation modes and associated with a high dissatisfaction cost. Moreover, T_{ij}^{R} is the repositioning time between each node in repositioning network. Therefore, this objective function aims to find a most efficient way to serve the largest amount of users in DESSS. Several numerical experiments are tested, and the results are reasonable and show that this model is capable of providing useful information of deployment and dynamic repositioning routes.

3 Conclusions

The objective of this research is to develop a model to provide deployment and dynamic repositioning strategies in DESSS. Also, the model combines the geographic characteristics, power consumption, battery swapping and dynamic repositioning in dock-less system. A mixed-integer programming framework is developed to simultaneiously solve the deployment and dynamic repositioning problems.

Operations constraints including origins, destinations, and departure times of users, locations of scooters, and battery power charging and consumption, and location and capacity of reposition fleets are explicitly modeled, which is the first in the literature. In conclusion, this research could help tactical and operational decision-making for operators in electric sharing mobility system, and the strategies are able to support them to offer better service and manage the system more efficiently. Furthermore, the optimization of DESSS has potential on improving the efficiency of DESSS, decreasing private vehicle ownership, and reducing traffic congestion and emission.

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Resolving the dispute about the impact of on-demand ride-sourcing services on traffic congestion: a simulation study

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1 Introduction

The term *sharing economy*, a popular buzz word, has been extensively used worldwide in both mass media and academic research articles in recent years, with the two eye-catching success stories of Airbnb and Uber in Silicon Valley[1]. During the past decade, the rapid growth of sharing economy, in part as the push by Web application and mobile Internet, and its dramatic impacts on various aspects of today's social economic system have attracted increasing public attention. Needless to say, ride-sourcing (or ridesharing)[1] emerges at the right moment under the background of sharing economy and becomes one of the most representative implementations of such a sharing concept-exchange of services(see [2], [3] for comprehensive reviews of ride-sharing). According to the annual report by Didi Chuxing[4], a tremendous number of trips reaching up to 7.43 billion (including taxi trips), out of which include 1.05 billion trips in particular for carpooling service, have been completed in more than 400 cities of China. Meanwhile in the US there exists, not surprisingly, 4.2 billion passengers sharing a ride with others, an increase of 140 percent from 2012[5]. As the consequence of excessive automobile volumes and severe traffic congestion in urban cities, vehicle emissions are playing the dominant role in air pollutants as well as the main source of carbon dioxide release associated with global warming[6]. Ride-sourcing service, however, sheds some light on mitigating aforementioned issues by significantly reducing the car number in urban road network since it is able to bring together those travelers who share the surrounding trip origin and/or destination with similar time schedule, which makes it possible to fully use available vacant. Some transportation network companies (TNCs), such as Uber, Lyft, and Didi develops carpool-like models (UberPool, Lyft Line, and Didi ExpressPool, respectively) to promote ride-sharing and claim that they help greatly to reduce traffic congestion in dense cities.

Nevertheless, recent findings on the impact of ride-sharing services on traffic congestion are mixed. It has been reported recently that rather than alleviating traffic, conditions have become worse after the activation of ride-sharing programs in some cities. Shared rides are not, in fact, diminishing the mileage that people travel in cars, but adding to it [5], [7]. Among researchers and the public media, the heated debate has been sparked over the role of ride-sourcing service in urban transportation system. It is generally expected that ride-sourcing platform improves vehicle utilization and alleviate traffic congestion. Nonetheless, the extent to which ride-sharing actually reduces congestion relies on a few key factors. One key factor for a successful ride-sourcing program is the detour distances for picking-up and dropping-off multiple passengers, which contributes to traffic congestion. Evidently, the detour distances for ride-sharing critically depend on the density of the passengers opting for ride-sharing programs. When the density is low, the actual detour distances become long, resulting in ride-sharing programs aggravating traffic congestion. Therefore, it is crucial to discern the relationship between extra detour distance (and hence traffic congestion) and the passenger density for ride-sharing, and to identify the critical density for a socially desirable ride-sharing program. To the best of authors' knowledge, very limited research so far has been done to quantitively reveal this intricate relationship between critical density and the impact of ridesharing on traffic congestion. The exact magnitude of ridesharing demand (passenger density) is not well understood. In this study, based on a simulation case, we attempt to figure out the critical density to verify our findings when and how the

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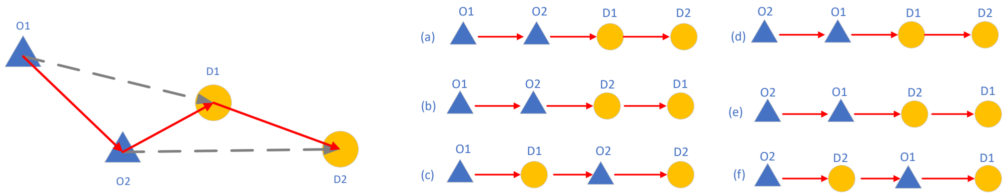
[1] We note that there are a few confusing terms in the literature, such as ride-sourcing, ride-sharing, carpooling and dial-a-ride, and on-demand (dynamic or real-time) ride-sharing. Ride-sourcing refers to TNCs using network applications to dispatch affiliated drivers to passengers. Ride-sharing is a general concept describing a travel mode in which travelers with similar routes and time schedules share one vehicle and split trip fare or costs. In this study we consider ride-sharing as one type of ride-sourcing services offered by TNCs.

benefits of ride-sharing prevails its negative effects. This study will offer valuable insights by additional evidence and contribute to resolve the current dispute about the impact of ride-sourcing services on traffic congestion.

2 Methodology

Thanks to the rapid growth of mobile technologies, ride-sharing services are now able to accommodate on-demand requests and no longer require users to schedule their routes in advance. Given a moment , with the help of GPS-enabled mobile, we assume the taxi location, the origin and destination of each trip are already known ahead of dispatching moment. Without ridesharing, a trip directly from its origin to destination is called a separate trip, while a joint trip means two or more trips are matched by a car (as depicted in figure 1, the grey dash line and the red solid line represent the separate trip and joint trip, respectively). We will look into the aforementioned issues, to analyze how the average trip length before and after implementing ridesharing varies with the increasing demand of ridesharing. For simplicity, consider an extreme case in certain city where the density of population is distributed homogeneously in space and time. All the origins and destinations of trips are generated in random and uniformly. If a resident decides to take a trip, he/she would give a specific destination through the mobile application and then awaits the coming of car assigned by the TNCs. Furthermore, we assume taxi is the unique traffic mode to be considered if and only if two trips are matched. The cost of a road segment for the vehicle is equal to the travel time in this study (shortest distance can be also used here). With appropriate matching algorithms, an on-demand ride-sharing program could be successfully implemented even in relatively sprawling urban areas. One of the most important components is the optimization algorithm, which matches drivers and riders in real-time. A good matching strategy minimizes system-wide vehicles miles and system-wide travel time and maximizes the number of participants to provide the most in terms of societal and environmental benefits. We choose the classic assignment algorithm as described in [8].



(▲ Origin ● Destination - - → Separate trip → Joint trip)

Figure 1 Detailed analysis on six scenarios(a-f in the right) of different pick-up sequence for two trips

Here to illustrate the pairing cost in more clear and understandable way, we give an example as shown in figure 1. Consider two trips from O_1 to D_1, O_2 to D_2. The sum of separate cost for both trips (also called non-sharing cost for paired trip) is $C_{non-sharing} = C_{O_1,D_1} + C_{O_2,D_2}$, where C_{O_1,D_1} is minimum travel time between O_1 to D_1, similar meaning to C_{O_2,D_2}. According to the pick-up and drop-off sequences of the two trips, there are six possible scenarios as depicted from (a) – (f) in the right-hand side of figure 1. We define the cost of joint trip between trip 1 and trip 2 as

$$C_{12-sharing} = min\{(C_{O_1,O_2} + C_{O_2,D_1} + C_{D_1,D_2}), (C_{O_1,O_2} + C_{O_2,D_2} + C_{D_2,D_1}), (C_{O_1,D_1} + C_{D_1,O_2} + C_{O_2,D_2}), (C_{O_2,O_1} + C_{O_1,D_1} + C_{D_1,D_2}), (C_{O_2,O_1} + C_{O_1,D_2} + C_{D_2,D_1}), (C_{O_2,D_2} + C_{D_2,O_1} + C_{O_1,D_1})\} \ (C_{12} \text{ for shorthand}).$$

By above defined cost, we can extend easily to n trips, then obtain a symmetric cost matrix-n by n. $C_{ij}(i \neq j)$ denotes the paired cost between trip i and j . When $i = j$, i.e. the diagonal elements, assign a sufficient large number M to it, $C_{ij}(i = j) = M$, which means trip i and j can't be matched. Then we formulate this assignment problem as

$$\min C = \sum\nolimits_{j=1}^{n} \sum_{i=1}^{n} c_{ij} x_{ij} \, , subjected\ to \ \sum_{i=1}^{n} x_{ij} \leq 1, \sum_{j=1}^{n} x_{ij} \leq 1,$$

where x_{ij} is a binary variable. $x_{ij} = 1$ represents trip i and j are paired successfully. This problem can be easily solved by the Hungarian algorithm[8] (also known as Kuhn-Munkres algorithm)

3 Numerical results and preliminary analysis

The Sioux-fall network, with 24 nodes, 76 links, is quite common in transportation study as shown in figure 2. The simulation of this study is also taking the Sioux-fall network as an illustration. The results are given in figure 3.

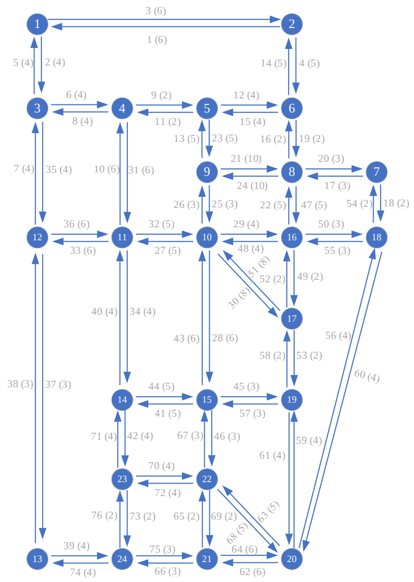


*Figure 2. Sioux-Fall network, link-node-weight diagram (*the first number alongside the link denotes link number, the latter surrounded by parenthesis is the distance of that link*)*

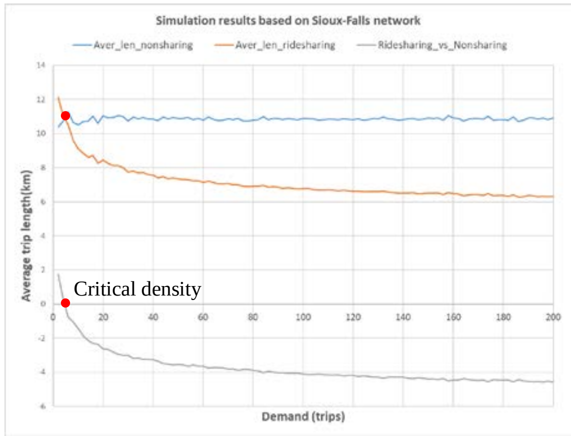


Figure 3. Simulation result-average trip length varying with the different demand

Analysis:1) Without ridesharing, the average trip length keeps stable with the increase of demand, around 10.7 min per trip. 2) With ridesharing, the average trip length decreases with the growing of demand. 3) It converges to half of the no ridesharing average trip length since we assume every two trips are paired when the demand is sufficient large. 4) When the demand is extreme small, if we still conduct the ridesharing, it would increase the average trip length. For this small network, when demand is less than 6 trips per second, average trip length after ridesharing is greater than the no ridesharing average trip length. This result is consistent with our findings that there exists a demand (critical density) for the implementation of ridesharing services. In future, to test our proposed findings on real macroscopic network such as New York, Hong Kong, Beijing as shown in figure 4, we will continue further simulation-based study if the related OD data are available.

Manhattan (4491 nodes, 9816 links) Beijing (14155 nodes, 31732 links) Hong Kong (4646 nodes, 8477 edges)

Figure 4. Ongoing simulation on vehicular networks

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Analysis on Impacts and Characteristics of Collaborative Pickup Lockers

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1 Introduction

E-commerce is one of the fastest growing businesses. Total global e-commerce revenue is expected to rise to $4.5 trillion in 2021 from $1.3 trillion in 2014 [1], while last mile delivery operations makes up to 53% of total transportation costs [2]. On the other hand, transporation activities were the highest contributor to GHG emission production with 28.5% of total emission in 2016 in the US [3]. In addition, urban population is expected to rise to 9 billion in 2100 from less than 1 billion in 1950 [4].

As freight activity increases in urban areas, traffic congestion, pollution, accidents and GHG emissions increase [5]. With the increase in e-commerce and urbanization, the negative impacts of last mile delivery are expected to increase as well. Sharing economy practices are among the promising solutions for reducing negative impacts and costs, such as using multi-echelon networks, integrating public and freight transportation systems, and using pickup lockers [6].

Pickup lockers are employed by several companies to deliver online purchases. Amazon is one of the companies that offers the locker delivery in the US with lockers that are located at places where customers regularly visit [7]. To use this service, customers use a locker location as delivery address. After the purchased product is placed into a locker at the chosen location, customer receives a single use code to open the locker. Also, customers can use the lockers to return the purchased product.

The lockers provide advantages for consumers and companies. For consumers, locker delivery provides a secure place to receive their orders if their homes do not have a safe location such as a lobby. Also, they can pick up the packages anytime they want from the lockers without waiting at home for delivery. For the companies, consolidating deliveries reduce costs. Also they do not have to deal with problems such as going to a wrong address or not finding the customer at home.

Although companies providing locker delivery exist, there are not many studies on impacts of the system. To the best of our knowledge, the only study with its main focus on pickup lockers is [8]. [8] studies a dynamic system where all orders are delivered to lockers by autonomous vehicles via direct dispatches. [9] studies consolidation of student online purchases that are to be delivered to halls of residence. They consider an Urban Consolidation Center to reduce cost and emission production of the last mile delivery operations [9]. The problem also resembles the first part of a two-echelon city logistics [10].

2 Problem Definition

In this paper, we study a company that offers home delivery and pickup locker service. When placing the order, customers can request the delivery to an address or a locker location. Delivery personnel pick up packages from an origin, a store or a depot, drive through the route, and drops them off at their destinations along the route. The company performs the deliveries with its own vehicle fleet. Each vehicle has a limited capacity, and each delivery personnel works through a certain shift. All routes start from and end at the depot. For simplicity, we assume that packages have unit sizes.

Locker locations and number of pickup lockers are given. Although there are other constraints related to lockers in real life applications, such as package size, these constraints are validated when the orders are placed. Each order has pick up and delivery time windows. We assume that a package placed in a locker is picked up by the customer at the end of its delivery time window, and the locker is free for the next delivery. We assume the company does not offer on-demand delivery service and all of the orders to be delivered are known prior to planning.

We analyze the characteristics that affect the system efficiency. We conduct the analysis with different number of locker locations, number of lockers, and proportion of customers chosing the service.

3 Methodology

To conduct the aforementioned analysis, we developed an Adaptive Large Neighborhood Search (ALNS) algorithm. The ALNS algorithms have been applied to several variants of vehicle routing problems [11], [12], [13]. Also, generic version of the algorithm in [11] updated some of the best known solutions of benchmark instances of different vehicle routing problems [14]. These show that the ALNS is capable of finding good solutions for different types of problems and for problem instances with different characteristics. Thus, we use ALNS for our analysis as it is robust against different instance characteristics such as geographical distribution and size.

4 Initial Results

For initial testing, we use PDPTW benchmark instance ‘lr103’ from [15] that has 52 requests. The results for single locker location are given in Table 1, which are averages of 5 runs. We chose the center of delivery locations as the locker location. We assume all locker requests are accepted. Locker requests are chosen randomly with different probabilities.

Table 1. Initial results for a single locker scenario

Locker Probability	Number of Infeasible Requests	Number of Locker Requests	Number of Vehicles	Total Distance	Number of Deliveries per Locker Visit
0	0	0	14	1292.68	NA
0.1	0.4	4.4	16	1359.03	1.158
0.3	2	12.4	17.8	1368.17	1.632
0.5	2.4	21.4	18	1389.92	1.911
0 (no tw)	0	0	10	1043.49	NA
0.1 (no tw)	0	2.8	10.2	1032.98	1.167
0.3 (no tw)	0	16	10	943.91	2.286
0.5 (no tw)	0	27.6	9.2	858.89	3.136

In cases with time windows, tight time windows and distant locker location do not provide a pooling opportunity as shown in number of deliveries per locker visit, so total distance and number of vehicles increase and some deliveries become infeasible. Thus, we test the system without time windows. In this case, total distance and number of vehicles reduce as locker probability grows. Enhanced pooling of locker deliveries impacts the improvement. This shows that certain attributes, such as time windows, and number of locker requests, affect the outcomes of the system.

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Crowdshipping with Stochastic Occasional Drivers and Time Windows

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1 Introduction

The extensive development of on-line retailing and of collaborative consumption systems, such as Uber, has led large retailers to consider new ways of making deliveries to their on-line consumers. One of them is *crowd-shipping*, which consists in having goods bought on-line delivered to final customers by other customers or other *occasional drivers*. In either case, individuals who are not employed by the retailer or one of its logistics subcontractors are used to make deliveries.

For instance, Amazon.com has established the Amazon Flex Driver program in which regular people with a car deliver parcels to on-line customers [3]. Anyone with access to a vehicle, a valid driver license, and a smart phone can sign up for the program. Flex drivers can select their working schedules and the area where they wish to make deliveries, which gives them incredible flexibility, while Amazon.com has a lot to gain from this endeavor, as it reduces the cost of same-day last-mile delivery. The main difference between regular drivers and crowd drivers, besides the ownership of the vehicle, is the degree of flexibility that they have over their work. This flexibility makes the availability of crowd drivers uncertain. How will the flexibility and independence of crowd drivers impact the cost of last-mile deliveries? In this talk, we attempt to see how resorting to flexible crowd drivers could impact last-mile deliveries for on-line retailing.

2 Literature Review

Not much research has considered the problem of same-day deliveries for on-line retailing with occasional or crowd drivers. A notable exception is the paper by Archetti et al. [1] that defines and solves the *Vehicle Routing Problem with Occasional Drivers* (VRPOD), a problem setting in which a company has a fleet of vehicles available for delivery, as well as a group of occasional drivers (e.g., in-store customers) who are willing to deliver a single package to an on-line customer as long as her location is not too far away from their destination. The authors propose a model and a heuristic solution approach. They also show that the cost reductions of employing occasional drivers can be significant, ranging from 18% up to 45% in some instances.

Another interesting paper is the one by Arslan et al. [2], which formulates the problem of using crowd drivers for on-line retailers as a Dynamic Pickup and Delivery Problem. They consider an on-line crowd-sourcing platform that receives new delivery tasks and driver trip announcements continuously over time. The solution method utilized is an event-based rolling horizon approach that solves the problem of matching tasks to drivers repeatedly each time that a new task becomes known or a driver arrives, with the objective of minimizing the total system-wide delivery cost. The company is also assumed to have a fleet of regular drivers who can deliver the parcels without flexibility restrictions. Arslan et al. consider the possibility of multiple deliveries for ad-hoc drivers and time constraints as more restrictive than capacity constraints for the drivers.

3 The Problem

We consider a crowdshipping platform (CP), which allows individuals to sign up if they are interested in working part-time or full-time delivering parcels with their personal vehicles. This provides the CP with a pool of occasional drivers who can be used to perform delivery tasks. To keep things simple, we suppose that each vehicle has at least a minimum pre-specified capacity Q_o available. While occasional drivers could arrive at various times, we assume that they all show up at the depot early enough to handle the delivery tasks at hand. Therefore, the only source of stochasticity that we consider is the availability of the occasional drivers for the current planning period, which can be modeled using a binomial distribution.

The CP has a known list of delivery requests by online customers. Each request has a specific demand or quantity and must be delivered within a specific time window. To complete the delivery tasks, the CP can use the occasional drivers or its own fleet of Professional Vehicles (PVs) with capacity $Q_{pv} > Q_o$. Routes must be planned for both PVs and the vehicles of occasional drivers, which we call Occasional Vehicles or OCs.

The compensation scheme that we utilize to pay occasional drivers is flexible and consists of a fixed cost that every driver gets by showing up at the depot, a variable cost associated with the total distance traveled on the route performed, and a reward that is paid for each parcel delivered. These three types of compensations can be applied in any proportion to incentivize different types of behaviors in occasional drivers. Similarly, there are three costs associated with PVs, a fixed cost, a variable cost, and a cost to service each customer.

4 The Model

The basic structure of the model is that of a two-stage stochastic programming problem. The main decisions are all taken in the first-stage problem, in which we create a set of routes serving all customer requests. These routes correspond either to routes for PVs or OCs. It is assumed that these routes are planned before we know the exact number of occasional drivers that will show up. The first-stage problem thus corresponds to 3-index formulation for the Heterogeneous Vehicle Routing Problem with Time Windows (HVRPTW) and two classes of vehicles. The second-stage problem is used to evaluate the costs of routes designed for the OCs depending on the number of occasional drivers who actually show up: routes for OCs cost more if they need to be performed by PVs. It should be noted that, given a set of routes for OCs, one can easily compute the expected cost of these routes and, therefore, of the complete solution.

5 Solution Method and Computational Results

To solve this problem, we propose a dynamic programming procedure based on the Bellman-Held-Karp algorithm for the travelling salesman problem. This procedure is applied to the giant tour representation of the problem at hand. In order to test this solution approach, we will construct a set of instances from the Solomon benchmark and perform an extensive computational study. Results will be reported at the workshop.

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Can ride-sharing alleviate traffic congestion?

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1 Introduction and literature review

It is generally expected that successful designs of ridesharing programs can improve vehicle utilization rate, and subsequently achieve various societally beneficial objectives, such as reducing traffic congestion and air pollution. However, what are the potential implications of ride-sharing for both traffic congestion and transit ridership? The answer lies in whether or not ridesharing adds to vehicle traffic by shifting travelers from space-efficient modes like walking, transit or biking, or reduces vehicle traffic by diverting trips otherwise made in private, single occupancy cars. Indeed, existing empirical studies showed that dynamic ridesharing program brought different impacts to the urban traffic in different cities. Alexander et al. (2015) used mobile phone records to explore the influences of ridesharing services on the network-wide traffic congestion. They matched the origin-destination trips from both auto and non-auto travelers, and found that, when the number of ridesharing adopters from drivers is greater than from non-drivers, there will be a reduction in total vehicles, and vice versa. Based on datasets from Uber and Urban Mobility Report, Li et al. (2016) found that the entry of Uber ridesharing service significantly reduced the traffic congestion in the urban areas of the United States.

However, a recent consulting report (Schaller, 2018) found that the shared ride services such as UberPool, Lyft Line did not offset the traffic congestion impacts of the TNC services. It is reported that the ride-sourcing services put 2.8 new ride-sourcing vehicle miles on the road for each mile in auto travel taken off, while the implementation of shared services only led to marginal reduction on mile increase—2.6 new ride-sourcing vehicle miles for each mile of auto travel removed. The main reason is that the drivers' detours to pick-up the second or third passenger also added mileage to the roads, and some of the trips involves just one passenger even in ride-sharing (e.g., between the first and second pick-up). Furthermore, it is claimed that the ride-sourcing services or the commercial dynamic ride-sharing services are actually a competitor, rather than a complement, to public transits. The convenience, efficiency, and relatively low trip fare of these ride services essentially attract some riders shifting from public transits, which contributed to big-city traffic congestion and falling transit ridership.

A few recent studies are conducted to ascertain the minimum number of vehicles needed for serving passenger demand in cities under a ride-sharing program. For example, Alonso-Mora et al. (2017) proposed a general mathematical model that enables real-time high-capacity ride-sharing. Based on simulation experiments with New York taxi data, the authors showed that only 3,000 high-capacity taxis were needed for serving 98% of the taxi rides that were currently served by over 13,000 taxis. Santi et al. (2014) introduced the shareability networks or 'vehicle-share-networks' to address the minimum fleet problems and assess the potentials of ride-sharing on reducing minimum required number of vehicles. However, more theoretical and empirical studied are needed to understand the impacts of ridesharing on traffic congestion in connection with urban characteristics, such as population density and city size.

2 Methodology

Consider an urban road network that is used by ride-sourcing riders (with a demand q_r and average trip distance l_r) and normal private car users (with a demand q_n and average trip distance l_n). Let $\bar{L}$ denote the total length of the road network, and let k denote the average density of vehicles and v the average vehicular speed. A macroscopic fundamental diagram (MFD) can be utilized to characterize the relationship between the speed and density: $v = V(k)$ with $\partial v/\partial k < 0.$ For simplicity, two extreme scenarios in a stationary state are first examined and compared: (a) all ride-sourcing passenger requests are served without ride-sharing; (b) all ride-sourcing passenger requests are served through ride-sharing.

In scenario a), each ride-sourcing vehicle is only occupied by one passenger (assuming one request by one passenger), thus the arrival rate of ride-sourcing vehicles is identical to the demand of ride-sourcing passengers. At any instant of the stationary state, the number of ride-sourcing vehicles and normal vehicles (private cars) running on the roads, denoted as N_r and N_n, equals the product of their arrival rate, q_r and q_n, and the average trip time, l_r/v and l_n/v, respectively. Then, the density of all vehicles in the road network equals $N_r + N_n$, divided by the total length of the road network, $\bar{L}$. Therefore, the equilibrium in scenario (a) can be characterized by the following system of simultaneous nonlinear equations:

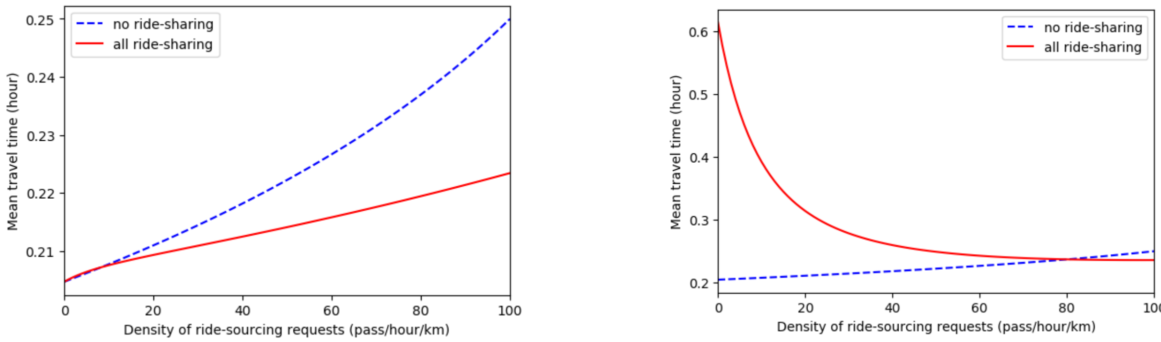
$$N_r = q_r \cdot \left(\frac{l_r}{v}\right),\ N_n = q_n \cdot \left(\frac{l_n}{v}\right),\ k = \frac{N_r + N_n}{\bar{L}},\ v = V(k) \tag{1}$$

Then the speed and density at equilibrium, denoted as v^{NR}, k^{NR}, can be spelled out, where 'NR' stand for 'no ride-sharing' under scenario (a). In scenario (b), we examine the extreme case where all passengers opt for ride-sharing and ride-pairing is detour-unconstrained (all passengers are paired without setting a maximum allowable detour time). Under this simplified scenario, the arrival rate of ride-sourcing vehicles is half of the arrival rate of the ride-sourcing passengers (again assuming one request by one passenger). The average trip distance of a passenger by a ride-sourcing vehicle now becomes the sum of the normal average trip distance l_r and an average detour distance Δl (or an equivalent amount of detour time $\Delta l/v$). The average detour distance Δl shall be a decreasing function with respect to the demand (arrival rate) of passengers opting for ride-sharing services. Let $\Delta l = L(q_r)$ with $\partial L/q_r < 0$. Then the resulting speed and density at equilibrium under scenario (b), denoted as v^{AR}, k^{AR}, where 'AR' stands for 'all ride-sharing', can be spelled out from the following system of simultaneous nonlinear equations:

$$N_r = \frac{1}{2} \cdot q_r \cdot \left(\frac{l_r + \Delta l}{v}\right),\ N_n = q_n \cdot \left(\frac{l_n}{v}\right),\ k = \frac{N_r + N_n}{\bar{L}},\ v = V(k) \tag{2}$$

3 Numerical studies

Now a numerical example is provided to look at the impacts of ridesharing. Figure 1(a) shows the change of mean travel time of other riders (other than ride-sourcing passengers) with respect to different density of ride-sourcing passengers under two scenarios ('no ride-sharing' and 'all ride-sharing'). Clearly, mean travel time of other riders monotonically increases with the density of ride-sourcing passengers in both of the scenarios. This is because the increase of density of ride-sourcing passengers increases traffic congestion, and thus increases the travel time of other riders on the road. It is noteworthy that the mean travel time of other passengers under "all ride-sharing" scenario is even higher than that under "no ride-sharing" scenario when the density of ride-sourcing passengers is low. It implies that the implementation of ridesharing will even lead to heavier traffic congestion if the passenger density is extremely low. In this case, ridesharing will increase both the travel time of ride-sourcing passengers and other riders and thus lead to a "loss-loss" situation. Figure 1(b) shows that the mean travel time of ride-sourcing passengers increases with density of ride-sourcing passengers under "no ride-sharing" scenario (due to traffic congestion). It is shown that the mean travel time of ride-sourcing passengers roughly decreases with the passenger density under "all ride-sharing" scenario. This is because the detour time of ride-sourcing passengers decreases with the passenger density. A "win-win" situation can be identified where ridesharing can reduce the mean travel time of both ride-sourcing passengers and other riders if the density of ride-sourcing passengers is very high.



(a) Mean travel time of other passengers (b) Mean travel time of ride-sourcing passengers

Figure 1. Mean travel time versus density of ride-sourcing passengers

The proposed model is helpful for understanding the impacts of passenger density on the effects of ridesharing. It can be further used to identify the critical passenger density that lead to a sustainable ridesharing program, which can reduce traffic congestion and decrease the total travel costs of all passengers. In future study, passengers' mode choices will also be characterized in our model and we aim to answer another critical question: will ride-sharing encourages some private car users to give up driving (and thus reduce traffic congestion) or poach riders from public transits (and thus amplify traffic clog)?

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An Exchange Economy Approach to Coordinating Resource Sharing for Carrier Alliances (Extended Abstract)

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Many carriers today form alliances, such as 2M, OceanAlliance, and THEAlliance in liner shipping industry [5, 9, 12], and Skyteam Cargo in air cargo industry [6]. One of the key benefits of alliances is that resources, such as ship and flight capacities, empty containers, and cargo, owned by different carriers in the same alliance can be shared among them, so that the *efficiency* of the entire alliance can be enhanced with the total profit maximized. In order to keep the *stability* of an alliance, the total profit of the entire alliance has to be shared properly among members of the alliance, so that no members have incentives to leave the alliance or form a new alliance. Such profit sharing is often achieved through side payments transferred from users to owners of the resources, for which an *exchange price* of each resource needs to be determined.

In practice, the resource sharing scheme and the profit sharing scheme are determined in a centralized manner for the interests of alliance formation. However, when implementing them through daily operations, individual carriers often make decisions in a decentralized manner for the interests of maximizing their own selfish profits. As a result, individual carriers may not have *incentives* to implement the optimal resource sharing scheme or the profit sharing scheme determined for the entire alliance. This raises a problem on how to decide exchange prices to coordinate resource sharing for a carrier alliance via side payments, so that one can align the efficiency and the stability concerns for alliance formation with the incentive concern for implementation. In the literature, existence of such exchange prices for coordination is proved only for some special settings of the problem via an inverse optimization approach [4], where individual carriers are assumed to follow the same types of selfish behaviors (see [1, 2, 3, 8, 10, 14, 15]).

In this study, we propose a new approach to analyzing the coordination of resource sharing for carrier alliances. It extends a coalition game theory of a market with transferable payoff known from exchange economies [7, 13]. We utilize a competitive equilibrium of the market to show that under a very general setting, exchange prices for coordination always exist, and can be obtained by using convex optimization methods [11]. Such exchange prices can coordinate carriers, even when their selfish behaviors are of different types and are only partially known, and hence having significant practical values. With our new approach applied, we (i) unify and extend the existing results by simpler proofs, (ii) correct a faulty analysis and address an open question appeared in the literature, and (iii) derive exchange prices for coordination of carriers' resource sharing under several new and complicated settings that reflect practical concerns but have never been studied before, such as those with Nash equilibrium constraints and those with uncertainties in cargo demands. Besides, our study has also (iv) bridged the theories in exchange economies, the solution methods in convex optimization, and the applications in coordination of resource sharing for carrier alliances.

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Pseudo Node Insertion Method for Drone-Truck Combined Operations

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1 Introduction

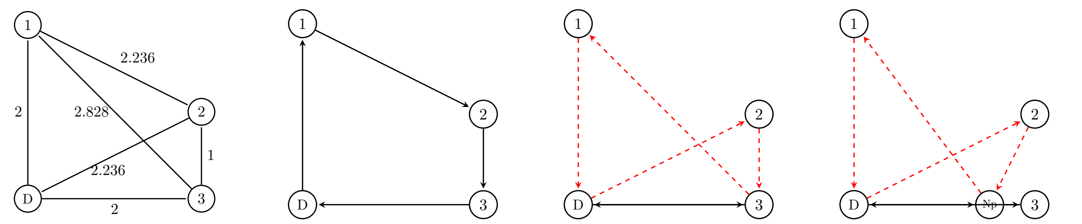
The increased application of drone operations can be seen especially in the several areas such as parcel delivery [12, 15], healthcare [20, 10], humanitarian logistics [18, 11], and military operations [17, 23]. Indeed, many companies such as DHL, Amazon, Google, and UPS have been preparing for a new era that will transform the current logistics system by a wide adoption of drone fleet operations. Especially in the area of last-mile delivery, which is labor-intensive and hence expensive logistics operation, the idea of drone delivery is becoming more attractive than before [3]. For example, Amazon has been testing drone delivery with Amazon Prime Air Service since 2016 [8], DHL has been operating an autonomous drone delivery system since 2016 [4], Matternet received an authorization for a drone logistics operation in 2017 [13], and UPS has tested their own drone-truck delivery system in 2017 where the truck not only delivers its own parcel but also serves as a carrier for the drone [9]. It is worth noting that AHA, Iceland's eCommerce company, has partnered with Flytrex, a drone delivery company, and has significantly cut down its parcel delivery time in conjunction with its existing vehicle network [21].

Drones have an advantage over trucks in fast delivery time with almost no constraint in the route but are at a disadvantage with loading capacity and delivery range [16]. As the AHA case demonstrates, a drone operation of light–weight and short range parcel delivery can be a perfect complement to a truck operation of a relatively heavy or long–range parcel delivery. Thus, the drone-truck combined operations (DTCO) has the great potential for achieving more effective and efficient last-mile delivery services. DTCO has received a surge of interest from researchers and practitioners over the last few years and, therefore, a sizable amount of research has been conducted [see, e.g., 12, 5, 6, 15, 19, 22, 2, 1, 7].

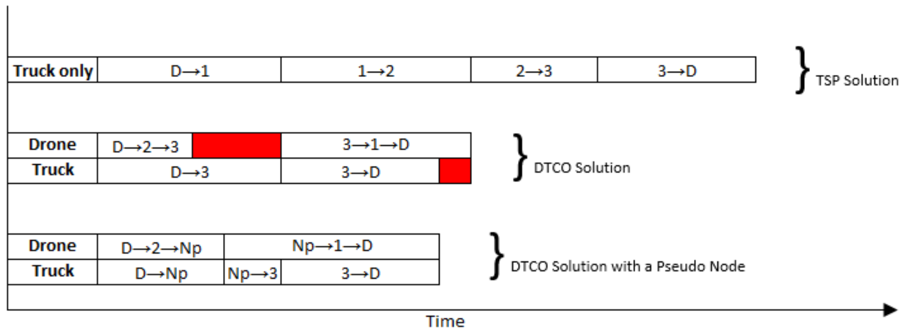
[12] define their drone-truck problem as the flying sidekick traveling salesman problem (FSTSP) in which they provide mathematical models for optimal routing of truck and drone working together for parcel delivery. They also present heuristic methods to solve the problem, which is critical because of the complexity of the model. [1] present an integer programming model of the drone-truck problem, called traveling salesman problem with drone (TSPD), and propose a heuristic method based on a local search and dynamic programming. They compare the heuristic approach of [12] with their approach. A vehicle routing problem with drones (VRPD), introduced by [22] and [14], could be seen as an extension of the FSTSP in the same fashion as vehicle routing problem (VRP) can be viewed as an extension of TSP. VRPD considers a fleet of m homogeneous trucks with k drones (multiple drones per truck) where the speed of a drone is α times the speed of a truck and drones can depart from and return to the truck at any customer locations. In both FSTSP and VRPD, a synchronization between drone and truck plays an important role because waiting for the counterpart (from both drone and truck perspectives) caused by asynchronization increases the total travel/delivery time. We explicitly tackle this asyncronization issue in this paper.

2 Basic Drone-Truck Combined Operations

In DTCO, some parcels from/to customers are picked-up/delivered by a drone while the others are done by a truck, and the drone and the truck work in synchronization with each other. DTCO introduces the concept of drone-sorties, defined as drone and truck separating at a certain node (e.g., a geographical locus) and meeting with each other at a different node, with the drone serving a different customer in between. In general, the objective of DTCO is to minimize the total travel time or travel completion time for pick-up/delivery using the drone and truck combination.



(a) Simple Example (b) TSP Solution (c) DTCO Solution (d) DTCO: Pseudo Node



(e) Comparison of Delivery Schedules (Red Box: Waiting Time)

Figure 1: Illustration of DTCO

To illustrate how DTCO works, let us present a simple example shown in Figure 1. Suppose at an instance a truck and a drone are at node D (depot), where a node represent a geographical locus, and an edge or arc, representing a road connecting nodes[1], labels indicate the distance between the nodes in miles. Customers are located at nodes 1, 2, and 3 to which a parcel needs to be delivered to each customer. We assume the drone speed (2 miles per minute) is twice as fast as the truck (1 mile per minute) and the travel completion time (time at which drone or truck – whichever later – comes back to the depot after delivery) is to be minimized. When only a truck is used, the optimal route is (D $\rightarrow$ 1 $\rightarrow$ 2 $\rightarrow$ 3 $\rightarrow$ D), as shown in Figure 1(b), and it takes 7.236 minutes to complete the travel, excluding the time needed for service/delivery. The DTCO solution of this problem is given in Figure 1(c) where the drone route is shown by dashed red lines (D $\rightarrow$ 2 $\rightarrow$ 3 $\rightarrow$ 1 $\rightarrow$ D) and the truck route (D $\rightarrow$ 3 $\rightarrow$ D) is shown by solid black lines. At node D (depot), the drone departs from the truck to serve a customer at node 2 while the truck goes on to serve a customer at node 3. The drone then returns to the truck at node 3. Note that the drone has to wait at node 3 until the truck arrives because it takes 1.055 minutes for the drone to go to node 3 from D via 2 while it takes 2 minutes for the truck to go to node 3 from D (ignoring the service/delivery time at node 2). Such waiting times are shown as red rectangles in Figure 1(e). In some other situations, however, a truck may have to wait until a drone arrives. In the sequel, the drone departs again

[1] We use the term edge and arc interchangeably in this paper

from the truck at node 3 to serve a customer at node 1, then goes to the depot to meet the truck while the truck goes back to the depot. It takes 4.414 minutes to complete the travel.

Now suppose that a pseudo node can be inserted between node D and 3, denoted by $\mathrm{N_p}$, as shown in Figure 1(d), where the drone and truck can meet to reduce the waiting time. Such pseudo node is not a customer location but assumed to be a geographical locus where a truck can be safely stopped for just a while[2]. The solution with a pseudo node is given in Figure 1(d) where the drone route is shown by dashed red lines ($\mathrm{D} \rightarrow 2 \rightarrow \mathrm{N_p} \rightarrow 1 \rightarrow \mathrm{D}$) and the truck route ($\mathrm{D} \rightarrow \mathrm{N_p} \rightarrow 3 \rightarrow \mathrm{D}$) is shown by solid black lines. It takes 4 minutes to complete the travel, which is a 9.28% improvement over the DTCO solution. Note that the total truck/drone waiting time may increase substantially as the size of problem increases and, therefore, the use of pseudo nodes has a great potential to improve DTCO.

In this paper, we tackle the DTCO problem in an attempt to minimize the total travel time or travel completion time by way of pseudo node insertion and eventually make the last-mile pick-up/delivery more efficient. In particular, we focus on the drone-truck synchronization issue to reduce waiting time for both drone and truck, for which we propose the pseudo node insertion approach. By pseudo node we mean an additional geographical locus on an edge in addition to customer nodes, at which a truck is allowed to meet a drone. We claim that the waiting time can be minimized by carefully selecting and inserting pseudo nodes in the delivery network. We propose methods to insert pseudo nodes in a road network, provide a detailed analysis for travel time saving conditions and associated maximum savings, and explore a variety of scenarios to enhance the efficiency of drone-truck combined operations. An algorithm for the pseudo node insertion method is provided and numerical examples are presented to discuss efficacy and efficiency of our proposed approach.

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Doubly-constrained rebalancing for one-way electric carsharing systems with capacitated charging stations

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1 Background

Carsharing services have been shown to be effective in reducing numbers of cars on the road (*[1]*). They have further incorporated electric vehicle (EV) fleets in some cities to be more sustainable. For example, car2go owns a fleet of 1400 EVs in Stuttgart, Madrid, and Amsterdam. Other companies like GM's Maven and Chevy Bolt EVs are available in cities like Los Angeles (*[2]*). However, EV carsharing is a risky investment that adds operational constraints from the EV requirement (*[3]*).The underlying problem is that one-way carsharing systems require some degree of rebalancing to be effective in meeting demand, depending on the service area covered and demand patterns. This operational constraint is further exacerbated in EV systems that have an additional requirement to rebalance vehicles for charging. Such systems are *doubly-constrained*: there is demand for vehicle service and demand for electric charging that both exhibit spatial-temporal imbalances.

While there are many studies on singly-constrained rebalancing problems (e.g. see (*[4]*)), a smaller subset of studies emerged in recent years to tackle this heightened challenge. Two general methods have been adopted. The first assumes demand is sufficiently deterministic in a multiperiod setting (e.g. *([5])*). This can be problematic for systems in which most of the demand is not made for repeated commute trips and/or the fleet is spatially distributed in such a manner that the vehicle density is fairly low as in most systems. The second group of methods assumes stochastic demand, either through stochastic programming *([6])*, simulation *([7])*, or with Markovian demand *([8])*. The latter Markovian queueing models in particular appear promising, but earlier EV studies either assume a simplistic relocation policy *([8])* or, in the case of queueing networks *([9])*, do not allow customers to pick up vehicles at nearby locations. Discrete network approaches have not been used with queueing models for EV charging setting.

2 Problem definition

We consider a doubly-constrained rebalancing problem at the start of each time interval $\tau \in T$ to issue rebalancing decisions to a fleet B_τ of available vehicles. Let N be a set of nodes on a complete graph where customers initially enter the system as a Poisson process at a rate λ_{ih}, pick up a vehicle with sufficient discrete charge $h \in H$ at a nearby node with access cost t_{ij}, exit the system with the vehicle for a duration d, and return the vehicle at a node $i \in N$ at the same or later interval $\tau' \geq \tau$. The number of idle vehicles at each node i with charge g, $y_{ig\tau}$, is known only upon reaching interval τ.

The distribution of pickup-dropoff coupled locations is known as is the distribution of the duration of use. A subset of nodes $J \subset N$ is composed of charging stations with capacities $u_j, j \in J$, where the number of all assigned vehicles for charging cannot exceed. Recharge time is assumed to be deterministic.

The objective is to allocate idle vehicles from the current locations to new locations to minimize the access cost and wait time for customers as well as rebalancing and recharging cost of the fleet over T. The problem is an extension of a multiple server relocation problem under stochastic demand *([4])* in the context of electric vehicle charging.

3 Proposed methodology

3.1 Network transformation

We propose to solve the problem by transforming the system into a node-charge multilayer network space to treat it as a relocation problem with minimum cost flow constraints and route capacities for the charging stations. Cast in this framework, the nonmyopic relocation optimization model in (*[4]*) considers minimum cost flow relocation and captures access cost (location problem), wait time (queue constraint), rebalancing cost (relocation), and charging capacity (route capacities at charging stations). This transformation is illustrated in Fig. 1. Charging stations are located at original nodes 1 and 3. Once transformed, a vehicle located at node 9 (4, 40%) can only cover nodes 1 through 10 because of charge level. A relocation solution in Fig. 1c would use up two charging stations whereas Fig. 1d uses one.

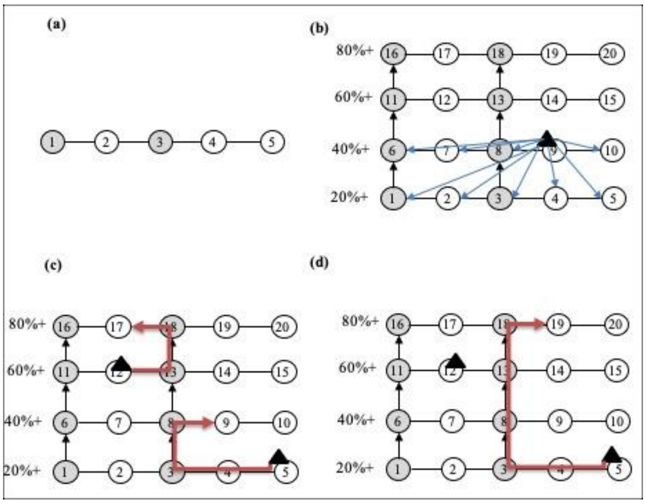


FIGURE 1. (a) Initial graph; (b) expansion to a node-charge graph with coverage illustration in blue arrows; (c) one possible rebalancing solution in red arrow; and (d) a second rebalancing solution.

3.2 Route-capacitated minimum cost flow relocation problem

Let $G(M, A)$ be a directed graph with M being a set of node-charge tuple $(i, h) \in M, \forall i \in N, h \in H$, and A a set of directed arcs, $A = \{((i, g), (j, h)) | \forall i, j \in N, \forall g, h \in H\}$. A node-charge tuple (i, h) is characterized by demand's spatial location $i \in N$ and current charging level (battery level) $g \in H$. An arc can connect upper layers only at nodes that are considered to be charging stations. In addition to binary variables for locating the m^{th} vehicle at node j with charge h, denoted as Y_{jhm}, binary variables for whether a located vehicle with charge h covers customer demand at node i demanding charging g, denoted as X_{igjh}, and rebalancing link flows (W_{igjh}), we introduce a set of path flow variables Q_{jgh} for charging station j where (g,h) account for all possible paths. For example, charging station at node 1 in Fig. 1a would have path set $\{(1,6),(1,6,11),(1,6,11,16),(6,11),(6,11,16),(11,16)\}$. This is very scalable as $|H|$ charging levels would have $(|H|-1)+(|H|-2)+\cdots+1=O(|H|^2)$ total paths. The path flow capacity constraint can then be set. The model is a mixed integer linear program with p-median location and minimum cost flow decisions (not shown in abstract due to space). We include a piecewise linear form of a queue intensity constraint from *([10])* in Eq. (1). When a customer arrives at an idle vehicle, there will be no more than b other customers waiting in line with a probability more than service reliability η.

$$\sum_{k=0}^{m-1}((m-k)m!\,m^b/k!)\,(1/\rho^{m+b+1-k})\geq 1/(1-\eta) \tag{1}$$

In Eq. (1), $\rho_{\eta jm}$ is the coefficient of the utilization rate constraint. If the queueing constraint is included, the model considers wait time in a steady state queue as a nonmyopic solution. Relaxing this constraint relocates vehicles without considering queue delay in a steady state as a myopic solution.

3.3 Proposed heuristic

The relocation problem is NP-complete since it generalizes the p-median problem. Computational tests on a range of random instances with up to $|N|=1000$ and $|H|=4$ can be solved using exact algorithms from commercial software (MATLAB) although the computation time reaches 7724 seconds with an Intel i5-6300U CPU with 2 cores and 8GB memory. We are interested in solving the problem for a system in Brooklyn, NY, with 304 zones and up to 8 charge levels. A heuristic is proposed to solve this model.

The heuristic is based on the greedy heuristic from (*[11]*) but modified to include (a) queueing constraints and (b) minimum cost flow relocation. A summary is provided here:

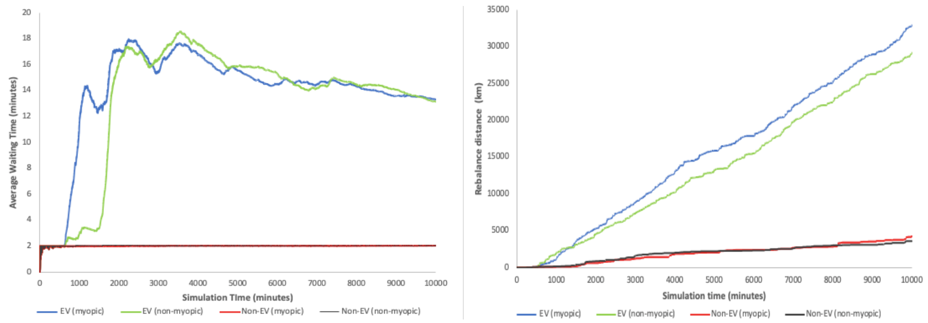
Proposed heuristic summary

1. Find the minimum number of servers needed at each node to satisfy constraint (1). Set this total as k and assign the k lowest charge-level current idle vehicles ($y_{ig\tau}$) to these locations as a minimum cost flow problem.
2. Let $k=k+1$. Compute the objective value of adding one new potential facility to each node-charge tuple based on the remaining idle vehicles; select the one with the lowest cost.
3. Repeat Step 2 until $k=B$.

4 Simulation-based experiments

We create a simulation environment in Matlab that generates customer arrivals and returns over continuous time with rebalancing decisions made for idle vehicles at the start of every time interval. Running the simulation with the proposed model on the simple network is promising, as shown in Fig. 2. Based on comparison between non-EV and EV as well as non-myopic and myopic, we can see that switching to EV inevitably increases rebalancing cost and queue delay for customers, but the non-myopic model outperforms the myopic model with the relaxed queue constraint.

The heuristic is tested on a network with $|N|=100, |H|=4$ under varying capacities. The optimality gap ranges from 5% to 9% and is ~ 20 times faster than the commercial software for capacities greater than one.



(a) (b)

FIGURE 2. (a) Accumulated rebalance distance over time, and (b) average waiting time.

The model and heuristic are compared to benchmark data provided by BMW ReachNow over the course of six months of operations in Brooklyn, New York in Fig. 3. The benchmark system is non-EV with no rebalancing and has 231 average pickups per day that last 6 hours each booking. Comparisons are made to the proposed model.

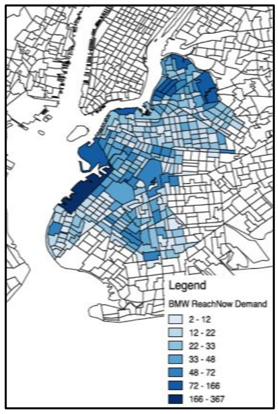


FIGURE 3. BMW ReachNow service area.

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Option contracts in supply chains: literature review and case study on capacity reservation

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The current business environment is charactarized by many uncertainties such as demand uncertainty, price fluctuations and production yield. Companies need to manage these uncertainties to compete effectively. This is challenging and these uncertainties can lead to inefficiencies in the supply chain that cause the supply chain partners to lose profit, either by decreasing revenues or by increasing costs[1].

Contracts may help to facilitate the supply chain operations in different business environments, and are an important means to align the incentives of individual supply chain parties so that the optimal supply chain profit can be achieved. This is referred to as supply chain coordination. Apart from this coordinating or channel improvement characteristic, contracts also serve as risk-sharing mechanism between the members of a supply chain. Some examples of contracts include wholesale contracts, buyback contracts and quantity flexibility contracts. The focus of this presentation is on option contracts. Such contracts give the buyer the right, but not the obligation, to buy or sell the underlying asset in a specified future period at a specified price. This is analogous to a financial option. However the option contracts we study here are related to real assets, not financial assets[1, 2].

In general, the option contract is characterized by two parameters. By paying the *option price*, the buyer of the option contract receives the right to buy or sell the underlying asset in the future. Later on the buyer has to decide how many options to exercise. Therefore he pays the agreed-upon *exercise price.*

The scientific literature distinguishes different types and characteristics of option contracts. A first distinction is between unidirectional and bidirectional option contracts. Unidirectional option contracts can be further classified as either call or put options, depending on what right the buyer acquires: the right to buy (call) or sell (put). Adjustments in a single direction might not be in the best interest of the of the whole channel. Therefore we distinguish a second category: bidirectional option contracts. Bidirectional options allow adjustment in either direction and so provide more flexiblity to the buyer. This can be interesting when markets are exteremely volatile and the buyer is not sure of the direction of the adjustment. A second distincion is whether the option contract is used as the only contracting mechanism between parties, referred to as a pure option strategy, or in combination with other contracting mechanisms, referred to as the mixed strategy [1]. Other relevant characteristics that influence the option setting are the (a)symmetry of information between the supply chain partners, and their risk neutrality or risk aversion. Our research shows that academic research so far mainly focuses on unidirectional call option contracts, and also on mixed strategy papers. Furthermore, the majority of the scientific papers does not address risk-aversion of (one of) the supply chain parties. [3] and [4] are some examples of studies that address the buyers' risk aversion in defining the optimal supply portfolio. However, there are many interesting opportunities for future research on option contracts in supply chains.

We present the results of a preliminary case study, based on (synthetic) data, in which we analyse the use of real options for capacity reservation. In such a setting, the buyer (user) of the capacity reserves a certain amount of capacity with the supplier using a real option. In our experiments we will use a call option contract. We show how the use of such option contract can help to coordinate the supply chain, i.e., how it helps to maximize the expected profit of the two parties combined. We also show that only specific combinations of option price and exercise price yield a successful contract, i.e., a contract where both parties are better off. Based on simulation studies, we analyse how the use of option contracts impacts risk: evidently, the true profit will vary around the expected profit. This is an important aspect in real life, as human decision makers are (commonly) risk averse. Risk aversion in the context of real option contracts has only be considered by a limited number of researchers so far. The insights from the case study can be relevant in different settings where capacity is being bought and sold while final demand is still uncertain (e.g., freight transport, contract manufacturing). To the best of our knowledge, option contracts have not been studied in this transport capacity setting before.

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Integrated Matching and Routing for Crowd-Shipping systems

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1 Introduction

Crowd-shipping (CS) promises social, economic, and environmental benefits covering a range of stakeholders. Yet, at the same time, many crowd-shipping initiatives face multiple barriers, such as network effects, trust, safety, and security.

It is clear that the supply of resources needed for CS is different than traditional delivery processes, where drivers are on the payroll of a logistics service provider. In the latter case, drivers are centrally managed, and deliveries are planned by these companies. Accordingly, drivers are expected to be available whenever needed (assuming good planning processes). In a CS context where the drivers are participating in the market mostly on a voluntary basis, their availability and their willingness-to-work are important aspects that need to be considered.

On-demand services typically make use of independent providers (e.g., the crowd) to fulfill customer requests quickly and are paid accordingly. Work participation is highly dependent on the actual earnings. Hence, the compensation paid for drivers is a key driver for the CS success and their willingness-to-drive.

2 Framework

The integration of routing and matching is illustrated in Figure 1. In the routing model, several distances are computed. A distance from the current courier's location to the pickup point is calculated to assign a courier to a package. A distance from package origin to destination is

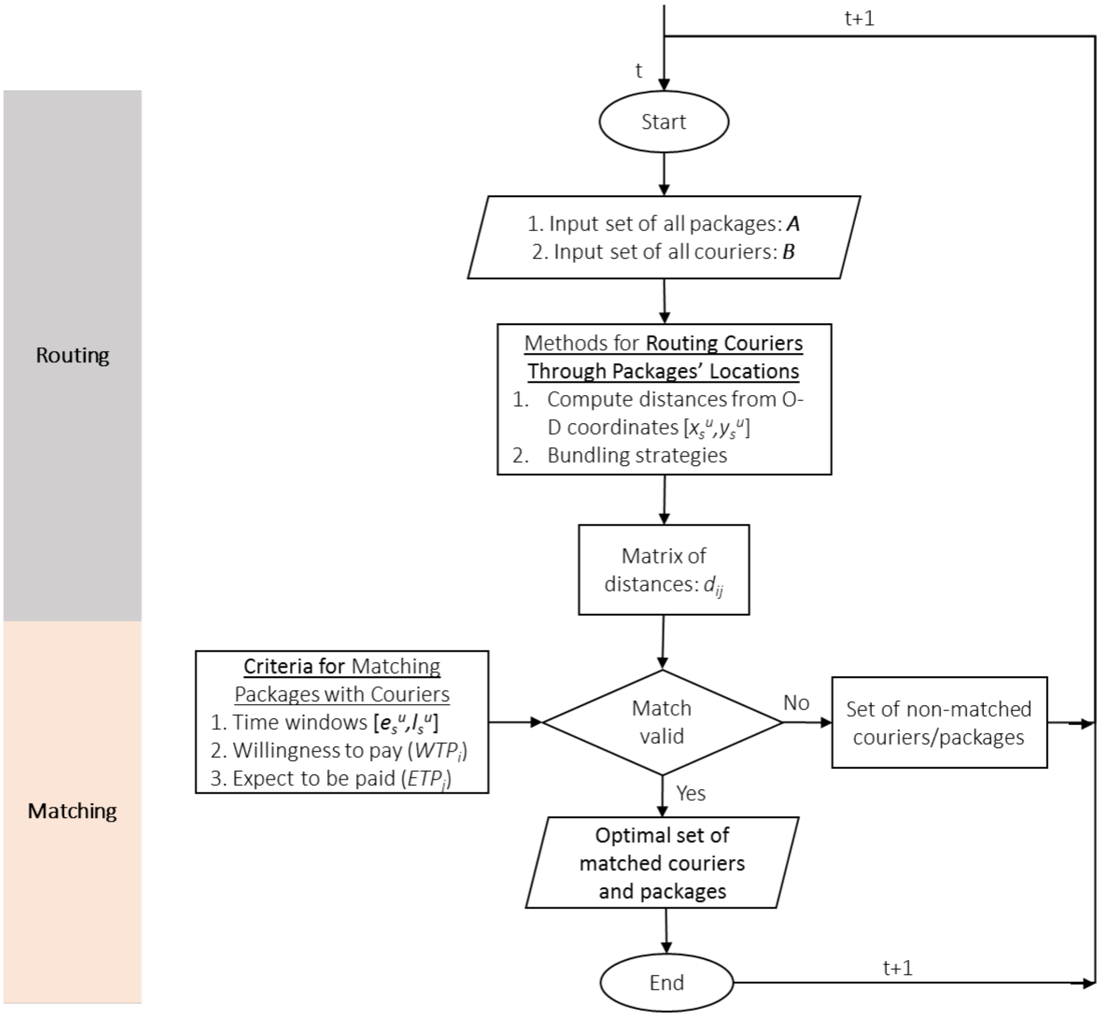

Figure 1: A framework for matching and routing problems

computed to estimate the delivery fare. In the matching model, inputs from the routing model (i.e. distance matrix) as well as the pick-up and drop-off time, willingness to pay, and expected to be paid values constraints of senders and couriers will be evaluated for the valid matchings. The matched couriers and packages will be proceeded, while non-matched couriers/packages will be re-matched in the next time interval.

3 Some results

In this paper, we examine different pricing and compensation strategies under 'flatted' and 'individual' settings. The 'flatted' setting means the price and compensation are the same for all requests and delivery trips, whereas the 'individual' setting means the price and compensation are applied to each request and delivery trip, respectively. Consequently, four different policies are generated from combinations of all settings which can be seen in Table 1.

Table 1: List of policies and meanings

Policy	**Meaning**
FPFC	Flatted Price, Flatted Compensation
FPIC	Flatted Price, Individual Compensation
IPFC	Individual Price, Flatted Compensation
IPIC	Individual Price, Individual Compensation

CS platform providers' profits increase from FPFC, FPIC, IPFC, to IPIC policies under all scenarios as can be seen from Table 2. The higher profits are obtained when the supply is close to or over the demand.

Table 2: The OPF's optimal values ($) and percentage changes compared to the base policy (i.e. FPFC)

	FPFC	**FPIC**	**% change**	**IPFC**	**% change**	**IPIC**	**% change**
SP0.5DM	14.14	16.32	15%	55.06	289%	56.66	301%
SP0.8DM	18.25	25.39	39%	70.63	287%	79.67	336%
SP1.0DM	7.18	12.56	75%	81.81	1039%	92.95	1194%
SP1.2DM	11.63	18.11	56%	95.23	719%	102.07	778%
SP1.5DM	9.55	18.23	91%	91.98	863%	96.92	915%

The benefits of the IPFC and IPIC policies significantly increase when the supply increases over the demand. However, the growth slightly decrease when the supply is about 1.5 times of the demand. On the other hand, the benefits of the FPFC and FPIC policies hit maximum at the supply equals to 0.8 times of the demand. As such, different pricing and compensation strategies should be considered to apply for different time of the day or day of the week where the demand and supply are imbalanced.

4 Outlook

Full results and references will be provided on the conference.

A new neighborhood search solution to urban integrated last mile delivery

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The technology advancement of Internet connectivity has also enabled the trading to be accessed from the consumers' finger tips through smart phones and other mobile devices, leading to the soaring of E-commerce in major markets around the world. In the United States, web-based sales comprise only 11.7% of the total retail volume in 2016. China, home of the technology giants Alibaba and Tencent, remains the world's largest E-commerce market in terms of trading value, representing around 39.2% of the global e-commerce transactions, with 19.8% growth from the year 2016. It is expected that E-commerce would continue to witness strong growth when more and more new markets are involved in the economy globalization.

The booming of E-commerce has played far-reaching impact on the urban logistics as it significantly boosted the volume of last-mile delivery, and thus increases dramatically the complexity of delivery operations. Besides the traditional E-commerce parcels, the prevalence of mobile internet has privileged the consumers with the convenience to place their on-demand orders, such as the delivery of restaurant take-out or fresh grocery, at any time and any location via mobile apps. Such online-to-offline (O2O) parcels brings enormous challenge and complexity for intra-city delivery as the increasing volume of orders which are often associated within a time window constraint.

In such cases, an increasing common practice for logistics service provider is to combine the traditional E-commerce parcels with O2O parcels in order to maintain competitiveness in a low margin last mile delivery markets. Many delivery companies have looked into various ways to implement such integrated delivery planning problems. For example, SF Express has started using same delivery crew to delivery e-commerce parcels and O2O orders. Consumers surprisingly receive their normal parcels and O2O parcels at the same time. In another example, Grab, a ride-hailing company launches its Grabfood and GrabExpress services in southeast Asia. GrabExpress provides express parcel delivery services, while Grabfood provides the online channel of local restaurants, offers food delivery service.

And moreover, consumers can book their food delivery online 1 day before. It's noted that Grab announces that they will use same pool of motorbikes to service parcel delivery and food delivery to lower cost. An ubiquitous feature among these cases is the integrating of E-commerce parcel delivery and O2O delivery. This highlights the popularity and trend of such a business model as well as the importance of better planning of various last mile delivery modes and the potential of an incentive in last mile application in sharing economy.

This research is motivated by a growing O2O market, particularly in an intra-city context, where most logistics service providers operate in a cost-efficient way that they combine O2O orders with normal E-commerce parcels. We follow the Grab practice that consumers can order beforehand, and we know the O2O orders when planning. While this assumption may sound simple, it is rather complex to implement in practice due to the huge volume of each delivery mode. In particular, when these two delivery modes combined, to the best of our knowledge there is no literature that gives exact solution of such combination. Moreover, this research can be regarded as a fundamental method which can extended to O2O real time planning as the methods presented can give solution in an efficient way. Due to the page limitations, this paper focus on given O2O orders and E-commerce parcels.

With the regard to E-commerce parcels, one motivation of this paper is to address the E-commerce last-mile delivery problem with a large number of parcels. This problem can be viewed as a typical vehicle routing problem (VRP), with the objective of designing a fleet of vehicle routes from one or multiple depots to a set of geographically scattered customers with the minimum traveling cost. In this paper, we consider multi-depot multi-trip E-commerce parcel delivery. Multi-depot implies that there are usually a number of depots in mega urban cities. Multi-trip means vehicles are allowed to visit their depots more than once. In other words, it relaxes the constraint of coupling each vehicle with a particular depot. Vehicles are free to end their trip at another depot and restart a new delivery route from that location. The multi-trip assumption is practical and has been frequently adopted by third-party logistics that operate throughout a mega-city. With proper optimization strategies, the service provider can support large-scale E-commerce parcel delivery with an economic scale of fleet size.

On the other hand, O2O delivery is associated with time windows in both pickup and drop off locations. Violating the temporal constraints would downgrade user experience. The O2O delivery can be seen as a variant of VRP with Pickup and Delivery (VRPPD). When the context is single-vehicle delivery, the problem is also known as pickup delivery traveling salesman problem (PDTSP). In this paper, we pay attention to VRPPD as we use a plenty of vehicles to handle the high volume of customer demand. Generally, there are two variants for VRPPD: vehicle routing problem with simultaneous pickup and delivery (VRPSPD) and vehicle routing problem with mixed pickup and delivery (VRPMPD). The former assumes that delivery and pickup requests of the same customer must be satisfied at the same time, and the delivery request is processed ahead of the pickup request. The latter problem relaxes the constraint and assumes that linehaul and backhaul customers are allowed in any order of sequence. In this paper, we define O2O delivery as paired pickup and delivery problem with time window (PPDPTW). Each O2O order is associated with an origin and destination, and the pickup and delivery are expected to be finished within given time windows. In addition, we further distinguish our PPDPTW as less-than-truck-load problem which allows other customers to be visited between a pickup and the associated delivery location.

With the aggressive expansion of E-commerce and O2O business, city logistics service providers have already paid attention to the growing market and made decisions to leverage the same fleet of vehicles to deliver the E-commerce O2O business under the concept of sharing economy. Motivated by this phenomenon, this paper is trying to address this integrated last mile delivery problem with the known O2O orders and e-commerce parcels. We define this integrated problem as multi-depot multi-trip with mixed paired pickup-and-delivery and time window constraints (MD-MT-MPPDTW).

In terms of technical contributions, we build the mathematical models to formulate the problem of MD-MT-MPPDTW that is solvable by CPlex programming to obtain the optimal solution. We also propose an effective neighborhood search strategy with two novel contributions. First, we propose a two-level pruning strategy to significantly reduce the running time in each iteration of neighborhood search. This allows us to achieve a much better trade-off between CPU time and result quality. Second, we propose an effective hybridization of Tabu search and ALNS to combines the merits from both approaches. ALNS is able to cover more diversified solutions, whereas Tabu search is good at intensification in local search regions. In our hybrid method, we iteratively apply these two local search strategies to achieve the goal of diversification and intensification. Experimental results verified that the hybrid approach established clear superiority over either Tabu or ALNS.

Service network design with mixed autonomous fleets and cooperative platooning

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1 Introduction

Logistics service providers (LSPs) suffer from a shortage of qualified drivers to carry an increasing demand for parcel delivery goods while satisfying economical and service quality goals. Automated driving has emerged as a promising technology to efficiently guide vehicles without a human driver in the future. However, full autonomy is still not technically feasible for safety reasons. Rather, current developments point towards autonomous vehicles (AVs) in SAE level 4, where the automated system's ability to control a vehicle mainly depends on the infrastructure conditions surrounding it. Especially in urban traffic networks, LSPs need to consider a heterogeneous infrastructure which comprises feasible streets for autonomous driving. Outside of these parts of the network, manually operated vehicles (MVs) with a human driver may guide AVs in platoons, that is, groups of vehicles following each other closely [1].

In dense cities, urban planning agencies urge commercially competing LSPs to cooperate with the aim of reducing their joint impact on residents' living conditions [2]. Cooperation can significantly contribute to a smaller number of vehicles and less total distance traveled, thus reducing pollution. While vertical cooperation between companies serving adjacent sections of the supply chain is already common practice (e.g. in two-tier city logistics), horizontal cooperation in the same section is starting to gain traction [3]. However, LSPs competing in the same field commonly fear to weaken their competitive advantages when sharing resources or order requests. Although central planning, e.g. by a city logistics committee, promises superior global solutions, companies risk losing self-determination and unlikely accept revealing too much information.

With this research, we provide a concept for achieving horizontal cooperation between multiple LSPs in city logistics. Using cooperative platooning, AVs from different LSPs share one platoon which is led by one LSP's MV, thus achieving consolidation of vehicles in groups. To agree on forming shared platoons, the participating LSPs exchange information on their transportation services during tactical planning. We integrate cooperative platooning into a service network design problem with mixed autonomous fleets [4]. We further adapt the dynamic discretization discovery algorithm which refines partially time-expanded networks iteratively to solve the integer program within reasonable runtimes. In a computational study, we analyze the efficacy of our algorithm and assess the effects of cooperation.

2 Problem Description

Multiple LSPs contribute to one joint city logistics network consisting of two layers of facilities. Commodities need to be transported from external zones, which are distribution centers usually located outside of the city center, to satellites, which are transshipment points distributed within the city center. While the origin and destination of each commodity are known for the medium-term planning horizon, the exact commodity volume varies on a day-to-day basis. Each LSP defines regular transportation services of appropriate capacity which are operated day after day, whereas the routing of commodities through the transportation services is planned day after day. If a demand cannot be satisfied by any transportation service, a third-party service needs to be hired ad hoc as a more expensive outsourcing option.

On a tactical level, each LSP decides on a fleet mix of MVs and AVs, then schedules robust transportation services that are repeated over the planning horizon. MVs can operate anywhere and can guide a limited number of AVs within platoons. AVs can only travel alone on a predetermined set of AV arcs but need to be guided by MVs in platoons elsewhere. A fixed schedule provides advantages for both vehicle types: for MVs and particularly the human driver, it facilitates driving tasks in navigating and synchronizing the platoons, for AVs it allows for synchronization with surrounding infrastructure and traffic management. As we seek repeatable schedules, each external zone ends a day with the same number of MVs and AVs it begins with.

Since, in large parts of the city, the AVs of each LSP rely on the platooning capacity of MVs, all LSPs of the city logistics network cooperate with respect to platooning. Therefore, MVs of an LSP not only guide AVs from the own fleet but also from the fleets of cooperating LSPs. This way, an LSP can share platooning capacity that would otherwise be unused by its own AVs. Since platooning as such does not impose additional costs other than the transportation costs of each individual vehicle, any additional following AV is free of charge for the platoon leader. The LSP that provides a platooning service is compensated with a fee paid by another LSP that uses it with the objective of avoiding outsourcing. In total, each LSP aims to minimize 1) the fixed costs for acquiring and maintaining the fleet, 2) the transportation costs for performing services, 3) the compensation fees for platooning paid to other LSPs deducting the fees received from other LSPs, and 4) the outsourcing costs.

3 Methodology

We consider a two-stage stochastic integer program in which the first stage determines robust transportation services based on all demand scenarios, whereas the second stage assigns the commodities in each demand scenario to the transportation services. We derive a time-expanded network by replicating each facility in various time points throughout the planning horizon.

When setting the size of the time intervals, we usually face the following trade-off: smaller time intervals better approximate the solution quality compared to the continuous-time problem, while larger time intervals reduce the size of the network, thus improving computational tractability. We tackle this trade-off with an adaptation of the dynamic discretization discovery algorithm by [5]. Fundamentally, the algorithm refines partially time-expanded networks iteratively until it terminates with the exact solution to the continuous-time problem without building the complete time-expanded network a priori. In each iteration, an integer program is solved on the current partially time-expanded network. We develop an enhanced algorithm that builds on this framework but for the first time considers cyclic vehicle routes, platooning of vehicles, horizontal cooperation of multiple LSPs, and stochastic demand scenarios.

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A Learning Large Neighborhood Search for The Dynamic Electric Autonomous Dial-A-Ride Problem

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1 Introduction

In the Dial-a-Ride Problem (DARP), minimum cost routes and schedules are defined for a fleet of vehicles exiting known depots and serving a set of customers with given pickup and dropoff locations [1]. The optimization can take into consideration multiple criteria and can include multiple type of users and destination depots (e.g. [2],[3]). Typical operational constraints include vehicle capacities, maximum vehicles-route duration, and maximum user ride times. In addition, service start times at pickup and dropoff locations are usually limited by time-window constraints. A recent work in [4], has considered a new mathematical model for the DARP with the use of electric autonomous vehicles (e-ADARP). Integrated operational constraints include battery management, decisions regarding detours to charging stations, recharging times, and destination depots. The objective of the e-ADARP minimizes a weighted-sum objective consisting of the total vehicle travel time and user excess ride time.

The DARP literature can be divided into two main streams, namely, static and dynamic DARP. In the first case, demand is fully known in advance, whereas, in the second case, demand is revealed online. This study focuses on the development of a metaheuristic approach for the dynamic e-ADARP. For a review on dynamic DARP studies, the reader is referred to Section 6 in [5].

The operation of electric autonomous vehicles (e-AVs) introduces new opportunities that must be taken into account in real-time planning processes. First, e-AVs offer more flexibility to modify vehicle plans in real-time according to changing conditions. Such changes do not only correspond to the arrival of new transportation requests but also to unexpected increases in traffic conditions and modified availabilities at recharging facilities. That is, differently from human-driven vehicles, the dispatching system can easily divert e-AVs as often as desired in the course of operations. Second, e-AVs can operate non-stop. While this feature might help saving vehicle deadhead miles to decentralized depots, service quality aspects can arise in a multi-period context. The employment of e-AVs also introduces new challenges that need to be tackled on-line. That is, the planning process needs to continuously re-optimize the vehicle battery levels, decisions regarding detours to charging stations, recharging times, and destination depots together with the classic Dial-a-Ride features.

In this work, we propose a two-phase heuristic approach to solve the dynamic electric Autonomous Dial-a-Ride Problem (e-ADARP). In the first phase, an insertion heuristic algorithm is designed to efficiently introduce new transportation requests into vehicle routes, modifying the vehicle schedules and recharging times. Current work is focusing on the design of the second phase, in which an improvement heuristic re-optimizes the vehicle plans after the insertion of new customers, and on computational experiments. For these latter, we introduce an event-based simulated environment to generate dynamic scenarios from existing benchmark instances and real-world data from ride-hailing services.

2 First Phase: Insertion heuristic

A new transportation request is represented by a generation time and a time-window around the pickup or dropoff location. Note that the time-window around the pickup can be easily computed from its dropoff by consideration of the user maximum ride time. Furthermore, the time-windows can be further tightened by considering the vehicle current locations and times. As a result, the earliest arrival at the newly generated request depends on the vehicle. Vehicles that cannot arrive to the customer pickup by its latest arrival time are not candidates for the insertion.

Given a number of candidate vehicles for the insertion, operational costs need to be computed for each vehicle. A first screening to find feasible insertions for the new transportation request (both in terms of its pickup and dropoff) and a particular vehicle can be performed through time-window considerations. That is, having computed the forward and backward time slacks for the users scheduled in a vehicle (as proposed in [6]), it is possible to identify segments of its static plan where the insertion of the new customer would not violate time-windows constraints. In consideration of precedence and capacity constraints, such segments can be further restricted. That is, knowing the vehicle maximum capacity and loads from the static plan, the newly generated request cannot be inserted when the vehicle is planned to travel at capacity.

Consider a candidate insertion satisfying time-window, precedence and capacity constraints. Then, the remaining problem may be stated as a linear program aiming at minimizing the total user excess time while satisfying battery constraints. Scheduling problems in the standard Dial-a-Ride Problem (DARP) are typically heuristically solved by employing the forward and backward time slacks and by delaying the pickup time of the customers [7]. Note that such a procedure does not provide excess-time optimal solutions and does not guarantee battery feasibility. In this work we propose an efficient procedure to optimize schedules based on the excess time objective subject to time-window and battery considerations.

Finally, for each candidate vehicle, multiple insertions of the new transportation request can be evaluated against a given objective function. The chosen insertion is then the one resulting in the lowest operational cost.

3 Second Phase: Improvement Heuristic

Given that no information about future demand is available during the first phase, vehicle plans might be improved once a number of myopic insertions have been performed. To this end, we are currently developing an improvement metaheuristic approach to re-optimize vehicle plans through intra-route and inter-route customer exchanges and charging plan modifications (i.e. the second phase).

Multiple works in the dynamic DARP have considered metaheuristic solution approaches based on Large Neighborhood Search (LNS) ([8],[9],[10]). In this work, we propose a new metaheuristic approach for the dynamic e-ADARP in which multiple neighborhoods are defined from problem-specific characteristics and the search mechanism is ruled by a machine learning approach.

During the search, the neighborhood operators are selected according to a prediction scheme derived from Classification And Regression Trees (CART) [11]. CART recursively partition the input space through a series of binary splits which are chosen through a mathematical model which maximizes a goodness of split function. The depth of the tree is typically controlled by a parameter which provides an upper bound on the maximal number of splits and, consequently, sub-regions. The class of each sub-region is decided by computing the largest number of representative samples in the sub-region (the "majority vote"). The predicted class for a new input point is then obtained by passing the point through the tree until a final node (or sub-region) is reached. In order to increase the accuracy of the prediction, multiple decision trees are typically combined through a technique called *bagging*, which essentially generates multiple models based on bootstrap samples of the input space. The final prediction is the aggregation of the predictions of all models. For a classification task, the aggregation corresponds to the most frequently-predicted class. In the context of the e-ADARP, we introduce the Learning Large Neighborhood Search (LLNS) metaheuristic. We formulate the choice of the operator by a classification problem (i.e. CART) in which each operator represents a class, while selected characteristics of the problem instances and solutions represent the features. Therefore, an instance of class i is an instance for which operator i is the best. Finally, the training data is a collection of examples of problem instances for which the best operator is known.

4 Computational tests

Computational experiments are performed on benchmark instances from literature and instances based on ride-sharing data from Uber Technologies Inc. in 2011 [4]. In order to generate dynamic scenarios, an event-based simulated environment is employed. The simulated events consider vehicle departures, arrivals, recharges, customer pickups, dropoffs and generations. New visits to recharging stations can be triggered after the generation of new customer requests. Given a cumulative density function, customer generation times are drawn through the inverse transform method [12]. Different cumulative density functions are employed in order to analyze the impact of advanced time on the service quality and cost. Furthermore, different dynamic scenarios are employed to test the limits of the proposed framework. Collected statistics include the ratio of accepted and rejected requests, static and dynamic customer excess ride times, vehicle idle times, recharging times, travel times, and end battery levels. Computational tests are currently under development and are therefore omitted from the extended abstract.

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Cooperation of customers in traveling salesman problems with profits

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In the profitable tour problem, a profit-maximizing carrier decides whether to visit a particular customer with respect to the prize the customer offers for being visited and traveling cost associated with the visit, all in the context of other customers. Our focus is on the prizes customers need to offer to ensure being visited by the carrier. This can also be formulated as a cooperative game where customers may form coalitions and make joint decisions on the prizes to be offered.

Such situation occurs in shipping for example when a carrier is able to serve demands of several customers with a single vehicle. Whether it comes to delivery or pickup of goods, the customers might need to induce the carrier to visit them by offering sufficient rewards. Subsequently, negotiation with other customers in the same position could lead to better prizes while the carrier's visit would remain guaranteed. This knowledge could also be utilized by the carrier by offering specifically tailored discounts on multiple orders from the same area or by evaluating and pricing of new customers.

We show that models currently present in the literature, such as the traveling salesman game [1] or the routing game with revenues [2], cannot be utilized to describe this problem due to additional assumptions on traveling costs. Therefore, we propose a definition of the profitable tour game and analyze the cost associated with each coalition of customers as well as prizes that help in achieving it. Then, our attention turns to investigation of the optimal prizes to be offered when the grand coalition is formed. We focus on properties describing relationship between the prizes and the underlying traveling salesman game to provide connection with extensive literature on core allocations in traveling salesman games [3], [4], [5]. We show that, if the core of the underlying traveling salesman game is non-empty, the set of optimal prizes coincides with the core. For problems in which this core happens to be empty, we present a linear optimization model to find the optimal prizes to be offered by the customers.

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Stakeholder requirements to the design of a cooperatively used urban logistics hub

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1 Introduction

Due to lower property prices, the majority of goods distribution centres is situated at the outskirts of urban spaces. In the past, the idea of urban hubs and urban consolidation centres has been taken up in many European cities. They are mostly used by only one courier, express and parcel (CEP) service provider to deliver and pick-up shipments in a limited city area.

The presented study evolved from a research project, which deals with urban hubs using the example of Vienna. Real-world experiences of the project partners revealed that the consolidation of the last-mile among different CEP service providers harbours feelings of resentments. The customer presence is of major importance for companies. We look into a hub concept with separate last-mile distribution, the hub's space; however, should be shared among various service providers. This could allow to reduce the total space and equipment needed due to a cooperative nature and therefore to obviate land sealing and decrease pressure on public space. Existing literature underlines that collaboration in urban freight logistics is a promising topic to improve the overall efficiency of supply chain activities (Gonzalez-Feliu & Salanova, 2012). And Marucci et al. (2017) argue that there's a need to include stakeholders' preferences regarding urban freight transport decisions to a greater extent.

The overall objective of this research is to derive a comprehensive requirements analysis to the design of a cooperatively used urban logistics hub by finding a balance between conflicting stakeholder interests. The gained insights contribute to ensure acceptance among all stakeholders groups of infrastructure development and, thus, can support public authorities to realise similar logistics projects. In contrast to previous research, we pay particular attention to the sharing of space and conduct a structured consultation process with representatives of three different stakeholder groups.

2 Methods

The work combines multiple methods to gain more insight into the different viewpoints of three stakeholder groups: CEP service providers, citizens and city government. At this point, the fourth stakeholder group to allow a pluralism of knowledge creation, the academia, (Carayannis & Campbell, 2009) plays merely the role of an observer, who documents and analyses results. Based on a scientific literature review, a review of national funding schemes in the transportation sector and grey literature, we develop a conceptual framework of potential goals that are linked to the implementation of a collaboratively used logistics hub in an urban context. Which importance the stakeholders ascribe to the single goals was assessed in a multi-method consultation process. Semi-structured interviews with top-level managers of four CEP service providers were recorded, transcribed and analysed with a content analysis using Atlas.ti software. Furthermore, a two hour focus group session with 20 citizens allowed residents to discuss their possible benefits linked to urban logistics hubs in three moderated roundtable discussions. The consultation procedure of the city administration of Vienna was organised by the city department responsible for urban development and planning and involved 12 city administration representatives of six different public bodies. The process allowed to pick up new topics or concerns that were collected in descriptive statements and served as preparation for the forthcoming quantitative survey. The quantitative survey used a Likert scale, ranging from 1 (very important) to 5 (not important at all) and was answered by the same stakeholders. Its results can be understood as an analysis of requirements the different stakeholder groups have regarding the design of urban logistics hubs. We use the median for result interpretation and discuss outstanding divergences.

3 Results and Discussion

The literature review resulted in 37 potential goals when realising an urban logistics hub. The goals included aspects such as the hub's location and its role in forming the cityscape of Vienna, its environmental, social and economic impact, and its added value including the potential service offer. Taking into regard the shared use of infrastructure, the review paid special attention to e.g., operator independence, standardised access rules and operational flexibility.

The interviewed CEP service providers indicated that goods would be transported to the hub via truck or van coming from distribution centres at the outskirt of the city. At the hub the parcels would be mainly transhipped to lighter vehicles depending on the actual demand points. The hub would be used as a short-term storage, e.g. if a delivery is not successful. The interviewees underlined that they expect economic benefits by sharing infrastructure costs. The results indicated that different customer structures, e.g., B2B/B2C shares, could help in achieving an efficient use of limited hub space. At the focus group session, citizens paid particular attention to the service offer of hubs, which could increase customer benefits and, thus, ensure public acceptance. They came up with known examples, e.g., parcel delivery or pick-up stations, and new ideas such as caring services for houseplants during holidays or tool lending stations. The consultation process revealed a quite large ambiguity within the answers of the city administration, e.g., regarding the use and incentivising of cargo-bikes or e-vehicles.

Looking at the results of the quantitative survey, Table 1 lists the three most important aspects when planning an urban logistics hub from the viewpoint of the three different stakeholder groups. It also presents objectives that matter most considering the viewpoints of all three groups. The median value is used for their ranking.

Citizens	City administration	CEP service providers	All stakeholder groups
1.Help to reduce traffic without compromising supply quality-1.10 2.Help to decrease CO_2 emissions-1.40 3.Use existing infrastructure instead of new buildings-1.63	1.Help to reduce fine dust in the surrounding area-1.33 2.Help to decrease CO_2 emissions-1.42 3.Help to reduce noise pollution-1.50	1.Allow the use of cargo-bikes and e-vehicles-1.00 2.Hub location should be very close to the city centre-1.25 2(3). Standardised access regulation, high security standard-1.25	1.Help to decrease CO_2 emissions-1.44 2.Help to reduce fine dust in the surrounding area-1.51 3.Help to reduce traffic without compromising supply quality-1.56

Table 1: Most important aspects when designing an urban logistics hub.

In brief, we can conclude that at a strategic level the hub should have a rather central location with good arterial road connection and public-transport links for citizens. Waterway and rail connections were considered as unimportant. Stakeholders prefer to adapt existing infrastructure instead of new buildings and charging stations for electric vehicles, lockable spaces for cargo bikes and loading bays are required. Temporary parking spaces for trucks and permanent parking spots for lighter vehicles need to be thought of. On the tactical level, standardised access controls are considered important and additional services need to be thought of to ensure public acceptance. At the operational level, the CEP service providers require both, fixed core times-of-use and spaces with flexible booking options. The biggest challenge is to plan for an efficient sharing of space, including its access and traffic flow management. The indicated time windows of the CEP service providers are found to be very similar. All of them require one transhipment slot in the early morning and one in the late afternoon. Especially the strong demand during similar morning hours could cause a peak of infrastructure utilization and a temporary lull at other times of the day. Nonetheless, some differences can be observed, e.g. regarding the B2B/B2C share, which by occasion allow variations in the delivery times or second delivery shafts. Furthermore, staff rooms can be shared. Important operations at the future hub are found to be unloading, loading and transhipment, short-time storage, and customer service, while information must flow consistently.

The stakeholder consultation revealed various challenges when designing a cooperatively used hub. The sharing of infrastructure poses organisational challenges and one needs to consider the different stakeholder groups and the potential diversity of their expected benefits. Both, future customer, and user acceptance are of major importance for the success of such urban logistics hubs.

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Estimating the success rate of matching for en-route ridepooling services - an analytical approach

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1. Introduction

Ridepooling, defined as two or more passengers share the same in-vehicle space during a proportion of their taxi/ride-sourcing trips, is widely believed to be an effective and promising approach to improve the service efficiency of taxi and/or ride-sourcing services while imposing less traffic burden on the urban transportation network. With the advances of information technoglogies and the popularity of smartphones, ridepooling service evolves from advanced booking to dynamic enroute ridepooling. Different from those early ridepooling services which require all demand information being known in advance of vehicle dispatching, en-route ridepooling service dispatches vehicles first and searches for matching orders enroute.

As vehicles are usually dispatched without matching orders in hand, a prior knowledge of the success rate of matching enroute for each individual order is important to both passengers and dynamic ridepooling service providers. Previous studies have shown that there are strong correlations between the average sucess rate of matching of a whole system and the maximum allowed inconvenience (e.g., maximal detour time allowed, maximal customer wiating time allowed) set by the platform. But these revealed relationships are at an aggregate level[1], thus can not be applied to estimate the sucess rate of matching(SRM) for each individual order. And to our best knowoledge, in industry, the model of SRM for each order is generated by data-driven methods, with a unsatisfactory performance.

In this paper, we make the first attempt to estimate SRM for each order through a mathematical modelling approach, and the SRM of orders estimated based on our model exhibits a ≤5% relative error under 98.2% of 10086 simulation experiments.

2. Model

2.1 The three-phase searching framework and matching conditions

Our model is based on a universal three-phase searching framework: Upon receiving an order, the platform checks instantaneously whether the order can be matched to an existing trip (Phase A); if no, the platform keeps searching for ridepooling partners in the following δ seconds (Phase B); and if no matching order is found after Phase B, an empty vehicle will be dispatched to serve the passenger, and along this passenger's trip, the app keeps looking for matching orders (Phase C).

Since it is usually intolerable for passengers to have more than one ridesharing partners in a single trip, we assume without loss of generality that each passenger share a vehicle with at most one another passenger. Under this simplified setting, a passenger who chooses ridepooling may be matched as either the first or the second passenger of a ridepooling trip.

No matter which phases are orders in, an order is said to be matching with another order only if they meet the following matching conditions: *1) the detour time experienced by both passengers should not exceed the maximum detour time* $\Delta\hat{t}$ *; 2) the waiting time for pick-up of the second passenger should not exceed a maximum value* $\Delta\hat{t}_w$.

2.2 The major challenge

Under the above searching framework and matching conditions, we show how challenging it is to predicting the SRM of each individual order. Consider, for example, the simplified scenario as in Figure 1 with only three OD pairs. If the platform set the maximal detour allowed for each passenger and the maximal waiting time of the second passenger both to be two blocks, then for a green passenger who is waiting at location (2,3), s/he could be matched to red passengers who travels to position (1,2) during his waiting. Then it is intuitive to expect that the SRM for the green passenger to be matched at his origin should be dependent on the arrival rate of red passengers at point (1,2). However, the arrival rate of red passengers at point (1,2) could be quite different from its demand rate at origin (1,1), as they could be matched to other red passengers between the same OD pair or to the blue passengers whose origin is before that of the green passenger. So there are complex interactions among passengers of the green, red and blue OD pairs. ***And due to the existence of such interactions, we have to consider the ridepooling demand rates of all these OD pairs when predicting the SRM for a single OD pair.***

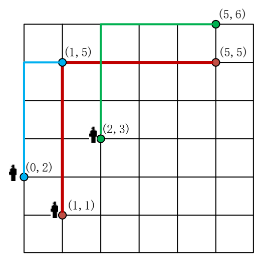


Figure 1. A simple example for illustration of matching competition among different OD pairs

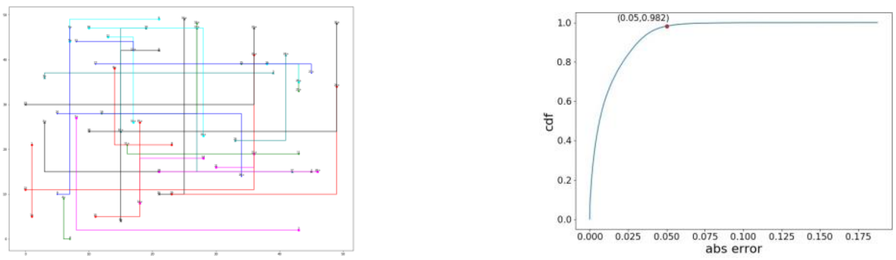
2.3 The modelling framework

Consider a ridepooling system $(W, \boldsymbol{\lambda})$, with W being the set of OD pairs and $\boldsymbol{\lambda} = (\lambda_w, w \in W)$ the vector of mean arrival rates, where λ_w is the mean demand rate of ridepooling orders for OD pair $w \in W$. we devide the route of each OD pair $w \in W$ into a number of small segments, and let Ω_{MW}

to be the set of all segments. Under the three-phase searching framework as mentioned above, passengers may either get matched at the starting point of a segment or while travelling on a segment. So we define p_{mw}^{0} and p_{mw}^{1} to respectively indicate the passengers' matching probabilities when they arrive at the starting point of segment $mw \in \Omega_{MW}$ and when they are travelling on segment $mw \in \Omega_{MW}$. To determine p_{mw}^{0} and p_{mw}^{1}, $mw \in \Omega_{MW}$, we let M_{mw} to be the set of matching segments when a passenger arrives at the starting point of segment $mw \in \Omega_{MW}$, $\hat{\mathrm{M}}_{mw}$ be the set of matching segments whose starting points is matching with segment $mw \in \Omega_{MW}$, and introduce the following four types of new variables: 1) p_{mw}^{E}, the the probability of passenger existence on segment $mw \in \Omega_{MW}$; 2) $\lambda_{mw}^{m'_{w'}}$, the matching rate of passengers on segment $mw \in \Omega_{MW}$ with passengers newly appeare or arrive at the starting point of segment $m'w' \in \hat{M}_{mw}$; 3) λ_{mw}^{A}, the arrival rate of passengers at the starting point of segment $mw \in \Omega_{MW}$; and 4) λ_{mw}^{D} the departure rate of passengers from the starting point of segment $mw \in \Omega_{MW}$. Under any given arrival rate $\boldsymbol{\lambda}$, a system of equations is developped to describe the relationships among p_{mw}^{0}, p_{mw}^{1}, p_{mw}^{E}, $\left(\lambda_{mw}^{m'_{w'}}, m'w' \in \hat{M}_{wm}\right)$, λ_{mw}^{A}, λ_{mw}^{D}, $mw \in \Omega_{MW}$. We prove the existence of solutions to the system of equations based on Brouwers' fixed point theorem, and solve it with the simple iterative method.

3.Effectiveness of the model

To demonstrate the effectiveness our model in predicting the SRM for different OD pairs, we conduct an event-based simulation based on a 50*50 grid network with 30 randomly generated ODs (routes) as in Figure 2. A total number of 11616 secenarios with different combinations of the maximal detour time $\Delta\hat{t}$, the maximal waiting time of the second passenger $\Delta\hat{t}_{w}$, the time length of Phase B δ, and the demand rate scalar θ are simulated and estimated. Our model succeeds to converge by the simple interative method under 10086 scenarios, and the estimated SRMs exhibits less than 5% absolute errors under 98.2% of the 10086 scenarios.



(a) (b)

Figure 2. (a) 30 OD pairs on a 50*50 grid network and (b) the cumulative distribution function (cdf) of absolute errors between estimated and simulated RMS of different ODs

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Combining people and freight flows using a scheduled transportation line with stochastic passenger demands

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1 Introduction

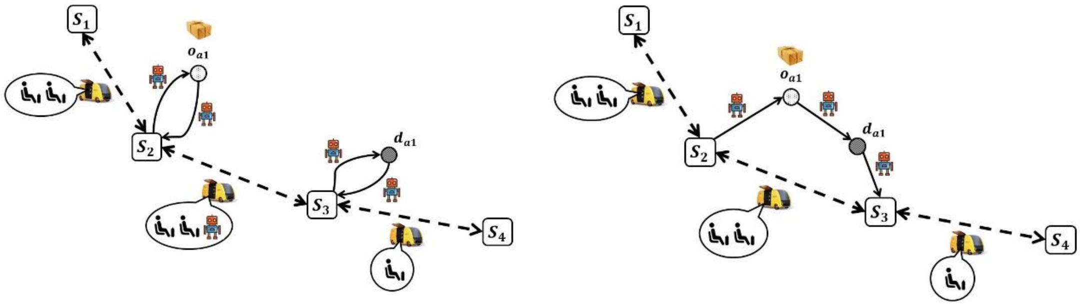
As both people and goods move in the urban environment, a successful integration of their streams has the potential of enhancing the quality of their existing transportation services as well as reducing congestion and pollution levels [1]. For example, spare capacity in public transport systems can be used for retail store replenishment or a taxi can deliver freight when transporting a paseenger or during idle time. As this combination can lead to minimizing vehicle-miles traveled, it can also yield some transportation cost reductions for both passengers and freight. This paper considers an integrated system in which a set of freight requests need to be delivered using a fleet of grounded robots where a public transportation service (referred to as *scheduled line (SL)*) can be used as part of a robot's journey[1]. In addition, we consider that passengers and robots (carrying goods) share the same SL capacity where passenger demands are stochastic. Thus, depending on passenger demand realization, a robot might not be able to use the SL service and some recourse actions need to be applied. Thus, we develop a stochastic approach for operating this system and we perform an extensive computational study to analyze its performance and potential benefits.

2 Problem description

In this problem, a set of autonomous shuttles operate through a fixed-route scheduled line (SL) service for transporting passengers in both directions. This service consists of a set of transfer nodes (i.e. stations) and a set of scheduled lines linking them. Every SL has a capacity and a timetable. In addition, a fleet of grounded, pickup and delivery (PD) robots are located at transfer nodes to serve freight requests. Each PD robot has a capacity and a maximum service distance indicating the maximum

[1] This integrated system was inspired from Toyota new e-Palette concept.

distance it can go from a transfer node. Moreover, SLs and PD robots are associated with a shipping cost per one time unit.



(a) Direct delivery – PD robot (b) Indirect delivery – PD robot and scheduled line

Figure 1: Request service modes: direct & indirect delivery

Furthermore, a set of freight requests need to be delivered using the fleet of PD robots. Each request is associated with an origin, a destination, pickup and delivery time windows, and a demand quantity. Thus, each request has to be served within its corresponding time windows. Depending on the availability of vacant places, PD robots carrying freight may travel with passengers through SLs. Therefore, delivering a request can be done in either direct or indirect way. In a **direct delivery**, a request is delivered directly to its final destination by a PD robot without the use of SL (**Figure 1 (a)**; request a_1 is picked up at its origin o_{a_1} by a PD robot coming from transfer node s_2, and delivered to its final destination d_{a_1} before the PD robot returns to transfer node s_3). This direct delivery is only feasible if the distance between request origin and destination locations is less than the maximum distance the PD robot can travel. On the other hand, in an **indirect delivery**, a request is collected by a PD robot, transfered through SL, and delivered afterwards to its final destination by the same PD robot (**Figure 1 (b)**; request a_1 is picked up at its origin o_{a_1} by a PD robot, transported through SL from s_2 to s_3 and finally delivered to its final destination d_{a_1} by the PD robot). We assume that a passenger or a PD robot take over one place in a shuttle and that passengers are prioritized. For the sake of simplifying the problem, we assume that each PD robot can serve only one request at a time and that freight quantities are known in advance. On the other hand, passenger demand is only learned upon shuttles' arrivals to SL stations. Thus, the number of available places for PD robots at each SL departure is stochastic which might yield two capacity violation outcomes: **(i)** PD robot not being able to take the next SL departure due to the high passenger demand at the corresponding station, and **(ii)** PD robot having to get off the shuttle at an intermediate station in order to give its place to a passenger. In both situations, the same capacity violation outcome, which is not having enough capacity for transporting passengers and PD robots within shuttles, will be obtained. When such route failures occur, recourse actions are needed in order to recover feasibility where applying these actions might lead to extra transportation costs compared to original routes. In this study, we consider the following recourse actions (respectively): **(i)** if PD robot cannot take the current departure due to high passenger demand, it will wait for the next SL departure which yields no extra costs as long as waiting the next departure does not violate request delivery time window. Second, **(ii)** if waiting the next departure also leads to violating SL capacity or request delivery time window, the PD robot will deliver the request directly to its final destination if this delivery is within the maximum distance it can travel. This recourse action implies additional costs as the PD robot will perform a longer trip than planned. Finally, **(iii)** if none of the first two actions leads to recovering route feasibility, the request will be transported to its final destination using an outsourced service (i.e. a dedicated vehicle) which induces extra transportation costs.

3 Solution approach

Similar to [2], we model this problem as a two-stage stochastic problem, where the first-stage aims at defining routes for PD robots carrying freight, and the second-stage involves evaluating these routes over a set of scenarios and computing their recourse costs. A scenario indicates the realized passenger demand at each departure from transfer nodes, and thus, the number of vailable places for transporting PD robots. As such, we provide a MIP formulation for the proposed pickup and delivery problem where the overall objective is to minimize the sum of the routing and recourse costs. Then, we propose a *sample average approximation (SAA)* method along with an *Adaptive Large Neighborhood Search (ALNS)* algorithm to solve the stochastic optimization problem.

4 Expermintal study

We test the proposed approach over a set of instances with different network topologies (triangle and line networks) and freight request distributions (clustered, randomly-clustered and uniform-randomly distributed). In addition, we evaluate the posposed ALNS method by comparing its returned solutions with those obtained by solving the MIP using a CPLEX solver. We also analyze the performance of the removal and insertion operators that are used iteratively within the ALNS method to enhance an initial solution. Then, we quantify the impact of passenger demand realization on such delivery service by comparing the stochastic solutions with the deterministic ones and we highlight the potential gains that can be achieved from this combined delivery compared to classical freight delivery systems.

5 Conclusions

To conclude, our key contributions can be seen in the problem setting we consider, the modeling and solution approach we propose to handle it, and the experimental study we provide to assess its different aspects as well as the potential benefits of such combined systems.

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Exact solution approaches for competitive hub location problem with attraction function

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1 Text

In this paper, we study the hub location problem in the presence of competition caused by the presence of already existing airlines in the network. For this, we model the market share captured by the entrant airline as a proportional gravity based attraction function. This leads to a non-linear integer program, for which we propose several customised exact methods . From our extensive computational experiments using two of the publicly available datasets, namely the Civil Aeronautics Board (CAB) dataset and the Australian Post (AP) dataset, we suggest the method which performs the best in trems of computation times. We further provide insights into the computational performance of the four methods.

Through this paper, we make the following contributions to the literature on hub location problems. To the best of our knowledge, our paper is the first to solve a competitive hub location problem with attraction functions exactly. We propose four different exact approaches for the problem, based on the model proposed by [1]. Since this model is a non-linear MIP, it can't be solved using an off-the-shelve MIP solver like CPLEX. The first approach is based on approximating the non-linear terms using supporting hyperplanes, which are generated as needed. This method is called a constraint generation method as introduced by [3] . We also provide a proof of finiteness of this method along the lines of [2]. We will refer to this method as CPA. On implementation we realised that for solving many of the instances, the system was running out of memory. Hence to solve this memory issue, we reformulated the problem as an MISOCP. MISOCP are a special class of non-linear problems that can be handled directly using CPLEX. Then to improve the computational results even further, we propose the third method. It is a customised approach where we use Lagrangian Relaxation in combination with SOCP to solve the problem. We will refer to this method as LR-SOCP. This method decomposes the problem into two problems. One of which is an IP which we are able to solve exactly using a tailored algorithm and the other is SOCP with only continuous variables. This type of decomposition has advantages as the nework size increases. Also we develop a fourth method to use Lagrangian relaxation in combination with the aforementioned constraint generation method. We will refer to this method as LR-CPA.

We compare the computational time for all the four proposed methods within a time frame of 4 hours. We find that using CPA we were able to solve 76 % of the 120 benchmark instances to 1% optimality gap . Also we were able to solve 81% of the instances to optimality by reformulating the problem as MISOCP. This percentage significantly increases to 95% and 88 % for LR-SOCP and LR-CPA respectively. We subsequently show, through rigorous experimentation that LR-SOCP and MISOCP are the computationally fastest of the four methods. Also for smaller instances of upto network size of 15 nodes, MISOCP has the best computational performance. As the network size increases, LR-SOCP performs better. This is expected of any lagrangian relaxation based method. We also provide insights into which method is performs better if the practical requirement is to close optimality gap at 2%. From the numerical experiments across various network sizes, it is clear that the LR-SOCP reaches optimality gap of 2% from 5% at an exponential rate but starts tailing to reach to a gap of 1%. As opposed to this, LR-CPA stedilty reaches from optimality gap of 5% to 2% and then 1%. With these results we conclude our work. The work reported in this paper can be extended in several ways. Assumption in the current work was that the market conditions remained steady during a planning horizon. During this planning horizon, market conditions like buying power of customers, attarctiveness of given hubs etc. may change. Such changes in market condition will have a definite impact on optimal location of hubs by entering airline. Future researches may try to incorporate this into their model.

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Modeling Service Class Constraints in Autonomous Mobility-on-Demand Systems: A Data-Driven Approach for Dispatching and Rebalancing Vehicles

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1 Introduction

The upcoming *autonomous vehicle (AV)* revolution is expected to re-shape urban transportation in the next decades. The current personal mobility paradigm, mainly based on vehicle ownership, is likely to phase out as *autonomous mobility-on-demand (AMoD)* systems develop [1]. Major car manufacturers (e.g., Ford) have already anticipated this impending shift, announcing their plans to use AV fleets to provide transportation services to travelers rather than selling individual AVs to consumers [2]. Under the assumption of a centralized operation, fleets of *shared autonomous vehicles (SAVs)* have been shown to be capable of adequately addressing current transportation demands with a fraction of the formerly operating fleet (taxis or private cars) [3, 4, 5]. Such replacement rate is even higher when different riders can share a single vehicle on short notice, that is, *dynamic ridesharing (DRS)* is enabled [6, 7, 8].

However, studies on DRS generally do not consider that different groups of customers widely vary in their behavior and desires [9]. Companies from various sectors acknowledge that profits and perceived *service quality (SQ)* can be improved by directly catering levels of their customer base. For example, airline passengers can generally choose from first, business, or economy class, whereas current on-demand urban transportation network companies, such as Uber, offer a range of service tiers, spanning from pooled riders up to executive limousine services. Therefore, future ridesharing systems are likely also to consider customer preferences when matching overlapping itineraries to construct viable routes.

Moreover, to the best of our knowledge, there is no DRS study actively controlling service reliability. In general, once a particular service level is defined (in terms of maximum waiting times), most studies try to determine a fleet size that maintains such level at a reasonable rate. As high this rate might be, even a small lack of reliability undermines the appeal of mobility-on-demand services, which end up being preemptively shunned by customers who cannot afford service rejection. User acceptance, however, is a crucial factor: ridesharing systems reach peak performance only when a sufficiently large number of riders are willing to participate [10].

In this study, we aim to explore service quality and reliability fully, by considering a no-rejection scenario where service deterioration (i.e., increased delays) is only allowed at previously defined rates. To this end, we take the perspective of a ridesharing mobility-on-demand company catering to a diversified customer base with varying expectations regarding three quality parameters:

- **Maximum delay -** Combination of pickup and ride delays;
- **Service rate -** The rate at which maximum delays are guaranteed to be fulfilled;
- **Sharing -** User can opt either for a shared or private ride.

By varying such parameters, we define three service quality classes, namely, low-cost, standard, and business. To investigate the impact of the relative predominance of one class over the other, we assign these classes to a subset of the New York taxicab trip demand in different ways, leading to six customer base segmentation scenarios. For each scenario, we determine a dynamic ridesharing routing policy that fulfills the quality requirements of class members. Whenever the operating fleet cannot sustain the service quality demanded by incoming requests, third-party vehicles are hired on-the-fly to guarantee the expected user experience entailed by each quality class. We assume that in a highly automated scenario, such vehicles are readily available to join the operating fleet, working during predefined periods or idle moments.

Moreover, actively distributing idle vehicles to mitigate spatiotemporal mismatches between vehicle supply and transportation demand, that is, rebalancing, has been demonstrated as an effective activity to decrease waiting time as well as fleet size [6]. Accordingly, to get the most of the operational fleet under the specific requirements of a heterogeneous user base, we apply a vehicle rebalancing strategy based on the New York trip data. In particular, our method harnesses class-dependent spatiotemporal demand patterns, prioritizing areas with the highest occurrence of high-SQ users. First, we assume transportation requests of a certain SQ-class are more prone to be placed in certain areas. Then, we use a reinforcement learning inspired approach to teach vehicles whether to take a rebalancing action, based on both current and historical class-specific demand patterns. Our results indicate that our prioritization strategy leads to shorter delays and fewer hiring operations in comparison with rebalancing approaches where SQ profiles are disregarded.

Therefore, AMoD companies can achieve superior service quality and customer satisfaction by incorporating user preferences and observed trip data into fleet management methods, especially when dealing with a heterogeneous user base.

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Inland waterway efficiency through skipper collaboration and joint speed optimization

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1 Problem statement and related literature

The growing sense of resource scarcity and climate change motivates companies to rethink their logistical operations and, if possible shift towards a more sustainable transport mode. In comparison to other transportation modes, the use of barges is more sustainable and relatively cheap. Moreover, as a single barge can replace over 100 trucks, increased use of the water network is likely to reduce congestion on the road network.

Besides longer travel times, mainly due to the relatively low density of the network, the high uncertainty in arrival time is one the major drawbacks of freight transport over inland waterways. This uncertainty is caused by the presence of many river obstacles, such as low bridges, narrow river segments, harbors and locks, which give rise to uncertain congestion and waiting time. This requires the skipper to increase the speed afterwards to guarantee an on-time arrival at the destination. The operational cost for the skipper is, however, largely determined by the fuel consumption, which is related directly to the required power and, therefore, the speed of the vessel. Consequently, this required speeding up results in a direct increase of operational costs for the skipper. In this research, we investigate how coordination and scheduling of all movement around these river obstacles can help to reduce congestion and waiting times, and therefore increase the efficiency of inland waterway transport.

Previous research on optimization of river obstacles is mainly focused on finding an optimal lock schedule (see, e.g. [1] and [2]). In all contributions rely on the assumption that lock operators have full power to determine the operating schedule. In practice, e.g., this schedule is typically determined using the first-come-first-serve principle, based on the order at which vessels arrive at the lock. If skippers know this, they will have the incentive to speed up when approaching a lock in order to pass their predecessors, get served first and avoid extensive waiting times. Preliminary research has shown that the adjustment of speed to reduce waiting time at queues results in significant economic benefits [3].

Adopting a collaborative view, our aim is to minimize the aggregated fuel consumption for all vessels on the river, while keeping in mind that each skipper is a rational individual with the sole goal of minimizing his personal fuel cost or emissions. This research project is motivated by our close collaboration with *Trapps Wise*[1], a Dutch company that develops smart technology for sustainable transportation.

2 Model Definition

We assume a waterway with a single lock and load-dependent operating times. Let L_u and L_d be the distances between the upstream and downstream end points of the waterway respectively and the lock. For each vessel i, we are given an arrival time at the upstream/downstream end point of the river, denoted by a_i, and a deadline d_i, the latest time when the vessel has to reach the downstream/upstream end point of the waterway. Moreover, the fuel consumption is given by $E_i(v_i) = L_u E(v_{i,u}) + L_d E(v_{i,d})$, where $v_{i,u}$ and $v_{i,d}$ represent the speed of the vessel in the upstream/downstream part of the river respectively. We assume the minimum and the maximum speed for any vessel is bounded by $v_{\min}$ and $v_{\max}$. Now, the total fuel consumption of the system is given by $E(v) = \sum_i E_i(v_i)$. Following the conventions from the related literature, we assume that fuel consumption is equal to zero if the vessel is not moving, and convexity of $E(v),\ v > 0$.

Each skipper i aims to minimize its total fuel consumption $E_i(v_i)$, given its deadline (denoted as d_i) on the arrival time at the destination. We define the cost function for skipper i by $C_i(\mathbf{v}) = E_i(v_i)$ if $a_i + L_u/v_{i,u} + L_d/v_{i,d} + q_i(\mathbf{v}) \leq d_i$ and $C_i(\mathbf{v}) = \infty$ otherwise, where $q_i(\mathbf{v})$ is the total processing time of vessel i at the lock, i.e., waiting and operating time. The waiting time depends on the congestion induced by the strategy profile, i.e., individual speeds of all vessels in the system. The operating time depends on the current load.

[1]https://trappswise.nl

3 Research contributions

Non-cooperative game. Here, we assume skippers do not have any means to collaborate. We show that the existence of a Nash Equilibrium depends on the queuing disciplined applied by the lock operator. For a queuing discipline that prioritizes ships that arrive earlier at the lock, there are scenarios in which a Nash Equilibrium does not exist. For queuing discipline that prioritizes ships that arrive earlier into the system, there always exists a Nash Equilibrium. However, it may result in an arbitrarily bad social cost. Therefore, neither of these options are desirable.

Cooperative game. If skippers can make binding contracts and allow mutual payments, they can incentivize each other to adapt speeds by reimbursing the extra costs. We introduce a payment system that fulfills two criteria. First, the cost of a player can never be higher than when he/she did not participate. Second, the payment system should give a vessel an incentive to behave as in the social optimum. We provide an algorithm that returns for each vessel a speed v_i, and the payment scheme $P_{i,j}$ indicating payment of skipper i to skipper j for the requested speed adjustment and show that this payment scheme satisfies the two criteria mentioned. Both a static and online variant of the problem are considered.

Computational experiments. The application of the proposed solution is impaired by its computational complexity. Consequently, the research is being extended by developing heuristic approaches for river segments with a sequence of locks. The speed advice provided by these approaches results in a good social cost while not giving skippers an incentive to deviate from the proposed advice. These heuristics are also tested on real life data provided by our industrial partners.

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Alternate Second Order Conic Programming Reformulations for Hub Location with Capacity Selection under Demand Uncertainty

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Hub location is a widely studied problem as it finds immense applications in supply chain network, airline network, telecommunications, postal deliveries etc. The key idea behind a hub-and-spoke network is to route all flows through intermediate facilities, called hubs, where they are aggregated before being sent to their respective destinations. Hubs serve as centres to collect, sort, break-bulk or switch modes of travel while transferring flows. The main cost advantage in a hub-and-spoke network comes from the economies of scale in inter-hub transfers achieved due to aggregation of flows.

In this paper, we focus on hub-and-spoke network in an air transportation system. Hub-and-spoke network is considered as one of the predominant architectures for airline route system since the US Airline Deregulation Act (1978). It is also recognized as the "seventh in the American Marketing Association series of Great Ideas in the Decade of Marketing" (Marketing News, June 20, 1986). After deregulation, increase in the market share of the US national airlines (annual revenue \$75 million - \$1 billion), as compared to the other major airlines (annual revenue greater than \$1 billion), was mostly attributed to their hub-and-spoke network structure [1]. One of the key concerns that affects the service quality at the hub airports is uncertainty in demand. Although flights follow a schedule, they are subjected to delays due to a variety of reasons like technical problems, weather conditions, and operational issues [2]. During peak hours, when the hubs are already operating at their capacity, any further unscheduled arrivals due to delayed flights can cause congestion at hubs, which further deteriorates the service quality. We study the problem of hub location with capacity selection in the presence of congestion due to demand uncertainty. For this, we model the hub-and-spoke network as spatially distributed M/G/1 queues, whose locations and capacities need to be selected in order to minimize the total cost. The total cost consists of the capacity installation cost, the transportation cost, and the congestion cost. The congestion term introduces non-linearity in the objective function, which makes the resulting hub location problem with capacity selection under congestion a non-linear mixed integer program (NLMIP). Hub location problems, even without capacity selection decision and congestion, is known to be NP-hard [3]. Capacity selection decision along with the non-linearity introduced due to congestion, makes the problem even more challenging. The objective of this paper is to solve the resulting problem efficiently. To this end, we present several alternate MISOCP-based reformulations of the problem, and compare their computational performances against outer approximation (OA) based formulations.

Through this paper, we make the following contributions to the literature on hub location problems. First, we propose two new NLMIP-based formulations for the hub location problem with capacity selection under congestion, based on the model (without capacity selection and congestion) proposed by [4]. We refer to these models as EK-based models. We compare our proposed formulations with two other NLMIP-based formulations from the literature [5, 6], which are based on the well-known model proposed by [7]. We refer to these models as SK-based models. We subsequently show, through computational experiments, that the two formulations proposed by us significantly outperform the latter two formulations. Second, for each of the four (two SK-based and two EK-based) NLMIP-based formulations, we present several MISOCP-based reformulations which we compare with the respective outer approximation (OA) based formulations.

From our extensive computational experiments using two of the publicly available datasets, Civil Aeronautics Board (CAB) dataset and the Australian Post (AP) dataset, we suggest the overall best formulation for the exact solution of the hub location problem with capacity selection under congestion. We also show that our MISOCP-based reformulations outperform the OA-based method for the proposed NLMIP for all instances. We further provide theoretical insights into the computational results, based on the properties of the second order cones. The theoretical insights should be useful as a general guideline for the selection of a given MISOCP from among several alternatives. To the best of our knowledge, ours is the first application of MISOCP-based reformulation to hub location problem under congestion.

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Uncapacitated p-Median Facility Location Problem Under The Risk Of Interdiction

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The serial bombing of 18 electrical stations in Mexico by a drug cartel in 2013, caused a total blackout for around 15 hours[1]. An electrical systems failure in Ohio in august 2003 resulted in a complete blackout of many parts of United States adversely affecting transport, production, financial markets and communication[2]. These are some of the many instances when disruptions have brought service systems to a complete standstill, leading to an environment of panic and extreme shortages. Disruptions to a service facility system can be caused by either natural forces like earthquakes, floods, hurricanes, etc; accidental like fire, security issues, etc; or intentional like terrorist strikes, warfare strategies, etc. Due to the extent of damage caused by disruptions, there has been an increased focus to build resillient and robust systems. In view of this, the following questions are asked: What are the critical elements in an existing service facility system that will cause maximum damage in case they fail? How to design robust systems by considering the possibility of a future disruption during the design phase itself?[3] In the literature, the first question falls under the category of Facility Interdiction Problem while the latter under the broad heading of Facility location problem under the risk of interdiction. These two problems are NP Hard and there are very few papers that have solved them to optimality.

In this article, we look at the p-median Facility location problem under the risk of interdiction.

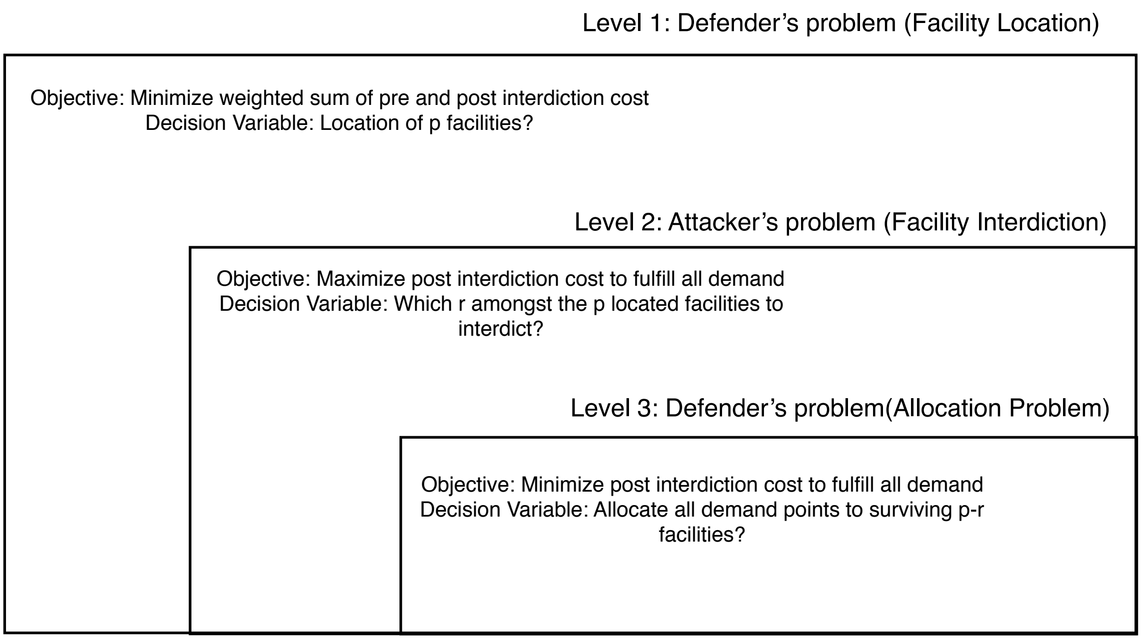

Figure 1: Tri-Level Problem Structure

This is a tri-level optimization problem formulated as a Stackelberg game. At the first level is the defender who locates p facilities in a given network by taking into consideration the risk of a possible attack by an adversary. At the second level is the attacker who interdicts r facilities from amongst the located p facilities, with the objective to cause maximum damage to the defender. The defender at the lowest level then reroutes the flow through the remaining $p - r$ facilities so as to minimize the demand weighted cost of flows to fulfill all demand (see Figure 1).

Ours is the first paper to solve the Tri-level Facility Location problem optimally using decomposition method. The approach utilised here reduces the lower bi-level problem (known as Facility Interdiction Problem) into single level and then applies Cutting Plane approach using a

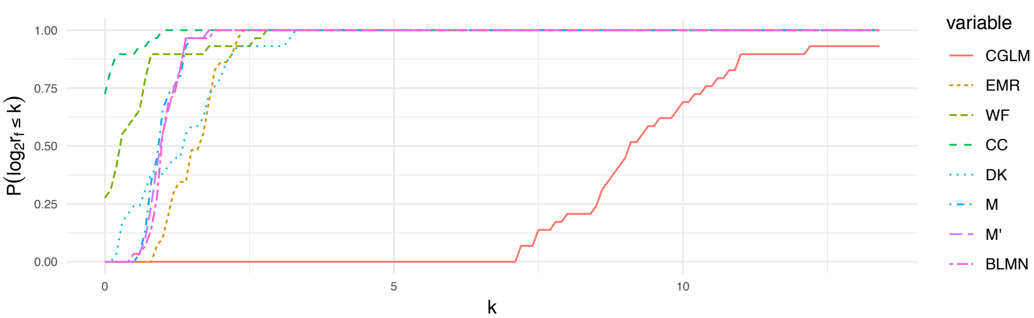

Figure 2: Performance Profile of CACs for 200 nodes data

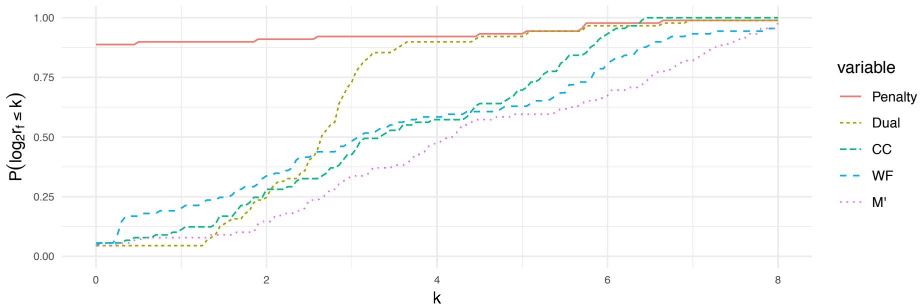

Figure 3: Performance Profile of CACs ,Dual and Penalty Methods

Super Valid inequality to find optimal solution to the tri-level problem. In the literature, the lower bi-level problem is reduced to a single level by replacing the lowest level problem with Closest Assignment Constraints (CAC). Ours is the first study to present a comparison of the available CACs in the literature in terms of their computational efficiency and find that CC, WF and M' are the best performing CACs (as shown in Figure 2). Additionally, we propose two exact methods (Dual and Penalty) to reduce the lower bi-level Facility Interdiction Problem to a single level. Both these methods involve the use of BigM. We exploit the structure of the problem to obtain some valid as well as tightest values of BigM which significantly improves the performance of both these methods. We also compare the computational performances of the best performing CACs with Dual and Penalty Methods (using tightest BigM for both)and obtain that Penalty Method works best (see Figure 3).

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Sequence and Speed Optimization for Delivery Robots

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1 Delivery Robots and the Optimization Problem

The growth rate in Courier Express Parcel markets presents a major challenge for the logistics industry worldwide. Innovative approaches and solutions are needed. For densely populated areas, so-called delivery robots[1] are a promising alternative to traditional trucking. Delivery robots represent a rather new technology, capable of transporting small goods autonomously on sidewalks. These robots drive at walking speed and are equipped with the same technology used for autonomous driving. The advantage of a robot delivery is that the delivery can commence upon receiving a request, which helps to enhance customer satisfaction.

In this study, we assume that the driving speed of the robots is controllable and can be optimized, in order to minimize the energy needed. This gives rise to a joint sequencing and speed optimization problem to serve a given set of customers within pre-specified time intervals, by using a fleet of robots. There exist two relevant studies to the problem just described. The first is [1], who show that, for a given sequence of tasks, each with a time window, there exists a polynomial time algorithm that calculates speeds for each task optimally, provided that the cost function is convex and non-decreasing. The second study [2] combines speed optimization with a vehicle routing problem, where the objective is to find routes that minimize the total fuel consumed by respecting the service time windows, for which a branch-and-cut-and-price algorithm is presented.

[1] www.starship.xyz

2 Problem Description

Let $D = (V, A)$ denote a directed graph, where $V = \{0, 1, 2, \dots, n\}$ is the set of vertices, vertex 0 denotes the depot, set $C = \{1, \dots, n\}$ denotes the customers, and $A = \{(0, i) : i \in V\} \cup \{(i, 0) : i \in V\}$ is the set of arcs. There are m identical robots, each with unit capacity, available at the depot. Each customer $i \in C$ has a unit demand and a time window $[a_i, b_i]$ within which service should commence, and requires a service of duration τ_i. For each arc $(0, i)$ and $(i, 0) \in A$, d_i denotes the travel distance between the depot and customer i, where $d_0 = 0$. The travel distance d_i only depends on customer i, because the only arcs that exist in graph D are those between the depot and the customers, in either direction. The energy consumed per unit distance traveled at speed v is represented by a convex and non-decreasing function $f(v)$.

Let $(i_0, i_1, i_2, \dots, i_h, i_{h+1})$ denote a *route*, where $i_0 = i_{h+1} = 0$, $i_j \in C$ for $j = 1, \dots, h$. Implicitly given is a depot visit between each pair of customers $i_j, i_{j+1} \in C$. The optimization problem involves finding m routes that minimize the total energy consumed, such that (i) each customer is visited only once by any of the m robots, (ii) each customer $i \in C$ is served within its time window $[a_i, b_i]$ and (iii) the travel speed on an arc in A remains within the bounds $[l, u]$.

For the described problem, it can be shown that for two consecutive customers, $i_j, i_{j+1} \in r$, the speed on the return trip from customer i_j and the speed on the way to customer i_{j+1}, both shown by $v_{i_{j+1}}$, have to be equal in an optimal solution. The cost c_r of a route $r = (i_0, i_1, i_2, \dots, i_h, i_{h+1})$, for which an optimal speed vector $\mathbf{v} = (v_1, v_2, \dots, v_{h+1})$ can be computed using the speed optimization algorithm described in [1], is given by $\sum_{k=1}^{k=h+1} (d_{i_{k-1}} + d_{i_k}) f(v_{i_k})$.

3 A Branch-and-Price Algorithm

This section presents a set partitioning formulation to solve the described problem using a branch-and-price algorithm. Let Ω be the index set of all feasible routes. A binary coefficient a_{ir} is equal to 1 if customer $i \in C$ is contained in route $r \in \Omega$. Let x_r be a binary decision variable equal to 1 if and only if route $r \in \Omega$ is in the optimal solution. The robot sequencing and speed optimization problem can be formulated as the following Master Problem (MP),

$$\text{minimize} \quad \sum_{r \in \Omega} c_r x_r \tag{1.1}$$

$$\text{subject to} \quad \sum_{r \in \Omega} a_{ir} x_r = 1 \qquad \forall\, i \in C \tag{1.2}$$

$$\sum_{r \in \Omega} x_r \le m \tag{1.3}$$

$$x_r \in \{0, 1\} \qquad \forall\, r \in \Omega. \tag{1.4}$$

In the formulation above, constraint (1.2) ensures that each customer is visited exactly once, and constraint (1.3) ensures that at most m robots are used. Since set Ω contains an exponential number of columns, the MP is initially solved with only a subset Ω' of routes, which is named as the Restricted Linear Master Problem (RMP). Set Ω' is then extended using a column generation algorithm, where a pricing problem is solved to determine the variables to be added in.

Let the dual variables corresponding to constraints (1.2) and (1.3) be π_i, $i \in C$, and π_m, respectively. Let $\mathcal{R}$ be the set of all feasible routes for the RMP. The pricing problem for generating a new column to be added to the RMP is formulated as $\bar{c}_r = \min_{r \in \mathcal{R}} \{c_r - \sum_{i \in C} a_{ir} \pi_s\} - \pi_m$. If the reduced costs are negative, the variable representing this route will be added to the RMP. The pricing problem corresponds to a resource constraint elementary shortest path problem (RCESPP). The RCESPP involves finding an elementary shortest path from node w_0 to w_{n+1} with the minimum net prize that satisfies speed limits and vertex time window constraints. The net prize for a path $P = (w_0, w_{i_1}, w_{i_2}, \ldots, w_{i_h}, w_{n+1})$ using an optimal speed vector $\mathbf{v}$ obtained by the algorithm given in [1], is given by $\sum_{k=1}^{k=h} (d_{i_k} + d_{i_{k-1}}) f(v_{i_k}) + d_{i_h} f(l) - \sum_{k=1}^{k=h} \pi_{i_k} - \pi_m$.

4 Preliminary Results

Tests were carried out with the branch-and-price algorithm and an alternative formulation of the problem that uses discretized speeds, on random instances with a grid layout, and where the customers have non-overlapping time windows. Even with a few speed levels, the latter was only able to optimally solve instances of up to 15 customers, whereas the former was capable of solving instances of up to 30 customers to proven optimality under a common time limit of one hour.

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Predictive dynamic relocations in carsharing systems implementing journey reservations

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1 Introduction

Carsharing is an on-demand shared-mobility service that aims at providing a level of service similar to private vehicles while mutualizing the transportation resources. Several benefits linked to its implementation have been identified both at user and society scale ([1, 2, 3]). In this study, we focus on station-based carsharing systems which allow one-way rentals, namely vehicles can be picked-up and dropped-off at different stations. In addition, the system imposes a reservation policy denoted as complete journey reservation policy, in which both a vehicle and a parking spot have to be reserved at the booking time. Reservations can be made up to one hour in advance and the corresponding resources are kept reserved until the pick-up and drop-off times, respectively. Note that the exact times are not known to the system as users are not required to specify them in advance. Such rental conditions are attractive to customers but they result in a less efficient use of vehicles and spots due to extended reservation locking. In order to maximize resource availability in the system, the operator may introduce dynamic relocation schemes. Two main approaches exist in the literature: staff-based relocations, where car-sharing system employees move vehicles ([4, 5, 6, 7, 8, 9, 10]) and user-based relocations, where customers adapt their trips according to the operator's suggestions ([11, 12]).

This study presents a new proactive dynamic staff-based relocation algorithm tailored for the type of systems considered, which aims at both reducing present imbalances in vehicle and spot availability and preparing the system for the future demand. The algorithm is based on a Markovian model that incorporates reservation information and historical data in order to estimate the near future expected demand loss at a station. Through a collaboration with the car-sharing system in Grenoble, France, we have conducted field experiments and extensive simulation experiments based on data retrieved from the system. The outcome of the experiments demonstrate the superiority of the proposed algorithm over other existing approaches.

2 A Markovian estimation relocation policy

We apply a Markov chain based modeling approach to quantify the impact of relocation choices on the expected demand loss due to shortages in vehicles or parking spots. This approach was initially proposed by [13], and was later adopted by several studies in the vehicle sharing literature. However, in this work we utilize for the first time reservation information in the model. Such information is important especially for short term estimation periods as it reduces uncertainty regarding vehicles and parking spots that are about to become available. On the one hand, this leads to a more complex model, on the other hand, it allows us to enhance near-future estimations.

Consider a single station with C parking spots. Under the complete journey reservation policy, the state of each station can be described at any time by the triplet (x_{av}, x_{rv}, x_{rp}), with x_{av} the number of available vehicles, x_{rv} the number of reserved vehicles and x_{rp} the number of reserved parking spots. As capacity is fixed, the number of available parking spots is $C - x_{av} - x_{rv} - x_{rp}$. The transitions between the inventory states of the station are due to four events: (i) reservation of an available vehicle with mean vehicle inter-reservation duration λ_v^{-1}, (ii) pick-up of a reserved vehicle with mean time between booking and pick-up μ_v^{-1}, (iii) drop-off of a vehicle with mean time between booking and drop-off μ_p^{-1} and (iv) reservation of an available spot with mean spot inter-reservation duration λ_p^{-1}. Transition rates out of state (x_{av}, x_{rv}, x_{rp}) are detailed in Table 1.

Event	**Current state**	**Next state**	**Transition rate**
Booking of available vehicle	(x_{av}, x_{rv}, x_{rp}) $x_{av} > 0$	$(x_{av} - 1, x_{rv} + 1, x_{rp})$	$\lambda_v(t)$
Pick-up of booked vehicle	(x_{av}, x_{rv}, x_{rp})	$(x_{av}, x_{rv} - 1, x_{rp})$	$x_{rv}\mu_v(t)$
Drop-off of vehicle	(x_{av}, x_{rv}, x_{rp})	$(x_{av} + 1, x_{rv}, x_{rp} - 1)$	$x_{rp}\mu_p(t)$
Booking of available spot	(x_{av}, x_{rv}, x_{rp}) $x_{av} + x_{rv} + x_{rp} < C$	$(x_{av}, x_{rv}, x_{rp} + 1)$	$\lambda_p(t)$

Table 1: Transitions between states in the independent station Markov chain model

Let $(x_{av}^t, x_{rv}^t, x_{rp}^t)$ be the state of the station at a decision time t, δ the estimation horizon and $\pi_{x_{av},x_{rv},x_{rp}}^{x_{av}^t,x_{rv}^t,x_{rp}^t}(\tau)$ the probability that the station is in state (x_{av}, x_{rv}, x_{rp}) at time τ, $t \geq \tau \geq t + \delta$. The expected demand loss due to vehicle and parking shortage at station s during δ is:

$$EL_{t,\delta}^s(x_{av}^t, x_{rv}^t, x_{rp}^t) = \int_t^{t+\delta} ((\sum_{i=0}^{C}\sum_{j=0}^{C-i} \pi_{0,i,j}^{x_{av}^t,x_{rv}^t,x_{rp}^t}(\tau))\lambda_v(\tau) + (\sum_{i=0}^{C}\sum_{j=0}^{C-i} \pi_{i,j,C-i-j}^{x_{av}^t,x_{rv}^t,x_{rp}^t}(\tau))\lambda_p(\tau) d\tau$$

The first (resp. second) term in the integral represents the rate of requests that cannot be fulfilled due to shortages in available vehicles (resp. available spots), obtained by multiplying the probability for vehicle shortage (resp. spot shortage) at time τ by the arrival rate of requests for vehicles (resp. spots) $\lambda_v(\tau)$ (resp. $\lambda_p(\tau)$). The evaluation of the expected demand loss is numerically obtained with the approximation method of [13]. In a single run of the procedure, expected demand losses for all stations, all initial states and the desired estimation horizon δ are obtained and stored to be used later in the on-line relocation algorithm.

The output of the model is applied in real-time decision making as described in the following. In the considered operation mode, relocators are required to reserve a vehicle and a spot as users do. If a station in state (x_{av}, x_{rv}, x_{rp}) at decision time is selected as the origin of the next relocation task assigned, it transitions to state $(x_{av} - 1, x_{rv} + 1, x_{rp})$ and the resulting avoided expected demand loss at this station is:

$$O_{t,\delta}^s(x_{av}, x_{rv}, x_{rp}) = EL_{t,\delta}^s(x_{av}, x_{rv}, x_{rp}) - EL_{t,\delta}^s(x_{av} - 1, x_{rv} + 1, x_{rp})$$

Equivalently, if this station is the destination of the next relocation task assigned, it transitions to state $(x_{av}, x_{rv}, x_{rp} + 1)$ and the resulting expected avoided demand loss is:

$$D_{t,\delta}^s(x_{av}, x_{rv}, x_{rp}) = EL_{t,\delta}^s(x_{av}, x_{rv}, x_{rp}) - EL_{t,\delta}^s(x_{av}, x_{rv}, x_{rp} + 1)$$

At a decision point, deciding to relocate a vehicle from station s_1 to station s_2 represents an expected avoided demand loss of $O+D$. If $O+D$ is negative for any pair of stations, no relocation is triggered. In selecting an origin-destination pair for a relocation task, we wish to balance the expected avoided demand loss against the time required to execute the relocation task. In order to do so, we calculate the expected avoided demand loss per time unit spent relocating. Let $move(s)$ be the time required for the relocator to move from his current location to station s, and let $drive(s_1, s_2)$ be the driving time from station s_1 to station s_2. The selected relocation pair $(o^\star, d^\star)$ is the one with the highest expected avoided demand loss per time unit spent relocating:

$$(o^\star, d^\star) = arg \quad max_{(s_1,s_2)\in P} \frac{O^{s_1}_{t,\delta}(x^{s_1}_{av}, x^{s_1}_{rv}, x^{s_1}_{rp}) + D^{s_2}_{t,\delta}(x^{s_2}_{av}, x^{s_2}_{rv}, x^{s_2}_{rp})}{move(s_1) + drive(s_1, s_2)}$$

Practically, the decision process is initiated any time a relocator completes a relocating task or when the state of the system is changed while some relocators are idle.

3 Case study and results

A collaboration with the car-sharing system in Grenoble has provided us unique opportunity to test our proposed algorithm in the field. In addition, we were able to base our simulation analysis on trip transaction data obtained from the system. The Grenoble car-sharing system consisted of 27 stations, each with 3 to 8 parking spots adding up to a total of 121 parking spots. The available fleet size varied frequently between 40 to 55 vehicles, due to maintenance issues.

In the experiments, we compared the Markovian estimation policy to the operators' relocation policy, to a no-relocation policy and to a purpose-built state of-the-art reactive inventory rebalancing relocation policy (OVOS). The description of the OVOS policy is omitted from this abstract due to space limitations. In addition, we adapted a centralistic full-knowledge relocation model [6] to generate an approximated upper bound on the performance of the dynamic relocation policies.

A three weeks field experiment conducted in June/October 2017, has shown that the OVOS policy and the Markovian estimation policy performed significantly better than the operator's policy and the no-relocation policy. In addition, it demonstrated the ability to implement of our policies in the field and built knowledge which allowed us to enhance the simulation framework.

In the simulation experiment, we considered cases with 40, 60 and 80 vehicles in service. The daily demand levels investigated ranged between 100 and 400 and the staff size ranged between 1 to 3 relocators working simultaneously. For each demand level, 100 demand realizations consisting in 10 consecutive days of operation were drawn from real data. The simulation results have shown that the Markovian policy served on average 1.3% to 4.5% more requests than the OVOS policy. As compared to the OVOS policy, which by itself resulted with high performance, the Markovian policy was able to close 10% to 30% of the gap to the approximated upper bound. As the approximated bound is based on decision-making using full information of the demand, the relative improvement is much higher than it seems.

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Analyzing the impact of delays in an integrated mobility system

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1 Introduction

In many Western countries, governments are currently implementing an innovative demand-driven mobility policy. Providers of collective door-to-door transport, called dial-a-ride services [1], are increasingly invoked to replace unprofitable public transport in rural areas. This requires an integrated mobility system in which a user's trip may consist of a combination of dial-a-ride services and regular public transport. In order to optimally integrate both systems from an operational point of view, dial-a-ride providers need to solve a challenging routing problem. Their flexible vehicle routes should be synchronized to the timetables of the remaining public transport services, while the optimal selection of the users' transfer terminals depends on the actual structure of the dial-a-ride routes.

In earlier work [2], the theoretical benefits of implementing such an integrated mobility system - relative to a standalone dial-a-ride system - were illustrated through the development of a matheuristic routing algorithm, including an integrated scheduling procedure that enforces time synchronization between multiple dial-a-ride routes and public transport services. However, this (static) procedure scheduled all transfers based on the assumption that public transport services respect their prefixed timetables at all times. In reality, dial-a-ride providers should adequately respond to structural or occasional delays of the public transport services. Whenever such delays are likely to cause broken connections or violated quality requirements, the dial-a-ride provider needs to make real-time adaptations to its routes and schedules, restoring the feasibility of the solution at an additional cost. To assess the applicability of such an integrated mobility system in a more realistic setting, the present work aims at quantifying the sensitivity of integrated routing solutions with respect to delays on the public transport network.

2 Problem description

The problem context studied in this work is an extension of the formulation by [3]. Its essential problem characteristics are briefly repeated below:

- a set of heterogeneous users (ambulant or non-ambulant) who define a request that consists of a pickup and delivery location, as well as a time window on one of both locations;
- a maximum user ride time constraint that limits the time between the departure from a user's pickup location and the arrival at his delivery location;
- a set of dial-a-ride vehicles with two-dimensional capacities, located in multiple depots;
- a network of public transport services (with fixed lines, stops, timetables, etc.), to which the routes and schedules of the dial-a-ride vehicles need to be synchronized;

The objective is to design a set of minimum-distance dial-a-ride routes. All user requests need to be satisfied and trips of ambulant users may partly be covered by public transport.

As an extension of this problem context, delays are now added to the public transport network in a stochastic and time-dependent manner, such that particular services (especially around peak hours) may run later than provided by their original timetable and cause broken connections.

3 Computational experiments

Using the aforementioned routing algorithm [2], an extensive computational study is performed on an artificial benchmark data set with real-life characteristics to quantify the robustness of integrated routing solutions with respect to delays in the public transport network. The data set includes ten artificial instances, each consisting of 200 user requests (100 paired inbound and outbound trips) and 20 dial-a-ride vehicles. The service area includes four densely populated cities or clustering poles around which most of the users' origin and destination locations are situated. The clustering poles are connected through public transport lines with cyclic timetables. Half of the user requests represent short-distance (long-distance) trips, meaning that their outbound location is clustered around the same (a different) pole. Random time windows of 15 minutes are imposed on either the user's origin or destination. The maximum user ride time is expressed as a multiple of a user's direct ride time and cannot exceed 1.5 times the corresponding direct ride time.

The results show that integrated mobility systems are relatively robust to small delays in the public transport network. In other words, the cost of rearranging routing solutions when delays occur is relatively low, assuming that the dial-a-ride providers receive timely and perfect information on the punctuality of the public transport services. As an example, the table below shows the additional percentage cost incurred for the combination of (1) the risk that a particular public transport service is delayed and (2) the average size of a delay in minutes, given that the theoretic timetables in this scenario provide one public transport ride every ten minutes.

Average delay	2.5 min.	5 min.	7.5 min.
Delay risk 25%	+1.33%	+1.55%	+1.67%
Delay risk 50%	+1.94%	+2.20%	+2.37%
Delay risk 100%	+5.21%	+9.06%	+13.33%

This illustrates that the aforementioned integrated scheduling procedure [2] provides reasonable flexibility to reschedule the dial-a-ride trips when delays occur. Obviously, these results are lower bounds on the actual cost of real-time delay management, as the availability of information may be limited in reality.

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Control of Autonomous Electric Fleets for Ridehail Systems

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1 Introduction

Ridehail systems have seen an explosion in popularity in the last few years, as evidenced by the success of companies such as Uber and Lyft [1]. Autonomous electric vehicles (AEVs, or simply, EVs) promise to improve transportation for everyone, but ridehail operators in particular will benefit. This is because AEVs will reduce costs and be safer, more efficient, and more predictable [2]. As such, ridehail operators will likely be among the first to adopt AEVs. Indeed, one such operator already exists in the United States [3].

A number of studies to date (e.g., [4] and [5]) have considered the operation of ridehail or ridehail-like systems, such as dynamic ridesharing or dial-a-ride problems. Some have also considered ridehail systems comprised of AEVs [6], [7]. Yet few have addressed the need to recharge these vehicles during operation. In fact, the only comparable work which does so is a recent study by Al-Kanj, Nascimento, and Powell [8]. Their work addresses many of the challenges associated with the operation of a ridehail company comprised of AEVs, including the assignment of vehicles to requests, and the recharging and repositioning of vehicles in anticipation of future requests.

In this research, we remove some of the limiting assumptions present in the work by Al-Kanj, Nascimento, and Powell [8]. In addition, we improve on state-of-the-art in two primary ways. First, we compare classical approximate dynamic programming solution methods with those of deep reinforcement learning, which have garnered enthusiasm but, so far, have enjoyed limited success in operational problems. We aim to clear this hurdle via new state representations in deep Q-learning. Second, we offer a dual bound that allows us to assess these solution methods' proximity to an optimal policy.

We refer to our problem as the Ridehail Problem with Autonomous Electric Vehicles (RP-AEV). In the coming sections, we describe the RP-AEV, outline a problem model, and describe our solution methods.

2 Problem Description

We consider random requests arising over a finite horizon within some geographical region. Requests are serviced with a homogeneous fleet of AEVs. Each vehicle has a known battery capacity and known energy consumption rate, speed, and charging rate. Distributed throughout the region are parking lots at which vehicles may idle, a subset of which is equipped with homogenous stations at which EVs may charge. In anticipation of future requests, vehicles may be repositioned to a lot or recharged at a station. Requests are responded to immediately, either rejected or assigned to an EV. If a request is assigned to an EV, the EV must serve the request as soon as possible and within a given duration of time (e.g., how long the customer is willing to wait). If the EV is currently servicing a request, it must finish before servicing the new request; otherwise, the vehicle serves the new request immediately. Once a request is assigned to an EV, service may not be preempted, rescheduled, or reassigned to another EV.

3 Model

We model the problem as a Markov decision process (MDP) and include here an overview of the states, actions, rewards, and objective comprising the model.

States. At an epoch k, the state of the system can be described by the tuple $s_k = (r_k, t_k, \mathbf{v}_k)$, where r_k is a new and unassigned request, t_k is the current time, and $\mathbf{v}_k$ is the vector of vehicle states. Epochs may be triggered by a new request, in which case r_k consists of the origin and destination locations of this request; but they may also be triggered by other events, such as the completion of a vehicle's recharging or repositioning, in which case, $r_k = \emptyset$. The ith element $v_k^{(i)}$ of $\mathbf{v}_k$ specifies vehicle i's location, charge, and job queue as well as the time and charge at which the vehicle began the job at the head of the queue. Jobs in a vehicle's queue define its current and next tasks, which may include serving a request, charging, repositioning, and/or idling.

Actions. In each epoch, we may assign new jobs to all vehicles. When a new request is observed, we choose to which vehicle, if any, to assign it. Further, we may instruct vehicles are not currently serving requests to continue idling at their current location, to reposition, or to recharge.

Rewards & Objective. When a request r_k is assigned to an EV, the decision maker receives a reward which includes a fixed and variable component, the latter proportional to the distance from a request's origin to its destination. Our objective is to find a policy that maximizes the expected sum of per-epoch rewards over the operating horizon.

4 Solution Methods

To solve the RP-AEV, we consider two families of solution methods: approximate dynamic programming (ADP) and deep reinforcement learning. Further, we propose a procedure to establish a dual bound which will be used to gauge the effectiveness of these approaches.

From the domain of ADP solution strategies, we explore novel heuristic policies, both alone and combined with lookaheads, such as rollout algorithms (see [9]). From deep reinforcement learning, we build on the approach from [10], which addresses multi-driver vehicle dispatching and repositioning. Our approach employs neural networks (NNs) both to determine the state representation (using single-layer NNs) and to learn state-action value functions (using deep NNs) by way of Q-learning (see [11]).

To establish a dual bound, we calculate the expected value with perfect information. Under a perfect information relaxation, along a given sample path, the RP-AEV may be decomposed into an assignment problem and an energy feasibility problem. We solve the relaxation using a Benders-style approach, wherein the master problem prescribes requests to be served by each vehicle and the subproblem identifies charging operations for each vehicle. Solving RP-AEVs across many sample paths and averaging the solution values provides a dual bound, as guaranteed by [12].

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Planning and simulation of intermodal freight transport on international networks. Hub&Spoke System in Euro-Mediterranean Area

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1 Problems, context and research aims

The remarkable demographic growth and the economic development of the Southern and Eastern Mediterranean regions stimulate an ever increasing need for trade among shores, especially from regions of North Africa and the Middle East towards Western European countries. Today these exchanges take place mainly by sea and by Ro-Ro ships; but, the connections by container ships and by road transport are important too. Ro-Ro services are particularly concentrated on some North-South directions, with relationships among few ports and with rather limited frequencies. Road transport, especially between the Middle East and Europe, has different limits in terms of cost, safety and reliability. In the recent past, hypotheses of new shipping lines have been made, called Motorways of the Sea [1], in order to intercept significant freight demand shares and to offer competitive services with high performances. However, few studies have been effectively translated into facts.

The paper proposes a hypothesis of a logistic organization on a Euro-Mediterranean scale, through the transition from a maritime network of direct links to a Hub and Spoke (H&S) network, according to the scheme envisaged for air transport in many parts of the world. But, in this case, the problem is complex due to many economic, political and technical reasons such as the structural differences of regional economies, the consolidated political balances and the customs barriers, the heterogeneity of goods and the size of the Mediterranean basin, the security requirements in commercial exchanges, the different interests of shipowners and companies, the multimodal articulation of transport networks.

The research aims to show, within a framework of the socio-economic system and the mobility demand system, the feasibility of a H&S network for Ro-Ro freight in the Mediterranean basin, based

on a hub with high logistical performances, limiting the planning to supply and processing consequent impact assessments.
The research is part of the activities carried out within the ISTEN project *(Integrated and Sustainable Transport in the Efficient Network)*, funded under the ADRION Community Program aiming to improve the intermodal connections among the maritime ports of the Adriatic-Ionian area and among the ports and their hinterlands.

2 Methodological approach

A simulation approach has been used; some analyses are also underway using the optimization approach. The starting point is a representation of transport supply through an international and intermodal network.
A first application is proposed on a test network, in order to highlight the potential advantages of a structural change in the transport services network, from a Point to Point (P2P) to an H&S network. The impacts induced by an alternative organization of transport network are evaluated, assuming an Origin/Destination matrix of freight mobility and given determined supply characteristics in terms of navigation lines, service frequency, travel time and costs, capacity, etc.
A model representation of networks asset and of trade in the Euro-Mediterranean area is proposed. The representation derives from an extended survey, using the information acquired by transport operators and previous studies. On this basis the simulation on the current and project network has been carried out to evaluate the traffic flows and the impacts with a view of a shipowners and a MTO (Multimodal Transport Operator). The analyses have been made with reference to standard load units (TIR with and without trailer). Furthermore, some evaluations have been carried out in terms of environmental and economic impact on the community. The objective is also to highlight the existence of problems to take on H&S alternative more attractive.

3 Hub and Spoke networks. Density and scope economies

The term "Hub & Spoke" (H&S) refers to a network model in which there is a central node (hub) where most of the movements are crammed, which is connected to a group of peripheral nodes through a set of spokes. This model has considerable advantages compared to a solution that implies a P2P connection among all the network nodes.
The spatial efficiency of a transport network deriving from its configuration and structure involves consideration of economies of scale, economies of density and economies of scope [2], [3].
The H&S model allows a reduction in the average cost due to the economies of density on the individual routes. The presence of these economies and the possibility of adding new connections to the network structure, achieving economies of scope, makes convenient to adopt an H&S structure [4].
The H&S network configuration contributes to improving the cost/service level by reducing the efficiency losses associated with P2P transport due to low reliability, high costs and time, low frequency, restricted catchment areas, unbalancing of traffic by direction, low lines load factor. H&S system, therefore, offers the opportunity to exploit the economies induced by the concentration of flows coming from numerous traffic directions at a transhipment point; but it naturally requires an

efficient organization of the dégroupage, storage and groupage services, in order to make sorting and distribution operations easier.
For its peculiarities and its strengths, the H&S model is proposed, with appropriate adjustments, for the modelling of Euro-Mediterranean freight transport networks; as hub of this H&S network it is considered a regional logistics platform organised in Calabria region, evident geographic centre of gravity in the Mediterranean basin.

4 Projects Scenarios. Potentialities and limits

Short Sea Shipping (SSS) services are typically assembled in few relationships, since a Ro-Ro line needs great traffic volumes. In fact, to limit the service costs it is necessary to use high capacity vessels, while to assure competitiveness on operational times with the road haulage and the railway transport by land, high frequencies and fast ships are needed. This would lead to a development concentrated on few routes and few ports.
The port of the Mediterranean for Ro-Ro services is very rich: about 55 ports and a spread network of relationships (about 90 lines). In the last 20 years, Ro-Ro traffic in the Mediterranean has overcome 4 million units, with a 255% increase, which has led the transported freights to reach the container traffic. In 2017, 70.000 positions of Ro-Ro ships were recorded in the Mediterranean Sea, with an increase of 7.4% compared to 2012 [5]. This increase in freight traffic has led to new market requirements, not only transport services, but also integrated network logistics services. Currently the SSS services are ranged on pairs of ports, and mostly on direct connections without intermediate stops. The absence of some maritime relationships can be explained in part by the lack of consistency in the demand for transport between pairs of Mediterranean regions, partly due to the non-competitiveness of maritime relations compared to road transport.
Maritime transport in the Mediterranean needs to recover competitiveness and increase the growth rate. Regulatory and infrastructural conditions are required that allow to consider the mobility as a set of technically complex relationships and processes, but complementary and integrated too. There is a priority problem of intermodality including the maritime transport component.
With this awareness a scenario design, based on H&S approach for a SSS network structure in the Mediterranean Region, has been suggested. The hub is located in Calabria, in the heart of the basin, being the region equipped with ports of large and medium capacity (Gioia Tauro, Vibo Valentia, Crotone, Corigliano), able to play the role of an integrated European logistics platform. The ongoing adaptation of the Italian railway transport network along the Ionian-Adriatic coast with the international important port of Gioia Tauro (C-class railway; transit capacity for 750 m trains), with structured services in order to link up in sequence the 4 ports, prefigure a further spoke option towards Central Europe that could be very advantageous. Furthermore, the use of unaccompanied transport (trailer without tractor) can represent a step forward, in order to reduce both maritime costs and the inoperative truck costs.

5 Results discussion and research developments

In this section the results of the research and scenario simulation will be presented and discussed. Future research developments include an analysis of the issues through an optimization approach (what to approach).

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Dynamic Prices as Incentives for Collaborative Transportation: Using Side Payments for Individually Rational and Stable Horizontal Cooperation

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Efficiency of transportation systems is critical to improve to deal with increasing demand as well to reduce the costs and the environmental impacts. When appropriate methods are developed, utilization of transportation resources can be optimized and cooperation is one of the promising directions to reach that ([1]; [2]). With the advances in information and communication technology different players (e.g., transport providers, shippers) in the transportation system can communicate through innovative (web-based and/or app-based) platforms. Real-time data is becoming more and more available so that transport decisions can be adapted in real-time and transport providers can share information to cooperate in serving the demand. However, methodologies to allocate profits in such cooperation settings is still not fully developed [3]. Successful implementations require planning models that consider cooperation incentives for individuals to form coalitions and enable effective collaboration. Apart from computational issues, applying major allocation methods in cooperative game theory reveals that (1) collaboration is often not favorable for some individuals of a group and (2) some individuals might want to establish cooperation in smaller sub-groups. The first scenario refers to the game theoretic condition of individual rationality that requires that a cooperating player receives at least as much they could obtain on their own, without cooperating with anyone else. The second scenario refers to the game theoretic stability condition known as the core (or coalitional rationality) which requires that no subset of players could improve their payoff by forming a coalition outside of the group.

As basic problem setting, group of cooperating truckers with trucks and orders can be assumed. If trucker A conducts the order of another trucker B, A receives a "side payment" from B. This side payment is commonly a pre-defined, static value. Schulte et al. [4] developed a collaborative planning model in the context of truck appointment systems through a multiple traveling salesman problem with time-windows. They motivated cooperation with side payments that are paid to the truckers that provide the service on behalf of another trucker. This side payments need to compensate the interests of the both parties. The authors show that coordinated truck schedules provides reduction in emissions and transportation costs. Schulte et al. [5] worked on a similar context but from a game-theoretical perspective. Profits obtained by providing the transportation service are allocated between the cooperating parties based on the core and the Shapley value in cooperative game theory. Individual rationality is accounted for such that the cooperation should not provide less profit to a trucker than operating on his/her own. Depending on the setting of the transportation problem at hand, no solution may be present that ensures the stability, that means, there is no allocation that satisfies the core condition. In such scenarios, a dynamic side payment can enable individual rationality and coalitional rationality, i.e., the core conditions, though they are otherwise violated. The range for the dynamic pricing has natural minimum and maximum bounds. Minimum is defined by individual rationality so that coalition is attractive for the truckers and the maximum can go as high as the total earnings from the transportation service. Different ranges between this minimum and maximum are interesting to experiment with for analyzing the impacts on the formation of coalitions as well as on the overall transportation network in terms of profit, emissions and level of service.

This paper extends the collaborative truck planning concept with dynamic prices (side payments). Individual rationality is considered in order to make sure that cooperation provides benefits in terms of individual profits. Depending on the characteristics of the transport to be provided it may not be straightforward to reach this for all the cooperating parties. Therefore, we model the profit allocation across cooperating truckers based on dynamic pricing so that new solutions are obtained by altering the prices based on individual and coalitional rationality. In other words, dynamic pricing gives flexibility to adjust prices in order to obtain clear incentives for all parties and stimulate collaboration. On the downside, this increases the size of the mathematical problem as now we have a new dimension of decision variables. Therefore, methodologies are developed in order to keep a realistic number of players in the game.

This paper provides a proof-of-concept for the proposed dynamic pricing in the context of collaborative transportation. The experiments analyze different scenarios of individual and coalitional rationality as well as the range of the dynamic side payments.

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Mobile Facility Location Problem in Crowd-shipping

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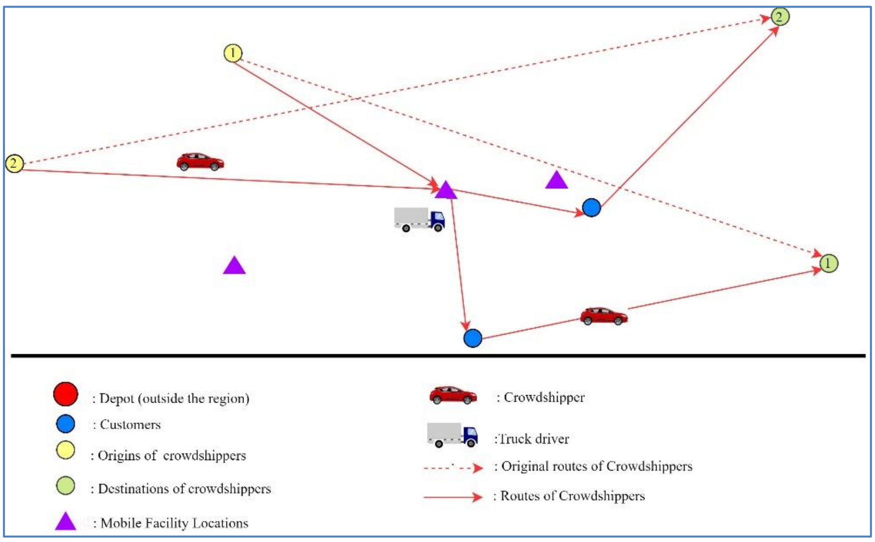
The phenomenon known as "crowd-shipping" has been introduced recently as a potential solution to last mile delivery challenges [1]. Launching a crowd-shipping delivery system for the last-mile delivery might look challenging for transportation companies at first glance. These companies should persuade both demand (e.g., customers) and supply (e.g., crowdshippers) sides to engage in this new operation, which makes the crowd-shipping a high-risk investment. However, these challenges would not undermine the crowd-shipping due to the lower delivery cost opportunity [1].

Last-mile delivery has increased due to the boom in E-commerce in recent years. This has led to an increase in commercial vehicle traffic in cities bringing many negative externalities. Dense urban areas, which is our focus, are more susceptible to these negative externalities due to a higher density of demand for last-mile delivery, lack of curb-side parking spaces, and already congested urban network. For instance, in 2012, commercial vehicles received 66% of all parking tickets in downtown Toronto [2]. Therefore, reducing urban truck traffic seems necessary to diminish some of the negative externalities in dense urban areas. As an alternative to traditional vehicle routing, crowd-shipping can undertake a portion of last-mile delivery tasks to reduce truck traffic.

Dense urban areas provide access to a large number of potential crowdshippers boosting the supply side of crowd-shipping. However, most logistics facilities such as warehouses are outside of the urban centers because of a lower land cost. This makes these facilities unattractive to urban crowdshippers since they would require a larger deviation in their original routes to pick up packages from those facilities and deliver them to customers. Furthermore, this makes a significant portion of potential urban crowdshippers ineligible because they don't depend on (or even own) a private car. In addition, retrofitting existing facilities for crowd-shipping imposes long service times to crowdshippers due to the limited number of these facilities. On the other hand, establishing new "fixed" facilities in urban areas for attracting crowdshippers requires a large investment which is not desirable. Furthermore, customer locations and availability of crowdshippers vary day to day, which leads to more challenges in making strategic decisions, e.g., establishing new “fixed” facilities.

In order to exploit the benefits of crowd-shipping, especially in urban areas, a potential solution is the incorporation of mobile (i.e., non-fixed) facilities. To the best of our knowledge, the study of Kafle et al. [3] is the first and only attempt to introduce mobile facilities (i.e., relay points) to pass packages from trucks to crowdshippers. The authors propose a new crowd-shipping system incorporating truck deliveries with local cowdshippers. They consider cyclists and pedestrians who are close to customer locations and willing to receive packages from trucks to deliver them to customers. These local crowdshippers submit bids and then the truck carrier decides on bids to be accepted, relay points, truck routes and schedules. The generated bids in their study only involve routes of the crowdshippers which start and end in a specific relay point. Crowdshippers should conform themselves with the time window of customers and arrival time of trucks to relay points after their bids are selected by the truck carrier. Therefore, the route cost of the bids is determined without considering customers’ time window [3]. In contrast to the study of Kafle et al. [3] which primarily focuses on modeling truck routes and considers pure time flexibility of crowdshippers, we are interested in focusing on crowdshippers’ schedules, modeling the assignment of crowdshippers to customers, and the selection of mobile facilities. We believe companies can attract more crowdshippers by conforming their plans to crowdshippers’ schedules.

We define a slightly different business model to the one existing in the literature and accordingly define the *mobile facility location problem in crowd-shipping* (MFLC). In MFLC, crowdshippers undertake the last-leg of package delivery by picking up packages from trucks at mobile facilities. More specifically, we are interested in dispatching trucks, which are loaded with customers’ packages, from a depot to mobile facility locations in the urban areas (e.g., parking lots). These trucks spend time in these locations and crowdshippers pick up packages from the trucks and deliver them to customers. The crowdshippers are compensated based on the additional mileage they incur by deviating from their original route, i.e., the direct distance between their origin and destination. The figure below depicts a delivery operation with mobile facilities.



This delivery operation has multiple potential advantages. First, dispatching trucks to urban areas provides an aggregation in the last mile delivery operation which may decrease the company’s operational cost and externalities to urban networks. Second, trucks spend some time in mobile facilities in urban areas where they have access to a large number of crowdshippers regardless of their mode of transport, providing more options for the company to assign the last leg of the delivery to crowdshippers. Third, companies can exploit crowdshippers' daily commuting patterns in urban areas. Fourth, the initial investment for launching this operation is drastically lower than establishing fixed facilities; the only cost is for the truck operation and rental of the selected mobile facilities, e.g., reservation and rent for a space in a parking lot. Fifth, this operation model is fairly flexible. Companies can make a choice for mobile facility locations based on customer locations and crowdshippers' origins and destinations. Sixth, the waiting time of crowdshippers for picking up packages is lower due to the decentralization resulted from sending packages from an existing facility to multiple mobile facilities.

We propose a mixed integer programming formulation for the MFLC. We assume that each crowdshipper can only provide a service for one customer. We also consider hard time windows for crowdshippers' origins and destinations, and customers. The binary variables represent opening mobile facilities, assigning customer packages to the mobile facilities, and assigning customer packages to crowdshippers. The continuous variables identify the opening and closing time of the mobile facilities, departure time of the crowdshippers from their origin, and arrival time of crowdshippers to the mobile facility, the customer, and their destination. The objective function minimizes total cost of opening mobile facilities, operating mobile facilities, and incurring additional mileage for crowdshippers as a result of deviating from their original route. However, availability of crowdshippers is usually uncertain, which makes the planning for choosing the mobile facility locations and assigning the customer packages to those locations challenging. We incorporate this uncertainty in to decision making via stochastic integer programming. We formulate the *stochastic mobile facility location problem in crowd-shipping* (SMFLC) as a two-stage stochastic integer program. The first stage decisions consist of choosing the mobile facility locations and assigning of customer packages to the selected mobile facilities. Whereas, the second stage decision is about assigning crowdshippers to customers. The objective function is to minimize first stage cost plus the expected second stage cost. To the best of our knowledge, this the first attempt in proposing and formulating the deterministic and stochastic versions of the above-mentioned business model.

In order to illustrate potential benefits of crowd-shipping in urban areas, we provide a comparison between the traditional vehicle routing problem and the MFLC in small instances, by doing a sensitivity analysis. We also compare the MFLC and SMFLC to provide insights regarding the value of incorporating uncertainty.

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A Network Design Approach for the Restricted Truck Platooning Problem

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1 Introduction

Advances in autonomous driving technology have fostered the idea of truck platooning. Thereby, several trucks drive in close succession, connected by a data link, thus exploiting the reduced air drag due to the predecessor's slipstream. This cooperative transportation mode allows for fuel savings by up to 14% for the trailing trucks, which can help to reduce transportation cost and pollution. The formation of platoons can either be "on the fly" or centrally coordinated [1]. In the latter case, [1] further distinguish if there are any restrictions regarding the maximum size of platoons and and their flexibility of path choice, i.e. they have to remain on the shortest paths (fixed routes) or if they are allowed to deviate from their route while still arriving at their destination in time (flexible routes).

In recent years, many authors have studied the *Unrestriced Platooning Problem* (*UPP*) with fixed and flexible routes. Among the examined aspects are the adaption of speed profiles, the effects of delays and the development of efficient solution methods [1]. Since [2] showed that the UPP with flexible routes is NP-hard, most authors develop heuristic methods that rely on matching or searching for platoon opportunities within a corridor along the trucks' shortest paths [1]. Assuming that all trucks have the same origin, [2] can solve instances with 200 trucks in the German highway system with a matching heuristic to near optimality. In contrast to the growing body of literature on the UPP, the *Restricted Platooning Problem* (*RPP*) has not been studied so far.

The goal of this work is to close this research gap by studying the RPP with flexible routes by formulating a mixed-integer linear program problem and developing an efficient solution method.

Due to the NP-hardness of the RPP, we propose a matheuristic that uses both decompositions of the network and of the trips. By solving instances of a realistic size (e.g. the European or North American highway network), we aim at gaining insights regarding the efficiency of the heuristic, the value of centralized planning and the sensitivity to different parameters of the model.

2 Problem setting

We assume that there exists a platform where all carriers register their trips, including information about the origin and destination of the trucks, as well as the earliest start and latest arrival time. Out of the registered trips, the platform creates platoons and returns information to the carriers about whether or not a trip is accepted and what the savings will be. Furthermore, the platform provides the carriers with individual routes and schedules for their tour. Since we look at long distance networks like the European or the North American highway system, a planning period may cover several days or weeks. As a result of this long planning period, we distinguish between two types of trips: on the one side, we have *regular trips*, which are registered some days or weeks in advance (e.g. factory traffic, inter-hub traffic of parcel services), on the other side, we have *ad-hoc* trips that are dispatched on short notice (e.g. transports of seasonal products). We use the regular trips to establish a *platoon network*, where a platoon is seen as a *service* that transports a certain number of trucks between two points. As soon as an ad-hoc trip is announced, it can be included into the existing network.

We presume that all trucks are equipped with the necessary technology for platooning. Furthermore, we restrict the option of platooning to highways since they form a highly isolated environment where it is easier to implement the technology of autonomous driving. Each truck is traveling with the same, constant speed. Therefore, platoons can only be formed and disbanded on parking lots and service areas next to highways. Trucks are allowed to wait for other trucks at these locations to form a platoon. However, the capacities of the parking lots and service areas are limited. Since the origins and destinations of the trucks are located away from the highways, we assume that the trucks have to drive the first and last mile individually.

The objective is to achieve a system-optimal solution that reduces the total traveling cost of all registered trucks. This implies the assumption that the savings are fairly distributed among all participating trucks. This way of sharing the cost is justified by the fact that an individual carrier does not have full information about all trips in the system. Platoons can be of different sizes up to a certain limit. We assume that there is enough highway capacity for several platoons - eventually of the same size - to travel simultaneously on a highway section.

3 Model formulation and solution approach

The long planning period, a sufficient lead time between the registration and the start of regular trips, as well as the limited capacities of parking lots and the restricted platoon size motivates us to follow a scheduled service network design approach. Similar to [3], we introduce a time-expanded two-layer network. In the first layer, we track the movements of the trucks in time and space, while platoons move in the second layer. The formation and disbanding of truck platoons is modeled by introducing *interlayer arcs* that lead to or from the platooning layer. Exploiting the trucks' time windows, we only generate those arcs that are feasible in time.

Due to the complexity of the problem and the large size of problem instances to be solved, we focus on a geographical decomposition of the network either into corridors or regions and on a hierarchical decomposition of the trips based on their length. As soon as a platoon network is established, ad-hoc trips can be added by searching for platoon opportunities within a corridor around the shortest path of the corresponding trip.

4 Managerial insights and extension

By solving the RPP on larger instances, we want to provide the following insights: (i) How much travel cost does a centralized planning of platoons save? (ii) By how much does the integration of ad-hoc trips improve the savings? (iii) How beneficial is the partition of trips into *regular* and *ad-hoc* trips? (iv) How do the savings factor, platoon size, parking lot capacity and network structure affect the solution?

Using trip forecasts in the network based on historical information, we can extend the model to improve capacity planning for ad-hoc trips.

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The Station Location Problem of Bike Sharing Systems

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1 Introduction

Today, 55% of the world population lives in urban areas. As the population increases rapidly, the number is expected to reach an all time high of 68% by 2050 [3]. Naturally, this entails large shifts in how we live and travel, and, as a result, traditional transportation modes may not be sufficient to meet the surging demand. Over the last decade, the world has seen an increasing trend towards transportation methods that use the concept of Mobility as a Service (MaaS), such as car sharing and bike sharing programs, with the goal of reducing air pollution and improving transport efficiency [1]. Of these services, Bike Sharing Systems (BSSs) has come to be perhaps the most successful service, with more than 1600 active systems worldwide in July 2018 [2].

The BSS concept is simple: users arrive at their selected station, pick up an available bicycle, ride to their preferred station, and lock the bicycle using an available lock. These systems enable the public to share bikes, and entails great freedom for the users. The idea behind BSSs is to offer the population mobility solutions based on individual travel needs, while at the same time reducing pollution and traffic congestion.

However, this freedom entails operational, tactical and strategic challenges for the operators of BSSs. As users are free to ride the bikes to their preferred stations, the system may experience imbalanced capacity levels throughout the day. This is largely due to the fact that some stations have much greater demand for pick-ups than deliveries, or the opposite, resulting in the same few stations often being empty or full. As a result, if bikes and locks are not available at the right time and place, the system may be unable to satisfy demand, leaving customers discontented.

The challenges of BSSs can either be approached on an operational level involving relocation strategies, also called re-balancing, or on a strategic level, where the operator decides on a set of station locations and system capacity. The latter is of great importance in order to accommodate customer preferences, and is unlikely to change substantially in a foreseeable future. This strategic task is called the Station Location Problem (SLP). The SLP mainly consists of three parts; selecting the number of stations, a set of locations and capacity of each station. These are all crucial, yet difficult, decisions for BSS operators, as the number of possible locations is infinite and customer demand uncertain, making the SLP a highly complex problem. Well chosen station sites could potentially satisfy a larger share of demand and increase the customer base, whilst simultaneously contributing to reduced operational expenses.

2 The Station Location Problem

The objective of the SLP is to maximize the overall system value and performance, both from the operator's and the users' perspectives. This is done by determining the locations of fixed stations and supplementing these with virtual stations during periods with high demand. This entails maximizing profit and the value of customers served throughout the day. In this context, both users and operators have costs related to the BSS. Costs are specified as travel cost for users, and investment and operating costs for the operator. The operator also aims to maximize revenues from advertisement, as selected stations can display advertisement. Further, revenues related to customer subscriptions are disregarded, but instead, each trip yields a positive contribution to the customer service level.

A fixed station is a bike station that requires equipment installed, and is comprised of physical bike racks. The choice of whether or not to open a fixed station is a one-time decision. A virtual station, on the other hand, does not require any physical equipment. Virtual stations are simply geographical areas restricted and defined by the system operator, either temporarily or permanently, using geo-fencing technology. The operator can specify the number of virtual locks, the location and for what time window the virtual station is opened.

BSSs may experience imbalanced inventory levels at stations throughout the day, due to customer movements. To tackle this problem, the operator may use service vehicles to relocate bikes. To avoid congestion, bikes are picked up by service vehicles freeing up locks, and moved to stations suffering from starvation, making bikes available for customers at different locations. Empty zones are said to be starving, whilst full zones are said to be congested. This requires a set of service vehicles that move around the operating area, loading and unloading bikes wherever needed. The operator has a finite number of vehicles available, each with a maximum bike capacity. Rebalancing operations entail a cost both when visiting a zone, i.e. driving costs, and for the time spent handling the bikes.

3 The Work

We will present and discuss a mathematical formulation for the SLP. The main contribution of the work is twofold. Firstly, the inclusion of both physical stations and temporary stations made up of geo-fenced areas, i.e. virtually constrained areas based on GPS locations, where the latter can be moved and adapted throughout the day, is lacking in BSS literature. Secondly, as re-balancing costs comprise a large share of operator expenses, we include these costs by anticipating operational activities.

The formulation is tested using demand data from the BSS in Oslo, operated by Urban Infrastructure Partners. By partitioning the system area into a set of zones based on geographic coordinates of existing stations, we obtain a set of demand zones and possible candidate zones for bike stations. Further, the SLP is solved for a 24-hour period, partitioned into a set of time periods, aiming at reaching a system layout assumed optimal for the average operational day. Preliminary testing shows that final system layout depends heavily on the number of candidate zones, whereas increasing the number of demand zones shows negligible impact.

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Inferring commuter's values of time in ride-sourcing service: a multi-stage deep learning approach

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1 Abstract

Commuter's values of time is thought of being one of the most significant components for transportation analysis and pricing strategies. Theoretical studies have investigated commuter's time-of-decisions by incorporating commuters shadows values of schedule delay and waiting time with homogeneity as well as heterogeneity[1][2]. Empirical studies also explored commuters values of time, schedule delay and reliability by using stated preference data and revealed preference data. Previous studies have found that commuter's values of time differs in individual sociographic and the transportation modes such as private cars or public transport[3][4].

With the development of ride-sourcing service in the e-hailing platform such as Uber and Didi, passenger's commuting behaviors may be different from traditional transport system and their values of time are able to be investigated more comprehensively by collecting various data via the platform such as the cancellation records, waiting time and weather condition, etc. Peak hour ride-sourcing service may have different behavioral consequences depending on the structure of the service. Passengers can decide to travel at other times, change mode or to car-pool at any time via the platform. Hence it is important to explore commuter's values of time under such new ride-sourcing service to provide valuable solutions for peak hour service and pricing with the potential to benefit passengers, company and society as a whole.

This research aims at analyzing passenger's values of time in queuing condition by using a multi-stage deep learning approach with various data source. Commuters queuing behavioral data are collected from Didi Chuxing Technology, which has introduced an first-in-first-out queuing system during the peak period since 2017 and displayed the real-time waiting time and fare cost of different

modes to passengers in e-hailing platform. Hence commuters can choose to queue up for a service but are able to change to other modes at any time during the queue. To explore commuters choice of modes based on their values of time, we extend Small's scheduling trip model [5][6] such that commuter's utility of requesting a service at time t can be expressed as

$$U_t = \beta_0(X_0) \cdot \Delta t + \beta_1(X_1) \cdot t_{w,t} + \beta_2(X_2) \cdot t_{c,t} + p_t$$

where Δt denotes the sunk waiting time which is the time that a commuter has already spent in the queue, $t_{w,t}$ denotes the remaining waiting time, $t_{c,t}$ denotes the schedule delay and p_t denotes the fare cost. The coefficients of β_0, β_1 and β_2 measures the shadow values of waiting time and being early or late. The variables X_0, X_1 and X_2 represent the different feature matrix for the corresponding coefficient.

In the queuing process, each behavior change is recorded as an event that contains the attributes describing the characteristics. Typical attributes are the origin and destination of the trip, the sociographic of individual, the timestamp of the event and the lifecycle transition ('start', 'cancel', 'complete', or 'change'). Commuters utility is different by the corresponding event occurrence. In the 'start' event when a commuter request a service at time $t = 0$, the corresponding utility is

$$U_0 = 0 + \beta_1(X_1) \cdot t_{w,0} + \beta_2(X_2) \cdot t_{c,0} + p_0$$

In the 'cancel' event when a commuter cancel the order during the queue at time t, the corresponding utility is

$$\overline{U_t} = \beta_0(X_0) \cdot \Delta t + \beta_1(X_1) \cdot t_{w,t} + \beta_2(X_2) \cdot t_{c,t} + p_t$$

In the 'complete' event when a commuter is answered by the service at time t and hence the corresponding utility is

$$\widehat{U_t} = \beta_0(X_0) \cdot \Delta t + 0 + \beta_2(X_2) \cdot t_{c,t} + p_t$$

In the 'change' event, when a commuter choose to change another mode k at time t, the corresponding utility for mode k is expressed as

$$\widetilde{U_t^k} = \beta_0(X_0) \cdot \Delta t + \beta_1(X_1) \cdot t_{w,t}^k + \beta_2(X_2) \cdot t_{c,t}^k + p_t^k$$

while the utility for the initial mode is

$$U_t = \beta_0(X_0) \cdot \Delta t + \beta_1(X_1) \cdot t_{w,t} + \beta_2(X_2) \cdot t_{c,t} + p_t$$

A novel multi-task deep learning model is then established, named Learning-to-Value Network (LTVN), which incorporate pairwise algorithm to estimate passenger's shadow values of time, schedule delay and reliability. The multi-stage deep learning approach is developed to predict commuter's mode choice and hence derive their values of time. Commuters behavioral consequences are categorized into three stages which are 'complete', 'cancel' and 'change'. Each stage consists of the events and utility inequalities.

For 'complete' stage, commuter's utility for mode k is no greater than other modes hence he or she wait until the request is answered, the inequality conditions are

$$U_t < \widetilde{U_t^k}$$

For 'cancel' stage, commuter's utility of 'cancel' event is greater than that of the 'start' event but less than the utility of changing to other modes, hence the inequality conditions are

$$U_0 < \overline{U_t}, U_t^k > \overline{U_t}$$

And for the 'change' stage, commuter's utility of changing to the mode k is less than all the other available mode choice set k', hence inequality can be expressed as

$$\widetilde{U_t^k} < \widetilde{U_t^{k\prime}}, \widetilde{U_t^k} < U_t$$

The multi-stage model is then trained end-to-end with the pairwise ranking loss via stochastic gradient descent[7][8]. Results indicates that commuters shadow values of sunk waiting time and schedule delay are highly concentrated within the interval (0,1) and (0,0.25) respectively. However, the shadow values of waiting time are spread more evenly over the interval (0,3), as shown in Figure 1.

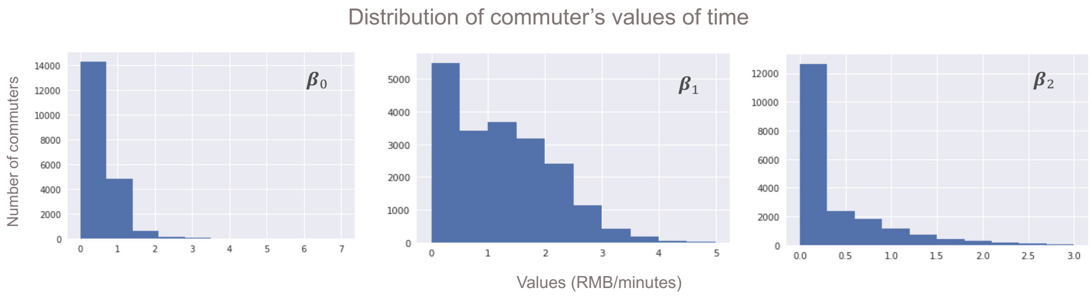

Figure 1. Commuter's values of time

The preliminary results reveal interesting findings. It quantifies commuter's mode choice based on their utility hence provide valuable solutions for ride-sourcing service and pricing. Furthermore, we will assess the stability and variability of the LTVN by using the utility function as commuter's mode choice determination and compared it with other prediction models such as the Random Forest, SVM, etc.

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Global diversity of the Brazilian air transportation network

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1 Introduction

Air transport systems have been studied from the point of view of complex networks and several measures in this direction have been made in works over the last decade, as in the references [1], [2], [3], [5], [6], [8], [9]. Traditional measures in the studies of complex networks were used to verify if the air transport networks would be of the small world type [6]; the hubs were identified through centrality measures and other measures were established to try to conclude about the importance of airports [9]. Some works, such as that of [6], mention a layered structure, without, however, exploiting properties of such layers. In [7] the multilayer structure of the European airport network is explored, analyzing propagation of network delays and concepts of multiplexed networks were applied to obtain properties of a European air transportation network in [4].

Multiplex networks are interconnected layered structures, where each layer is formed by a set of elements, nodes, whose interactions are represented by links. In these structures the interactions exist only within single layers: node *i* in layer *p* is not linked with node *j* in layer *q* [4].

A useful concept from the point of view of transport networks is diversity. As mentioned in [4], diversity refers to the variety of connectivity configurations that make up the network (i.e. nodes and layers).

Here, in this work, we treat Brazilian Air Network (BAN) as a complex system with multiplex structure. The Brazilian airports are the nodes, and the different routes are the links that connect them. The network consists of about 60 layers representing different airlines operating in Brazil in different years.

2 BAN diversity study

The objective is to measure the global diversity of the Brazilian network in different years, analyzing the changes undergone by the network during a period of great political, structural and economic changes caused by several factors, such as the growth of the country's economy, the emergence of low cost and the holding of major events such as the Football World Cup, in addition to the privatization of airports that were previously administered by the Brazilian government.

Differently from the work in [4], it has been considered here that two airports serving the same metropolitan region, equate to a single destination - which brings some changes to the interpretation of the network.

By analyzing the diversity between the layers of the network, it will be possible to identify which airlines serve similar routes, and which ones connect different regions of the country. Knowing that airlines make alliances to enable their operations, through this study it is possible to conclude which alliances are capable of connecting the largest number of airports, covering more regions of the country in the current scenario. In addition, as mentioned in [4], this study can be used to detect which elements need to be modified to increase or decrease the diversity of the system, thus increasing the coverage of Brazilian air transportation.

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Economic and Environmental Benefits of Digital Platforms Connecting the Trucking Sector's Shippers and Carriers

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Abstract

CO_2 emissions from freight transport will rise 76% between 2015 and 2050 unless action is taken, a reduction by 65% is required to meet the expectations of the Paris Climate Agreement in containing the global temperature increase within 2 degrees celcius by 2100 [1].

The efficiency of road freight transport, as the dominant mode of freight movement, is a major cause of the overall environmental impact of logistics. With today's average vehicle fill rates (ratio of capacity used to total capacity available) of less than 50% [2] and with 21% of trucks' annual mileage running empty [3, 4], the current road freight industry is not sustainable. The potential economic and environmental benefits of ensuring that freight vehicles run at full capacity, make raising vehicle utilization an attractive decarbonization option. In Europe, this would account for €160 billion and 1.3 percent of EU27 CO_2 footprint annually [5]. In Canada, a near one percent improvement from the present 25% empty truck rate would be worth $140 million annually [6].

It is argued that raising vehicle utilization through improved vehicle fill rate and reducing empty running is attainable given real-time knowledge of the location of loads and vehicles with under-utilized capacity [7]. Many load matching opportunities are missed due to a lack of direct communication between potential carriers and shippers (i.e. the users of transport service). Today, rapid growth in digital platforms for online freight exchange between carriers and shippers is helping to deal with the inefficient and eco-negative practice of running empty or partly-filled trucks on the roads [8]. Because of the inherent transparency of digital platforms, idle transport capacity can be shared between unassigned loads in real time.

Despite growing discussions both in research and practice, the extent to which digital platforms can improve the eco-efficiency of freight transport remains unclear. Several attempts have been made to identify the potential benefits of digital platforms to their clients (e.g. [9]; [10]; [11]) but, as some researchers acknowledge, the economic and environmental benefits have 'yet to be empirically tested in depth' [12]. Moreover, load matching opportunities realized in this system does not necessarily generate an optimum solution [7], making the best use of each vehicle's capacity.

In this research, we first illustrate through a theoretical experiment how using a digital platform can improve the eco-efficiency of carriers. Second, using an IBM based Digital Freight Platform with more than three thousand carriers across North America, we seek to empirically quantify and optimize the economic and environmental benefits resulting from improved truck utilization based on digital platforms. In particular, we evaluate how emerging digital platforms can increase the eco-efficiency of transport in terms of vehicle fill rate and empty running miles, and transport CO_2 emissions. We perform a statistical comparison between carriers' efficiency before and after joining the platform. We conduct an online survey to gather data on the carriers' efficiency prior to their subscription to the platform. We further compare their efficiency after joining the platform with the industry average, both in Europe and North America. We calculate the environmental benefit (CO_2 reduction) achieved by the carriers using the platform. We adopt the carbon calculation methodologies adopted by Global Logistics Emissions Council (GLEC) for road freight transport [13]. We also develop an algorithm to use the platform to optimize the eco-efficiency of logistics in real time. Specifically, we incorporate bundling, back-hauling (i.e. load-carrying on a return journey), and round-trip strategies into a pick-up and delivery routing strategy. This will optimize the real-time assignment of loads to idle transport capacity in the transport network. The innovative aspect of the proposed algorithm is utilization of available vehicle capacity and its load compatibility in real time.

Our research provides with quantifiable evidence that to what extent digital logistics platforms can improve the eco-efficiency of the transportation system through the real-time assignment of shipments and promotion of collaborative shipping.

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Behavior-dependent Pricing: an IoT-empowered Pricing Model in a Car-sharing Business

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Abstract

The business model adopted by Car-sharing providers falls under the servicizing business model [1]. The servicizing business model, under which a firm sells the use or functionality of a product rather than the product itself, is being recognized as a sustainable business model [2], [3], [4]. In recent years, many car manufacturers have adopted the servicizing business model to complement their traditional model. For example, BMW recently launched a new car-sharing service called "Reach-Now" which enables customers to rent a BMW on a short-term basis instead of purchase or lease [5]. Moreover, Ford, Peugeot and Volkswagen operate car-sharing programs in European cities [6], [7].

The sustainability aspect of the servicizing business model is argued from both environmental and economic perspectives. Form the environmental perspective, servicizing might encourage firms to produce more durable and efficient products. Moreover, it incentivizes customers to lessen their usage when they pay a fee to the firm based solely on product usage (i.e. pay-per-use) [2], [3], [8]. From the economic perspective, as the focus on access rather than on ownership of assets has gained attention, it can be a business opportunity for firms to adopt the servicizing business model. In particular, car manufacturers can leverage the growing demand for car-sharing services and thus strengthen their position in the market by adding servicizing to their traditional business model.

Notwithstanding all these compelling arguments, the economic and environmental aspects of servicizing is a disputable subject. Even thought, the adoption of the servicizing business model leads to less product usage, higher

product durability and a business opportunity, it might yield product misuse. [9] refers product misuse to as a moral hazard that might arise in customer-user servicizing. In fact, the way a customer uses the product, which we refer to as customer's behavior, might increase operating costs (e.g. repair and maintenance cost) and environmental impacts, and shortens the product's lifetime. For instance, a consumer who buys the functionality of a car may not consider the sustainability impact of her driving behavior [10] when the manufacturer maintains the ownership of the car and is responsible for the operating costs. This argument may offer one possible explanation as to why many manufacturers are reluctant to adopt servicizing, and some have failed to implement it profitably [8]. For instance, in June 2018, BMW has shut down its car-sharing services in Brooklyn due to high operating cost including high damage to vehicles and maintenance costs [11].

Currently, most of the car sharing programs have adopted a pricing model under which they charge their customers with a price independent of their driving behavior. Due to possible negative impact of customer's driving behavior, discussed above, a car-sharing provider needs to encourage its customers to use the car in a more sustainable way. Adopting a pricing model under which a customer is charged based on her driving behavior might be recognized as a promising strategy to encourage customer's better behavior.

The use of Internet of Things (IoT) technology has become common in practice in which it enables firms to collect the data related to customers' actual behavior. For instance, a number of car insurance companies are using IoT to track drivers' driving performance and offering a discount to those with better driving performance. Thus, in practice, IoT technology would enable firms to track their customer's behavior.

In this study, we aim to show how a manufacturer can leverage an IoT-empowered pricing strategy to encourage its consumers to utilize the products in an eco-efficient manner. We consider a monopolist manufacturer who adopts the servicizing business model. We assume the manufacturer is responsible for the operating cost and incurs a technology cost per unit of usage to monitor a customer's level of usage and driving behavior. We allow the firm to choose between two pricing models, the behavior-independent pricing and behavior-dependent pricing. Under the behavior-independent pricing the firm charges the customers with a price per unit of usage regardless of their behavior. Whereas, under behavior-dependent pricing the customers are charged with a price per unit of usage corresponding to their behavior. Under this pricing model, the manufacturer assigns each customers a score commensurate with her driving behavior and offers cheaper price in higher score of behavior. We assume customers pay an effort cost per unit of usage that is increasing in the score of behavior.

We develop a sequential firm-customer game in which a monopolist moves first and chooses between offering the behavior-independent pricing and behavior-dependent pricing. Then, under each pricing model the firm sets the price per unit of usage (e.g. driving time) and the customers decide on their level of usage and their driving behavior. We analyze the conditions under which the behavior-dependent pricing model results in a win-win-win pricing strategy where it can simultaneously improve the profitability and its environmental impact and increase consumer welfare compared to the behavior-independent pricing.

Our results indicate that when the operating cost is sufficiently high it is more profitable for the firm to adopt the behavior-dependent pricing model. We find a threshold above which servicizing business model can be a win-win-

win pricing strategy. The threshold decreases when the cost of applying the technology decreases and/or it is easier for customers to improve their behavior.

This paper contributes to the current body of literature by bridging the gap between three streams of research on servicizing, pricing models and the application of new technologies in innovative business models. In practice, under the servicizing business model the firm incurs high operating cost as the customers have no responsibility for operating cost. This moral hazard might threat business success. This study shows how a firm can leverage the application of behavior-dependent pricing to encourage customers' better behavior and decrease its operating cost. A decrease in operating cost contributes to both higher profit and less negative environmental impact.

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Empirical Investigation on the Range Anxiety for Electric Vehicles

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Transportation holds the key to our sustainable future. Not only does it account for 27% of all greenhouse gas emissions in the US, it has also been one of the worst-performing sector in terms of curbing emissions growth. In the US, emissions from transportation grew by 15.5% from 1990 to 2015, compared with a 3.5% growth in total emissions by all sectors. In the EU, transportation was the only major economic sector to have increased its emissions (by 25%) during the same period, compared with a 22% reduction in total emissions. The major difficulty in greening the transportation sector is the high growth in travel demand. For instance, the vehicle miles traveled is the US increased by over 40% from 1990-2015. Worldwide, governments and industry are moving toward the consensus that fundamental changes in fuel technologies will be needed. China, France, India, the Netherlands, Norway and the UK have all announced plans to completely phase out the sale of combustion engine (CE) cars by 2040 or before, and to replace them with zero emissions cars, in particular, electric vehicles (EVs) which, thus far, have shown the most promise.

Currently, EVs only account for about 1% of the US new cars market. With the long-term goal of mass adoption in mind, EVs must overcome major hurdles. Whereas early adopters can be enticed by environmental and novelty factors, mass market consumers are unlikely to compromise on attributes such as in price, performance and convenience to switch from CEs to EVs. Among the major shortcomings of EVs on the market is the limited range and long recharging times, creating psychological concerns to drivers that the driving range of EVs may be insufficient to meet their driving. The direct implication of such psychological fear, called *range anxiety*, is that drivers are reluctant to adopt EVs unless their driving ranges well exceed their travel needs.

Quantifying range anxiety carries important implications on EV market development, policy design and infrastructure planning. In the near term, the present battery technology and production cost impose a hard trade-off between the EVs affordability and range. The notion of range anxiety suggests that drivers would require EVs to deliver a longer range than is physically needed. Thus, statistical estimates of range anxiety can inform product line decisions as automakers design their lineups of EVs with different ranges and price points. Furthermore, in the near to medium term, adoption of EVs will heavily depend on government incentives and the provision of charging infrastructure. Developing a quantified understanding of drivers' psychological needs for EV range will guide policy design and infrastructure planning decisions.

In the longer term, the industry expects battery technology and manufacturing costs to further improve such that the range-cost trade-off will be alleviated. Nevertheless, as EV becomes mainstream, natural bottleneck will arise in the battery supply chain. Toward the long-term goal of completely electrifying the vehicle fleet, as stipulated by a number of governments worldwide, it is important to make prudent use of these elements that could become supply constrained as adoption continues to grow. Therefore, in the long run, it is important to equip EVs with range that is sufficient but not excessive. Determining the range that is sufficient depends on a good understanding of both the physical and psychological (i.e., range anxiety) preferences of drivers.

Despite these important implications of measuring drivers' range anxiety, there have been only few studies attempting to quantify range anxiety, and the few existing ones mainly focus on stated preference surveys on drivers' preferences. Revealed preference studies, on the other hand, are difficult and costly to perform due to the high stake involved in the decision to purchase a car. To circumvent this difficulty, we attempt to identify and quantify range anxiety at the the decision level of making a single trip rather than purchasing a new car. Specifically, We use a novel dataset collected from an on-demand car sharing system, Car2go, that operates CE and EV fleets in different cities. Based on this dataset, we empirically identify and quantify the effect of a car's effective driving range on its attractiveness to drivers on a single-trip basis, and contrast the findings for EVs and CEs.

Car2go operates a free-floating car sharing service in a number of cities worldwide. In each city, Car2go deploys a fleet of cars in a defined *service region*, within which users can flexibly start and end their rentals anywhere, and users are charged a fee based on the duration of the rental. The locations of available fleets are provided on its website from which we recorded the following variables for the *available* cars at five-minute intervals: the unique vehicle identification number (VIN), GPS coordinates, street address and fuel level (in %). Comparing these snapshots over successive time stamps, we can identify instances of cars beginning a rental (if the car is shown as available in one period but not in the next), and ending one (unavailable in one period but available in the next). We record the following variables associated with a total of 162,365 rentals.

In San Diego, Car2go first started operating with a fleet of about 350 EVs in 2009. The fleet was homogenous and consisted of a single car model, the Smart Fortwo Electric Drive, a two seater EV with 135km of driving range on a full battery. In May 2016, the company replaced the entire fleet with 250 CEs, also homogenous and comprised of only the Smart Fortwo car model. The electric and gasoline models are almost identical in size, engine power and appearance, with the only differences being the fuel types and driving range (135km for EV vs. 560km for CE). Through collecting the usage data before and after the fleet change, we are able to collect samples of trips for EVs and CEs, and contrast them in our analysis. There were 24,550 and 137,815 trips completed with EVs and CEs, respectively.

Our analysis consists of estimating three complementary econometric models. Our first analysis aims at identifying drivers' aggregate preferences on fuel type. Specifically, making use of a fleet change event (i.e., the company switching its entire fleet from EVs to CEs) as a quasi-experiment, we perform a difference-in-differences (DiD) analysis to model the effect of a change in fuel type (gasoline vs. electric) on the demand of the car sharing system. After controlling for the effects of time and geographic region of the rentals as well as the weather conditions, the Poisson regression results show that, replacing the EVs with CE vehicles in San Diego reduces the demand rate by 20-25%. We used four different US major cities as the control group where only CE vehicles are operated, and the results are quite consistent over these different control groups.

The results from our first analysis suggest that fuel type has a major effect on usage demand for a car sharing fleet. Our second analysis focuses on narrowing it down to the effect of fuel level of an individual car on said car's attractiveness to drivers, and contrast the findings for the two fuel types. For this, we apply logistic regression model to estimate the effect of an individual car's fuel or battery level (i.e., effective range) on its hazard rate of being rented out by drivers. An important challenge in this estimation is that the fuel availability of a car interacts endogenously with demand rates. For example, when there is a demand hike, cars available for rental tend to have lower fuel levels but are more likely to be rented. To address such an endogeneity problem, we use the previous trip's fuel consumption as an instrumental variable. We find statistically significant evidence that the fuel level affects the vehicle's attractiveness for EVs. Specifically, the result shows that 10% increase in fuel level enhances the chance of rental by 1%. For CE vehicles, however, the effect of fuel level is not statistically significant.

Third, we use a discrete choice model to estimate drivers' preference between alternative cars with different fuel levels. In this model, we explicitly evaluate drivers' trade-off between a car's fuel level versus the cost of access (using walking distance as a proxy). This provides a quantification on the willingness to pay for range. Our results show that the customers' choice history indeed reveals significant range anxiety for EVs. In contrast to CE vehicles, drivers renting EVs are willing to walk significantly farther distances: on average four to ten times as far as they would do for CE vehicles to have one more percent of additional range (measured as a percentage against the full range). It is intuitive that if range anxiety pervades, it will be proportional to the fuel consumption levels, and our results suggest that the range anxiety increases dramatically as the realized fuel consumption increases. Also, even for very short trips (e.g., spending less than 5% of the full fuel level) the estimated range anxiety level turned out to be noticeable compared to the CE vehicle users.

A Continuous Solution Method for the Multi-Visit Drone Routing Problem

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1 Drones in Last Mile Delivery

The use of unmanned aerial vehicles ("drones" or "UAVs") for both commercial and governmental purposes has recently drawn increased interest from private industry and academia alike. The applications of UAV technology arise in many fields: agriculture, surveying land or infrastructure, security, cinematography, network communications, health care, emergency operations, and package delivery, to cite only a few. An excellent survey describing many UAV applications and related papers is presented in [1]. Despite the broad array of potential domains of application, we motivate and describe our model through the lens of online order fulfillment for consumer goods.

Amazon CEO Jeff Bezos publicly announced in an April 18, 2018 letter to shareholders that the Amazon Prime service, which offers free two-day shipping of millions of Amazon products, had surpassed 100 million subscribers and that 2017 saw the largest subscriber growth in the history of Amazon Prime [2]. Thus, an interview with Bezos discussing the possibility of Amazon delivering packages up to five pounds (2.3 kg) via drone within 30 minutes of order placement has continued to stir great interest in the operations research community [3].

One of the first papers that considers a hybrid truck-and-drone delivery [4] and most of the subsequent papers in the literature have used the following simplifying assumptions: 1) all packages are homogeneous; 2) the drone is capable of carrying a single package at a time; 3) the battery life of a drone is a fixed amount of time, not dependent on the weight of the package(s) it is carrying; and 4) the set of allowable locations for launching/retrieving a drone from the truck is identical to the set of customer locations. In this context, a new truck-and-drone delivery model that does not rely upon these assumptions, called the Multi-Visit Drone Routing Problem (MVDRP), was proposed in [5].

2 The Multi-Visit Drone Routing Problem

The MVDRP delivery model allows the drone to visit multiple customers consecutively without returning to the truck in between. Rather than using a fixed time limit for drone flight, it assumes the drone has a fixed energy capacity. Moreover, the model assumes that the amount of energy depletion depends on the sum of the weights of the packages the drone is carrying and on the direction of travel. Finally, the delivery problem allows for the set of allowable drone launch/retrieval locations to be defined independently of the set of customer locations. In [5] a flexible solution heuristic, called Route, Transform, and Shortest Path (RTS), was proposed to determine a solution to the MVDRP.

The solution obtained by the RTS algorithm is based on the assumption that the network vertices are the only possible launch/retrieval locations. This assumption pushed us to develop a method that overcomes this limitation. Our proposed method makes intelligent use of the RTS algorithm within a general framework developed to determine potential interesting launch/retrieval location points along the edges. In particular, the proposed method consists of two phases. In the first phase, the network edges are discretized and more launch/retrieval locations are added to the network. Then, a MVDRP solution is obtained using the RTS algorithm. This procedure is repeated until the truck route is the same in two consecutive solutions. We note that at each iteration, we remove the intermediate points previously inserted and then add new ones on the basis of the last solution obtained.

In the second phase, we solve a Mixed Integer Second Order Cone Programming (MISOCP) model to determine a solution where the completion time is minimized allowing the drone to be launched/retrieved at any point from the truck route of the solution obtained in the first phase. We developed the MISOCP model on the basis of the assumption that knowing the truck route and the set of drone operations it is possible to reduce the completion time by carefully synchronizing truck and drone routes. Indeed, we exploit the flexibility of the drone route, which can move forward or backward between launch/retrieval locations in such a way that the truck's waiting times are minimized.

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Modeling and solving the multimodal car- and ride-sharing problem

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1 Introduction

Inspired by the concept of sharing economy and future mobility systems we study the multimodal car- and ride-sharing problem (MMCRP) that assigns different modes of transport (MOT) to ride requests. We aim to employ a pool of shared cars as efficiently as possible, join ride requests by offering ride-sharing and assigning different modes of transport to the remaining requests. In the literature car- and ride-sharing are usually considered as independent problems. Systems considering car-sharing involve a pool of cars that are shared among a set of users, who are usually known in advance [1, 4]. Ride-sharing and car pooling (frequently used as synonyms) describe co-riding of one or more persons between an origin and a destination or sub-paths of it [2, 3]. To the best of our knowledge, it is one of the first models including both car- and ride-sharing.

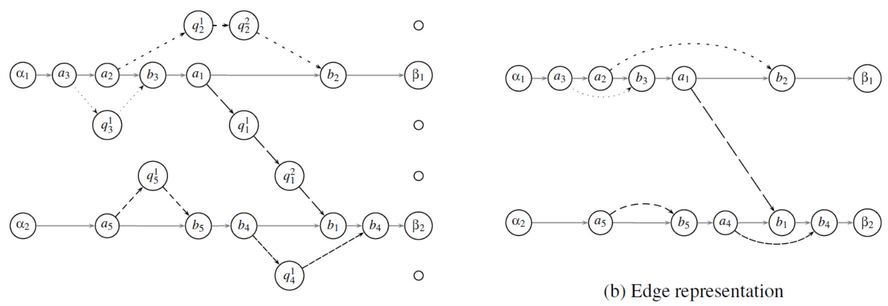
1.1 Problem formulation

The MMCRP aims at determining the optimal MOT-assignment for each travel request (of a user between a pair of visits) and to schedule the routes of the cars. We assume a predefined set of users in a closed community (e.g. company or home community) having one or more depots from where the users have to cover various visits during a day. Each visit involves one specific user. The number of cars are limited, ride-sharing may at most involve one co-rider and all other MOTs have unlimited capacity. Ride-sharing between persons is allowed, even when two rides do not have the same origin and/or destination. Users specify which modes can be used, since e.g. a person without a driving license cannot be the driver of a car. We maximize savings obtained by using a car rather than any other mode of transportation. The cost of transportation not only includes distance cost but also cost of time in order to properly reflect the trade-off between fast (but expensive) and slow (but cheap) modes of transportation. We aim to find vehicle tours by efficiently employing cars, including ride-sharing and assigning MOTs to paths whilst ensuring that all visits are covered at the right time by the right user. A vehicle tour depicts a route of a vehicle during the day encompassing one or more drivers, handing over the vehicle at a depot including possible ride-sharing activities. Ride requests not covered by a car or ride-share are appointed to take the cheapest other MOT.

2 Modeling and solving the MMCRP

In order to solve the problem, an auxiliary graph is constructed in which each route starting and ending in a depot, and covering possible ride-shares, is modeled as an edge in a time-space graph.We produce a directed acyclic graph where vertices are given by their time-space coordinates (i.e. time and depot).

Figures 1 (a) and (b) show the first step of the graph transformation. We start by considering all paths of each person p starting at a_p and ending at b_p through the whole planning horizon, which then start and end at α_d and β_d, respectively. α_d and β_d represent the depots d at the start and end of the planning horizon. In Figure 1(a) user tasks $q \in Q_p$ are still in the graph, denoted as q_p^n. From this graph, we transform all a_p, b_p connections to the edges as represented in Figure 1(b). Then, for each person $p \in P$ we enumerate all possible trips from the person's start depot a_p to the person's end depot b_p. A person may co-ride herself or pickup and drop off co-riders during her trip.



(a) Graph including information on tasks

(b) Edge representation

Figure 1: Illustration of the auxiliary graph.

Due to the many combinations of ride-sharing, the auxiliary graph may become quite large, and a compact formulation is not efficiently solvable. We therefore propose a two-layer decomposition algorithm based on column generation, where the master problem ensures that each task can only be covered once, and the pricing problem generates new promising routes by solving a kind of (time constrained) shortest path problem, aiming to find the paths with largest savings.

In the first layer of the decomposition, sub-paths (including all possible ride-sharing possibilities) are enumerated. In the second layer, the sub-paths are combined into vehicle-paths. The first-layer decomposition is solved through complete enumeration, while the second-layer decomposition is solved through column generation.

We solve the linear relaxation of the master problem by column generation and thereafter solve the restricted master problem to integer optimality, using only a subset of routes. Although we cannot guarantee an optimal solution to the original MMCRP in this way, the results will show that in most cases the gap is very small, and the solution quality is more than sufficient for practical applications.

3 Computational results

The algorithm is tested on a number of generated instances of increasing size and complexity. Various pricing schemes are compared, and the efficiency of all parts of the code is evaluated and various algorithmic as well as socio-economic tests are presented. Computational experiments based on realistic instances are reported.

Tablee 1 shows CPU times in seconds and the respective gaps (between the LP-bound found through column generation, and the integer solution on the same columns) for instances with 250 and 300 persons ($|P|$) and increasing number of vehicles m. Our results confirm that large instances can be solved to near-optimality in reasonable time, making it possible to use the algorithm for daily planning of multimodal car- and ride-sharing systems.

$\|P\|$	250		300	
m	time	gap (%)	time	gap (%)
20	493	0.07	1734	0.11
40	842	0.12	2994	0.16

Table 1: Gap and computational running time (in sec.) comparison for $m = 10, 20, 40$ and $p = 250, 300$

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Asymmetric driving behavior analysis using field trajectories

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1 Abstract

Asymmetric driving behaviors (including gap difference, intensity difference, reaction time difference and discrete driving difference) in accelerating and decelerating in the car-following (CF) condition are well-known by many researchers [1], [2], [3] which can affect traffic flow [4] and the validity of numerical simulation [5]. In order to improve the performance of longidudinal driving model, many car-following models are proposed based on some assumption of the real driving behaviors [6],[7],[8]. However all these models are not as good as the car-following models that considering asymmetric driving behaviors [3], [5], [9], [10], [11], [12]. For instance, the AFVD (asymmetry full velocity difference) model that proposed by [9] considering the gap difference and intensity difference outperforms the OVM (Optimal Velocity model) that proposed by [7] and didn't consider the asymmetric driving behavior.

Asymmetric driving behaviors in acceleration and deceleration in car-following condition can affect traffic flow in numerical simulation. To improve the model performance, the mechanism of the

asymmetric driving behavior and the effects between themselves should be studied in depth by field data. In fact, the four asymmetric driving behaviors do affect to each other. For instance, both [6] and [13] believed that the gap of a driver is influenced by reaction time. [2] also proposed two formulations for acceleration and deceleration, in which, the gap increases with the reaction time increasing. Besides, [2] proposed that the discrete driving in deceleration are more frequency which leads to the short reaction time. However, this theory is not proved by the field data. [14] proposed the car-following model based on the assumption that the acceleration increase with the gap.

In this study, the formation mechanism of the asymmetric driving behaviors (gap difference, reaction time difference, response intensity difference, discrete driving difference) and the effects between themselves are investigated. Quantification methods for the asymmetric driving behaviors are proposed and the asymmetry of driving behiaviors are proved using the NGSIM data sets. Then, the correlation between the four asymmetric driving behaivors are implemented. And the analysis results indicate that the relations of gap, reaction time, response intensity, and discrete intensity between acceleration and deceleration are asymmetric. what's more, the four asymmetric driving behaviors are not independent.

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A Globally Convergent Discrete Simulation-Based Optimization Algorithm for Complementing Transit Accessibility with Car-Sharing Service

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1 Introduction

Car-sharing is a widely used transportation mode in urban areas nowadays NCSL (2017). In this work, we focus on two-way car-sharing, which has a set of vehicles assigned to a set of fixed locations. A customer should make a reservation by specifying the car pick-up location, the start time and the reservation duration before using a car, and then return the car to the same location on time. Studies indicate that car-sharing has the potential to complement private vehicle ownership (Firnkorn and Müller, 2011), reduce household transportation costs (Duncan, 2011), mitigate greenhouse gas emission and vehicle-miles-traveled (Shaheen and Cohen, 2013; Becker et al., 2017).

Many studies have discussed the relationship between car-sharing and public transportation service, but no clear conclusion has been drawn. Stillwater et al. (2009) found that car-sharing demand is correlated positively with the existence of light-rail service and negatively with the existence of regional-rail service. Martin and Shaheen (2011) found that car-less households decreased the use of transit systems after joining car-sharing programs. Besides, it is difficult for public transportation to provide good level of service to the entire metropolitan area. There are only 42%

of the Boston residents have access to a subway station, a stop of key bus routes, a bike sharing station or a car-sharing station within 10-minute walk distance from home (Imagine Boston 2030, 2017). We hope to design a car-sharing network (determine the number of cars assigned to each station during the study period) which complements the existing transit system, yielding ultimately improved transportation accessibility across the urban region. From the company's perspective, we want a network design with higher profit; from the public perspective, we want residents with low transit accessibility to have close access to a car-sharing station.

Assume there is a existing transit network in the region of study. The region is cut into several non-overlapping cells. Each cell generates customer demand for the two-way car-sharing service and is a candidate location for car-sharing station. Let $\boldsymbol{x}$ be the decision vector. Each element of $\boldsymbol{x}$ is a non-negative integer variable, representing the number of cars assigned to a cell. Given a $\boldsymbol{x}$, let $h(\boldsymbol{x})$ be the metric of accessibility and $g(\boldsymbol{x})$ be the expected car-sharing profit. Let $\mu \in [0, 1]$ be the scalar parameter adjusting the relative importance of the two metrics. The problem feasible region, denoted by $\mathcal{F}$, is convex and bounded. We want to optimize both the overall accessibility provided by adding the car-sharing service to the region and the profit of car-sharing service. The problem is defined as

$$\max_{\boldsymbol{x} \in \mathcal{F}} \quad \mu h(\boldsymbol{x}) + (1 - \mu) g(\boldsymbol{x}). \tag{1}$$

2 Challenges and proposed method

Traditional methods of optimizing the design and operation of car-sharing service is to build and then solve one or several analytical models. These models are usually mixed-integer programs (MIPs). Methods such as stochastic programming or robust optimization are used to account for demand uncertainty. These models usually describe the demand and demand-supply interaction in an aggregated way, which enhances the computational tractability and scalability. However, through the data aggregation, a large amount of detailed information will be lost.

Recently, major transportation technology companies start to make decisions by using the information in their disaggregate data directly. Ride-sharing companies use high-resolution simulator that samples directly from disaggregate data to evaluate their service performance (Greenhall, 2016). For car-sharing, years of operation leaves the service providers with abundant data which provides high-resolution description of demand, vehicle supply, and the interaction between demand and supply. It is worthy to note that the historical reservations reflect a "truncated", rather than true, demand. When the supply of cars is limited, the true demand may be unobservable, as customers who cannot find an available car at their desired pick-up/return location/time may change their location/time (i.e., spillback) or even do not make any reservation (i.e., lost). Detailed discussion on the demand truncation can be found in Fields et al. (2018).

One challenge for us is how to better utilize such data with rich disaggregate historical data. Given the un-observable nature of two-way car-sharing demand distribution and the intricacy of demand-supply interaction, we propose to evaluate the performance of the car-sharing system (g in Equation (1)) by simulation. The simulator will draw from disaggregate car-sharing reservation data to estimate latent disaggregate demand, then simulate the mapping between disaggregate latent demand and disaggregate car-sharing reservations. Hence, function g is simulation-based. It can be estimated by running our car-sharing simulator formulated in Fields et al. (2017). The simulator was used for car-sharing service design in Zhou et al. (Working Paper). This paper extends the work of Zhou et al. (Working Paper) by accounting for accessibility in the design of the car-sharing service. The evaluation of accessibility (h in Equation (1)) remains to be analytical.

From a methodological perspective, our contribution is the following. Zhou et al. (Working Paper) proposes a computationally efficient locally convergent algorithm for discrete simulation-based optimization (SO) problems and applies it to a high-dimensional car-sharing service design problem. In this work, we extend the method of Zhou et al. (Working Paper) to formulate a globally convergent discrete SO algorithm suitable for high-dimensional problems. Discrete SO algorithms inherit the curse of dimensionality of discrete optimization. Their performance are often illustrated using examples with fewer than 20 decision variables. To the best of our knowledge, there is no globally convergent discrete SO algorithms suitable for high-dimensional problems.

We propose to use a metamodel discrete SO algorithm that combines a metamodel and a general purpose globally convergent discrete SO algorithm. Metamodel is an analytical approximation of the simulated objective function. We adopt the framework of Osorio and Bierlaire (2013), which uses a metamodel that contains problem specific information. We propose an MIP model to approximate the simulation-based objective function. This model can be solved to optimal efficiently using commercial solvers. We embed the metamodel into Empirical Stochastic Branch and Bound (ESBB), a general purpose globally convergent discrete SO algorithm proposed by Xu and Nelson (2013). In each iteration, ESBB will partition a subregion of the problem feasible region into several non-overlapping parts. Then we can solve the metamodel with constraints limiting the search space within these parts. The use of metamodel enhances the computational efficiency of the globally convergent algorithm in high-dimensional spaces.

In this work, we carry out a Boston case study using transit data from Massachusetts Bay Transportation Authority (MBTA). On the car-sharing side, we use historical high-resolution two-way car-sharing reservation records from Zipcar, the main car-sharing service provider in Boston area and one of the largest car-sharing companies in the world. We use the car-sharing system simulator of Fields et al. (2017), designed in collaboration with Zipcar.

Due the limit of space, we do not present the details of the metamodel and algorithm in this abstract. At the conference, we will present the most recent results of the Boston case study.

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An analytical approach to planning rail hazmat shipments in the presence of random disruptions

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1. Introduction and Contributions

Hazardous materials (hazmat), though harmful to humans and the environment, are integral to industrial lifestyle and thus need to be transported in significant volumes. In North America, railroad is the primary mode for moving (non-bulk) hazmat shipments. For example, in 2012, railroad carried around 111 million tons of hazmat in the United States (U.S. Department of Transportation, 2015), whereas the number for Canada was 48.38 million tons in 2014 (Transport Canada, 2016). It is important that the quantity of rail hazmat shipments has been increasingly steadily since 2009, and there are strong indications that the trend will continue because of two reasons: *first*, the increased utilization of intermodal transportation to move chemicals (Verma et al., 2012); and *second*, the most recent need to move an increasingly large number of crude oil shipments from the Bakken shale formation region in the United States and Canada to the refineries along the southern and eastern coast of the continent (AAR, 2014; CAPP, 2014). Railroad is one of the safest modes for transporting hazmat, in large part because of the implementation of a comprehensive safety plan and a host of industrywide initiatives, however, the possibility of spectacular events resulting from multi-railcar incidents do exist (Vaezi and Verma, 2017, 2018). The derailment and explosion of several crude oil rail tank cars causing irreparable destruction and loss of human life in Lac-Megantic (Quebec, Canada), in July 2013, is an example of the possible catastrophe associated with rail hazmat shipments.

A significant volume of freight (regular and hazmat) transits the railroad transportation network, which is crucial to the economic growth of North America, and thus the associated infrastructure could be deemed *critical*, i.e., systems and assets whose destruction (or disruption) would have a crippling effect on security, economy, public health, and safety (US DHS, 2018). Disruptions, induced by nature such as hurricane Kartina in 2005 or man-made threats such as the 9/11 terrorist attacks in the United States, could either threaten the transportation networks (Jabberzadeh et al., 2016) or render a single transportation mode such as railways unavailable (Veelenturf et al., 2015). Given the potential for spectacular events, it is not surprising that both the academic and industry initiatives have focused on the assessment and management (mitigation) of risk from hazmat shipments (Batta and Kwon, 2013), including the works that incorporate the specific nature of railroad shipments (Verma and Verter, 2013). Unfortunately, the existing risk management techniques have limited efficacy in the event of disruptions, and the resulting unavailability of rail-links. Thus, there is a need to study disruption to railroad operations, especially since such events are not infrequent (WS DOT, 2014, Kroon et al., 2014). For example, sixty-one disruptions were registered for just the Seattle-Vancouver Amtrak operation between 2009 and 2013 (Azad et al., 2013). It should be evident that the resulting risk management methods and optimization techniques should not only incorporate disruptions but also prescribe contingency plans for rail hazmat shipments. However, implementing such techniques so that the transport risk and the transport cost are within reasonable bounds under both normal and disruption situations is challenging because of two reasons: *first*, both the risk and the cost elements would tend to increase during disruptions since safe and economic routes might not be available; and *second*, it is difficult to evaluate the effectiveness of contingency plans because of the inherent trade-off between upfront cost to the railroad operator versus the possible mitigation (of risk and cost) resulting from the disruption.

We make the first effort to fill the gap by developing a bi-objective two-stage stochastic program that considers random disruptions in the tactical planning of rail hazmat shipments. A new measure of hazmat risk that combines expected risk with the variability in risk, and whose goal is to ensure that the risk measure remains within tolerable limits, is developed. The complexity of the resulting optimization program, and the inherent structure, motivated deploying an augmented ε-constraint technique to generate a formulation involving single objective. The proposed analytical approach was used to study the transportation system of a Class I railroad operator in North America, and the resulting analyses led to the following conclusions. *First*, rail hazmat risk can be reduced by using proactively adding extra capacity to the safer links, and/or reactive strategies of re-routing and using third party logistics. *Second*, the new risk measure that combines expected risk and variability in risk could be a very valuable tool for both the railroad industry and the regulators who deal with low probability – high consequence hazmat events. *Third*, any given railroad network can be preprocessed to ascertain the critical and near-critical service legs for adding extra capacity to be commensurate with the risk attitude of the decision maker. *Fourth*, cost savings is higher from adding extra capacity vis-à-vis re-routing railcars. *Fifth*, safer service legs are chosen for capacity addition even in the absence of disruptions, because that would help cope with disruptions and also reduce hazmat risk under normal operating conditions.

To sum, our paper contributes to the study of railroad disruption risk in the following way. First, this is the only attempt to develop an analytical approach to study random disruptions for rail hazmat shipments. Second, this is the first work to develop a new measure that combines expected hazmat risk with variability, which in turn facilitates ascertaining the vulnerability of the given railroad network to random disruptions. Third, this is the only effort that seeks to propose different contingency plans such as adding rail-link capacity, re-routing, and utilizing third party, to deal with disruptions. Finally, this is the only work that applies a bi-objective two-stage stochastic programming model to study a realistic size railroad network in the United States, and to provide resulting insights.

In the next section, we propose the mathematical model developed in this paper.

2. Mathematical model

Consistent with the prevailing literature on hazmat transportation, we propose a bi-objective optimization program to address the interests of two stakeholders, i.e., the regulatory agencies and the railroad companies. We use expected consequence as the measure of transport risk. The information about the service legs impacted in a disruption is captured via a two-stage stochastic program with recourse, which is a general-purpose technique to deal with uncertainty. For the managerial problem of interest, the 1st stage decisions to be taken before the disruption event comprise determining the number of trains of different types, and proactively adding extra capacity to the service legs. Occurrence of disruption triggers the 2nd stage decisions (i.e., reactive), which entails re-routing rail shipments and fulfilling proportion of demand through third party.

In developing the mathematical formulation, we make four assumptions. *First*, the planning is conducted on a weekly basis, and hence the demand is expressed in terms of the number of railcars to be shipped per week. *Second*, disruptions can only affect the service legs, and that there is no direct damage to either the trains or the railcars. *Third*, the disrupted service legs cannot recover in a week and thus are unavailable. *Fourth*, all the hazmat being shipped on a train possess similar chemical properties and the undesirable consequences of their interactions can be ignored.

Sets and indices

A: set of service legs, indexed by *a*
L: set of train services, indexed by *l*
M: set of demand, indexed by *m*
I: set of itineraries, indexed by *i*
I_m: set of itineraries for demand *m*
I_l: set of itineraries using train service *l*
I_a: set of itineraries using service leg *a*
A_i: set of service legs on itinerary *i*
S: set of disruption scenarios indexed by s and s. Note that normal situation where all service legs are operational is the first element in this set.

Parameters

c_{im} cost of moving one hazmat railcar of demand *m* on itinerary *i*
$\bar{c}_{im}$ cost of moving one non-hazmat railcar of demand *m* on itinerary *i*
c_l fixed cost to operate train service of type *l*
c_m third party transportation cost of moving one hazmat railcar of demand *m*
$\bar{c}_m$ third party transportation cost of moving one non-hazmat railcar of demand *m*
c_a cost of adding one unit of extra capacity to service leg *a*
Υ_a probability of derailment and release from a hazmat railcar on service leg *a*
q_a consequence of derailment and release from one hazmat railcar on service leg *a*
d_m number of hazmat railcars in demand *m*
$\bar{d}_m$ number of non-hazmat railcars in demand *m*
t_m^{max} maximum delivery date of demand *m*
t_{im}^s travel time on itinerary *i* of demand *m* under scenario *s*
n_l capacity of train service of type *l*
n_a capacity of service leg *a*
E_a^{max} maximum extendable capacity of service leg *a*
β maximum percentage of demand that can be met through the third party
λ_a^s equal to 1 if service leg *a* is available in scenario *s*; 0 otherwise
p^s probability that scenario *s* will realize

Decision Variables

1st stage
N_l number of trains of service type *l*
E_a extra capacity added to service leg *a*

2nd stage
X_{im}^s number of hazmat railcars of demand *m* using itinerary *i* under scenario *s*
$\bar{X}_{im}^s$ number of non-hazmat railcars of demand *m* using itinerary *i* under scenario *s*
D_m^s number of hazmat railcars of demand *m* that are delivery by the third party under scenario *s*
$\bar{D}_m^s$ number of non-hazmat railcars of demand *m* that are delivery by the third party under scenario *s*
Z_{im}^s equal to 1 if itinerary *i* is used for demand *m* under scenario *s*; 0 otherwise

Formulating the hazmat risk objective: The first objective is to minimize the total risk from routing railcars with hazmat cargo, while accounting for random disruptions at service legs. It should be evident that since the set of disrupted service legs would vary from one scenario to the other, it is reasonable to assume that the corresponding hazmat risk resulting from using the available service legs could also vary. To account for this variability, we introduce a new measure of risk that has two components -*viz.*, expected risk and variability in risk, as follows:

$$Expected\ Risk\ (\mu) = \sum_{s\in S} p^s \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A} \Upsilon_a q_a X_{im}^s \tag{1}$$

$$Variability\ in\ risk\ (\sigma) = \sum_{s\in S} p^s \left|\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A} \Upsilon_a q_a X_{im}^s - \mu\right| = \sum_{s\in S} p^s \left|\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A} \Upsilon_a q_a X_{im}^s - \sum_{s'\in S} p^{s'} \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A} \Upsilon_a q_a X_{im}^{s'}\right| \tag{2}$$

The inner terms in (1) determines the expected consequence resulting from a given number of hazmat railcars using the different service legs in the railroad network, which is then summed over each disruption scenario to estimate expected risk. Equation (2), on the other hand, facilitates tracking how hazmat risk varies across different disruption scenarios vis-à-vis expected risk as determined in (1). It is important that the new hazmat risk measure combines expected risk and variability in risk because of the following reasons: *first* equation (1), consistent with hazmat shipment routing proposed in the literature, would focus on minimizing (average) hazmat risk; and *second* equation (2), more importantly, will ensure that solutions with low average risk but high variability across different scenarios are discouraged. In other words, the presence of the second term can provide more stability for planners to decrease variability in the post-disruption hazmat risk. The two equations can be combined by using a weighting parameter, ω, on variability in risk term. The weighting parameter could be used to perform trade-off analysis between expected risk and variability in risk. Hence, the proposed risk measure assumes the following form.

$$Minimize \sum_{s\in S} p^s \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^s + \omega \sum_{s\in S} p^s \left|\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^s - \sum_{s'\in S} p^{s'} \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^{s'}\right| \tag{3}$$

Equation (3) is non-linear because of the presence of the absolute term. However, we could use the linearization technique as outlined in Yu and Li (2000) to generate an equivalent linear form, as depicted via (4) to (6).

$$Minimize \sum_{s\in S} p^s \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^s + \omega \sum_{s\in S} p^s \left[\left(\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^s - \sum_{s'\in S} p^{s'} \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^{s'}\right) + 2\theta_s\right] \tag{4}$$

Subject to:

$$\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^s - \sum_{s'\in S} p^{s'} \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i} \Upsilon_a q_a X_{im}^{s'} + \theta_s \geq 0 \qquad \forall\, s \in S \tag{5}$$

$$\theta_s \geq 0 \qquad \forall\, s \in S \tag{6}$$

where θ_s is an auxiliary variable. It should be evident that the linear model (4)-(6) is equivalent to (3), because if $\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i}\Upsilon_a q_a X_{im}^s - \sum_{s'\in S} p^{s'}\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i}\Upsilon_a q_a X_{im}^{s'} \geq 0 \quad \forall\, s\in S$, then the minimization objective in (4) will ensure that $\theta_s = 0$. However, if the resulting value is less than 0, constraint (5) requires that $\theta_s = \sum_{s'\in S} p^{s'}\sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i}\Upsilon_a q_a X_{im}^{s'} - \sum_{m\in M}\sum_{i\in I_m}\sum_{a\in A_i}\Upsilon_a q_a X_{im}^s$. Hence, in both cases, the solution from the linear model (4)-(6) will be equivalent to that from (3).

Formulating the cost objective: The second objective is to minimize the expected total cost, which has four components: cost of moving railcars, MC^s; cost of fulfilling demand through a third party, TC^s; cost of adding extra capacities on service legs, EC; and, fixed cost of operating trains of different types, OC.

$MC^s = \sum_{m\in M}\sum_{i\in I_m} c_{im}X_{im}^s + \sum_{m\in M}\sum_{i\in I_m} \bar{c}_{im}\bar{X}_{im}^s$ (7)

$TC^s = \sum_{m\in M} c_m D_m^s + \sum_{m\in M} \bar{c}_m \bar{D}_m^s$ (8)

$EC = \sum_{a\in A} c_a\, E_a$ (9)

$OC = \sum_{l\in L} c_l\, N_l$ (10)

Collecting the four terms would yield:

$Minimize\ EC + OC + \sum_{s\in S} p^s(MC^s + TC^s)$ (11)

Hence, the complete bi-objective two-stage stochastic optimization program would be:

(P)

$First\ objective: hazmat\ risk$ (4)

$Second\ objective: expected\ cost$ (11)

Subject to:

Constraints (5) and (6)

$d_m \leq \sum_{i\in I_m} X_{im}^s + D_m^s \qquad \forall m \in M, \forall s \in S$ (12)

$$\bar{d}_m \leq \sum_{i\in I_m} \bar{X}^s_{im} + \bar{D}^s_m \qquad \forall m \in M, \forall s \in S \qquad (13)$$
$$\sum_{m\in M}\sum_{i\in I_m\cap I_l} (X^s_{im} + \bar{X}^s_{im}) \leq n_l N_l \qquad \forall l \in L, \forall s \in S \qquad (14)$$
$$\sum_{m\in M}\sum_{i\in I_m\cap I_a} (X^s_{im} + \bar{X}^s_{im}) \leq \lambda^s_a\,(n_a + E_a) \qquad \forall a \in A, \forall s \in S \qquad (15)$$
$$t^s_{im} Z^s_{im} \leq t^{max}_m \qquad \forall m \in M, \forall i \in I_m, \forall s \in S \quad (16)$$
$$X^s_{im} \leq d_m Z^s_{im} \qquad \forall m \in M, \forall i \in I_m, \forall s \in S \quad (17)$$
$$\bar{X}^s_{im} \leq \bar{d}_m Z^s_{im} \qquad \forall m \in M, \forall i \in I_m, \forall s \in S \quad (18)$$
$$E_a \leq E^{max}_a \qquad \forall a \in A \qquad (19)$$
$$\frac{D^s_m + \bar{D}^s_m}{d_m + \bar{d}_m} \leq \beta \qquad \forall m \in M, \forall s \in S \qquad (20)$$
$$Z^s_{im} \in \{0,1\} \qquad \forall m \in M, \forall i \in I, \forall s \in S \qquad (21)$$
$$N_l \geq 0\ INT \qquad \forall l \in L \qquad (22)$$
$$X^s_{im} \geq 0\ INT \qquad \forall m \in M, \forall i \in I, \forall s \in S \qquad (23)$$
$$\bar{X}^s_{im} \geq 0\ INT \qquad \forall m \in M, \forall i \in I, \forall s \in S \qquad (24)$$
$$D^s_m \geq 0 \qquad \forall m \in M, \forall s \in S \qquad (25)$$
$$\bar{D}^s_m \geq 0 \qquad \forall m \in M, \forall s \in S \qquad (26)$$
$$E_a \geq 0 \qquad \forall a \in A \qquad (27)$$

Constraints (12) and (13) ensure that demand for both hazmat and regular cargo are met, and assume that demand can be met using multiple itineraries (i.e., shipment could be split) and/or a portion of it could be procured from the third party. Constraints (14) state that the number of trains of different types needed in the network is determined by the number of railcars, belonging to various itineraries, needing that specific train service. Constraints (15) enforce capacity limitations on the service legs, and includes the possibility of adding extra capacity. Constraints (16) ensure that the travel time associated with the chosen itinerary to meet a demand does not exceed the specified delivery due date, while (17) and (18) restrict the selection only to available itineraries. More specifically, given a disruption and consequence rerouting, constraints (16)-(18) would ensure that specified delivery time is not violated. Constraints (19) impose the maximum extendable capacities on service legs, while (20) specifies the limits on the percentage of demand that can be met by the third party. Finally, (21) to (27) define the domain of the decision variables.

3. Results

The complexity of the resulting optimization program motivated using an augmented ε-constraint solution technique, which is used to study the transportation system of a Class I railroad operator in North America. Through extensive numerical experiments, we conclude the following. *First*, hazmat risk in the railroad network can be reduced in one of the three ways: proactively adding extra capacity on safer links; re-routing hazmat shipments through longer but safer rail-links following a disruption; and, employing third party logistics services to move hazmat shipments following a disruption. *Second*, incorporating variability factor could potentially reduce variability in risk, which in turn could be a very valuable tool for both the railroad industry and the regulators who deal with low probability – high consequence hazmat events. *Third*, given the risk attitude of the decision maker, it is possible to estimate the number of trains and locations for adding extra capacity in any railroad network. *Fourth*, cost savings is higher from adding extra capacity vis-à-vis re-routing railcars, and hence the former should take precedence over the latter as a contingency plan. *Finally*, safer service legs are chosen for capacity addition even in the absence of disruptions, because that would help cope with disruptions and also reduce hazmat risk under normal operating conditions.

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Pricing for Goods Deliveries in the Sharing Economy

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1 Goods Deliveries in the Sharing Economy

We consider the delivery of goods, purchased through e-commerce websites or in shops, from stores or warehouses to homes in a few hours, the same day, or the next day within urban areas. The home deliveries utilize independent couriers who deliver with a variety of vehicles, such as bicycles, motorcycles, cars, and vans. These deliveries involve short-duration (less than a day) delivery routes, due to the characteristics of the goods (e.g., perishable goods), customer needs (e.g., urgent deliveries), and relatively small vehicle capacities.

On-Demand Delivery companies (ODDs) manage a two-sided market for the delivery of goods. They are intermediaries between consumers, retailers, and independent couriers. We consider an ODD's pricing problem in the two-sided market motivated by our collaboration with a last mile delivery company. The ODD operates a market for the delivery of goods from participating retailers to destinations specified by customers. For example, consider a customer who purchases a large item such as a piece of furniture or an appliance from a store. The customer needs the item to be delivered, and the store refers the customer to the ODD. The ODD quotes a menu of prices to the customer for delivery of the item. The prices in the menu depend on the origin, the destination, and the time window within which the customer needs the delivery to take place. The customer specifies the destination and chooses the time window for the delivery, or chooses not to accept the delivery offer from the ODD. The customer's choice of acceptance, and the choice of time window, may depend on the prices that the ODD quotes.

On the other side of the market, the ODD contracts with independent couriers who provide the vehicles and drivers for deliveries. The ODD offers different prices in this side of the market depending on the part of the city in which and the time slot during which the courier will make deliveries. Different couriers have different preferences for the parts of the city in which to make deliveries. For example, some couriers are more flexible, possibly because they know the entire city quite well, and they are willing to make deliveries in all parts of the city, whereas other couriers have strong preferences regarding the part of the city in which they make deliveries. Different couriers also have different preferences for the time slot of the day or week in which to make deliveries. For example, some couriers have other obligations for certain times of the day or week, and they cannot or do not want to make deliveries during those times, whereas other couriers are more flexible regarding the time slot in which they make deliveries. Couriers make deliveries with different vehicle types with different capabilities — not every product can be delivered with every vehicle type. A vehicle can typically pick up multiple shipments at a store or warehouse, and deliver these shipments at their respective destinations on a route.

The compensation of each courier consists of two parts: First, the primary compensation for the time slot that the courier commits to be available to make deliveries, the part of the city in which the courier is willing to make deliveries, and the vehicle type that the courier will provide. As mentioned above, different couriers have different preferences regarding work time and part of the city in which to work, and this part of the compensation reflects these preferences relative to the customers' demands. For example, if many customers would like to receive deliveries in the evenings after work or on Saturday mornings, but few couriers want to work during these times, then the prices offered to couriers to be available during these times will be higher. Similarly, if many customers would like to receive deliveries in the core of the city, but few couriers want to make deliveries in this part of the city, then the prices offered to couriers to be available to make deliveries in the city core will be higher. Also, different vehicle types have different capabilities, and the ODD offers a higher price for vehicles with greater capabilities. Once a courier signs up to make deliveries with a particular vehicle type in a particular part of the city and a particular time slot, the courier has committed to accept all deliveries assigned to the courier in that part of the city and in that time slot, subject to the constraints of the vehicle type, and the courier is entitled to the specified compensation, whether the courier ends up being assigned any deliveries or not. The second part of the compensation of each courier is the payment for the routes that end up being assigned to the courier and the deliveries made by the courier. This secondary part of the compensation is only determined after customers have placed their delivery orders, and the ODD has assigned these delivery orders, and their associated routes, to the individual couriers. The primary part of the compensation is intended to compensate the couriers for their delivery capability (including time) committed, whereas the secondary part of the compensation is intended to compensate the couriers for their costs incurred in making the deliveries. As mentioned before, the primary part of the compensation is driven by the couriers' work preferences relative to the customers' demands, whereas the secondary part of the compensation is determined by the estimated cost of the courier for driving a route and making deliveries. In cities with high labor cost, the secondary compensation tends to be small, about 25%, relative to the primary one.

We focus on the price planning problem in the two-sided market, that is, the problem of determining the menu of prices to quote to customers that can depend on the origin, the destination, and the time window for delivery, as well as the menu of prices to offer to couriers that can depend on the part of the city that the courier signs up to make deliveries in, the time slot that the courier commits to be available to make deliveries in, and the vehicle type that the courier will provide. These prices are selected, and the ODD and the couriers enter into their agreements, in advance of customer requests. That is, at the time that the ODD and the couriers enter into their agreements, it is not yet known exactly which deliveries will take place in each part of the city and in each time period. The ODD enters into these agreements because it needs to know that a courier will be available to make a delivery at a destination and in a time window before the ODD commits to a customer to deliver the customer's goods at that destination in that time window. Also, the courier would like to plan its own work schedule and its own compensation in advance. After the ODD has entered into agreements with various couriers, it still has an opportunity to modify the planned customer prices according to the committed delivery capacity before entering into delivery agreements with customers. For example, if the ODD failed to obtain an agreement with any courier to deliver in a particular part of the city or during a particular time window, then the ODD can exclude this part of the city or this time window from the menu of prices that it offers to customers, or it could set the price sufficiently high to pay for another delivery service.

2 Pricing Models

We use discrete choice models to model the probabilities of customers choosing particular time windows for their deliveries (or choosing not to use the ODD's delivery service). These choice probabilities depend on the menu of delivery prices offered to customers by the ODD. We also use discrete choice models to model the probabilities of couriers choosing particular parts of the city and particular time slots to commit to for making deliveries (or choosing not to commit to making deliveries). These choice probabilities depend on the menu of primary compensation prices offered to couriers by the ODD.

We consider two price optimization problems based on multinomial logit discrete choice models. In one model, the prices are discretized, resulting in a linear optimization problem. In the other model, the prices are modeled as continuous decision variables. The basic version of this optimization problem has a nonconvex objective function. We show how to reformulate the problem as an equivalent convex optimization problem. We present and compare numerical results for both models.

The Value of Prepositioning in Smartphone-Based Vanpool Services Under Stochastic Requests and Time-Dependent Travel Times

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1 Introduction

Smartphone-based vanpool services have become an emerging trend, which has attracted much attention in the research field [1, 2], and have been made available around the world. In smartphone-based vanpool services, passengers request vans from their smartphones for point-to-point pickups and deliveries, and vans are dynamically routed to passengers with committed pickup and delivery times. One of the fundamental issues in smartphone-based vanpooling is to schedule a fleet of vans to serve passengers efficiently, which corresponds to the classical dial-a-ride problem (DARP) and its many variants have been investigated extensively in the literature [2]. The dynamic and stochastic DARP is the most realistic one for dynamic vanpool services since it considers both dynamic requests and future stochastic information [3, 4]. One of the major limitations of existing literature is that when a vehicle is dispatched, it is limited to pickup and delivery locations of received requests. The operator would not preposition a vehicle to locations where future demand may appear.

We develop a metaheuristic scheduling algorithm for the dynamic and stochastic DARP. The algorithm uses multiple scenarios which include future requests and traffic conditions to generate and evaluate each potential decision. Prepositioning is considered in this algorithm. We use a real dataset, which includes requests from Pandabus in Dalian and travel speed data achieved from a map service provider, to test our algorithm. The results show that incorporating stochastic requests without considering prepositioning can improve the average profit by 18.6%. And the prepositioning improves the average profit by 23.8% and reduces the average waiting time by 74.7%.

2 Problem Description

Our research problem comes from Pandabus, which operates a pilot dynamic vanpool service in Dalian, China. They use several vans to provide transportation services for passengers within a service area. They have a smartphone app for passengers to send requests. Each request has a pickup location, a delivery location, and expected pickup time. They also have a smartphone app for drivers to receive scheduled routes and locations of requests.

They need an online scheduling algorithm to decide whether to accept each request and how to route each van. We model this problem as a DARP. $R = \{r_1, r_2, \cdots\}$ is the set of requests, which is being updated during the operation to include newly received requests. Each request r_i has its pickup node r_i^p, delivery node r_i^d, status r_i^s which can be new, rejected, waiting for pickup, picked, or delivered, route r_i^v which is the index of the van picking this request. Each request r_i has a pickup time window $[e_{r_i^p}, l_{r_i^p}]$ and a delivery time window $[e_{r_i^d}, l_{r_i^d}]$. We use the pickup time window to ensure passengers' expected pickup time and use the delivery time window to limit maximum detour. For the pickup time window, we set $e_{r_i^p}$ as passenger's expected pickup time, and $l_{r_i^p} = e_{r_i^p} + u_w$, where u_w represents the maximum allowed waiting time. For the delivery time window, we set $e_{r_i^d} = e_{r_i^p}$, and $l_{r_i^d} = l_{r_i^p} + u_d DTT(r_i^p, r_i^d)$, where u_d represents the maximum allowed detour ratio and $DTT(r_i^p, r_i^d)$ is the direct travel time between the pickup and the delivery node under average travel speed.

We use scenarios to represent the stochastic information about future requests and traffic conditions. $S^r(t) = \{s_1^r(t), s_2^r(t), \cdots\}$ is the set of request scenarios we use at time t. $S^s(t) = \{s_1^s(t), s_2^s(t), \cdots\}$ is the set of travel speed scenarios we use at time t. $S(t) = \{s_1(t), s_2(t), \cdots\}$, where $s_k(t) = \langle s_k^r(t), s_k^s(t)\rangle$, is the set of scenarios we use at time t, which combines request scenarios and travel speed scenarios. The goal of this research is to design an online scheduling algorithm to optimize the operating profit and the user experience. The operating profit is calculated as the operating cost minus the service revenue. The user experience includes the waiting time and the detour. In our implementation, the objective function is a linear combination of the cost, the revenue, the waiting, and the detour.

3 Solution Methods

To develop and test the scheduling algorithm, we need a simulation framework which provides a simulated online environment. It simulates the arrival of new requests, movement of vans and calls the scheduling procedure when needed, such as when new requests arrive or after a given time interval. The scheduling procedure uses scenario-based approaches to decide whether to accept each new request and design schedules for each van. For each given scenario, we need to solve a deterministic problem and this is done by a tabu search algorithm. In this abstract, we concentrate on the scheduling procedure. The scheduling procedure gets the following inputs: (1) the set of vans V which includes the position of each van; (2) the set of requests R which includes newly received requests and accepted requests with their status, such as, whether the request is picked or not, which van the request in on. The scheduling procedure first decides whether to accept each new request, then decides the routes of each van.

In the first step, to decide whether to accept each request, the brief idea is to compare the expected objective function value when accepting the request with the one when rejecting the request. To achieve this goal, we develop an evaluation procedure as shown in Figure 1. In this evaluation procedure, we need to input the current state of vans and requests, $state(t)$. The evaluation procedure estimates the average objective function value of current state. It loops through each scenario $s_k(t) \in S(t)$. With a given scenario $s_k(t)$, the stochastic problem becomes a deterministic problem. Tabu search is used to solve the deterministic DARP under the given state and scenario, which gives an optimal objective function value $obj_k(t)$ under each scenario. We use the average value of these objective function values under different scenarios to represent the expected objective function value of current state. With this evaluation procedure, we first mark the request as rejected and use the evaluation procedure to evaluate the average objective function value under given state, denoted as $obj_{rejected}$. Then we mark the request as accepted and insert it into a random route, run the evaluation procedure again, and get $obj_{accepted}$. If $obj_{rejected} > obj_{accepted}$ we reject the request, otherwise we accept it.

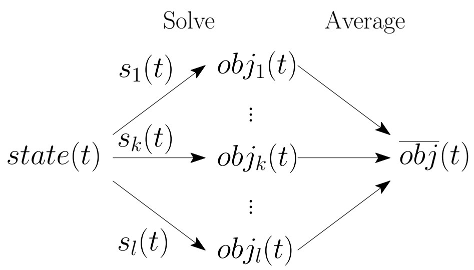

Figure 1: Illustration of the evaluation procedure.

In the second step, to decide the route of each van, we develop a scenario-based search to generate and evaluate potential decisions. The main idea is demonstrated in Figure 2. Similarly, the $state(t)$ represent the current state of the system. In each iteration of the loop, we select a scenario $s_k(t) \in S(t)$. We can use tabu search to find the optimal decision for the given state and scenario. For each scenario $s_k(t)$ we can get an optimal decision, denoted as $decision_k(t)$, which we call a candidate decision. Because $s_k(t)$ includes potential future requests, in some candidate decisions, the vans may be dispatched to future requests if this can lead to a better solution. After generating candidate decisions, we need to evaluate these decisions and choose a final decision. For each $decision_k(t)$, we first update the state according to the decision. By doing this, we get a new state $state_k(t + \Delta t)$ which represents the consequence of executing the decision. Then we use the evaluation procedure to loop through scenarios again to get an expected objective function value $\overline{obj}_k(t + \Delta t)$ of the candidate decision. Finally, we choose the candidate decision with the best expected objective function value as our final decision.

$$
\begin{tikzcd}
 & \text{Solve} & \text{Update} & \text{Evaluate} & \text{Select the best decision} \\
 & decision_1(t) \arrow[r] & state_1(t+\Delta t) \arrow[r] & \overline{obj}_1(t+\Delta t) \arrow[ddr] & \\
 & \vdots & \vdots & \vdots & \\
state(t) \arrow[uur, "s_1(t)"] \arrow[r, "s_k(t)"] \arrow[ddr, "s_l(t)"'] & decision_k(t) \arrow[r] & state_k(t+\Delta t) \arrow[r] & \overline{obj}_k(t+\Delta t) \arrow[r] & decision(t) \\
 & \vdots & \vdots & \vdots & \\
 & decision_l(t) \arrow[r] & state_l(t+\Delta t) \arrow[r] & \overline{obj}_l(t+\Delta t) \arrow[uur] &
\end{tikzcd}
$$

Figure 2: Illustration of the scenario-based search.

4 Conclusion

In this research, we develop a scheduling algorithm for dynamic vanpool services considering both stochastic requests and stochastic time-dependent travel times using scenario-based search and tabu search. Prepositioning is considered in the algorithm. We use a real dataset which includes requests from our partner in Dalian and travel speed data achieved from a map service provider. The results show that incorporating stochastic requests can improve the solution quality significantly, especially that prepositioning can increase profit and reduce waiting time significantly.

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Charging station placement in free-floating electric car sharing systems

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1 Introduction and problem description

Free-floating urban car sharing is a new mode of transportation that offers its customers much the same flexibility as owning a car without the associated ownership costs. Using electric vehicles in these systems offers both economic and ecological benefits, since (a) they operate very efficiently in urban settings, (b) they do not produce any local tailpipe emissions, and (c) they can be recharged from renewable sources, which reduces the system's overall environmental impact. Their limited range is less of a concern in these settings, as trips are rather short. However, electric cars must still be recharged regularly, which takes non-negligible time. A network of charging stations at which cars can be recharged between trips must therefore be built throughout the system's operational area. As such stations are expensive to build and maintain, placing them effectively is paramount to the system's economic viability. So far, this station placement problem has only been considered for station-based systems where cars must return to a station at the end of each trip (see, e.g., [1, 2]). Since free-floating systems offer both increased flexibility to the users and potentially improved demand coverage to the operator, we want to investigate this problem in their context.

The free-floating charging station location problem (FF-CSLP) extends the charging station location problem (CSLP) [2] insofar as cars no longer need to return to a station after each trip. While cars can now be parked anywhere, we assume that customers will only park either at their desired destination or at a nearby charging station. The street network in the operational area is represented by an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where each edge $e \in \mathcal{E}$ has an associated length

$\ell_e \geq 0$. Some of its vertices $S \subseteq \mathcal{V}$ are potential charging station locations, each with associated opening cost $F_i \geq 0$, per-charger cost $Q_i \geq 0$ and maximum charger capacity $C_i \in \mathbb{N}$. Expected customer demand is represented by a set of trips K, where each trip k has associated origin and destination $o_k, d_k \in \mathcal{V}$, start and end time $s_k, e_k \in T = \{0, \ldots, T_{\max}\}$, battery consumption b_k and expected profit p_k. From a trip's origin and destination, we can find its *start locations* $N(o_k)$ and *end locations* $N(d_k)$ as follows: a trip can *start* at any station within walking distance of its origin, as well as at the destination of any completed trip that is similarly close-by. Likewise, it can *end* at its own destination d_k or at any station that is within walking distance of it. Up to $H \in \mathbb{N}$ electric cars can be purchased, each with the same acquisition cost $F_\mathrm{c} \geq 0$, battery capacity $B^{\max} \geq 0$ and recharge rate $\rho \geq 0$. The objective is to choose which stations to open, how many chargers to build at each of them, and how many cars to buy in order to maximize the profit of those trip requests that can then be accepted, while staying within the available budget W.

A solution for the FF-CSLP therefore consists of a selection of stations from S that are opened, along with the number of chargers built at each of them, and a selection of up to H car routes from the set of all feasible routes Ω. One such route consists of a sequence of temporally non-overlapping trips in order of their start time where each trip is assigned a start and end location from $N(o_k)$ and $N(d_k)$, respectively. It is feasible if (a) the assigned start station of each trip is the same as the previous trip's assigned end station, and (b) the car's battery level never goes below zero. If a customer returns a car with low battery (i.e., below β_0) to a station instead of parking at the destination, he receives a monetary incentive. We model this with a reduced profit $p'_k < p_k$ that we collect instead of the full one.

2 Integer programming formulation and results

We formulate the FF-CSCP as an integer linear program containing (among others) an exponential set of route-variables (i.e., a set-packing formulation is used). A branch-and-price algorithm is developed and implemented where new routes are identified and added dynamically in each pricing iteration by solving a resource-constrained shortest path problem in a directed acyclic time-space network. We also observe that the aforementioned model may sometimes find overly optimistic solutions, since it gives the operator a lot of freedom regarding which trip requests to accept or decline and which start and end location to assign to each accepted trip. In practice, such decisions would be made by the system's users, with little chance for the operator to influence their behavior. Thus, we add additional constraints to the model that allow us to consider and analyze these behavioral aspects. These constraints ensure that (a) trip requests cannot be declined if they would be feasible, (b) customers always choose the closest sufficiently charged car as their start location, and (c) they always return a car as close to their destination as possible.

We evaluated the algorithm on a set of benchmark instances based on real-world data from Vienna. Potential stations were placed at supermarket parking spaces and near subway stations, while taxi trip data served as an estimation of car sharing demand. Results indicate that the profit attainable in free-floating systems can be much higher than that of station-based systems, though computational effort often increases. Incorporating user behavior mitigates this somewhat and also reduces attainable profit.

Acknowledgements

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A comparison of the energy efficiency of drone-based and ground-based parcel delivery services

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1 Introduction

Drones are regarded as one of the technological innovations which may trigger a revolutionary reshaping of logistics. This is mainly caused by the prospect of quick, cheap, and flexible deliveries which complies with current trends in the transport industry particularly in last-mile and city logistics. Therefore, a lot of pilot projects have been launched in order to exploit the potentials of drones in logistics applications.

However, it is noway sure to which extent drones can exploit the promised economic and ecologic potentials in large-scaled logistical systems. A crucial component to assess the overall potential of drone logistics is to compare the energy demands of all competitors. Since energy demand is the most important driver of both variable cost of transportation and ecological performance, analyzing the energy demand depending on the parameters of transportation allows us to assess the strategic advantages of different modes of transportation for varying scenarios.

2 Energy demand of delivery vans

For ground-based parcel delivery basically two types of vehicles can be used: Electric vans (EV) and traditional diesel-powered vans (DV). To calculate the energy demand of cars and trucks, most energy-consumption models rely on the basic physical formulation for the power P_M to move a point of mass by overcoming inertia, rolling as well as air resistance. In case of a DV, power is generated by a combustion engine. The corresponding energy transformation process incurs energy losses in the engine and in the gear system. For DV, total efficiency heavily depends on the rotational speed as combustion engines must operate in a certain rotation range. We use the model proposed in Kirschstein and Meisel (2015) where the energy demand to cover a distance d is calculated as

$$E_{DV} = NHV_{Diesel} \cdot F_{DV} = \frac{d}{v} \cdot \left(f^{idle} + \frac{f^{full} - f^{idle}}{\epsilon_{DV}^{trans}(v) \cdot P} \cdot P_M \right) \tag{1}$$

where f^{idle} and f^{full} are fuel consumption rates (in l/h) in idle and full-throttle mode, respectively, and P is the engine power (kW). The transmission efficiency function $\epsilon_{DV}^{trans}(v)$ and NHV_{Diesel} denotes the net heating value of Diesel which is about 10 kWh/liter

For EV, a constant engine and transmission efficiency of about 90% can be assumed such that $\epsilon_{EV}^{eng} \cdot \epsilon_{EV}^{trans} = 0.82$. Additionally, a battery charging efficiency ϵ_{EV}^{char} of about 90% has to be considered (see Goeke and Schneider, 2015). Hence, total efficiency of an EV can be approximated as $\epsilon_{EV} = 0.9^3 \approx 73\%$. Such that for the energy consumption of an EV holds

$$E_{EV} = \frac{d}{v} \cdot \frac{P_M}{\epsilon_{EV}} \tag{2}$$

for constant parameters.

3 Energy demand of drones

To calculate an UAVs energy consumption in a logistics application, four phases can be distinguished for drone flight: take-off, level flight, landing, and hovering. An idealized flight pattern for drone delivery services can be displayed as in Figure 1.

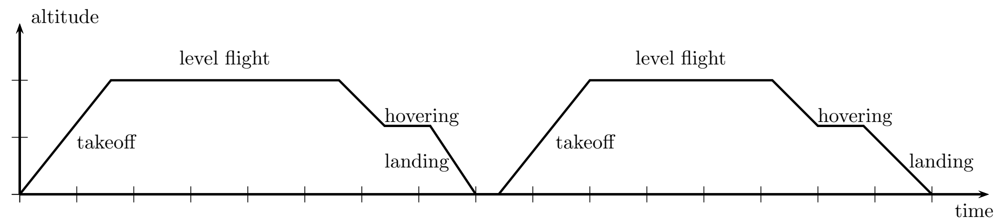


Figure 1: Idealized drone delivery flight pattern

To assess the energy demand of a typical drone delivery, in general power to overcome the body's and the rotors' air drag (P^{air} and $P^{profile}$, respectively), for lifting (P^{lift}), for climbing (P^{climb}) and for supplying internal electronics (P^{int}) needs to be considered

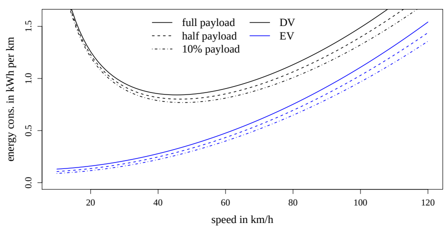
$$P^{UAV} = D_{body} \cdot \nu \quad + \kappa \cdot w \cdot T \quad + \rho \cdot R \cdot \nu_t^3 \cdot \left(1 + 2 \cdot \left(\frac{\nu}{\nu_t}\right)^2\right) \cdot \frac{\sigma \cdot c_{bd}}{8} \quad + m \cdot g \cdot \nu \cdot \sin\gamma \quad + P^{int}. \tag{3}$$

Details are described in Langelaan et al. (2017). To estimate the energy demand during an idealized delivery process as depicted in Figure 1, the power demand during the different phases is evaluated using (3) and weighted with the associated duration. We assume that the drone ascents and descents at an angle of 45°, a denotes the altitude of level flight (in km), t_{hover} is the total hover time, t_{tol} the time for takeoff and landing and v_{head} the headwind (if negative tailwind). Thus, total energy demand of one leg of the idealized drone delivery process can be expressed as

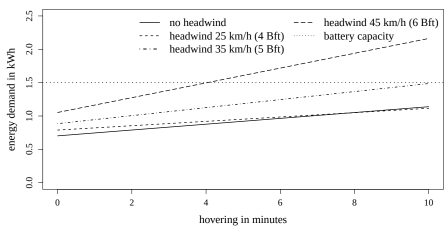
$$E_{UAV} = \frac{1}{\epsilon_{UAV} \cdot \epsilon_{UAV}^{charg}} \cdot (t_{tol} \cdot (P_{UAV}(m,\nu,45°) + P_{UAV}(m,\nu,-45°)) + t_{lf} \cdot P_{UAV}(m,\nu,0°) + t_{hover} \cdot P_{UAV}(m,|\nu_{head}|,0°)) + t \cdot \frac{P_{int}}{\epsilon_{UAV}^{charg}}. \quad (4)$$

4 Preliminary results

With the specifications of a standard DV and EV as well as current drone prototypes, the methodology outlined above can be used to estimate the energy demand of these vehicles under different conditions as outlined in Figure 2.



(a) Energy consumption depending on speed for DV and EV ($n_{acc} = 1$)



(b) Energy consumption depending on hover time for different levels of headwind

Figure 2: Energy consumption of UAV for idealized delivery profile

It appears that both wind conditions and hovering heavily effects the energy demand of drones which in turn affects the drone's operating range. For EV and DV, payload has only a small effect on total energy demand as in parcel delivery services parcel weights are usually low. For urban transportation with on average low travel speeds and more frequent acceleration processes, EVs show a much smaller energy demand.

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Vehicle routing with emission allocation preferences considering EN 16258

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1 Introduction

As freight transportation is responsible for about 24 % of the CO2e emission in Europe [1] the transport industry is required to substantially reduce greenhouse gas emission (GHG). Next to drive technology innovation and emission-oriented transportation management, the invention of an emission reporting standard is a further instrument to achieve this goal. A GHG reporting standard prescribes how to determine and allocate the total emission caused by a transport process to the shipments moved in the process. EN 16258 is a methodology proposed by the European Commission to declare GHG emission caused by transport services. With this paper we conceptualize an approach which enables logistic service providers to determine vehicle tours and to allocate cost as well as emission to the shippers according to their preferences with respect to EN 16258.

2 Emission estimation and allocation in vehicle routing

To assess the emissions of freight transportation, emission estimation models have to be applied in vehicle routing. There are multiple emission models available in literature [see 2, for an overview]. These emission models allow to anticipate the effects of vehicle routing decisions on the vehicles'

GHG emissions by estimating the fuel consumption. Major drivers of emissions are the selected vehicle, traffic conditions, its payload, its speed, and its tour [see 3]. In case of less-than-truckload (LTL) transports, the total emission quantity of a vehicle's tour has to be allocated to the served shippers. In the European Union the standard EN 16258 [see 4] establishes a methodology to calculate and allocate energy consumption and GHG emissions of freight and passenger transport services. For allocation, the norm prescribes a set of possible allocation parameters. The preferred measure is transport performance but also egalitarian, distance-based or load-based allocation is allowed. As an additional option, linear combinations of the above-mentioned allocation measures can be used. Thus, selecting an appropriate allocation measure establishes an additional instrument for the service provider to meet the shipper's emission preferences.

3 Vehicle routing with emission allocation

Incorporating emission estimation and allocation into a vehicle routing problem requires to model the emission-relevant decisions. In the following we assume the classical assumptions of VRP with heterogeneous capacitated vehicles. A node in the corresponding graph corresponds to a shipper location which is to be visited exactly once by one vehicle (except for the depot). For each shipper, an allocation distance and the payload is given. In the VRP, for each vehicle tour an allocation method is to be selected which is either egalitarian, distance-based, payload-based or based on transport performance. Equations (1)-(12) summarize the constraints of the proposed VRP.

$$\sum_{i\in C} \mathrm{Allo}_i^k = \sum_{a\in A} c_a^{\mathrm{fix}} \cdot x_a + c_a^{\mathrm{load}} \cdot l_a, \qquad \forall k \in K \qquad (1)$$

$$\mathrm{Allo}_i^k = \mathrm{AEgal}_i^k + \mathrm{direct}_i \cdot \mathrm{ADist}_i^k + d_i \cdot \mathrm{ALoad}_i^k + \mathrm{direct}_i \cdot d_i \cdot \mathrm{APerf}_i^k, \qquad \forall i \in C, \forall k \in K \qquad (2)$$

$$\mathrm{AEgal}_i^k \leq \mathrm{AEgal}_j^k + M \cdot \left(2 - y_i^k - y_j^k\right), \qquad \forall i,j \in C, \forall k \in K \qquad (3)$$

$$\mathrm{ADist}_i^k \leq \mathrm{ADist}_j^k + M \cdot \left(2 - y_i^k - y_j^k\right), \qquad \forall i,j \in C, \forall k \in K \qquad (4)$$

$$\mathrm{ALoad}_i^k \leq \mathrm{ALoad}_j^k + M \cdot \left(2 - y_i^k - y_j^k\right), \qquad \forall i,j \in C, \forall k \in K \qquad (5)$$

$$\mathrm{APerf}_i^k \leq \mathrm{APerf}_j^k + M \cdot \left(2 - y_i^k - y_j^k\right), \qquad \forall i,j \in C, \forall k \in K \qquad (6)$$

$$y_i^k = \sum_{a\in A:s(a)=i} x_a, \qquad \forall i \in C \qquad (7)$$

$$\sum_{a\in A:s(a)=0} x_a \leq 1, \qquad \forall k \in K \qquad (8)$$

$$\sum_{a\in A:t(a)=i} x_a = 1, \qquad \forall i \in C \qquad (9)$$

$$\sum_{a\in A:t(a)=i} x_a = \sum_{a\in A:s(a)=i} x_a, \qquad \forall k \in K \qquad (10)$$

$$\sum_{a\in A:s(a)=i} l_a = \sum_{a\in A:t(a)=i} l_a - d_i, \qquad \forall i \in C \qquad (11)$$

$$l_a \leq \mathrm{cap}_k \cdot x_a, \qquad \forall a \in A \qquad (12)$$

Details on decision variables and parameters of the VRP can be found in [5].

4 Outlook

To meet shipper preferences regarding allocated emissions and costs, various planning approaches can be discussed. In the talk, we will present some approaches and discuss their pros and cons. Particularly, one option is to formulate hard upper bounds on the allocated emissions for each shipper and seek for the cost-minimal solution under this restriction. A second possibility is to consider soft eco- and cost-preferences of the shippers and regard these parameters for the routing and emission and cost allocation problem. Another approach discussed is to decompose the planning problem into a routing problem and a separate allocation whereby for the routing problem various objectives can be pursued and the allocation model simultaneously allocates cost and emissions.

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How Scheduling Advances Affect Level of Service, Critical Mass, and Fleeting in Smartphone-Based Vanpooling

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1 Introduction

Smartphone-based vanpool services have become an emerging trend, which has attracted much attention in the research field [1, 2]. In smartphone-based vanpool services, passengers request vans from their smartphones for point-to-point pickups and deliveries, and vans are dynamically routed to passengers with committed pickup and delivery times. However, sharing vans and the dynamic nature of this service mode increases the difficulty of deploying and operating vanpool services. There are many interesting research topics related to vanpool services, some researchers focus on the daily planning for vanpool services, such as designed efficient scheduling algorithm, and some researchers focus on long term planning for dynamic vanpool services, such as how to decide the optimal fleet size for a service area, the minimum density of demand to support a vanpool services (i.e., the critical mass). This research focuses on the long term planning.

We found that most studies related to long term planning of dynamic vanpool services only consider simple scheduling methods. The existing studies can be summarized into two categories. The first category use simulation based method to model the operation of transportation system [3, 4, 5, 6]. In these research, the historical distribution of requests are usually used as the input. However, these studies use simple heuristics for scheduling. They do not use future information and do not consider the capacity of vans. The second category use approximate mathematical method[7, 8], since we usually do not have detailed information [8]. These studies usually assume the requests is from a simple distribution, such as uniform distribution. Similarly, only simple heuristics are considered in these studies.

From the existing studies related to daily planning of dynamic vanpool services [9, 10, 11, 12], there are some scheduling algorithms with advanced features which can improve scheduling performance. In recent studies [13, 14, 15], there are advanced scheduling algorithms which considers future information and prepositioning and it is found that these advanced features can improve the scheduling performance. These scheduling advances create complexity in deployment and have their associated requirements on input data. It is therefore of interest to quantify the impact of these scheduling advances in long term planning.

In this research, we test scheduling algorithms with advanced features under different settings. We compare the LOS metrics with or without looking-ahead and prepositioning to measure the impact of scheduling advances. We also test the LOS metrics under different fleeting settings to get the response surfaces of LOS metrics (rejection, waiting time, excess time) vs fleet size (number and capacity of vans). We then try to fit the surface and get an approximate function to represent the relationship between LOS metrics and fleet size. With this function, we can build a generalized profit function to balance the operating profit and the user experience. To test whether our proposed method can be used for different service area, we run a series of sensitivity tests by mutating the demand data and road network. From these tests, we found that the proposed method can be used for requests with different patterns. The test results also indicate some noteworthy characteristics of our real-world request datasets.

We summarize the contributions of this research as follows:

- Different algorithm features and fleet size are tested to measure the impact of scheduling advances, we also use functions to fit the relationship between LOS metrics and fleet size;

- According to the relationship between LOS metrics and fleet size, we build a model to predict the critical mass of given area and a fleet planning model considering both operating profit and user experience; and

- By mutating the characteristics of request data, we find that the dataset have specific spatial pattern, and the proposed method can be applied to new areas with different demand patterns.

2 Research framework

In smartphone-based vanpool services, the service providers use several vans to provide transportation services for passengers within a service area. They have a smartphone app for passengers to send requests. Each request usually has a pickup location, a delivery location, and expected pickup time. They also have a smartphone app for drivers to receive scheduled routes and locations of requests.

There are several key factors in vanpool services. In this research, we focus on the interaction among the demand pattern, fleet size, and level of service (LOS) metrics when using scheduling algorithms with advanced features. The demand pattern represents the characteristics of request data, such as, the spatial and temporal distribution of requests, and the density of requests. The demand density is the major factors which influence the load of services. And for a specific density, if the spatial and temporal distribution of requests change, the service performance may also change. The fleet size means the number and capacity of vans. Existing studies usually consider the number of vans but ignore the capacity of vans. However, both of them can influence the scheduling performance and the fleet cost. The level of service includes three aspects. The rejection ratio which is the fraction of rejected requests in all received requests. The waiting time measures how long each passenger waits before being picked. The excess ride time ratio which is the fraction of excess ride time in direct ride time by taxi or private car.

The goal of this research focus on the long term planning of vanpool services. When we plan to enter a new market, we may get the request data of the new area. We need to determine whether the market can support a vanpool service and how to determine the best fleet size for this market. We would like to know how the advanced features of the scheduling algorithm can save cost or improve user experience. We also want to know whether the proposed method can be used on different areas with different characteristics, since we use simulation based method on historical data to build and test the proposed model.

The core idea of this research is response surface method from simulation based optimization. When using advanced scheduling methods, it is difficult to get a closed form relationship between scheduling performance with fleet size. To build a fleet size model, we can run simulation tests on different fleet size, which includes the number of vans m and the capacity of each van Q. From the simulation result, we can get the response surface of LOS metrics against the fleet size. We can fit the response surface and get the average rejection rate $AR(Q,m)$, the average waiting time $AW(Q,m)$, and the average excess ride time ratio $AE(Q,m)$.

After fit the response surface, we can build a generalized profit function. This function includes both operation profit and user experience. Assume the average number of daily requests is p, the average revenue per request is r, the value of waiting time per minute is v, the excess ride time ratio penalty is e, and the daily cost of fleet is $C(Q,m)$. We have the generalized daily profit as

$$f(Q,m) = p[1 - AR(Q,m)][r - vAW(Q,m) - eAE(Q,m)] - C(Q,m),$$

where $p[1 - AR(Q,m)]$ is the number of passengers served and $[r - vAW(Q,m) - eAE(Q,m)]$ is the revenue per request minus the value of waiting time per request and the penalty of excess ride time. Then we can use this function to find the optimal fleet size which can optimize the generalized profit.

To find the critical mass, we need to include the demand density in our function. Since we only have a dataset with a specific demand density. We use a simple method to create data with different density. We combine the requests from k consecutive days and treat them as requests in one day. With this method, we can get datasets with k times density as the original dataset. Similarly, we run simulation under these settings to get the level of service metrics and get the average rejection rate $AR(Q,m,k)$, the average waiting time $AW(Q,m,k)$, and the average excess ride time ratio $AE(Q,m,k)$. Then generalized profit function can be modified to

$$f(Q,m,k) = kp[1 - AR(Q,m,k)][r - vAW(Q,m,k) - eAE(Q,m,k)] - C(Q,m),$$

where $kp[1 - AR(Q,m,k)]$ is the number of passengers served and $[r - vAW(Q,m,k) - eAE(Q,m,k)]$ is the revenue per request considering the user experience.

In existing studies about scheduling algorithms, it is found that the advanced features of scheduling algorithm, such as looking-ahead and prepositioning, can improve the scheduling performance a lot. In this research, we would like to measure the impact of these advanced features under different settings. Thus for the simulation tests, we set up three groups to inspect the benefit of these advanced features: Group 1, deterministic, we set the horizon of scenarios to zero, which means we do not consider future requests; Group 2, stochastic, we use normal horizon of scenarios and only consider dispatching vans to received requests; and Group 3, prepositioning, we use normal horizon of scenarios and consider sending the vans to locations with potential requests.

3 Conclusions

In this research, we test the impacts of advanced features in dynamic vanpool service scheduling algorithms. We find that the tested advanced features, such as looking-ahead and prepositioning, can improve level of service metrics. We propose a methods to derive the optimal fleet size and critical mass of given service areas by fitting the response surfaces and building a generalized profit function. We use operation settings to validate the proposed model and find that the advanced features can help to improve the generalized profit. It may be not profitable to run a dynamic vanpool service without these advanced features. Sensitivity tests are also performed to test whether proposed methods can be used in service areas with different demand patters and road networks.

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Service Network Design with Scheduled Lines for City Logistics

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Freight transportation is essential for supporting and supplying city residents and businesses. Figliozzi [2007] estimated that on average, for 13 US cities, freight transportation represented nearly 10% of total vehicle miles traveled within those cities. Many expect an increased demand for the transportation of freight into, within, and out of urban areas. However, this expectation is not solely due to an expectation of larger urban populations. Many of today's logistics and manufacturing "best practices", such as "Just-in-Time" with its philosophy of low inventories and small, timely deliveries, contribute to the large number of trucks delivering freight in urban areas. And, of course, the continued growth in business to consumer commerce, particularly with companies such as Amazon offering same-day delivery, will necessitate a greater number of freight deliveries in urban areas.

Figure 1: Metra rail line map

We study the potential of using regional passenger rail lines for part of this delivery process. As a motivating example, we consider the regional commuter rail system for the city of Chicago, (https://metrarail.com). This rail system provides, seven days a week, transportation for individuals throughout the Chicago suburbs to two locations in downtown Chicago. Like many commuter rail systems, the departure frequency varies from one hour to the next, with many inbound departures during weekday mornings, and fewer at other times. Figure 1 is a map of the system (taken from https://metrarail.com/maps-schedules/system-map), with white circles indicating stations along those lines.

Specifically, we study the operations of a transportation company tasked with delivering shipments to locations in a dense urban area. We presume that another transportation provider is responsible for final delivery and thus the carrier we consider only needs to transport these shipments to one of a known set of terminals in or near the city center. We illustrate this two-tiered logistics system in Figure 2. In addition to moving shipments to the city center over the road (e.g. trucks), the transportation company we consider can acquire the opportunity to utilize capacity on scheduled, public transportation lines when it is available. Thus, we presume that a subset of these stations possess the capability for loading and unloading shipments onto locations within a train that can be quickly converted from passenger areas to areas that can hold goods. However, passenger traffic takes priority over shipments; passengers can not already be in these areas.

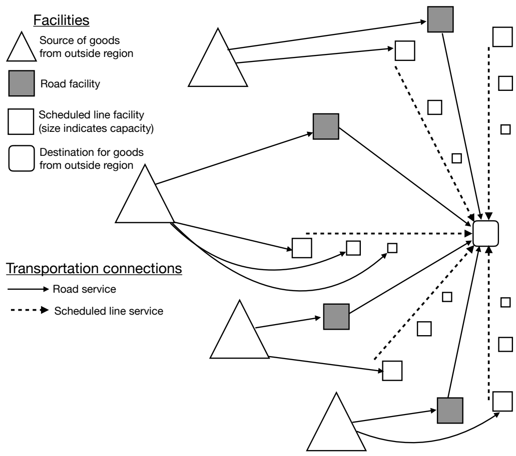

Figure 2: Transportation system

Each option (road or rail line) for transporting shipments has advantages and disadvantages. When using road transportation, the transportation company has control over when and how many trucks to dispatch at a given time. As a result, the transportation company has much greater control over available capacity. However, as these trucks are driving on highways to a densely populated city center, they must contend with traffic and fluctuations in travel times. When a rail line service is reliable, transporting goods via that line removes variability in travel times. However, the carrier no longer has control over dispatch times. Similarly, as the primary purpose of the rail line is passenger transportation, there is limited capacity available. Finally, unforeseen fluctuations in passenger volume may lead to uncertainty in the amount of capacity available on a rail line.

To summarize, the carrier must determine for each shipment a route that begins at its origin terminal in the first tier no earlier than the day and time at which it is available, and ends at a destination terminal in the city center no later than the day and time at which that shipment needs to be at that terminal for final delivery. This route will consist of a sequence of two transportation services, with the first involving road transportation. The second, however, can either involve road transportation or placing the shipment on a scheduled line. Road service costs are paid on a per-vehicle basis, and depend on the time at which the vehicle departs. The cost of a scheduled line service depends on the amount of capacity purchased and when and where it becomes available on the scheduled line. Use of the scheduled line service also involves other operational considerations, such as a limit on the time available to load goods onto the service and a limit on how many shipments can be held at a facility from which the service originates.

Thus, we seek to solve a variant of the *Scheduled Service Network Design Problem* [Crainic, 2000, Wieberneit, 2008], wherein services representing rail lines have capacity that is time-dependent and uncertain, and services that represent road transportation exhibit time-dependent travel times and costs. The use of scheduled lines has been studied in the context of a Pickup and Delivery with Time Windows setting [Ghilas et al., 2016b,a, 2018]. In addition to our problem setting being different, we also consider additional complexities such as uncertain capacity and time-dependent travel times. We are developing a solution method based on the Dynamic Discretization Discovery framework [Boland et al., 2017], which has been shown to be effective at problems with time-dependent travel times [Duc Minh et al., 2019]. While the methodology is still in development, we anticipate having a completed computational study, with extensive results, by the workshop.

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Estimating Primary Demand in Bike-Sharing Systems

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1 Introduction

Over the past decade, bike-sharing services have seen widespread adoption in cities across the world in response to urban congestion. Most bike-sharing services operate by providing a fleet of rentable bikes that are distributed over a fixed network of *stations*, each capable of holding a certain number of bikes at a given time. A commuter can pick up a bike from any station for temporary use and drop it off later by parking it in an available dock at the destination station.

In this paper, we focus on the problem of estimating the primary demand in a bike-sharing system, which is the crucial input to various operational models such as bike inventory allocation and rebalancing. Here, the primary demand refers to the demand that would be observed if the service never goes out anywhere—or equivalently, if every pick-up or drop-off request by a potential commuter is fulfilled at the station of her first choice. For operational purposes, the demand is usually quantified by the bike outflow and inflow rates at individual stations, or the flow rates between origin-destination pairs. Estimating these flow rates by naively aggregating past trip data, however, can be problematic for two reasons: *demand censoring* and *choice substitution*—both can introduce significant biases in the estimates if not properly corrected for. Demand censoring occurs when stations are temporarily out of bikes or docks, during which there is apparently zero demand. Choice substitution occurs when commuters substitute their first choices for other alternatives due to service unavailability. Choice substitution in bike-sharing can happen in two ways: commuters may decide to use available stations nearby instead of their first choices—in which case, the demand is *recaptured* elsewhere; otherwise, commuters may leave the system for external alternatives, such as other modes of transportation, hence the demand is said to be *spilled* or lost. Both factors can contribute to either overestimation (by recaptures) or underestimation (by spills) of the primary demand.

2 Methodologies and Contributions

We consider a bike-sharing system with N stations, denoted as $\mathcal{N} \triangleq \{1, ..., N\}$. We define the commuter's choice set as $\mathcal{N} \cup \{0\}$, where 0 denotes the choice of not using the service. To model the demand, we assume that commuters arrive to the system according to a Poisson process with rate λ per unit time. Each arriving commuter is characterized by a *type* $\sigma : \{0, \ldots, N\} \mapsto \{0, \ldots, N\}$, a bijection that specifies a strict ordering over the stations as follows: for any two stations $i, j \in \{0, \ldots, N\}$, i is preferred over j if and only if $\sigma(i) < \sigma(j)$, i.e., choice i is ranked *higher* than choice j. We assume that the type of each arriving commuter is drawn independently from a probability distribution over the set of all possible types, $\Sigma \triangleq \{\sigma_1, \ldots, \sigma_K\}$. We parametrize the probability mass function of this distribution with a vector $x \triangleq (x_1, \ldots, x_K)$, where x_k is the probability that the commuter is of the type σ_k. Overall, the demand model is parametrized by the arrival rate λ and the type probability vector x, both of which are unknown and have to be estimated from data. Suppose we observe a pick-up at station j while the set of available stations is $S \subseteq \mathcal{N}$ (S is called the *offer set*). We say that a type σ is *compatible* with the observed choice $j \in S$ given the offer set S if $\sigma(j)$ corresponds to the highest rank among the alternatives in S. The set of all such types, $\mathcal{M}_j(S)$ is defined as follows,

$$\mathcal{M}_j(S) \triangleq \{k \in \{1, \ldots, K\} : \sigma_k(j) < \sigma_k(i), \forall i \in S, i \neq j\}.$$

For a given probability vector x that parametrizes the type distribution, the probability that a commuter chooses option j when presented with the offer set S is given by

$$\mathbb{P}(j \mid S\,; x) \triangleq \begin{cases} \sum_{k \in \mathcal{M}_j(S)} x_k, & \text{if } j \in S \cup \{0\}, \\ 0, & \text{otherwise.} \end{cases}$$

The function $\mathbb{P}(\cdot \mid \cdot\,; x)$ fully specifies a choice model that predicts the fraction of commuters picking a bike from any station or not using the service under any service outage pattern. In particular, $\mathbb{P}(j \mid \mathcal{N}\,; x)$ and $\lambda_j \triangleq \lambda \mathbb{P}(j \mid \mathcal{N}\,; x)$ correspond to the *first-choice* probability and *primary demand* for station j, respectively, while $\rho(S; x) \triangleq \sum_{j \in S} \mathbb{P}(j \mid S; x) = 1 - \mathbb{P}(0 \mid S; x)$ is the probability that given the offer set S, an arriving commuter will stay and use the service.

Based on this rank-based demand model, we summarize the main contributions of this paper in two areas: *modeling* and *estimation*.

Modeling. We propose to augment the aforementioned rank-based choice model with a *substitution graph*, which allows us to precisely characterize the set of substitutable alternatives for each station in the bike-sharing network. The introduction of these substitution constraints serve two purposes: (i) to model commuters' tendency to explore only alternatives that are in close proximity to their first-choice stations, and (ii) to reduce the number of parameters of the model by eliminating preference rankings that imply unrealistic substitution behaviors. Further, we extend the rank-based choice model to jointly account for pick-up and drop-off substitutions using *paired* rankings of OD choices. This extended model allows us estimate the primary demand for trips between all origin-destination (OD) station pairs, which are useful for inventory planning operations (e.g., Shu et al. (2013)).

Estimation. Our proposed model is characterized by a set of parameters—the Poisson arrival rate and the probability mass function of preference rankings—that can be estimated by maximum likelihood estimation (MLE). One issue, however, is that the number of preference rankings grows factorially with the number of alternatives. Therefore, it is usually not feasible to solve the fully parametrized MLE problem using off-the-shelf optimization solvers. Instead, large-scale optimization methods such as constraint sampling (Farias et al. 2013) and column generation (van Ryzin and Vulcano 2014) have been applied. However, the column generation subproblem requires solving an integer program that is NP-hard, making it intractable when there are hundreds of stations, as is the case in many bike-sharing systems. In this paper, we take a different approach by proposing a dimensionality reduction technique that is based on *sparse representations.* More specifically, given a sequence of observed available stations (offer sets) over time, our algorithm will generate a parsimonious set of preference rankings that sufficiently explain the observations, subject to the constraints imposed by a substitution graph. For our application, we find that this approach can reduce the problem dimension by orders of magnitude, making it feasible to solve the MLE problem without resorting to large-scale optimization methods. Our second contribution is focused on estimation. We show that the MLE problem, while nonconcave in general, can be reduced to a *difference-of-convex* (DC) program. Based on this reduction, we apply an iterative DC programming technique that estimates the parameters by solving a sequence of convex programs and each convex program can be solved efficiently by the Frank-Wolfe method.

3 Results

We evaluate our methods on synthetic and actual data sets of Hubway, a bike-sharing service in the Boston metropolitan area. We demonstrate the efficiency and practicality of our method on a city scale. We further show that across a wide range of simulated conditions, our method consistently outperforms several benchmarks, including the independent demand and MNL models. Specifically, we achieve error reduction by more than 20% when the average stockout frequency is close to the actual levels observed in Boston during the evening peak hours. These improvements translate into ridership increases of up to 3% when bikes are allocated based on the estimated demands, using a bike deployment model by Shu et al. (2013) with a planning horizon of several hours. When applied to the actual Hubway data set, our method achieves an overall out-of-sample error of 24.8% in ridership prediction, which is 10% lower compared to the best-performing benchmark.

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Multi-objective optimization framework for the integration of individual partner interests in a collaborative location-inventory model

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1 Research context and related literature

The constant search for logistical cost reduction is no longer sufficient to stay competitive in today's demanding market. The increasing importance for environmental sustainability while keeping customer service level high puts companies under increased pressure. Encouraged by the emergence of carbon taxes and cap, the reduction of the carbon footprint has therefore received increased attention by both practitioners and researchers. At the same time, maintaining high service levels, e.g., by ensuring a reasonable delivery frequency, is of crucial importance to remain competitive nowadays.

A promising avenue is to engage in a collaboration. In this research, the focus is on horizontal cooperation, a partnership with companies (potentially competitors) that operate at the same level of the supply chain. Such a collaboration allows companies to share buildings, equipement and jointly plan their (logistical) operations. More specifically, we focus on a group of suppliers that all deliver goods to a number of retailers. By serving these retailers with vehicles that depart from one of the shared distribution centers, a reduction in operating cost and an increase in vehicle utilization can be established. Benefits are not restricted to cost reduction, as the shorter travelled distances and the more efficient loading of vehicles impact positively the ecological footprint of cooperating companies by reducing the CO_2 emissions [1].

Several papers assess the economical and environmental benefits of horizontal collaborations through the analysis of theoretical and real cases studies [2]. The assessment is typically done by comparing the stand-alone scenario with a collaborative one. Typically, the collaborative scenario is simulated by aggregating the customers' demand of the different partners, and a single optimisation model is then solved for the group as a whole. To quantify the impact of this solution on each participating company, the costs and benefits have to be allocated again among the different actors. Multiple allocation models, ranging from proportional rules of thumb (e.g., proportional to the transported volume) to complex game theoretical models, such as the Shapley value or Nucleolus, are discussed and compared in the literature [3].

In almost all research contributions, individual preferences of the participating companies are ignored by forcing all partners to agree on a coalition objective that is used during the optimization procedure. As individual companies might have different, potentially conflicting, objectives, this might create an incentive for them to diverge from the proposed solution so to improve their personal outcome. As a result, the potential mismatch between individual partner objectives and coalition objectives jeopardises the long-term stability, and thus success, of the collaboration.

To the best of our knowlegde, the integration of individual partner interest has only be described and investigated in [4]. The authors propose a framework that allows for the inclusion of individual partner objectives while assuring a maximal synergy creation through collaboration. The presented framework assumes, however, that the coalition partners agree on a single objective at the coalition level, which implies that there exists a single optimal solution for the group as a whole.

2 Research contribution

Our current research project aims to extend the ideas presented in [4] by considering a multi-objective framework at both the coalition and the individual partner level. The proposed methodology is tested and validated on a collaborative location-inventory problem with the following two objectives: (i) minimize the total logistical cost and (ii) minimize the CO_2 emissions that result from the transport between the distribution centers and the retailers.

We consider an a priori preference articulation with respect to the effect of collaboration on both objectives. In other words, each individual partner is requested to state in advance the importance of a change in each of the objectives as a result of engaging in the collaboration. This approach differs from [4], in which an a posteriori preference articulation is assumed.

The goal of the location-inventory problem is to determine the number and location of distribution centers to open, an allocation of retailers to these distribution centers, as well as inventory optimization at the retailers (we consider a vendor managed inventory (VMI) system). We assume in the collaborative scenario that all distribution centers and vehicles are shared among the partners. To calculate CO_2 emissions, we make use of the formula proposed in [5], in which the total CO_2 emission depends on the load of the vehicle. We consider that the partners' products are distinct and have their own cycle inventory and safety stock at distribution centers and at retailers. The safety stocks allow to satisfy the uncertain demand during the lead time with a probability determined by the service level. We use auxiliary variables to move the non-linearity from the objective function (cycle inventory, order costs and safety stock costs at DCs) to the constraints. The objective is then linear and the constraints are either linear or conic quadratic, leading to a conic quadratic mixed integer program, which can be solved using commercial solvers. Once the problem solved, the final solution will meet the individual interests of each partners ensuring a sustainable collaboration. From these experiments, we also infer valuable managerial insights varying the individual objectives and the characteristics of the partners.

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The multi-attribute two-echelon location-routing problem with fleet synchronization at intermediate facilities

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1 Introduction

We study the multi-attribute two-echelon location-routing problem with fleet synchronization at intermediate facilities (MA-2ELRPFS), which is motivated by applications in city logistics [2]. The system topology is composed by sets of suppliers, platforms, satellites (or intermediate facilities), and customers as well as two vehicle garages, one for each echelon. The system requires the allocation of suppliers to platforms and the routing and scheduling of vehicles on each echelon to deliver the freight from platforms to customers, through satellite facilities. In this context, satellite facilities are considered shared infrastructures without storage capacity (for instance, outsourced terminals, parking lots). Hence, to allow transshipment operations, vehicles from each echelon must be synchronized in time at the same facility. In particular, the proposed problem deals with the simultaneous consideration of multiple attributes, such as, origin-destination demands and time windows at the customers. A feasible solution of a MA-2ELRPFS is depicted in figure (1).

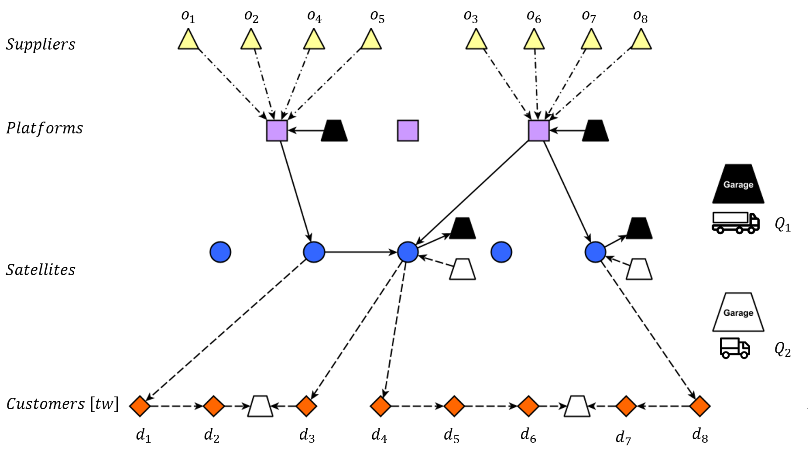

Figure 1: Example of a feasible solution for a MA-2ELRPFS.

We introduce the problem setting, present and compare two mixed-integer programming formulations as well as an exact solution framework for the MA-2ELRPFS, notably an arc-based and a multi-commodity flow formulation on a time-expanded network. We propose a solution framework based on an iterative refinement of the time-expanded formulation to exploit the temporal dependencies arising from customers' time windows and the interrelation with fleet synchronization at the intermediate facilities.

2 Solution framework for the time-expanded flow model

The time-expanded flow model is build from the generation of copies of the nodes and the arcs of the static network, one for each time interval, for the whole time horizon [3]. The reformulation of the time-constrained variables into sets of discrete variables in time is of particular interest in our study to efficiently model synchronization and time dependencies within the MA-2ELRPFS. However, as time expanded networks can become prohibitively large (and even be of infinite size if no discretization of time is provided), an efficient procedure is required to reduce the size of the underlying network without hampering the solution space.

The proposed solution framework for the MA-2ELRPFS is inspired by discretization methods based on the refinement of reduced time-expanded networks [1]. In general, our solution framework employs reduced time-expanded networks for solving the MA-2ELRPFS without creating a fully time-expanded network. This reduced network results from shrinking the time-expanded network with a specialized preprocessing scheme and a coarser granularity for the time interval. The solution space defined by the reduced network can be seen as a relaxation of the MA-2ELRPFS. Our method iteratively solves and refine this reduced network to extract lower and upper bounds for the MA-2ELRPFS with the proposed multi-commodity flow formulation. In our case, the refinement procedure repairs infeasible configurations within the reduced time-expanded network based on the analysis of its solution on the MA-2ELRPFS. The solution framework determines a sufficiently refined reduced network that provides a feasible solution space and solves the MA-2ELRPFS.

3 Experimental study

Computational experiments are extensively performed to study the efficiency of the proposed formulations and the solution framework for the MA-2ELRPFS. Since the MA-2ELRPFS is a new problem, no instances are available in the literature. We modify well-known datasets for the 2EVRP and VRPTW [4] to generate MA-2ELRPFS instances. We investigate the performance of the two formulations in terms of runtime, LP relaxation, and integrality gap. In this context, we test different mathematical properties within the multi-commodity flow formulation arising from its time-expanded representation, where the formulation is expected to provide a strong LP relaxation against the arc-based formulation. Finally, when testing the solution framework, we examine the different parameter configurations and valid inequalities. We provide the benefits involving the reduction of the time-expanded network, solution quality, and runtime improvements as well as the problem scale that can be solved. The computational study demonstrates that the iterative refinement procedure performs well on the proposed set of instances and is able to solve instances to optimality that otherwise cannot be handled by the ard-based model.

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Comparison of Different Carsharing Relocation Modes: Classification and Feature-Based Selection

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1 Introduction

In one-way (and free-floating) carsharing, it is necessary to "rebalance" the fleet periodically, as some "hot spots" (i.e., shopping malls) are more frequently origin of a customer trip than destination, whilst "cold spots" (i.e., residential areas) are more often destination than origin. These relocations are expensive, as workers can only transport a single vehicle at a time (by driving it), unless operators use relocation trucks which are difficult to maneuver in narrow city centers. In the former case, workers have to somehow get to the next "cold spot" after dropping a vehicle off at a "hot spot". Surprisingly, only little is known about which modes are used in practice. [4] report using bikes for rebalancing in their Car2Go Toronto case study. [5] state that the workers of a large Munich carsharing operator drive the vehicles themselves, and use folding bikes, bikesharing, cars driven by other workers, public transport or walking to continue to the next vehicle. In traditional car rental as well as bikesharing, vehicles are often relocated with a truck, a mode that is also possible in carsharing. Further, workers can also give each other lifts from a hot spot to a cold spot. Whilst several papers state a mode or implicitly assume a mode has been chosen, the question of modal choice has not been analyzed [2]. Our contribution is two-fold: We compare different modes with respect to total costs and classify whether operators choose a single mode or mix among different modes; and we contribute to the literature on Vehicle Routing Problems (VRPs) with Multiple Synchronization Constraints (VRPMSs) by presenting alternative formulations for special cases which are much easier to solve than the basic formulation, and we are the first to design and implement Variable MIP Neighborhood Descent (VMND) [3] for VRPMSs.

2 Model Formulations

We consider four different modes for the Carsharing Relocation Problem (CRP). From a pickup location to delivery location, cars can either be loaded on a truck or be driven by workers. Vice versa, those workers can either continue with the truck, use bikes and public transport, or hitch a ride with another worker who is currently relocating a vehicle. In the following, we first describe the individual modes in their pure form, before describing how to derive a hybrid model.

Relocation with Bike or Public Transport

If relocation workers drive the vehicles themselves and continue to the next vehicle by bike or public transit, every worker route will visit cold and hot spots in alternating order. We can, therefore, model the problem as an alternating pickup and delivery VRP in a two-index formulation with a time limit (shift length). To cater for shift lengths, we further include a time limit before each worker must return to the depot. The main difference between biking (CRP-B) and public transport (CRP-P) is then the definition of cost function and transition times. From delivery to pickup location, all workers drive by car and, thus, incur distance based costs for the vehicle and transition time based costs for the worker. In the opposite direction, costs and transition times depend on the distance and the selected mode. For the CRP-B, costs depend on the wage of workers, velocity of the bike, and distance. Costs in the CRP-P are calculated based upon actual travel times in a (real world or artificial) public transport network.

Relocation with Trucks

If one rebalances the carsharing system with a truck (CRP-T), one must consider the time limit (shift length) and the capacity of a truck serving simultaneous pickup and delivery of interchangable goods, but also the fact that some pickup locations (cold spots) cannot be reached with a truck (i.e., backyards). To include the latter constraint, we define a set of “entry points” for each pickup location where the worker can leave the truck and fetch the car, requiring additional time and incurring additional costs, and route the truck through these locations. One vertex can be entry point for multiple vehicles. It is sufficient to visit one of the entry points for each location. A worker without a truck has a capacity of 1, and must therefore return to the truck after each vehicle. Thus, we assign handling costs and times for each combination of entry point and pickup location, and model the problem as a variant of a so-called Family VRP [1] in which at least one vertice in each set of entry points must be visited and all delivery locations (hot spots) must be visited.

Relocation with a Group of Workers

If one allows a group of workers to help each other (CRP-GW), movements of workers and vehicles must be synchronized. No worker must travel without a vehicle, and no vehicle is allowed to travel without a driver. Further, the number of workers traveling in one vehicle must not exceed the capacity of this vehicle, and all workers must return to the depot within a predefined time limit. We synchronize worker and vehicle movement with respect to time, observing that all workers and vehicles must arrive before anyone leaves, if those vehicles are synchronized in this location. Given Euclidean distances for each worker and vehicle, we observe that every vertex is visited at exactly one point in time. We, further, observe that at every pickup location one vehicle arrives and two vehicles depart, whilst two vehicles arrive at every delivery location from where one vehicle departs. Also, an edge between any two nodes is used by at most two vehicles. We use these properties to reformulate the problem by simply tracking the flow of vehicles and workers.

Hybrid Relocation Problem

If operators have a sufficiently large group of workers, they can decide to use different modes (CRP). Whilst workers going by truck or by bike cannot switch to other modes during their operation, workers can easily hitch a ride with other workers on some trips, whilst using public transport on others. We use separate arc routing variables for trucks, workers with bike, workers with public transport, workers hitching rides (or driving themselves), and vehicles which are driven by workers (not loaded on a truck). We impose flow conservation for trucks, vehicles and bikes, separately, and jointly for public transport and hitching rides, as well as a time limit for all types. We link workers and vehicles (no vehicle must drive without worker, and no worker can travel without a mode of transport), and ensure that all locations are visited by at least one worker.

3 Solution Algorithm

We solve the CRP with an adapted branch-and-cut (B&C) procedure. We, first, observe that any single-mode model is a special case of the CRP and can, thus, serve as an upper bound. VRPs on bipartite graphs can be solved substantially faster than other VRPs (despite remaining NP-hard). We can, therefore, warm start the B&C tree at a solution retrieved for bike or public transport. In most instances, bike results in lower costs than public transport. Further, we design a VMND [3]. Whenever a solution is found, we search for better solutions in a set of neighborhoods. Besides classical neighborhoods, we also consider one in which we find improved solutions on intersecting arcs.

4 Feature-Based Selection

Obviously, the optimal mode/modal mix will depend on the fleet and the built environment, that is the infrastructure of the city. We aim at establishing classifier rules for preferred modes and determine key drivers regarding modal choice. We, thus, conduct a numerical study with the hybrid CRP model to derive the optimal worker assignment to modes and routes for different settings. Features of fleets and cities include, but are not limited to:

- Density and distribution of customers and vehicles: Number of customers and vehicles, proximity to public transport, accessibility with trucks, average and median distances.
- Cost structure: Hourly wages for workers, mileage-based costs for vehicles.
- Shift length (and average number of performed relocations during this time).
- Number of workers.

We consider data adapted from real world instances to derive the influence of the feature groups. With regards to single-mode solutions, we observe that mostly biking from hot spots to cold spots and a group of workers helping each other are preferable. In most instances, the optimal mode is a hybrid approach in which workers mix between different modes during the same shift. Unsurprisingly, modal choice vastly depends on the cost structure and differences in velocity as well as proximity to public transport and accessibility by trucks. Rather surprisingly, the number of customers plays only a minor role in modal choice.

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Dynamic and Stochastic Algorithms for the Transportation of Patients in Hospitals

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1 Introduction and Problem Description

This study investigates and optimizes the patient transportation flows that arise in a large hospital in Italy. The hospital is located in a campus and is composed of a set of pavilions, each containing a number of floors and representing a distinct hospital ward. Because of the huge overall extension, the hospital offers a transportation service for the patients that need to move between the floors of the different pavilions. Some transportation requests are known at the beginning of the day, whereas others, typically the most urgent ones, arrive on the fly. Each patient has her own level of urgency, and so her transportation should respect, when possible, a pre-defined time limit. The aim is to transport all patients with an available fleet of vehicles, while minimizing the total weighted lateness, where the weight is defined by the level of urgency of a patient.

More formally, we use a direct complete graph $G = (V, A)$, where each vertex $i \in V$ corresponds to a floor of a pavilion. Let R be the set of the requests. Each request $r \in R$ is received at a release time t_r and contains the vertex $p_r \in V$, where the patient should be picked up, and the vertex $d_r \in V$, where she should be delivered. It also contains: an early time window e_r that specifies the time in which the patient is available for the service; a soft late time window l_r that gives the last instant in which the service could be done without producing a lateness; a degree of urgency $u_r \in U$, where U is the set of urgency levels in which patients can be classified; a demand $w_r \in W$ which depends on the deambulation condition of the patient, where W is the set of all possible deambulation conditions. The condition $t_r \leq e_r < l_r$ holds for all requests, and $t_r = e_r$ means that the request is arrived on the fly during the execution of the service, whereas $t_r < e_r$ implies that the request was programmed from the previous day.

A fleet composed of m vehicles is available to perform the transportation services. The vehicles are grouped into two types: ambulances, which drive along the road network of the campus, and electric vehicles, which drive along an underground network. When the vehicle arrives at a pavilion, the team of operators on board performs the pickup/delivery operation by possibly taking an elevator to reach and descend from the indicated floor. Each vehicle is available during the entire workday, and is located at the beginning of the day at the depot $o \in V$, which corresponds to the ground floor of the emergency service pavilion. Each vehicle k has a capacity q_k that cannot be exceeded by the total demand of the loaded requests. Despite the capacity, ambulances can load at most one patient per time, because of a specific law, and thus can only perform *single trips* between a pickup and a delivery location. In contrast, electric vehicles can load more than a patient per time, and hence can perform *multiple trips* between several pickup and delivery locations, while satisfying the capacity restriction at any moment of the trip. The estimation of the time required by vehicle k to travel along arc (i, j) is set to $t^k_{i,j}$, and includes the elevator time when required.

The aim of the problem is to fulfill all requests by design m routes along a day, while satisfying the following operational constraints: (1) each route starts and ends at the depot; (2) a vehicle's capacity is not exceeded at any time; (3) pickup and the delivery operations of a request are performed by the same vehicle; (4) each pickup is made before its own delivery; (5) a request r cannot be picked-up before e_r, but vehicles that arrive before that time can wait. Let τ_r define the time in which the delivery of request r is performed in a solution. We define the lateness of the request as $\ell_r = \max\{0, \tau_r - l_r\}$. The objective is to minimize the total weighted lateness $\sum_{r \in R} u_r \ell_r$. Possible delays in the transportation services can cause severe damages to the urgent patients. In addition to that, they can cause low satisfaction for all patients and negative disruption effects on the work schedules adopted by the technicians and the doctors of the hospital.

The optimization problem that we face lies in the area of Dynamic (Stochastic) One-to-One Pickup-and-Delivery Problems, see, e.g., Ritzinger et al. [2] for an up-to-date survey. The paper that most resembles ours is the one by Beaudry et al. [1], but differs from ours because it considers only one type of vehicles, one road network, and the minimization of the total (unweighted) lateness.

2 Solution Algorithms and Computational Results

We developed a number of algorithms, all based on the use of an *Adaptive Large Neighborhood Search* (ALNS) that we implemented following the framework by Ropke and Pisinger [3]. The ALNS is used to assign requests to vehicles and drive vehicles along the networks.

In the first approach, called *A-posteriori*, we suppose to know beforehand all the requests of the day, and run our ALNS just once to look for the best routes. This serves to provide an estimation of the best possible weighted lateness. The next three approaches are Dynamic Algorithms, that invoke the ALNS each time a new request is revealed. Such algorithms have no knowledge of future events and differ one another in the strategy adopted at the end of a delivery: in *Dynamic 1*, the operators remain at the same floor in which they performed the delivery; in *Dynamic 2*, the return to their vehicle but they remain at the same pavillon; in *Dynamic 3*, the vehicle goes instead back to the depot. The last approach that we present in this abstract makes use of stochastic information on future events, collected from the past and stored in a number of scenarios. The resulting *Dynamic Stochatic* algorithm simulates every possible assignment of patients to vehicles, repositioning of vehicles, and waiting strategy. Each decision is evaluated by running the ALNS on all scenarios, and the decision inducing the best average cost is implemented.

We coded our algorithms on C++ and ran them on a PC equipped whit an Intel 2.667 GHz Westmere EP X5650 processor. We performed extensive tests on 300 instances, corresponding to an interval of real activities occurred at the hospital in 2016. Aggregate results are presented in Table 1. The results show that the A-posteriori approach can achieve a weighted lateness of less than a minute on average per patient, which is extremely good. Among the dynamic methods, the third one is the best one as it produces a weighted lateness below 14 minutes, although this is obtained by a remarkable increase in the number of minutes spent on travelling. The dynamic stochastic algorithm decreases by about two minutes the average weighted lateness obtained by Dynamic 3, showing that the use of stochastic information is valuable. This is, however, achieved at the expenses of a high computational effort. Current research focuses on producing new faster high-quality dynamic stochastic algorithms.

Table 1: Aggregate computational results on 300 instances.

Average Values	A-Posteriori	Dynamic 1	Dynamic 2	Dynamic 3	Dynamic Stochastic
Traveled time (min)	1289.42	1574.08	632.57	1664.80	1789.64
Weighted lateness (min)	0.94	16.12	14.05	13.89	11.94
Computational time (sec)	4900.02	72.18	73.18	83.45	57646.31

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Vehicle Routing Decisions with Steep Roads

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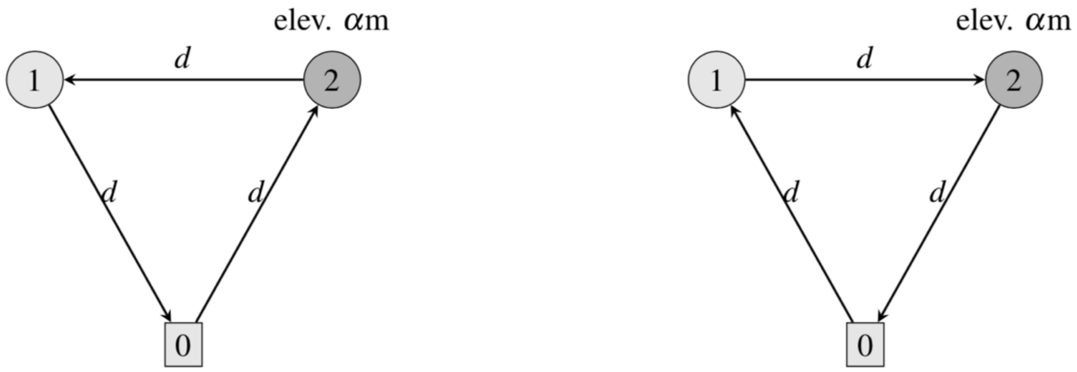
1 Introduction

The scientific literature on VRPs is extensive [1], but to our knowledge previous research on VRP assumes that routes are executed over a flat and horizontal terrain. VRP related costs are typically modeled as a weighted sum of total distance and total time spend by all routes representing fuel consumption costs, and fleet and driver wages, respectively. Moreover, only a small fraction of the VRP literature consider the effect of weight transported in fuel consumption, [2, 3, 4, 5, 6, 7]. A more realistic fuel consumption model is discussed in [8] depending on vehicle characteristics, speed, road grades and weight transported. The authors comment that it is cheaper to traverse roads downhill than uphill and account that the impact of weight transported over costs depends on road grades. No VRP model within the literature combines the effect of road grades and vehicle weight in the cost function model and, therefore, a classic VRP solution might be inefficient when routes are not planned considering the impact of steep roads.

Consider the example in Figure 1 presenting a single vehicle instance with a depot (0) and two customers (1 y 2). Both customers and the depot are located at the vertices of an equilateral triangle with side d km. Assume, for simplicity, that arc travel times are proportional to distance. The quantity of product demanded by customers 1 and 2 are q_1 ton and q_2 ton, respectively. Also, assume that $q_2 > q_1 > 0$ and that the vehicle has an unlimited freight transportation capacity. The depot and customer 1 are both at Sea Level (SL), while customer 2 is at α meters above SL. Also, consider that all roads represented by arcs are straight lines having constant road grades.



(a) Route $(0,2,1,0)$ (b) Route $(0,1,2,0)$

Figure 1. Feasible routes for a VRP instance with two customers

Both routes, *i.e.,* (0, 2, 1, 0) in Figure 1(a) and (0, 1, 2, 0) in Figure 1(b), are optimal when distance (or time) is minimized in the objective function. If we consider the effect of vehicle weight in fuel consumption, then we should first meet the heaviest demand and travel lighter most of the road reducing the ton-Km. In our example, we should deliver first to customer 2, who requested the heaviest load, and later to customer 1. In this case, the total ton-Km transported is $2\text{d}\cdot q_1+\text{d}\cdot q_2 < 2\text{d}\cdot q_2+\text{d}\cdot q_1$. In addition, if we consider the cost-function model proposed in [1] as our objective to minimize, one can show that (0,1,2,0) minimizes fuel consumption if 2 is placed at a high-enough elevation α above SL. For instance, the cost savings compared to route (0,2,1,0) are 9.2%, when $d = 2$ km, $q_1 = 5$ ton, $q_2 = 8$ ton, speed is 30 km/hr and $\alpha = 100$ meters. Intuitively, the vehicle incurs in less fuel consumption by gradually climbing the hill even if it incurs in additional ton-Km.

The previous exercise illustrates the value of considering the effect of slopes on fuel consumption. A cost-efficient routing model over geographies with varying altitudes requires to distinguish different vehicle cargo levels and road grades in arc costs. This problem is especially relevant to urban logistics operations in cities with important differences in altitude, such as coastal cities located between mountains and the sea, *e.g.* Valparaiso, Chile.

In this paper, we study a Vehicle Routing Problem in regions with Steep Roads (VRP-SR) integrating a fuel consumption model, that includes varying profiles of road grades per road segment and varying vehicle loads into a vehicle routing problem model. Our main objective is to quantify the potential savings in operational costs obtained by planning vehicle routes considering these effects in the cost function compared to one assuming a flat geography.

2 Proposed Model and Solution Method

We formulate the VRP-SR as a mixed integer linear problem considering arc costs that depend on the load of the vehicle. We build a solution algorithm that obtains a good feasible solution for any VRP-SR instance. Our algorithm exploits the VRP structure of a feasible solution and is based on heuristic frameworks for VRPs found in the literature. It combines solution construction heuristics, intra-route and inter-route local search moves and route partitioning strategies adapted to the VRP-SR. To do this last, all potential candidate solutions to local search moves where computed considering load dependent arc costs. Compared to the VRP, we account for two additional difficulties when implementing heuristics for the VRP-SR. First, a local search move is sequence dependent and cannot be evaluated only based on the arcs involved in the move; the cost of all routes involved in a move is recomputed from a point of change onwards. Second, the maximum vehicle load Q may be too large and could result in an intractably large number of arc cost, since they are load dependent. To avoid depending on the size of Q and reduce the number of queries, we reduced evaluations and only computed costs for a predefined load grid $\{q_1 = 0, q_2 ..., q_k, ..., q_K = Q\}$ of size K. In our experiments we set K=10.

3 Case Study

In order to estimate the potential benefits that could be generated, when including road grades in the cost function of the VRP, we conducted experiments with real geographical data from a hilly city, such as Valparaiso, Chile. We generated problem instances with different number of customer locations, $N \in \{10,20,50,100\}$, in which the set of customers are randomly selected through a geographical sampling stratified by heights among all nodes in the network, so that the set of customer locations to be visited in any instance are representative of customer locations in the city. Then for each problem size, we randomly generated 20 different instances. In all these instances, we assumed that the depot is located at the same location, which correspond to the address of the city port.

For comparison purposes, we considered two scenarios: (i) the uncapacitated scenario (UCS), in which weight loads are negligible, thus vehicles always travel with the same total weight and can visit as many customers per route; and (ii) the capacitated scenario (CS), which assume that all vehicles have a maximum capacity of 13 tons, and, to simplify our setting, we assume that each customer demand a load of weight equal to 1 ton. Therefore, thirteen is the maximum number of customers that can be visited per route.

In Table 1, we summarize a comparison of the results obtained from the application of our model, which explicitly considers the vehicle weight and road grades in fuel consumption, versus a benchmark model, in which road grades are not considered, also referred as the Flat-VRP.

Table 1: Cost savings as % when slopes are considered: Uncapacitated and Capacitated Scenarios

	N = 10		N = 20		N = 50		N = 100	
	max	Average	max	Average	max	Average	max	Average
Uncapacitated Scenario (UCS)	2.3	0.9	3.0	1.3	3.0	1.4	3.8	1.2
Capacitated Scenario (CS)	13.2	4.8	9.1	3.4	7.1	3.5	6.2	2.7

Our results show that in the capacitated scenarios (CS), regardless of problem size, the savings are significant, being on average 3.6% and ranging between 2.7% up to 4.8%. These savings on average tend to be larger on smaller size instances, and can reach up to 13.2%, however in the uncapacitated scenarios (UCS), with negligible weight loads, the savings are smaller and tend to be insignificant as the size of instances decrease.

In general, the routes suggested by solving the VRP-SR tend to sacrifice distance traveled to obtain reductions in fuel consumption. They tend to cluster customers in zones with similar altitudes so that changes in altitude along the route are avoided, particularly with a loaded vehicle. In particular, the routes generated avoid climbing steeped roads with a heavily loaded vehicle. Moreover, split routes are suggested to climb hills with lighter vehicles, even without using the maximum vehicle load capacity or route duration limit.

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On the Analysis of Time-Space Flow Model Reformulation of Dial-A-Ride Problem for Autonomous Taxi System

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Abstract

Key Words: Time-expanded Network, Space-Time Network, Network Flow Problem, Dial-A-Ride Problem

1 Introduction

We propose Autonomous Dial-a-Ride Problem (ADARP) as a variant of the Dial-a-Ride Problem (DARP) that models an autonomous taxi system. That is, with autonomous vehicles, the cost of taxi service will dramatically be reduced and it will become a primary mode of transportation replacing a significant portion of current private automobile trips. Robotic drivers may drastically cut the operating cost of the service, making the pricing highly competitive. Potential centralized control of the fleet may make it possible to operate the fleet in a systematic optimal way and reduce congestion and deadhead time, which may not only benefit the passenger by providing unprecedented service level, but also reduce environmental impact.

DARP is known to be NP-hard and its scalability is limited for real-world application. If an autonomous taxi system is solved as a DARP, the computational time may very well be cost prohibitive, if solvable at all. To provide a more realistic solution approach, the goal of this paper is to approximate the solution of ADARP by solving a time-expanded flow model called autonomous car-sharing system (ACSS) and re-construct a feasible solution for ADARP from ACSS. The quality of this approximation is analyzed and an upper bound is provided under certain assumptions.

Modeling a large-scale car-sharing system as a time-expanded flow model provides favorable computational properties as a linear network flow problem. Flow over time is a well-established research topic and has been successfully applied these models to various transportation systems. Hall et al. [2007] provides an overview of flow models theoretically and present an efficient algorithm to solve the multi-commodity flow problem over time. One notable application for a time-expanded flow model is for trucking industry where local shipments are consolidated at fixed hubs and sent in bulk from hub to hub [Wieberneit, 2008]. Researches have successfully exploited the structure of time-expanded flow model to facilitate the continuous-time routing models [Dash et al., 2012, Mahmoudi and Zhou, 2016].

There are two types of assumptions we make to model the continuous-time ADARP as a time-expanded flow model, ACSS. First is time discretization which helps transform a continuous time line with infinite possible time to a finite and more tractable subset of time stamps. As a consequence, the input and output of the model become time stamp based and therefore subject to errors.

Space aggregation is to group the demand based on nearby locations and only consider traffic between zones. To clarify, some transportation systems by their nature have hub-to-hub traffic and therefore no aggregation is necessary. However, under the context of an autonomous taxi system, the sheer amount of trips can reach hundreds of thousands or more within single metropolitan area. These trips do not necessarily need to have the same origin/destination. Therefore, it is necessary to group trips by the traffic analysis zones and only analyze zone-to-zone traffic.

Time discretization and space aggregation come at the cost of resolution. Researchers have been aware that the granularity of time stamps affect the error associated with time discretization or **time error** [Boland et al., 2017]. However, the impact of time error is yet analyzed systematically. Space aggregation tends to be very application specific. The error associated with the space aggregation or **space error** has yet been explicitly accounted for. This paper fills the gap by providing systematic analysis on the time and space errors and investigate the potential bounds for each error. The result provides basis to reconstruct solutions for a more challenging ADARP from the solution of a more tractable time-expanded flow model, ACSS. The formulations of ADARP and ACSS are presented as follows:

$$\textbf{(ADARP) Min:} \qquad \sum \mathbf{cx} + \sum \mathbf{hw} \tag{1}$$

Subject to:

$$\sum_{i\in\mathcal{O}}\sum_{j\in\mathcal{P}} x_{i,j} \leq |\mathcal{P}| \tag{2}$$

$$\sum_{i\in\{\mathcal{O},\mathcal{P}\}} x_{i,j} = \sum_{i\in\{\mathcal{P},\mathcal{D}\}} x_{j,i} = 1, \quad j \in \mathcal{P} \tag{3}$$

$$T_i + e_i - f_i = k_i, \quad i \in \mathcal{P} \tag{4}$$

$$x_{i,j} = 1 \Longrightarrow w_{i,j} \geq T_j - T_i - t_{i,j} - d_i \geq 0, \quad i \in \mathcal{P}, j \in \mathcal{P} \tag{5}$$

$$x_{i,j} = 1 \Longrightarrow w_{i,j} \geq T_j - t_{i,j} - a \geq 0, \quad i \in \mathcal{O}, j \in \mathcal{P} \tag{6}$$

$$x_{i,j} = 1 \Longrightarrow w_{i,j} \geq b - T_i - t_{i,j} - d_i \geq 0, \quad i \in \mathcal{P}, j \in \mathcal{D} \tag{7}$$

$$x_{i,j} = \{0,1\}, \quad (i,j) \in \mathcal{A} \tag{8}$$

$$T_i, w_{i,j} > 0, \quad i \in \mathcal{P} \tag{9}$$

Where x is the vector of binary flow variables and w is the vector of waiting time. c and h are cost of flow and vehicle inventory, respectively. $\mathcal{O}$, $\mathcal{P}$, $\mathcal{D}$ are the set of origin nodes, activity nodes, destination nodes. $\mathcal{A}$ is the set of arcs. To clarify, each node i represents a complete trip with one pick-up and one drop-off. Thus ADARP falls into the realm of vehicle scheduling problem [Haghani and Banihashemi, 2002].

$$\textbf{(ACSS) Min:} \qquad \sum \mathbf{cx} + \sum \mathbf{hV} \tag{10}$$

Subject to:

$$U_{i,j}(t) \geq U_{i,j}(t-1) + D_{i,j}(t) - X_{i,j}(t) \quad (i,j) \in \mathcal{A}, t \in \mathcal{T} \tag{11}$$

$$V_i(t) = V_i(t-1) + \sum_{j\in\mathcal{N}(i)}\sum_{\tau<t} \alpha_{j,i}(\tau,t)X_{j,i}(\tau) - \sum_{j\in\mathcal{N}(i)} X_{i,j}(t) \quad i \in \mathcal{N}, t \in \mathcal{T} \tag{12}$$

$$\sum_{i\in\mathcal{N}} V_i(0) = \sum_{i\in\mathcal{N}} V_i(|\mathcal{T}|) \tag{13}$$

$$X_{i,j}(t), U_{i,j}(t), V_i(t) \geq 0 \quad (i,j) \in \mathcal{A}, t \in \mathcal{T} \tag{14}$$

Similar to ADARP, the objective function is a combination of flow cost and vehicle inventory cost. X is the flow variable at each time stamp. U stands for back-ordered demand while V is the vehicle inventory.

2 Error Approximation and Solution Construction

ADARP can be viewed as a more general and disaggregate version of ACSS and the solution from ACSS (P_2) may work as a lower bound for the solution from ADARP (P_1).

$$P_1 = P_2 + \epsilon \tag{15}$$

There are two major parts of the error ϵ resulted from the loss of resolution in ACSS: the time error ϵ_T and the space error ϵ_S. To be clear, the time and space errors are intrinsically correlated and by no means they are independent to each other. However, by analyzing the time and space error independently, we may obtain the worst case scenario for each error. Although it is unlikely that the worst case scenario for both error types happens simultaneously, the combination of the worst case scenarios from the time and space errors may form a valid upper bound for the total error ϵ.

$$\epsilon \leq \max(\epsilon_T) + \max(\epsilon_S) \tag{16}$$

We derive analytical forms of expectation and maximum of space and time errors for each trip. The results reversely inform us about how time discretization can be made by setting acceptable maximum errors. These maximum errors also represent optimal solution gaps.

In addition, we conduct a case study using data from NYC Taxi & Limousine Commission to derive the actual empirical errors. Based on the understanding of the errors, we develop an algorithm to construct a feasible ADARP solution from the optimal ACSS solution with more granular time and space representation while the quality of the such solution quality is bounded by the upper bound of the errors.

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Geographic Pricing in Ridesharing Services

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1 Introduction

The optimal pricing of rides is one of the major challenges of the ridesharing services and in some cases such as surge pricing controversial [1]. Price discrimination or customer segmentation is a foundational idea in revenue management. The traditional approaches for price discrimination has had numerous advances in segmenting customers based on customers social affiliation, time of purchase, purchasing channel, quantity of purchase, offering coupons, and opaque selling. However, they lag behind when it comes to the usage of geographic information (location) of the customers. Obviously customers from different cities or different parts of a city are from different types and have different valuations and hence the price discrimination based on geographical information of customers can increase the revenue.

Most pricing research on the ridesharing services either do not consider geographical aspects, e.g. [2, 3, 4, 5, 6], or they consider spatial pricing in discrete settings over a large network, for example the paper [7] considers a spatial price discrimination model of a ride-sharing network with n locations equidistant from one another. This paper is among the very first to consider geographical price discrimination in ridesharing service in the continuous space.

In the classical price discrimination based on location [8], the customer segmentation $R_1, ..., R_n$ is exogenously given and for each segment R_i the demand function $d_i(p_i) = d(\boldsymbol{x}, p)$ for $\boldsymbol{x} \in R_i,\ p = p_i$ is knownand we are looking for optimal prices. It is natural to assume conversely that the set of prices is given (using other pricing methods such as surge pricing and data analysis the balance between supply and demand, and we look for the optimal segmentation. In this setting the demand distribution is known for each given price and we need to find the optimal segmentation, i.e. the optimal sub-region for applying each one of the prices, to maximize the revenue. This model is presented in section 2.

2 Problem Definition, Model, and Algorithm

Consider a geographic region R, not necessarily convex, in which a single seller wants to sell a single product and assume there is no competition or its effect is negligible. Let $\boldsymbol{p} = \{p_1, ..., p_n\}$ be the set of possible prices for the unit of the product in n sub-regions, and let $f_i,\ i = 1, ..., n$ denote the spatial distribution of demand for given price p_i. Let c denote the unit production cost, assuming it is the same in the entire region. This is our basic model and we try to relax these assumptions later. The objective is to find the optimal sub-regions $R_1, ..., R_n$ such that if we apply price p_i in sub-region R_i for all $i = 1, ..., n$, the total revenue of the seller is maximized. The demand in sub-region R_i must not exceed a given capacity k_i. This is the capacity of the facility that serves that sub-region. This problem can be formulated as follows

$$\begin{aligned} \underset{R_1,\dots,R_n}{\text{maximize}} \sum_{i=1}^{n} \iint_{R_i} (p_i - c) f_i(\boldsymbol{x})\, d\boldsymbol{x} \qquad & s.t. \\ \iint_{R_i} f_i(\boldsymbol{x})\, d\boldsymbol{x} \ \leq\ & k_i\,, \quad \forall i \\ R_i \cap R_j \ =\ & \emptyset\,, \quad \forall i \neq j \\ \cup_{i=1}^{n} R_i \ =\ & R. \end{aligned} \tag{1}$$

The problem (1) is equivalent to the following infinite dimensional integer program

$$\begin{aligned} \underset{I_1(\cdot),\dots,I_n(\cdot)}{\text{maximize}} \iint_R \sum_{i=1}^{n} (p_i - c) f_i(\boldsymbol{x}) I_i(\boldsymbol{x})\, d\boldsymbol{x} \qquad & s.t. \\ \iint_R f_i(\boldsymbol{x}) I_i(\boldsymbol{x})\, d\boldsymbol{x} \ \leq\ k_i\,, \qquad & \forall i \\ \sum_{i=1}^{n} I_i(\boldsymbol{x}) \ =\ 1\,, \qquad & \forall \boldsymbol{x} \in R \\ I_i(\boldsymbol{x}) \ \in\ \{0,1\}\,, \qquad & \forall i \end{aligned} \tag{2}$$

The linear programming relaxation of this is as follows

$$\begin{aligned} \underset{I_1(\cdot),\dots,I_n(\cdot)}{\text{maximize}} \iint_R \sum_{i=1}^{n} (p_i - c) f_i(\boldsymbol{x}) I_i(\boldsymbol{x})\, d\boldsymbol{x} \qquad & s.t. \\ \iint_R f_i(\boldsymbol{x}) I_i(\boldsymbol{x})\, d\boldsymbol{x} \ \leq\ k_i\,, \qquad & \forall i \\ \sum_{i=1}^{n} I_i(\boldsymbol{x}) \ =\ 1\,, \qquad & \forall \boldsymbol{x} \in R \\ I_i(\boldsymbol{x}) \ \geq\ 0\,, \qquad & \forall i \end{aligned} \tag{3}$$

which is useful since we can show that the integrality gap of this problem is zero.

The dual of the problem (3) is

$$\underset{\boldsymbol{\lambda} \geq 0}{\text{minimize}} \sum_{i=1}^{n} k_i \lambda_i + \iint_R \max_i \{ f_i(\boldsymbol{x})(p_i - c - \lambda_i) \} d\boldsymbol{x} \tag{4}$$

which is a non-smooth convex optimization problem. We will later propose a subgradient algorithm to solve this problem to optimality. The optimal partition $R_1^*, ..., R_n^*$ can be recovered from the optimal solution λ^* of the dual problem, due to the zero integrality gap of the problem (3).

Note that in this analysis the region R is not required to be convex and it can even have obstacles and in such cases the demand density of points located in obstacle area is zero.

Theorem 2.1 *For any point $\boldsymbol{x} \in R$ the optimal sub-region is determined by the index i such that $f_i(\boldsymbol{x})(p_i - c - \lambda_i^*) > f_j(\boldsymbol{x})(p_j - c - \lambda_j^*), \forall j \neq i$. The boundaries between any pair of optimal sub-regions R_i^* and R_j^* are of the form*

$$\partial(R_i^*) \cap \partial(R_j^*) = \left\{ \boldsymbol{x} \in R : \frac{f_i(\boldsymbol{x})(p_i - c - \lambda_i^*)}{f_j(\boldsymbol{x})(p_j - c - \lambda_j^*)} = 1 \right\},$$

which are the level sets of the function $\frac{f_i(\boldsymbol{x})}{f_j(\boldsymbol{x})}$.

Now, let h denote the objective function of problem (4). A vector $g \in \mathbb{R}^n$ is a subgradient vector for h at point λ if

$$h(\lambda') \geq h(\lambda) + g^T(\lambda' - \lambda), \ \forall \lambda'$$

Let vector $g \in \mathbb{R}^n$ be defined by $g_i = -\iint_{R_i} f_i(\boldsymbol{x}) d\boldsymbol{x} + k_i, \ i = 1, ..., n$. We can show that

$$h(\lambda') \quad \geq \quad h(\lambda) + g^T(\lambda' - \lambda), \tag{5}$$

Hence the vector $g \in \mathbb{R}^n$ is a subgradient for the objective function of dual problem (4). Using this subgradient we can easily develop a cutting plane algorithm to solve problem (4) to optimality and then use it to recover the optimal partition $\{R_1^*, ..., R_n^*\}$ for problem (1).

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A Dynamic, Peer-to-peer Ridesharing Model for Transit First Mile Access Problem

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1 Introduction

Suburban commuters often face the transit first mile access problem due to limited transit network coverage. To deal with this, they either drive to a park-and-ride location to take transit, or have to drive directly to the destination. Ridesharing, an emerging mode of transportation, can potentially solve this problem. In this setup, a driver can drive a ride-seeker to a transit station, from where the rider can take fixed route transit to their destination. The problem requires solving ridesharing matching problem with routing of riders in a multimodal transportation network. This makes the problem significantly more complex because in addition to matching with drivers, riders should be assigned optimal transit stops and optimal transit itineraries toward the destination.

In the literature pertinent to emerging transportation modes, limited research is devoted to the integration of ridesharing with transit. Masoud et al. (2017) used the dynamic programming framework in Masoud & Jayakrishnan (2017b) to solve the ridesharing problem by including the transit stops and transfers as go-to-points[1, 2]. The algorithm suffered from computational time issues in considering all transit stops as a drop-off location. They presented a small example of Los Angles metro red line and limited the number of transfer points to reduce the computational time. Stiglic et al. (2018) also presented a matching framework to match riders and drivers for transit, park-and-ride, or ridesharing mode [3]. They considered the closest stop to the destination as the alighting stop and used frequency-based transit service to simplify the problem. Neither of the studies have considered the complexities of the transit part of the trip or showed application in a real transit network.

We develop a transit-based ridesharing matching algorithm to solve this problem. The method uses a schedule-based transit shortest path algorithm to generate feasible matches and then uses a matching optimization program to find the optimal match between riders and drivers. The proposed method not only assigns an optimal driver to a rider, but also assigns an optimal transit stop and a transit vehicle trip departing from that stop for the rest of the riders itinerary. We also introduce the application of space-time prism in the context of ridesharing by utilizing constrained rider and driver movement in the network depending on available time budget and current location. Simulation tests show that the transit-based ridesharing can solve the first mile access problem efficiently and reduces vehicle-hours in the system significantly.

2 Methodology

The problem is addressed in two steps. The first step leverages *schedule-based transit shortest path* algorithm proposed in Khani et al. (2014) for finding feasible matches between drivers and riders by incorporating space-time constraints [4]. The algorithm returns a set of feasible matches which comprises of a rider, driver, drop off transit stop and the shortest path itinerary for the rider. The second step is to find an optimal match between riders and drivers. This is formalized as an Integer Linear Program (ILP). Two objectives are considered for the matching problem, 1) maximizing total number of matches, and 2) maximizing total vehicle-hours saving.

3 Preliminary Results

The activity-based travel demand forecasting model for Twin Cities, Minnesota, simulates more than 11M daily trips in a highway network with 23,812 nodes and 56,688 links. The transit network contains 13,672 stops and 9,042 vehicle trips provided by 191 routes. We tested the proposed model on a sample of 1,088 drivers and 1,097 riders in the morning peak period. The proposed space-time prism algorithm found 12,338 matches in about 7.7 minutes and only 263 drivers and 386 drivers were found feasible to match. The matching problem was solved in a fraction of a second. When the number of matches is maximized, on average, drivers make 11.4 min detour and riders wait for 0.5 min, ride transit for 5.3 min, and walk for 10.5 min (mostly at the destination), and the system saves 61.5 vehicle-hours from 200 matches. When the number of vehicle-hours saving is maximized, similar results, but with average 9.2 min driver detour and 6.3 min transit ride, the system saves 71.6 vehicle-hours from 198 matches.

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Multiwave Algorithm and Cluster-based Relocation Strategy for On-demand Crowdsourced Urban Delivery

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1 Introduction

Last-mile urban delivery is undergoing an exciting and challenging time with the rapid growth in e-commerce. The growth is particularly prominent in online food ordering and retail, compounded by the rising demand for on-demand deliveries, for example, within a couple of hours after the order is placed online. These demand-side evolutions have forced delivery service providers (DSP) to increase the resources (drivers, vehicles, and dispatching control capacity) allocated to meet delivery demand. The resulting jump in logistics cost imposes signficant financial burden on DSPs. Meanwhile, traditional employee- and vehicle asset-based deliveries have caused many negative consequences to the urban environment including increased congestion, pollution, wear-and-tear of road infrastructure, and shortage of parking space, which are increasingly at odds with the need and trend of developing livable and sustainable communities.

As an alternative to the traditional employee- and vehicle asset-based delivery model, crowdshipping has emerged recently as a new form of urban delivery thanks to the technology advances in crowdsourcing and mobile computing. In crowdshipping, a DSP solicits ordinary people, i.e., *crowdsourcees*, who have available time and may walk, bike, or drive to perform delivery to earn payment. By using crowdsourcees as "*ad-hoc* couriers", crowdshipping brings significant cost advantages to DSPs. In the real world, crowdshipping has been rapidly developing with many companies such as UberEats, Grubhub, DoorDash, Postmates, Deliv, Piggy Baggy, Amazon Flex, and Dada-Jing Dong Dao Jia reshaping the dinning, e-grocery, and online retail businesses.

In this paper, we investigate a specific type of crowdshipping that deal with on-demand shipping requests that constantly emerge from spatially distributed locations such as restaurants, and retail, grocery, and drug stores destined to customers who are also spatially distributed, within a short guaranteed time for delivery. Different from most existing crowdshipping research, we consider an online environment where crowdsourcees are spatially distributed, dedicated but with limited time availability, and dynamically entering and existing the crowdshipping system. A multi-start multi-wave algorithm (MWA) is designed to periodically assign shipping requetsts to en-route and idle crowdsourcees. A cluster-based strategy for crowdsourcee relocation is further developed that enables spatial balancing of shipping requests and crowdsourcees with look-ahead considerations. The combined implementation of MWA for shipping request-crowdsourcee assignment and cluster-based strategy for crowdsourcee relocation shows superior computational performance.

2 Multi-wave algorithm and crowdsourcee relocation strategy

The assignment of shipping requests to crowdsourcees is performed periodically in short intervals, e.g., once every 10 minutes. Each time an assignment is performed, the DSP updates the information about en-route and idle crowdsourcces, and assigned and unassigned crowdsourcees. An unassigned request may be inserted to an existing crowdsourcee route, or given to an idle crowdsourcee. Many possibilities exist for route updates, adjustment, and construction. For example, after a new request is accommodated by an existing crowdsourcee route, shipping cost may be reduced by moving the request to an early part of the route (intra-route move), or moving the request to a different route (inter-route move), or exchanging the request with another request in another route (1-exchange). Obviously, routing improvement based on exhaustive permutation is computationally expensive, not suitable for an on-demand delivery environment.

A multi-start multi-wave algorithm (MWA) is proposed in this paper to efficiently and effectively cope with dynamic shipping request-crowdsourcee assignment. Each time when the DSP performs an assignment, the algorithm first generates different intial solutions using primitive (but intuitve) assignment rules, e.g., based on crowdsourcee time availability or delivery urgency. For a given starting solution, MWA is then implemented.

The MWA developed in the crowdshipping context adapts the newly proposed framework by Glover (2016) for iterated neighborhood search which builds on probablistic solution selection, adaptive move record (AMR), and strategic oscillation. Each wave in MWA corresponds to a route, where each of the requests belonging to the route is moved to another route to reduce shipping cost. Each wave is built on routing improvement from previous waves. A wave in MWA consists of vertical and horizontal phases. The vertical phase performs inter-route move and adds good routing solutions to AMR. More specifically, MWA first generates candidate routing solutions by moving each request from the route of interest (with which the wave is associated) to another route. These solutions form the candidate list (CL). Based on on the cost improvement made by each solution compared to the initial solution, a portion of the solutions are subsequently chosen through probabilistic selection. These solutions are dropped out of CL and enter AMR. As the selected solutions are likely to lead to good solutions, further inter-route move is performed between the route of interest and another route, which generates complementary solutions.

Next, in the horizontal phase, strategic oscillation is applied to AMR, imitating the adaptive nature of human memory that a solution that repeatedly appears in one's head is likely to be a good solution. As such, AMR tracks the quality of a solution as well as the number of times the solution appears in AMR. If the number of appearances of a solution exceeds certain threshold, then the solution is tabued. The strategic oscillation requires repeated dropping of solutions from the beginning of the AMR list, and returning these solutions or their complementary solutions (whichever is better) to CL. Then probabilistic solution selection is again performed, which selects solutions from CL. Intra-route move are applied to the selected solutions, and the resulting new solutions are added to the end of the AMR list. The vertical and horizontal phases repeats until reaching the concluding phase. The minimum-cost solution from the tabu list is chosen to give the best result for request-crowdsourcee assignment.

As the origins of shipping requests (restaurants, and grocery, retail, and drug stores) and customers are likely to have different spatial distributions, overtime an imbalance between where crowdsourcees are located and where they are demanded will appear. This will compromise the ability of the crowdshipping system to promptly respond to new requests and meet delivery time requirement. To mitigate this problem, a cluster-based strategy is proposed to proactively relocate crowdsourcees. The strategy consists of first constructing clusters of unassigned existing and anticipated future requests, and then formulating the problem of idle crowdsourcee relocation as a minimum cost flow problem. Totaly unimodularity of the problem can be shown which suggests that relocation decision can be made in short time.

3 Numerical implementation

The combined MWA for shipping request-crowdsourcee assignment and cluster-based strategy for crowdsourcee relocation is implemented in a simulated crowdshipping environment with over 800 requests and 150 crowdsourcees in the course of a day. We find that MWA alone works very efficiently, meeting the real-time requirement for efficient crowdsourcee assignment, at the same time generating lower system delivery cost than simple insertion- and intra-route move-based heuristics, and tabu search- and simulated annealing-based metaheuristics. The addition of the relocation strategy results in even further cost reduction. Several operational insights are obtained about the interaction between system total shipping cost, delivery time guarantee, the cost competitiveness of a crowdsourcee vs. a backup vehicle, and service zone size.

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Dynamic Pricing and Matching in Ride-Hailing Platforms

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1 Introduction

Ride-hailing platforms such as Uber, Lyft and DiDi have achieved explosive growth and reshaped urban transportation. The theory and technologies behind these platforms have become one of the most active research areas in the fields of economics, operations research, computer science, and transportation engineering. In particular, advanced matching and dynamic pricing algorithms – the two key levers in ride-hailing – have received tremendous attention from the research community and are continuously being designed and implemented at industrial scales by ride-hailing platforms. In this paper (Korolko et al. 2018), we first review matching and dynamic pricing techniques in ride-hailing, and show that these are critical for providing an experience with low waiting time for both riders and drivers. We point out that if dynamic pricing is utilized as the single marketplace lever, price can be high and volatile. To address this issue, we link the two levers together by introducing a pool-matching mechanism called dynamic waiting which varies rider waiting and walking before dispatch, which is inspired by a recent carpooling product Express Pool from Uber.

2 Methodologies

The first part of the paper reviews most practically relevant literature with respect to dynamic pricing and matching. We then introduce how dynamic waiting (DW) works. Assume each driver (car) can hold up to two riders (which can be readily generalized to more riders), and all riders opt into pooling with other riders. Two riders are pool-matched if their pickup locations as well as dropoff locations are close; i.e., the distance between the pickup locations as well as the dropoff locations is within walkable range (*walking radius*). Furthermore, they are picked up and dropped off at the same time and location, with the pickup and dropoff locations set to be the middle points so that two riders can walk equal distances. DW also asks rider to dynamically wait up to certain time (*waiting window*) before dispatch. At the end of each waiting window, we examine all the batched requests and find the maximum number of matches out of all requests.

We study a steady-state model for pricing and matching in ride-hailing. The platform determines the dynamic price as well as window of time to wait before dispatching drivers to incoming ride requests. We characterize the system equilibrium of supply and demand under different prices and waiting windows. We reveal insights on system performance, as well as welfare-maximizing pricing and waiting strategies.

3 Results

We show using San Francisco data from Uber that by jointly optimizing dynamic pricing and dynamic waiting, price variability can be mitigated by 48%, while increasing total social welfare by 1.4%. We also highlight several key practical challenges and directions of future research from a practitioner's perspective.

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Reliable Parcel Routing Policy in a Physical Internet

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1 Introduction

We introduce a logistic model for the delivery of parcels to Service Points (SPs) that are used as drop off, pickup and intermediate storage locations. A parcel may be carried from its origin to its destination in several legs via several possible intermediate SPs. Such a system constitutes a physical internet (PI) service network [4]. The PI network is a generalization of the current practice of using a hierarchical network. For the design of such service networks see [1], [2]. The PI service network topology presents an opportunity to improve service network in terms of robustness, delivery time and efficiency. In this abstract, we focus on the online optimization of the routes of the parcels in PI.

2 Problem Definition

The problem is defined by the following input: a set of capacitated SPs, a distance matrix between the SPs, and a set of fixed routes and schedule of the delivery vehicle that constitute the service network. Parcels of identical dimensions arrive at the system according to a known stochastic process. Each parcel is characterized by an origin and a destination. When a parcel arrives at the system, it can be admitted or rejected. Parcel rejection is at the discretion of the operator and may occur even if the SP is not at full capacity at the parcel arrival moment. After the parcel reaches its destination SP, it is collected by the recipient and the capacity it occupies in this SP is released. The time between the arrival of the parcel and its pickup is random but bounded from above. The parcel routing problem is to find a reliable policy for rejection and routing of parcels with the following two objectives: minimizing the expected number of rejected parcels and expected delivery time. The route of a parcel is defined by a series of pickup and drop-off by several vehicle tours. To increase robustness a buffer time between each drop-off and pickup of a parcel is imposed. A routing policy is reliable if the exact delivery time of each parcel can be determined upon its admission.

3 Methodology

The current and planned future states of the system are represented by time expanded graphs. Each planned arrival of a courier at an SP is referred to as an event. For each event, we define a pair of nodes in the graph, referred to as a route-node and a storage-node. Both nodes are associated with the time of the event and its SP. The arcs in the graph are as follows: loading arcs, which connect each storage-node to the route-node of the same event; storage arcs, which connect each storage-node to the storage-node of the next event in the same SP; route arcs, which connect the route nodes and represent the tours of the vehicles and their schedule; and finally, the buffer-arcs, which connect each route-node to the storage-node of the earliest event at the SP that occurs at least a buffer-time later. Each arc in the graph is associated with two properties, i.e., cost and remaining capacity. The length of each arc is initially set to the time difference between its start and end nodes. The remaining capacity property represents the maximum number of additional parcels that can be assigned to the respective resource. In the case of route-arcs, this represents the available capacity of the vehicle, and in the case of the storage-arcs, this is the available capacity at the SP during the epoch between the two events. The buffer-arcs are not associated directly with capacity, but their utilization is accounted for by their parallel storage-arc(s). The initial capacities represent the physical capacity of the corresponding resources.

Whenever a parcel arrives at the system, a minimum cost path from the previous storage node in its origin to the earliest possible storage-node in its destination on the time-expanded graph is calculated. Only arcs with positive remaining capacity are considered and only destination nodes with positive remaining storage capacity for the period allowed for pickup are considered. If no such path exists, or if its length is deemed unacceptable by the planner, the parcel is rejected. Otherwise, the parcel is, and the remaining capacity of the arcs along the path is reduced by one. At this point, the sender and the recipient are notified about the delivery time.

While the myopic parcel routing policy described above is optimal when the capacity constraints of the vehicle and the SP are unbinding, the policy is too short-sighted if this is not the case. Indeed, parcels that arrive earlier may congest resources that may be more beneficial later. To overcome this shortfall, we update the cost of each arc in the graph based on its congestion probability. The increased cost diverts some parcels to less congested routes if this does not require a substantial increase in their delivery time. The shape of this cost increasing function was created using a response surface analysis of several simulated systems. The details of this procedure are out of the scope of this abstract.

4 Numerical Experiment

In this section, we present a sample of the results obtained in our numerical study. We created a simulation environment where parcels arrive at the SPs according to a Poisson arrival process and are routed using our algorithm by two sets of scheduled tours of vehicles. One represents a hierarchical service network in a favorable setting, and one represents a simple PI service network. The two networks consist of a 20×20 grid with SPs that are located at equal distances of a five-minute drive from each other. This geography is equivalent in size to a relatively large metropolitan area with dense coverage of service points. For the hierarchical service network, the location of the depot coincides with the location of one of the SPs in the center of the grid. The hierarchical network is served by 40 tours that start and end at the hub and visit 10 SPs each. The tours are served in a round robin fashion by 40 couriers, and each SP is visited by a courier exactly every 3.5 hours. The PI service network consists of 40 tours each served by a single vehicle. Twenty tours run back and forth along the south-north lines of the grid and twenty along the east-west lines. The location of each vehicle at the beginning of the planning horizon was selected randomly. The total cycle time of each tour in the PI is 6.5 hours. The service time at each SP was assumed five minutes for the PI network and four minutes for the hierarchical network. We set the service time to be shorter for the hierarchical network since the amount and complexity of the work in this setting is slightly lower. The service time of the vehicle in the hub is 25 minutes, since the task of fully unloading, loading and sorting the parcels is more time-consuming. The buffer time was set to 5 minutes in both systems, i.e., a parcel can be sent on a different vehicle five minutes after the vehicle that dropped it off left the SP or the hub. The parcels arrived at a rate of 50 parcels/day to each SP, and their destinations were selected randomly. In total, this represents a rate of 20,000 parcels/day. The parcel pickup time by the recipient was drawn from U(0,12) hours. We considered only a single priority class. The capacity of the SPs was set to 100 parcels, and the hub was uncapacitated.

We tested two levels for the capacity of the vehicles, namely, 100 and 130 parcels. Under these conditions, both systems exhibited stable behavior and reached a steady state after a few days of simulation. The simulation was run for 40 days (excluding warmup times), and no parcel rejection was observed. In addition, we simulated without capacity constraints on the vehicles and SPs to explore the potential of both topologies when resources are abundant. Both service network topologies were tested under the myopic policy and the myopic policy with congestion cost.

Vehicle Capacity	SP Capacity	Hierarchical	PI Myopic	PI congestion
100	100	7:28	7:23	6:50
130	100	7:25	6:36	6:29
Unbinding	unbinding	7:25	6:28	n/a

In the table, we present the average parcel delivery time in hours and minutes for both topologies under some capacity conditions and routing policies. The capacities were selected such that the rejection rate is nearly zero in all cases. Moreover, with slightly smaller capacities the Hierarchical network rejects significant share of the parcels while the PI network with congestion cost still able to serve all the parcels.

5 Conclusions

We presented a routing policy for parcels in a PI that can provide reliable information on the delivery time in advance. We demonstrated that this policy performs better in a PI service network topology than in the traditional hierarchical one. We note that the PI topology does not require the expensive construction and operation of urban sorting facilities and may offer a robust and economical method to deliver parcels. The method should be tested and tuned with different service networks, and resource capacities. A method to design an effective service network that operates under such a parcel routing policy is an interesting topic for future research.

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A network flow approach to relocating vehicles and assigning operators for large-scale one-way carsharing systems

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1 Introduction

Carsharing is an emerging form of shared economy in the transportation sector, for which shared cars are either provided by a carsharing service company or circulated among private car owners and users in a neighborhood or community. Compared to private car ownership, carsharing offers a cost-effective and environment-friendly solution for personal transportation, and has been playing a critical role in transforming ownership-based transportation modes toward the so-called mobility-as-a-service paradigm.

Different from the *eodem loco* pickup-and-dropoff policy enacted by traditional car rental companies, most of current carsharing services allow for taking and returning a car at different service stations. The one-way setting greatly enhances the car renting and returning convenience of travelers and increases the attractiveness and competitiveness of carsharing in the transportation service market. This flexibility, however, comes up with an imbalance problem between car supply and user demand, under which some stations may face car shortage and hence a decreasing level of service while some others encounter car abundance and extra parking costs.

To reduce the negative impacts due to the supply-demand imbalance, carsharing planners and managers suggested various technological and management strategies in the past. The most primitive and widely accepted strategy is vehicle relocation, the main operation of which is to dispatch a group of full-time or part-time human operators to drive shared vehicles from those stations with car abundance to other stations with car shortage. The movement of an operator between two consecutive driving tasks, if any, typically relies on another dedicated or public vehicle. Obviously, in a large-scale carsharing system, these operator dispatchment and movement activities are rather cost- and time-consuming, involving a complex decision process executed at a frequent basis in real time, which must be implemented on the individual level and may comprise hundreds of or even thousands of vehicles and operators. This decision process relies on solving a *combined vehicle relocation and operator assignment problem*.

2 Relevant Research

Dependent on problem size and complexity, vehicle refueling requirement, relocation resource type, time dependence of the system, and other system operations features, the combined vehicle relocation and operator assignment problem with one-way carsharing systems may be studied in various mathematical forms and for different application purposes and scopes. The last decade observed a number of research efforts in developing modeling and computational methods for this type of problems, the majority of which are of the mathematical programming type.

Kek et al. [1] first developed a linear integer programming model for optimizing the combined vehicle relocation and operator assignment, in which four types of activities of operators, such as waiting, maintenance, relocation and movement are included. Taking into account the limited driving range of shared electric vehicles, Bruglieri et al. [2] treated their problem as a special paired pickup and delivery problem with time windows and proposed a mixed linear integer programming model. Nourinejad et al. [3] simply defined their problem as a combination of two multi-traveling salesman problems, one for the vehicle relocation and another for the operator movement, and wrote it in the linear integer programming form as well. Boyacı et al. [4] proposed a bi-objective linear integer programming model for their problem with lexicographically ordered objective functions: Maximization of the number of satisfied users and minimization of the total system cost. Recently, Xu et al. [5] presented a nonlinear integer programming model for not only optimizing vehicle relocation and operator assignment but also fleet sizing and trip pricing, where the latter decisions are typically made on the tactical level. In a similar modeling framework, Zhao et al. [6] simultaneously considered the optimal allocations of vehicles and operators on the strategic level and the vehicle relocation and operator assignment on the operational level and accordingly formulated this problem into a mixed linear integer programming model. In the last two studies, the driving range limit imposed by the battery capacity of shared electric vehicles are explicitly considered in their problem formulations.

3 Methodology

The aforementioned studies in the literature all use integer variables to represent the numbers of vehicles and operators at stations and in movement, implying that the resulting models can only be optimally solved for a small-size system with a very limited number of vehicles and operators. However, a carsharing company serving a metropolitan area may operate thousands of vehicles and employ hundreds of operators in its daily operations. For such a large-scale system, the previous models involving integer variables may be hardly operationable in practice. To overcome this computational difficulty, this research models the parking/waiting and movement of vehicles and operators as vehicular and human flows and reformulates the combined vehicle relocation and operator assignment problem via a network flow approach.

Specifically, given a time-expanded metanetwork where each node represents a station at a time moment and each link denotes a minimum-cost path between two stations or a parking/waiting action at a station between two consecutive time moments, we introduce the concept of trip chain, which is defined as a sequence or series of trips, where a trip may be a user's travel trip, an operator's relocation trip, or an operator's movement trip, for a sole travel purpose bounded by short-duration stops at parking stations. Here we use trip chain as the basic modeling element to describe the parking/waiting and movement of individual vehicles, operators and users. As shown in Figure 1, the combination of those different types of trips on the link level forms different network flows, such as user flows, vehicle flows, and operator flows, ultimately resulting in a minimum-cost flow problem of the three types of flows.

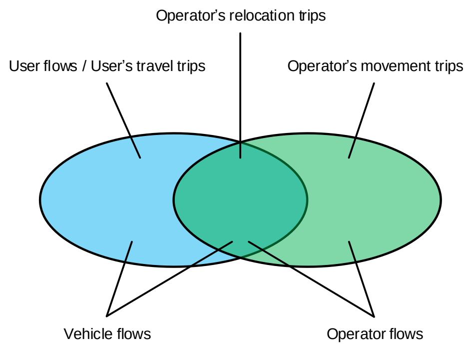

Figure 1 The relationship between trips and flows through combination

The modeling and solution advantage of this network flow problem stems from its linear programming form, in which the numbers of vehicles, operators and users are all written as non-negative continuous variables. As a result, the linear programming problem can be efficiently solved by well-known algorithms such as the simplex method or its more efficient implementation—the Dantzig-Wolfe decomposition—and conveniently analyzed by the primal-dual and sensitivity analysis techniques of linear programming. Moreover, since the coefficient matrix of the constraint set is totally unimodular and the right-hand-side parameters of the constraint set are all integers, the solution of this linear programming problem is guaranteed to be all valued at integers. This solution integrality property promises appealing practical implementability and interpretability of solutions.

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Station location and vehicle distribution for round-trip car sharing systems

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1 Introduction

Car sharing systems have existed since the 1970s and have become increasingly popular in the last decades. While these systems may operate under a variety of assumptions, there is often a trade-off between user convenience and operational cost for the operator [1]. In this study, we consider round-trip car sharing systems in which users are required to return their vehicle to the same station they departed from. A major advantage for operators of this type of system is that re-balancing is not an issue: the number of vehicles allocated to each station will remain constant. Consequently, the placement of the stations and the distribution of vehicles among the stations becomes the main driving factor of the system's ability to match the users' demands. We propose a tactical decision support model to optimize these two long-term decisions simultaneously. Integer programming formulations and a simulated annealing metaheuristic are proposed to solve the underlying combinatorial optimization problem.

2 Problem formulation

The considered geographic area is discretized into zones based on a grid overlay or some other more informed approach which, for example, takes into account user density in different parts of the geographic area. The main decision is to assign each vehicle of a fixed fleet to a zone. The number of vehicles which may be assigned to a zone is not restricted; it is assumed there is sufficient capacity in each zone for the assigned vehicles.

A second decision involves the assignment of user reservations to the vehicles. A reservation is characterized by a start and end time (which may be on different days), the zone in which it is made and a required vehicle type. Typically only a subset of all vehicles matches the required vehicle type. It is assumed that a user will only accept a vehicle if it is located in their own zone or in an adjacent zone.

The goal is to find a distribution of vehicles to zones such that as many reservations as possible can be assigned to a feasible vehicle. Overlapping reservations clearly cannot be assigned to the same vehicle. If a reservation cannot be assigned, a large cost is incurred. There is an additional cost if a reservation not assigned to a vehicle in an adjacent zone to account for user inconvenience. Finally, there is a cost associated with placing a vehicle in a zone to model operational costs for the car-sharing operator caused by, for example, commissions to the city administration for reserving parking spaces. The objective is to minimize a weighted sum of these three costs.

3 Solution approaches

We have formulated this problem as a compact integer programming problem. Computational experiments showed that this initial formulation suffered from symmetry when two or more vehicles may be assigned to the same set of reservations. This symmetry is broken by considering vehicle types rather than individual vehicles. A post-processing algorithm which runs in polynomial time ensures that complete solutions are derived again from the symmetry-breaking formulation's solution.

Even by reducing the symmetry, large problem instances could not be solved within reasonable computation time. For these instances, we propose a simulated annealing metaheuristic. Using a direct solution representation based on the two levels of decision-making, and a limited set of neighborhoods, we were able to obtain near-optimal solutions in limited computation time. Both solution approaches are compared in a computational study which includes both real-world problem instances and computer-generated instances in which parameters are varied in a controlled manner.

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A Branch and Price algorithm for the Pickup and Delivery Problem with Transfers

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1 Introduction

The pickup and delivery problem with transfers (PDP-T) consists of transporting items or passengers from pickup to delivery points allowing transfers to lower overall costs by taking advantage of available resources, resulting in a more difficult but realistic approach than the version without transfers. In the literature this problem has been treated mostly heuristically due to its complexity ([1], [6], [3], [4], [8], [12], [10], [5]), although we find some exact methods able to solve small instances ([11], [7], [2]). The objective of the present research is to solve the PDP-T through an exact method considering much larger instances in reduced computational times. To the best of our knowledge, the best effort solved 75 requests and 4 transfer points running for one hour with average gaps of 33.84% [9] including scheduled lines.

2 Set partitioning formulation for the PDP-T

Let n denote the number of requests. To obtain a set partitioning formulation of the PDP-T, we define three types of feasible routes that satisfy system constraints (1)-(9): the set K_1 are routes from depot to depot ($D \to D$), the set K_2 are routes from depot to the transfer point ($D \to T$), picking requests that will be served later by a route in set K_3, which contains routes from the transfer point to the depot ($T \to D$) allowing the delivery of requests that were previously served by a route belonging to set K_2. For each route $k \in K_1 \cup K_2 \cup K_3$, let C_k be the cost of the route and let a_i^k a binary indicator stating if node $i \in P \cup D$ belongs to route k or not. In addition, let X_k be a binary variable equal to 1 if and only if route $k \in K_1 \cup K_2 \cup K_3$ is used in the solution. The integer variable Z is the number of direct trips between the depot and the transfer point required since routes belonging to sets K_2 and K_3 can configure feasible paths with a section of the route not visiting nodes before arriving to or departing from the transfer point, being B_k the latest or earliest time that a vehicle serving route K_2 or K_3 reaches or leaves the transfer point, respectively. And finally, let $Y_{k\hat{k}}$ be a binary variable equal to 1 if feasible paths $k \in K_2$ and $\hat{k} \in K_3$ are served by the same vehicle. PDP-T can then be formulated as the following set partitioning problem.

2.1 The master problem

The objective function (1) minimizes the cost of the chosen routes, while constraints (2) ensure that every request is served once. Constraints (3)-(4) strengthen the algorithm in the branching scheme through the η_i variables. Constraints (5)-(6) control that routes belonging to K_2 can be paired with a route type K_3 and viceversa. Constraint (7) computes the value of variable Z. Constraint (8) cuts solutions where a request picked up by a route of set K_2 can not be delivered by a route in set K_3 (route K_2 does not arrive before route K_3 to the transfer point). Constraint (9) avoids the service of a route K_2 and a route K_3 by the same vehicle if both routes do not synchronize at the transfer point .

$$min \quad F_{PDP-T} = \sum_{k \in K} C_k \cdot X_k + C^z \cdot Z \tag{1}$$

$$(\alpha_i) \quad \sum_{k \in K} a_i^k \cdot X_k = 1 \quad \forall i \in P \cup D \tag{2}$$

$$(\omega_i) \quad \sum_{k \in K_2} X_k \cdot (a_i^k - a_{i+n}^k) - \eta_i = 0 \quad \forall i \in R \tag{3}$$

$$(\theta_i) \quad \sum_{k \in K_3} X_k \cdot (a_i^k - a_{i+n}^k) + \eta_i = 0 \quad \forall i \in R \tag{4}$$

$$(\gamma_k) \quad \sum_{\hat{k} \in K_3} Y_{k\hat{k}} \leq X_k \quad \forall k \in K_2 \tag{5}$$

$$(\lambda_{\hat{k}}) \quad \sum_{k \in K_2} Y_{k\hat{k}} \leq X_{\hat{k}} \quad \forall \hat{k} \in K_3 \tag{6}$$

$$(\pi) \quad \sum_{k \in K_2} X_k + \sum_{\hat{k} \in K_3} X_{\hat{k}} - 2 \cdot \sum_{\hat{k} \in K_3} \sum_{k \in K_2} Y_{k\hat{k}} = Z \tag{7}$$

$$(\delta_{k\hat{k}}) \quad X_k + X_{\hat{k}} \leq 1 \quad \forall \hat{k} \in K_3,\ k \in K_2 \quad if \begin{cases} B_{\hat{k}} - B_k < d_r \\ \exists i \in R :\ a_i^k = 1 \wedge a_{i+n}^{\hat{k}} = 1 \end{cases} \tag{8}$$

$$(\sigma_{k\hat{k}}) \quad Y_{k\hat{k}} = 0 \quad \forall \hat{k} \in K_3\ k \in K_2 \quad if\ B_{\hat{k}} - B_k < d_r \tag{9}$$

$$X_k \in [0, 1] \tag{10}$$

3 Subproblem: Constrained Shortest Path Problems

The subproblem can be viewed as a shortest path problem with precedence, capacity and time windows constraints. We build elementary shortest paths with resource constraints (ESPRC) using dynamic programming. For routes of type K_2 we assume that these routes are *left justified* i.e. each route performs the sequence as earliest as possible and similarly for K_3 we assume that these routes are *right justified* i.e. each route performs the sequence as late as possible.

3.1 The pricing problems

Specific label extension conditions for each set of feasible routes are imposed. The pricing problems associated with (1)-(10) for each set of routes are defined in the first paragraph of literal 2.

- The pricing problem for routes of type K_1 is similar to that developed for normal PDP problems found in the literature. Nonetheless, triangular inequalities do not apply (condition $O(L_1) = O(L_2)$ instead $O(L_1) \subseteq O(L_2)$). This is because constraint (2) applies not only to pickup nodes but also to delivery nodes, due to the existence of routes K_2 where the delivery point is not always reached. Pricing problem for routes K_1 is as follows:

$$\bar{C}_k = C_k - \sum_{i \in R} \alpha_i \cdot a_i^k \tag{11}$$

$$\bar{C}_{ij} = \begin{cases} C_{ij} - \alpha_i & \forall i \in P \cup D, \quad \forall j \in N \\ C_{ij} & \forall i \in \{transfer\ point,\ depot\}, \quad \forall j \in N \end{cases} \tag{12}$$

- The pricing problem for routes of type K_2 and K_3 cannot be performed totally by pricing arcs as in K_1 route types. Besides, the term π associated with constraint (7), dual cost of constraints (8) depends on the new route to be created; constraints associated with routes K_2 and K_3, are reformulated as equivalent set of equations (13):

$$(\delta_i) \sum_{\hat{k} \in \tilde{K}_3(i)} B_{\hat{k}} \cdot X_{\hat{k}} - \sum_{k \in \tilde{K}_2(i)} (d_r + B_k) \cdot X_k \geq 0 \quad \forall i \in R \tag{13}$$

  The problem here, is that new dual costs ($+\delta_i \cdot (B_k + d_r)$ and $-\delta_i \cdot B_k$ for routes K_2 and K_3 respectively) require parameter B_k which is not known until the end of the dynamic programming that need those values to perform the algorithm. We compute these terms at the end of the creation of new routes using the parameter as a constant to determine if the new route must be included in the model or not. The pricing problem for routes K_2 is as follows:

$$\bar{C}_k = C_k - \sum_{i \in R} \alpha_i \cdot a_i^k - \sum_{i \in R} \omega_i \cdot (a_i^k - a_{i+n}^k) - \sum_{i \in P \cup D} \gamma_i + \sum_{i \in R} \mathbb{1}_{\left[a_i^k - a_{i+n}^k = 1\right]} \delta_i \cdot (B_k + d_r) - \pi \tag{14}$$

$$\bar{C}_{ij} = \begin{cases} C_{ij} - \alpha_i - \omega_i - \gamma_i + \mathbb{1}_{\left[a_i^k - a_{i+n}^k = 1\right]} \delta_i \cdot (B_k + d_r) & \forall i \in P, \quad \forall j \in N \\ C_{ij} - \alpha_i + \omega_i - \gamma_i \quad \forall i \in D, \quad \forall j \in N \\ C_{ij} - \pi \quad \forall i \in \{depot\}, \quad \forall j \in N \end{cases} \tag{15}$$

- The pricing problem for K_3 type new routes are created similarly to routes K_2 as a mirror method, where we start from the depot but treating delivery points as pickup points and viceversa. Capacity and time windows parameters are recalculated properly to lead the problem. The pricing problem for routes K_3 is as follows:

$$\bar{C}_k = C_k - \sum_{i \in R} \alpha_i \cdot a_{i+n}^k - \sum_{i \in R} \theta_i \cdot (a_i^k - a_{i+n}^k) - \sum_{i \in P \cup D} \lambda_i - \sum_{i \in R} \mathbb{1}_{[a_i^k - a_{i+n}^k = -1]} \delta_i \cdot B_k - \pi \tag{16}$$

$$\bar{C}_{ij} = \begin{cases} C_{ij} - \alpha_i - \theta_i & \forall i \in P, \quad \forall j \in N \\ C_{ij} - \alpha_i + \theta_i - \mathbb{1}_{[a_i^k - a_{i+n}^k = -1]} \delta_i \cdot B_k & \forall i \in D, \quad \forall j \in N \\ C_{ij} - \pi \quad \forall i \in \{depot\}, & \forall j \in N \end{cases} \tag{17}$$

4 Branching strategy

In order to obtain integral solutions, we adopt a branching strategy in two levels. First, we are splitting the polyhedra of the problem by means of variables eta_i; these variables provide information about the attractiveness of serving request i through the transfer point, turning off all those routes that do not accomplish this condition. Second, we are branching through the typical criterium of arcs. Currently, we are working on establishing a third level that branch in the number of employed vehicles.

5 Computational experiments

Below we show some preliminary results of instances of 20 nodes (10 requests). Table 1 shows the solution cost, solution time, number of iterations to reach the optimal solution, total number of each set of routes that were created in the execution of the algorithm and the number of $Y_{k\hat{k}}$ variables (potencial synchronizations between routes).

Data set	**Solution cost**	**Solution time**	**Iterations**	**Col 1**	**Col 2**	**Col 3**	$Y_{k\hat{k}}$
1	2635.9	459	48	10	302	183	6631
2	3321.8	1562	254	11	893	2290	114164
3	2551.1	1683	27	10	215	148	4199

Table 1: Data set features.

Route	**length**	**Total load**	**Depot time**
0 1 2 0	394	0	394
0 17 18 0	30.2	0	629
0 7 15 19 TP	557.9	57	557.9
0 11 12 3 TP	512.6	42	512.6
TP 5 6 13 9 20 14 10 0	810	-3	588.8
TP 16 4 8 0	331.2	-96	613.5

Table 2: Data set 1

Route	length	Total load	Depot time
0 7 TP	473.1	35	473.1
0 3 TP	381.3	42	395.1
0 1 2 11 19 12 20 0	758.8	0	758.8
TP 5 13 6 14 17 18 0	674	0	321.3
0 15 9 16 10 0	560.1	0	838.7
TP 8 4 0	470.2	-77	474.5

Table 3: Data set 2

Route	length	Total load	Depot time
0 15 3 7 TP	331.2	96	826.5
0 5 6 13 9 10 14 19 20 TP	810	0	851.2
TP 11 12 4 0	512.6	-42	927.4
0 1 2 0	394	0	1046
0 17 18 0	30.2	0	811
TP 8 16 0	473.1	-54	966.9

Table 4: Data set 3

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Courteous or Crude? Understanding and Shaping User Behavior in Ride-hailing*

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Ride-hailing platforms such as Didi Chuxing, Lyft and Uber, are changing the competitive landscape in transportation and logistics industries. These platforms provide new ways to match supply and demand, create a marketplace, and as such provide improvements in efficiency.

In this paper we show that a ride-hailing platform could optimize its performance by utilizing rider ratings information when proposing matches to drivers. Specifically, we analyze system performance, including expected payoffs of both riders and drivers and asymptotic states of the system, in a setting in which drivers have an option to be selective, i.e., they can choose to incur cost in order to learn the rating of a rider in a platform-proposed match *before* deciding whether to accept or reject the ride. We establish that the platform can additionally use traditional instruments such as price and wage adjustments, to steer the system towards a sustainable equilibrium state.

The key to our analysis is an inherently asymmetric treatment of riders via their rating which reflects their conduct, and drivers via their selectivity which reflects (not) incurring cost of (not) learning about the rider before accepting/rejecting a platform-proposed match. Specifically, we assume that riders may be either *courteous* or *crude* during service. A courteous rider makes an effort at her own cost to conduct in a way that does not impose any negative externalities on her driver during service. (In this paper, "courteous" does not refer to specific behavioral patterns, but generally refers to rider behavior which does not negatively affect drivers' utilities.) A crude rider does not make such costly effort and imposes negative externalities on her driver. For example, riders who are not at the correct pick-up location or are late for the start of service waste drivers' time and reduce their earnings. Similarly, riders who are distractive during rides (e.g., loud use of mobile phone, late-night intoxicated home goers) might also impose hardship on the driver. In our

*Full paper is available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3263680` model, a rider's conduct is reflected in her rating. (Note that we use the word "crude" as opposed to "rude", as riders who do not make the effort to behave courteously are likely to be just senseless, i.e., they are crude, and are not necessarily hurting drivers deliberately, i.e., they are not rude.)

On the other hand, we assume that drivers may be either *selective* or *non-selective*, when accepting or rejecting a match proposed by the platform. A selective driver incurs a cost to check rider information (captured by the rider rating in our model) before making acceptance/rejection decision. A non-selective driver does not check rider ratings and accepts all matched riders.

Note that a *social dilemma* arises if a rider's cost of being courteous is less than the damage being crude would impose on her driver: it would thus be socially optimal for a rider to be courteous, but she needs to be incentivized to make such costly effort (in addition to paying the price for the service).

We adopt an evolutionary game theory model in which the behavior of drivers and riders evolves over time in response to their experiences in the platform. On ride-hailing platforms, drivers and riders generally have limited information about the market condition (e.g., local supply or demand shortage). However, over time drivers and riders calibrate the expected payoffs associated with particular behavior, and their collective behavior changes gradually. In our evolutionary model, the proportions of drivers and riders of each behavior describe the state of a dynamic system, and change based on drivers' and riders' expected payoffs in the system. For example, if crude riders receive a higher expected utility than courteous ones, then the proportion of crude riders will increase, and if selective drivers receive a lower utility than non-selective ones, then the proportion of selective drivers will decrease. As such, drivers' and riders' behavior evolves as a dynamic system over continuous time. By analyzing a system of ordinary differential equations describing the dynamic system, we characterize evolutionary trajectories and asymptotically stable equilibria (if they exist), which allow us to understand evolution of user behavior and their welfare, as well as platform performance. We establish that in such a system, there are only two sustainable asymptotically stable equilibria, i.e., equilibria in which the system is stabilized in a state where all drivers and riders have positive expected utilities, and is unaffected by small perturbations.

The first such equilibrium is one where no riders exert efforts to be courteous, while all drivers are non-selective. We show that such an equilibrium emerges when wages are sufficiently high. This equilibrium resembles a traditional taxi service, i.e., the platform's service simply reduces to matching supply and demand. The key for the emergence of this "taxi" equilibrium is that the damage crude riders impose on drivers is relatively small, i.e., negative externality due to lack of rider effort is negligible compared with driver wages.

The second equilibrium is one with non-trivial proportions of both courteous and crude riders and of both selective and non-selective drivers. We show that such an equilibrium emerges when wages (and prices) are sufficiently low. This equilibrium resembles multiple features of a successful ride-hailing platform, i.e., it keeps the price of service attractive by supplementing it with incentivizing courteous behavior from riders, without compromising too much with respect to the number of matched users (as drivers accept crude riders with non-zero probability). In this equilibrium, courteous drivers choose to "pay" for service both monetarily by paying the price platform sets, and non-monetarily by effort to be courteous. The key for the emergence of this equilibrium is that the cost selective drivers incur is low relative to the expected damage from accepting a proposed ride.

We show that this "ride-hailing platform" equilibrium requires that the social dilemma is not negligible: the cost of being a courteous rider is much smaller than the damage imposed to a driver by being a crude rider. A crude rider not getting a ride with some probability is a sufficient incentive for a proportion of riders to be courteous and behave in a socially optimal way (without completely shutting crude riders out of the market). Disclosure of rider ratings to drivers is critical for sustainability of this equilibrium.

In summary, this "ride-hailing platform" equilibrium not only provides a matching service, but also unlocks an additional value through facilitating an alternative transfer of utility from courteous riders to drivers.

More generally, our analysis indicates how operational tools can be used to influence the evolution and equilibrium states of the platform users' behavior. We find that, when the system is in a state with a large proportion of crude riders, the platform could incentivize drivers to be more selective (e.g., by lowering wages) to impose pressure on riders to be courteous. On the other hand, when the system is in a state with a large proportion of selective drivers, we find, somewhat surprisingly, that the platform might want to lower the price for riders in order to decrease the number of selective drivers, without necessarily affecting the number of courteous riders.

Note that it is socially optimal for all riders to be courteous as their cost of doing so is lower than the damage crude riders impose on drivers, and for all drivers to be non-selective so as to avoid incurring the cost of being selective. Interestingly, neither of the two sustainable asymptotically stable equilibria (i.e., taxi and ride-hailing platform) are socially optimal as they allow for the existence of (i.e., a non-trivial proportion of) crude riders in equilibrium. However, we show that under supply shortage, a small adjustment in the location-based real-time matching can ensure that the socially optimal state is the unique sustainable asymptotically stable equilibrium. In particular, we establish that a matching policy that locally prioritizes courteous riders under supply shortage (instead of breaking local ties randomly) can sustain this socially optimal equilibrium. Furthermore, we numerically analyze the impact of this adjustment to the matching procedure and show that the total welfare and driver welfare improve significantly, with negligible impact on rider welfare and platform profit.

The two-region multi-depot pickup and delivery problem

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Abstract

Motivated by a research on collaborative transportation between various parties, the two-region multi-depot pickup and delivery problem (2R-MDPDP) arises from the search for solutions from a completely centralized point of view. The problem aims at minimizing the costs of serving a set of pickup and delivery requests on a multi period setting. Request locations might be placed in different regions or in the same ones. Transportation between regions is only possible via long-haul means of transport, while short-haul vehicles perform the routing within each region. The 2R-MDPDP can be decomposed in three classical routing subproblems. An integrated ALNS algorithm for solving the problem is devised, with high performance operators tailored to each kind of subproblem. We show that an integrated algorithm, solving all subproblems at the same time, overcomes sequential approaches solving one subproblem at a time. New benchmark instances with different characteristics are generated for computational experiments.

1 Problem Description

The two-region multi-depot pickup and delivery problem with time windows (2R-MDPDP) is composed of two geographically distant regions, between which regular short-haul transportation is highly inefficient. Each region might have one or more depots, where goods are dispatched or consolidated. A set of pickup and delivery requests must be served, with service points located either in different regions (inter-region request) or in the same region (intra-region request). Inter-region requests can only be transported by long-haul means of transport (heavy-duty vehicles, train, plane) between regions. The problem is considered on a time horizon, where each request has an earliest and latest service days, as well as opening time windows for its pickup and delivery customers. Figure 1 shows a graphical representation of a possible structure of the problem. The goal of the problem is finding the least costly way of servicing all requests, providing that all time constraints are satisfied.

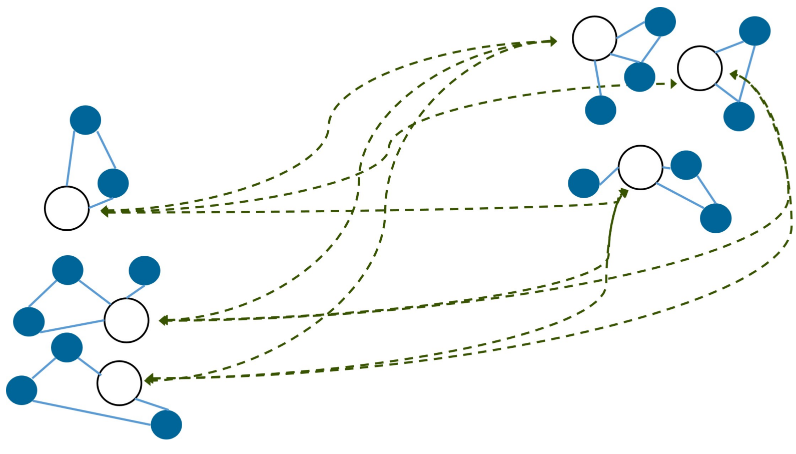

Figure 1: Network structure

Three different subproblems can be identified in the 2R-MDPDP: (S1) The assignment of intra-region requests to long-haul trips, (S2) the assignment of intra-region requests to depots in each region, and (S3) a multi-period vehicle routing problem with backhauls on each depot.

2 Solution method

An adaptive large neighborhood search algorithm (ALNS) is designed for tackling the 2R-MDPDP. ALNS algorithms are a well known meta-heuristic framework, consisting in destroying part of the solution by removing part of the current decision variables and repairing it to a complete solution afterwards. For this, different destroying and repairing operators are used. For the problem at hand, different operators tailored to one of the subproblems are designed. The algorithm starts with an initial solution, which we obtain by sequentially solving each subproblem (S1,S2,S3) with simple greedy construction heuristics.

2.1 Operators for ALNS

Different operators are designed for each of the three subproblems:

- *Operators for (S1).* These operators focus on the assignment of inter-region requests to long-haul lanes and vehicles.
  - Removal operators. Random, worst, related, vehicle, proximity removal.
  - Repair operators. Cheapest greedy, regret-2 and regret-3 insertion.
- *Operators for (S2).* The operators designed for the (S2) subproblem work on the assignement of intra-region pickup and delivery requests to depots within a region and their routing decisions.
  - Removal operators. Random, worst, related, proximity removal.
  - Repair operators. Cheapest greedy, regret-2 and regret-3 insertion.
- *Operators for (S3).* These operators focus on optimizing the routes within each depot.
  - Removal operators. Random, worst, related removal.
  - Repair operators. Cheapest greedy, regret-2 and regret-3 insertion.

3 Computational Study

Experiments are performed for two sets of 12 benchmark instances: set T considering custom time windows on the service points and set N where time windows equal depot opening times. They are generated with five variable characteristics: (i) number of inter-region requests, (ii) number of intra-region requests, (iii)number of depots, (iv) number of days and (v) vehicle capacities. Additionally, two sets of small instances *(TS,NS)* are generated for testing the MIP model.

3.1 Results on benchmark instances

Table 1 shows results for the sets T and N. Three runs are done for each instance, with the algorithm stopping after 3000 iterations without improvement.

DataSet	**Total_Dist**	**LH_Veh**	**SH_Veh**	**CPU(s.)**
T	4365.02	4.47	15.81	110.19
N	4144.33	4.11	14.92	550.09

Table 1: Results for 2R-MDPDP on instance sets T and N.

3.2 Integrated vs. Sequential algorithm

To asses the benefits of using an integrated algorithm working on all subproblems at the same time, we compare the results obtained with sequential approaches. A sequential approach solves the 2R-MDPDP by focusing in one subproblem at a time. We test two possible sequential approaches: (*High-Low*) solves the subproblems (S1,S2,S3) in that order, while (*Low-High*) solves the 2R-MDPDP focusing sequentially in (S3,S2,S1). Table 2 shows, for each instance set, the average gap of each sequential approach relative to the integrated algorithm approach.

DataSet	**High-Low**	**Low-High**
T	3.98%	4.16%
N	1.93%	2.26%

Table 2: Comparison between integrated and sequential ALNS.

Comparing Mechanisms for Request-Exchange Collaborative Transportation

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1 Introduction

The competitive environment in the transportation industry motivates companies and researchers to continuously study and test solution mechanisms to reduce operational costs and increase productivity. Over the past decades, efforts have been focused to the development of exact and heuristic methods that provide high quality and even optimal solutions in terms of traveled distance for a broad list of problems. However, due to their good results, collaborative initiatives have recently been considered as one main trend in transportation [4].

Horizontal collaboration in transportation includes the sharing of vehicles, locations and other resources, (re)allocation of tasks, requests exchange, among other collaborative operations. As for requests exchange mechanisms, Berger and Bierwirth [1] provided an auction framework composed by different processes following a determined order: Forming a request candidate set, Composition of bundles from the candidate set, Determination of marginal profits, Assignment of bundles to carriers and Profit sharing.

These authors stated that the only way to reduce decentralization costs is to increase the amount of information that is centrally known. For this same framework, Gansterer and Hartl [2] compared different request selection strategies.

For this work, we consider three main mechanisms: centralized auctions, sequential individual auctions and centralized posted price mechanisms. In all mechanisms, requests are grouped into bundles, therefore, a large number of evaluations have to be performed, encouraging the use of fast methods, such as the regression-based approximations for routing problems presented by Nicola et al. in [3]. Besides the detailed description for every single mechanism, we provide an analysis of special considerations that have to be taken into account in the design of the mechanism's processes. All mechanisms are tested on the same scenario, and from comparing their results, we look for a better understanding of their behavior that allows us to obtain insights for their application.

2 Request Exchange Mechanisms

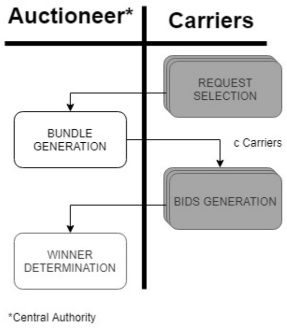
The exchange mechanisms described in this section correspond to double-side mechanisms, in which carriers that collaborate with each other are willing to procure services from other carriers to fulfill some of their requests and also sell part of their operational capacity to fulfill other carriers' requests. Request selection is the very first step to be taken in every mechanism. In order to obtain a request j value, fundamental for individual evaluation within the set of requests, a utility function should be used. In [3], models of the form:

$$E = \sum_i \kappa_i \times K_i \tag{1}$$

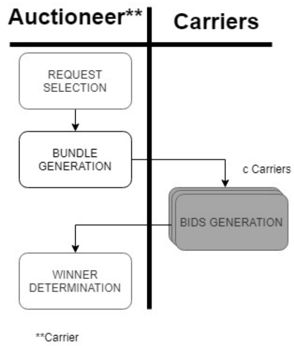
are presented. E is the estimation of the expected travel distance to be obtained by the problem solution and κ_i is the value of the regression parameter for variable K_i. Variables K_i can provide a measure to be considered as selection criteria. Carriers might select a large number of requests to be exchanged if their initial sets are costly, but also might select a few or no requests if the cost for their sets is low. This decision would of course depend on each carrier's own experience and information.

2.1 Auction-based Mechanisms

Our proposed auction-based mechanisms is based in the framework presented in [1] and [2]. Figure 1 shows the steps and their decision maker for centralized and individual auctions mechanisms. Bundles might contain requests from one or several carriers, depending on the auction format that is being used. The winner determination is solved by the auctioneer, who allocates bundles to carriers based on their bids.



(a) Centralized Auctions Mechanism

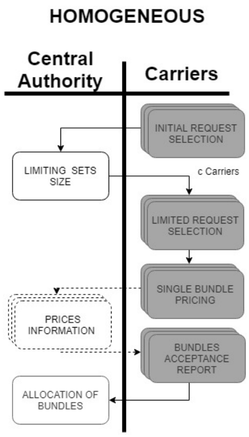


(b) Individual Auctions Mechanism

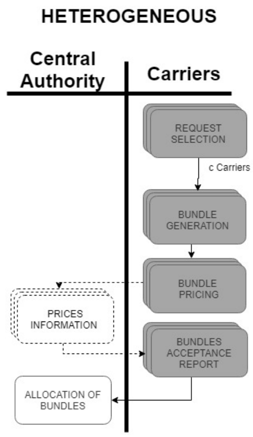
Figure 1: Decisions in Central and Individual Auctions Mechanisms

2.2 Centralized Posted-Price Exchange Mechanisms

A posted-price exchange mechanism differs from an auction-based mechanism fundamentally in one aspect: carriers set the prices for their selected requests themselves. We present an homogeneous and an heterogeneous mechanism. In an homogeneous mechanism, carriers select the same number of requests, in contrast to an heterogeneous mechanism, where the number of selected requests depends on every carrier. Figure 2 shows the logical order of the steps taken for these mechanisms, divided according to the party in charge of the decision making process.



(a) Homogeneous Posted-Price Exchange



(b) Heterogeneous Posted-Price Exchange

Figure 2: Decisions in Posted-Price Exchange Mechanisms

3 Experiments and Results

We analyze the auction-based mechanisms from Section 2.1 and the posted-price mechanisms from Section 2.2 in a two-region scenario with paired nodes. It is assumed that carriers taking part of a collaborative network are willing to exchange requests. These mechanisms are tested in 30 cooperation networks with four carriers each, every carrier services 25 customers. The difference between solutions before and after the application of a mechanism is reported as the obtained improvement. Results after 50 rounds, when carriers select different request selection criteria are shown in Figure 3.

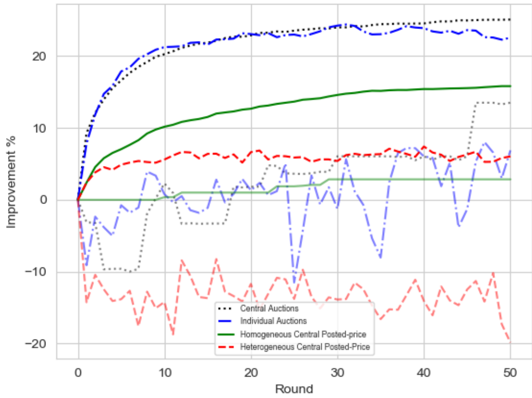


Figure 3: Total average improvement obtained for every round

4 Conclusions

While all considered mechanisms increase the collaborative network efficiency, auction-based mechanisms reach higher levels of improvement on average. The individual auctions mechanism provides similar results to the ones obtained by the centralized auctions mechanism, suggesting it is not necessary to have bundles containing requests that belong to different carriers if enough iterations are performed for this mechanism, for which a central authority is also not needed. Posted price mechanisms do not yield the same results, however, less information is provided by the carriers as they do not reveal their exact valuations for a bundle.

Acknowledgements

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Routing Optimization for On-Demand Ridesharing: Formulation, Algorithm and Implications

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This study deals with an On-demand Ridesharing Routing Problem (ORRP), which is a variant of Dial-a-Ride Problem (DARP)[1]. In various real-life applications arising in ridesharing, we particularly seek for the routing optimization for services such as UberPool, DiDi Pooling or Lyft Share. These services require customers meet vehicles at pre-determined pick-up locations different from their home locations, unlike DiDi Fast, or Lyft Standard that provides direct door-to-door services (i.e., in line of classical DARP). More convenient pick-ups (and drop-offs) help drivers avoid unnecessarily changing lanes or zigzag crossing the street, which leads to a more seamless experience for everyone involved [2, 3]. In the ORRP, the pick-up and drop-off locations are treated as decisions that should be made by drivers.

The ORRP is also a variant of Selective Travelling Salesman Problem (TSP) or TSP with profit, regarding not all customer orders are accepted. Given the current location of a driver, and a set of candidate O-D pairs of customer orders, the driver needs to select several orders to provide shared ride services. Each fulfilled order is charged, depending on the door-to-door distance rather than the real travel distance, because the latter involves detour in ridesharing. The objective of ORRP maximizes the driver's revenue that is the charges of the accepted orders minus the travel cost of the vehicle.

In essential, the ORRP is a single vehicle DARP with floating targets and with revenue maximization. It consists of (i) selecting a set of customer orders to serve, (ii) determining pick-up and drop-off locations for these selected customers, and (iii) optimizing the sequences of pick-ups and drop-offs. In a sense, the vehicle picks up additional customers while satisfying customers already in the vehicle, i.e., not bringing so much detour for on-broad customers. The routing optimization should consider vehicle capacity, maximum accepted order number, pairing and precedence order between a pick-up and a drop-off, walking distance range and acceptable detour distance of customers.

Complexities of ORRP are listed as follows. (a) Floating targets are considered. (b) Drop-offs are also determined in the ORRP, different from problems only considering pick-ups, e.g., Vehicle Routing Problem (VRP) with floating targets [4]. Therefore, vehicle load can both increase and decrease along the designed route of ORRP. (c) The classical arc flow formulation and associated valid inequalities [5] can not be directly used.

Our contributions are summarized as follows.

1. We introduce the ORRP, which is motivated by the emerging services of UberPool, DiDi Pooling or Lyft Share in the application of ridesharing. It is different from the DARP by considering floating targets and revenue maximization. The routing optimization benefits drivers who operate ridesharing vehicles for UberPool business or others while satisfying on-demand customers.

2. We formulate the ORRP as a mixed-integer second-order cone program (MISOCP). An extension model is also proposed for routing with obstacles. We provide safe settings for the big-M coefficients to benefit the relaxation bound of the formulation. To tighten the bound, we also proposed valid inequalities for the ORRP, which focus on pick-up and drop-off operations, pair and precedence order restrictions, and vehicle load conditions of the ORRP. These bound tightening methods speed up 30% of the CPU time of solving the model.

3. We express the explicit formulation of the shortest travel time for routing only one customer. This optimal structure in the special case is important for developing ORRP solution methods and for real-life applications, but it is not straightforward since the pick-up location needs to be determined and the walking distance range should be considered. By exploring the special case, some infeasible orders (i.e., the shortest travel time already exceeds the travel time restriction of the customer) can be directly removed from the candidate order set.

4. We propose a heuristic algorithm for the ORRP that can be directly used in the real-life

application. Experiments are conducted to evaluate the proposed valid cuts and to test the heuristic algorithm, based on real-world data. Comparisons between the model and the algorithm referring to the optimality gaps and CPU times are provided in different scenarios. Several insights are given by sensitivity analyses, e.g., revenues can be greatly improved by allowing floating targets (i.e., customers) instead of door-to-door services; the pick-up flexibility brings more benefits than the drop-off flexibility.

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PDP with alternative locations and overlapping time windows for a C2C setting

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1 Introduction

In a C2C (Customer to Customer) market consumers interact directly with each other without a commercial player in the middle. Well known online platforms such as eBay, Chraigslist or Willhaben enable persons to sell no longer needed or self made items to private buyers. eBay alone almost doubled their gross merchandise volume in the last 9 years to 83.76 billion U.S. dollars [1]. Willhaben.at is one of the biggest online platforms in Austria for (mainly) C2C second hand goods with a broad range of categories. The increasing popularity of smartphone applications for C2C transactions, i.e. OfferUp, Vinted and Tradesy, have greatly simplified the process and enabled a further utilization increase. Additionally, the C2C market gains relevance due to the second hand consumption movement [5] where environmentally concious consumers try to give goods a second live trough repairs, repurposing, recycling or reusing instead of buying new goods.

After an agreement is made the shipping of the item is done in favour of convenience of either the seller or buyer. Public post services or commercial shipping companies are not very accommodating for private mail by enforcing personal visits at pickup points or simply by maintaining rigid schedules and opening hours. Sender of parcels have to make an appearance at their local post office within their opening hours. On the other hand, missed deliveries at the receiver of a parcel is a prevalent problem in the industry. The cost of a missed delivery is more than just the last mile cost of a second delivery attempt. One has to include the environmental impact and the frustration of the carrier and receiver alike. Complaints take up customer service resources of the sender and the carrier and a repetition of missed deliveries results in the loss of customer loyalty, bad reviews and long-term losses of potential new customers. The current delivery options are not sufficiently accommodating for a C2C setting.

The C2C setting requires more convenient transport solutions, however the push for more convenient transportation has been mostly attempted in the B2C market i.e. by proposing trunk delivery [3], anticipatory shipping [4], drone delivery [6] or delivery to locker boxes [2].

2 Problem description

Due to the aforementioned requirements a new problem is proposed and classified as a PDPAL. The topic shares similarities with other already studied problems: mainly the vehicle routing with roaming delivery locations [3], however they have neither alternative pickups or overlapping time windows.

Our problem consists of a collection of request, i.e. specific products that have to be conveniently transported from the seller to the buyer. Since the seller is a private person and has usually no commercial store or designated pickup location it is assumed that on the day of the pickup the product stays with the person while they go about their day. This results in multiple possible (alternative) pickup locations throughout the day with non-overlapping time windows, since the product cannot be in two places at once. For a convenient delivery the parcel is no longer delivered to a single specific person, but rather to a 'household'. A household consists of multiple people in different locations that can be available simultaneously. Household members can accept the parcel at multiple locations throughout the day whether they are at work or at home. In short, there are multiple possible (alternative) delivery locations with overlapping time windows. Each request has multiple possible alternative pickups and alternative delivery locations, and an assigned quantity.

Figure 1 shows an example where request A has three (possible) pickup locations and request B has three (possible) delivery locations. A choice has to be made which of the alternative locations (ALs) are to be included in the route. The arrows depict the route of the vehicle. For request B the nodes nearest to the depot are selected, however for request A a more distant pickup node is selected due to time windows.

Figure 1: VRPTW with multiple pickup or delivery locations

Our time frame is a working day, the smallest unit of time is one minute. We have a single depot which is the start and end point of all vehicles. The vehicles are limited in number and in capacity. The goal is to select for each request one of the location possibilities, to determine the node sequence for all vehicles and to minimize cost. Cost are defined as the sum over all distances travelled by the vehicles while fulfilling time window and capacity constraints.

3 Solution methodology

The PDPAL is solved with a combined genetic algorithm (GA) and large neighbourhood search (LNS). For each request the pickup location, the delivery location and the information by which vehicle it is being served is necessary. Furthermore we are interested in the explicit vehicle routes, i.e. the sequence in which the location nodes are visited and the fulfilment times. Both the GA and the LNS only select the vehicle assignment, e.g. which request is served by which vehicle. For the selection of the alternative locations and the node sequence we call on a routing algorithm presented later in this section.

A solution pool for the GA is created by using a construction heuristic as well as randomly generated initial solutions. The total runtime is split between the GA and LNS part of the algorithm with the GA having the lesser portion (around 20 percent). Therefore, while the runtime limit is not reached as many generations as possible are generated using a uniform crossover with elite preservation and mutation. When the runtime limit for the GA is reached, we discard the worst 30 percent of the population and keep the rest for improvement with the LNS.

For the LNS we pick a solution based on a roulette wheel selection and apply it as long as improvements can be found. If no more improvement can be found for a certain number of iterations, the LNS is terminated, the solution returned to the pool, and a new solution is selected. Apart from standard destroy and repair operators a 'compatibility' repair operator has been developed.

For each pair of requests a compatibility indicator is calculated. We look how 'compatible' all pickup and delivery locations of a request are to all locations (pickup and delivery) of another request. The compatibility of the pickup and delivery locations of the same request are hereby not relevant. The compatibility values are calculated in a preprocessing step. When deciding to which vehicle to assign a requests we calculate the most promising vehicle assignment using the compatibility measure. The vehicle compatibility is the average of all compatibilities of already present requests.

For both the GA and LNS we use an underlying routing algorithm. The construction heuristic for the routing uses a modified farthest insertion heuristic with a roulette wheel selection that considers the best six possible insertions. Additionally, we include a penalty for waiting time and always consider all potential alternative locations. After a starting solution has been constructed the routing is improved by local search using 'move' and 'swap' operators.

Runtime:		#req. in sec		2x#req. in sec		5x#req. in sec	
Inst.	#req.	Δ H	Δ G	Δ H	Δ G	Δ H	Δ G
0-4	15	-0.4%	0.4%	-0.4%	0.3%	-0.4%	0.3%
5-9	20	-1.1%	1.0%	-1.1%	1.0%	-1.2%	0.9%
10-19	30	-0.1%	0.9%	-0.2%	0.7%	-0.2%	0.7%
20-29	60	-1.9%	-7.4%	-2.3%	-7.8%	-2.7%	-8.1%
30-39	120	3.5%	-18.7%	2.6%	-19.4%	1.2%	-20.5%
Avg.		0.2%	-6.1%	-0.2%	-6.4%	-0.6%	-6.8%

Table 1: Comparison to Reyes et al. [3]. The instances are numbered from 0 to 39 and averaged together by the number of requests '#req.' they have. The three main columns show the results for different runtimes, dependent on the number of requests. 'Δ H' shows the difference to their heuristic, while 'Δ G' shows the difference to the Gurobi results they provided. For the shortest runtimes (15 to 120 seconds) we are on average slightly worse than Reyes et al. however just by slightly increasing the runtime (30 to 240 seconds) we are already slightly better.

4 Preliminary computational results

We compare our work with Reyes et al. [3] since their paper on vehicle routing with roaming delivery locations is a special case of our problem where only one pickup location is available and the time windows of the delivery locations are not overlapping. The results are presented in Table 4.

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