Freie Universität Berlin

informs TSL
Transportation Science and Logistics Society

2015 TSL Workshop

Recent Advances in Urban Transportation through Optimization and Analytics

Hosted at Freie Universität Berlin, Germany

July 6th – July 8th, 2015


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The 4th INFORMS TSL Workshop
is sponsored by initplan GmbH.
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init

Foreword

Welcome to the 2015 Transportation Science and Logistics Society Workshop in Berlin!

There has been a significant body of research on making urban transportation more efficient and sustainable. Planning of urban transportation services is challenging due to the crowded traffic infrastructure, increasing customer expectations, and rules set by municipalities. In recent years, a vast amount of urban transportation data has become available, e.g., travel times and customer demand data. The workshop brings together researchers from the often-distinct fields of urban transportation and analytics to discuss recent optimization approaches and how to benefit from the increasing amount of detailed data.

This year's workshop will consist of 38 talks dealing with recent applications of urban transportation such as city logistics, urban traffic, shared mobility, e-mobility, pollution routing and public transport, environmental-friendly deliveries, and city logistics concepts in general. The program will feature a panel on "Challenges of Big Data in Urban Transportation Optimization", moderated by Bruce Golden and including a set of industry experts from different areas of urban transportation such as city logistics, public transport and shared mobility services. We are also happy that Michael Ball and Arne Strauss will contribute to the program with keynotes discussing challenges arising from detailed data in urban transportation optimization.

Last but not least, we look forward to networking and enjoying Berlin during the social program: We have planned a welcome reception at a rooftop bar overlooking downtown Berlin (Panoramapunkt) to start the event on Sunday evening. On Tuesday, we will limit talks to the first half of the day to explore the city in the afternoon. A city tour by boat followed by a guided walking tour will introduce you to historic sites of Berlin. We will end the day with a conference dinner in the historic heart of the German capital.

We hope that you will enjoy the workshop and look forward to meeting you. We thank you for participating, and give thanks to our sponsor INIT for supporting the workshop so generously.

Ann Melissa Campbell, Catherine Cleophas & Jan Fabian Ehmke

Recent Advances in Urban Transportation through Optimization and Analytics – Overview

Sunday, July 5th

17:30 – 19:30	Welcome Reception	“Panoramapunkt” Potsdamer Platz [1]

Monday, July 6th

09:00 – 17:00	**Workshop**	**Harnack House [2]**
09:00 – 10:00	Sessions 1a / 1b	Hahn Hall, Laue Hall
10:00 – 10:30	Coffee Break	Planck Lobby
10:30 – 11:30	Welcome **Keynote** Nudge the Customer – and Deliver Cheaper (Arne Strauss)	Hahn Hall
11:30 – 12:30	Sessions 2a / 2b	Hahn Hall, Laue Hall
12:30 – 13:30	Lunch Break	Planck Lobby
13:30 – 15:30	Sessions 3a / 3b	Hahn Hall, Laue Hall
15:30 – 16:00	Coffee Break	Planck Lobby
16:00 – 17:00	**Industry Panel** Challenges of Big Data in Urban Transportation Optimization (Bruce Golden)	Hahn Hall

Tuesday, July 7th

09:00 – 14:00	**Workshop**	**Harnack House [2]**
09:00 – 10:30	Sessions 4a / 4b	Hahn Hall, Laue Hall
10:30 – 11:00	Coffee Break	Planck Lobby
11:00 – 12:00	Sessions 5a / 5b	Hahn Hall, Laue Hall
12:10 – 13:00	**Keynote** Model Decomposition and Integration: Case Studies from Urban Transit and Airline Planning Problems (Michael Ball)	Hahn Hall
13:00 – 14:00	Lunch Break	Restaurant
14:30 – 18:30	**Boat and City Tour**	**Harnack House [2]**
19:30 – 22:00	**Conference Dinner**	**Restaurant “Altes Zollhaus” [4]**

Wednesday, July 8th

09:00 – 13:00	**Workshop**	**Harnack House [2]**
09:00 – 10:30	Sessions 6a / 6b	Hahn Hall, Laue Hall
10:30 – 11:00	Coffee Break	Laue Hall
11:00 – 12:30	Sessions 7a / 7b	Hahn Hall, Laue Hall
12:30 – 13:00	Farewell	Laue Hall

Scientific Program – Monday, July 6th

Session 1a Network Design
09:00 – 10:00, Hahn Hall

- Robust Transit Network Design Based on Big Unrepresentative Data — Chungmok Lee, Gavin McArdle & Rahul Nair
- Stochastic Service Network Design of Bike Sharing Systems — **Patrick Vogel**, Achim Koberstein & Dirk Mattfeld

Session 1b Urban Infrastructure
09:00 – 10:00, Laue Hall

- Optimizing Charging Station Locations for Urban Taxi Providers — Mario Ruthmair, Johannes Asamer, Martin Reinthaler & Jakob Puchinger
- A Bi-level Programming Model for the Workzone Scheduling Problem — David Rey, **Hillel Bar-Gera**, Vinayak Dixit & Travis Waller

Session 2a E-Mobility I
11:30 – 12:30, Hahn Hall

- Emerging Area in Urban Transportation System Research – Optimization and Analytics on Wireless Charging Electric Bus Systems — Young Jae Jang
- Optimal Deployment of Charging Lanes in Transportation Networks — **Yafeng Yin**, Zhibin Chen & Fang He

Session 2b Pollution Routing
11:30 – 12:30, Laue Hall

- Time-Dependent Pollution-Routing Problems with Path Flexibility in Mega-City Logistics — Yixiao Huang, Lei Zhao, Tom Van Woensel & Jean-Philippe Gross
- The Fleet Size and Mix Pollution-Routing Problem — Cagri Koc, Tolga Bektas, **Ola Jabali** & Gilbert Laporte

Session 3a Shared Mobility
13:30 – 15:30, Hahn Hall

- The Taxi Recourse Problem — Neža Vodopivec & Elise Miller-Hooks
- Optimizing Ridesharing Services – Complexity, Formulation and Solution Methods — Wei Lu & Luca Quadrifoglio
- Relocation and Balancing Strategies for Free-Floating Car Sharing Systems using Real-Time Data and Social Networking — Frederik Schulte & Stefan Voß
- Stochastic and Dynamic Inventory Routing in Bike Sharing Systems — **Dirk Mattfeld**, Viola Ricker & Marlin Ulmer

Session 3b Urban Delivery
13:30 – 15:30, Laue Hall

- Urban Distribution with Mobile Depots — Michael Schneider & Michael Drexl
- Some Recent Results on the Split Delivery Vehicle Routing Problem — Bruce Golden & Xingyin Wang
- Crowdsourced Same Day Delivery — Alp Arslan, Niels Agatz, Leo Kroon & Rob Zuidwijk
- Same-Day Delivery — **Barrett Thomas**, Stacy Voccia & Ann Campbell

Session chairs are shown in **bold**.

Scientific Program – Tuesday, July 7th

Session 4a E-Mobility II
09:00 – 10:30, Hahn Hall

- Applying Floating Car Data to Aid the Transition to Electric Taxi Services — Michal Maciejewski & Joschka Bischoff
- Enabling Urban Parcel Pickup and Delivery Services using All-Electric Trucks — Nan Ding, Rajan Batta, Changhyun Kwon & June Dong
- Adaptive Routing and Recharging Policies for Electric Vehicles — **Irina Dolinskaya**, Timothy M. Sweda & Diego Klabjan

Session 4b Public Transport I
09:00 – 10:30, Laue Hall

- Time Choice Data for Public Transport Optimization — Paul Bouman, Clint Pennings, Jan van Dalen & Leo Kroon
- A Column Generation Approach for Crew Rostering Problems in Public Bus Transit — Lin Xie, Natalia Kliewer & Leena Suhl
- On-Demand Public Transportation — **M. Grazia Speranza**, Claudi Archetti & Dennis Weyland

Session 5a Vehicle Routing
11:00 – 12:00, Hahn Hall

- Value-Function-Approximation-Based Rollout Algorithms for a Vehicle Routing Problem with Stochastic Customer Requests — Marlin W. Ulmer, Justin C. Goodson, Dirk C. Mattfeld & Marco Henning
- A Scenario-Based Planning for the Pickup and Delivery Problem with Scheduled Lines and Stochastic Demands — **Tom van Woensel,** Veaceslav Ghilas & Emrah Demir

Session 5b Public Transport II
11:00 – 12:00, Laue Hall

- Robust Efficiency in Public Transport: Minimizing Delay Propagation in Cost-Efficient Resource Schedules — Bastian Amberg, Boris Amberg & Natalia Kliewer
- Tariff Zone Planning for Public Transport Companies — **Sven Müller** & Knut Haase

Session chairs are shown in **bold**.

Scientific Program – Wednesday, July 8th

Session 6a — City Logistics I — 09:00 – 10:30, Hahn Hall

- Static MILP Solutions and Adaptive Solutions for Hub Decisions in Very Large Scale Logistics Networks — Alexander Richter, Yann Disser, Wiebke Höhn & Sebastian Stiller
- Optimization Approaches for the Truck and Drone Delivery Problem — Niels Agatz, Paul Bouman & Marie Schmidt
- Optimizing Time-Dependent Arrival Rates for Truck Handling Operations — **Axel Franz** & Raik Stolletz

Session 6b — Uncertain Travel Times — 09:00 – 10:30, Laue Hall

- Disruption Management in Local Public Transport: Service Regularity Issues — Emanuele Tresoldi, Frederico Malucelli, Stefano Gualandi & Samuela Carosi
- Assessing Customer Service Reliability in Route Planning with Self-Imposed Time Windows and Uncertain Travel Times — Panagiotis Repoussis, Anastasios Varias & Christos Tarantilis
- Robust Scheduling of Urban Home Health Care Services Using Time-Dependent Public Transport — **Klaus-Dieter Rest** & Patrick Hirsch

Session 7a — City Logistics II — 11:00 – 12:30, Hahn Hall

- Handling Travel Time Uncertainly in City Logistics Systems — Utku Kunter, Cem Iyigun & Haldun Sural
- Freight Consolidation in Urban Networks With Transshipments — Wouter van Heeswijk, Martijn Mes & Marco Schutten
- Loading Bay Time Slot Allocation by Core-Selecting Package Auctions — **Paul Karaenke**, Martin Bichler & Stefan Minner

Session 7b — Urban Traffic — 11:00 – 12:30, Laue Hall

- City Monitoring with Dynamic UAV-Sensor-Based Sweep Coverage as a Stochastic Arc-Inventory Routing Policy — Joseph Chow & Xintao Liu
- A Metamodel Simulation-Based Optimization Approach for the Efficient Calibration Of Stochastic Traffic Simulators — Carolina Osorio, Gunnar Flötteröd & Chao Zhang
- Information and Traffic Incident Management — **Kalyan Talluri**, Dmitrii Tikhonenko & Gregory Fridman

Session chairs are shown in **bold**.

Keynotes Hahn Hall

Keynote 1 Nudge the Customer – and Deliver Cheaper (Arne Strauss)

Many companies deliver goods or services to customers who need to be present to receive the delivery, and therefore can choose when the delivery should take place. Examples of such companies include online grocery retailing, parcel delivery or house visits of telecom engineers to install or repair devices. The delivery operation is often a major cost driver for these companies.

Since the customers' choices of their desired delivery times will impact the overall delivery cost, it makes intuitive sense to nudge the customers towards choosing time slots that are expected to be cheap to serve by using appropriate incentives. The latter can take many forms such as discounts, delivery charges, loyalty points or even non-monetary ones like environmental impact.

However, the identification of a time slot that will be cheaper than others for a given customer request may in itself pose a non-trivial problem since the cost also depends on unknown future orders. Also, prediction of customers' choice behavior and subsequent optimization of incentives to influence their choices may likewise be challenging.

In this presentation, I will outline research opportunities in delivery planning with customer choice behavior along with various examples of business applications against the background of recent developments in industry.

Arne K. Strauss is Associate Professor of Operational Research in the ORMS Group at Warwick Business School (WBS) since 2014. Previously, he held positions as Assistant Professor in the same group (2011-2013) at WBS and as Senior Research Associate (2010-2011) under the LANCS Initiative at Lancaster University´s Department of Management Science where he completed the Ph.D. programme in 2009 under supervision of Prof Joern Meissner. From October 2009 until September 2010, he held an EPSRC PhD Plus fellowship (now called EPSRC Doctoral Prize) at Lancaster.

During his doctoral studies, his main research area was revenue optimisation involving models of customer choice; an interest that he continues to pursue with various on-going projects, including industrial collaborations with Lufthansa Systems. He won several prizes for his doctoral dissertation including the doctoral prize of the Operational Research Society for the best PhD dissertation 2009. A paper resulting from his master thesis in the area of option pricing received the "Most Successful 2008 IMACS Paper Award" in the journal Applied Numerical Mathematics, and he was awarded the OR Society`s Goodeve medal for the best paper published in the Journal of the Operational Research Society in 2012.

Keynote 2 Model Decomposition and Integration: Case Studies from Urban Transit and Airline Planning Problems (Michael Ball)

The scientific study of transportation planning problems very often starts with the definition of a mathematical model that represents a real problem. That mathematical model could lead to extensive research on solution methods. These methods are typically compared on the basis of solution quality and computation speed. Yet even though the mathematical model might very accurately represent reality and the solution methods might produce an optimal solution very quickly, the model could have practical limitations because the problem defined exists in a broader application context.

In the case of urban transit planning, some key problems are vehicle scheduling, crew duty generation and crew rostering. While research exists on each of these three problems, crew duties are constrained by vehicle schedules, and crew rosters are in turn constrained by crew duties. It is also the case that operational disruptions, such as extreme traffic congestion, vehicle breakdowns and crew illnesses, can cause actual operational costs to exceed those calculated based on planned schedules. When one traces research on planning problems for important application systems such as urban transit and scheduled air transportation services, major progress not only involves better solution methods for “core” problems but also better models that consider the broader application context. These better models might integrate multiple problem steps, e.g. combined vehicle and crew scheduling, might employ objective functions or linking constraints that allow features of “downstream” problems to be taken into account when solving an “upstream” problem or might use other techniques to improve the daily performance of the overall application system. In this talk, we review and compare the progress in both transit and airline planning problems from these perspectives.

Michael Ball is the Senior Associate Dean and holds the Dean`s Chair in Management Science at the Robert H. Smith School of Business at the University of Maryland. He also has a joint appointment within the Institute for Systems Research (ISR) in the Clark School of Engineering and is a member of the Decision, Operations and Information Technologies Department within the Smith School.

Dr. Ball has over 100 scholarly publications, covering a range of subjects including air transportation, revenue management and pricing, supply chain management and system reliability. He is co-Director of NEXTOR-II, an 8-university consortium funded by the FAA to carry out research in aviation operations research. Several of his research and consulting projects have led to implementations in industry and government. In the past five years he has been a member of various expert panels that have given advice to the United Nations, the FAA, the National Academy of Engineering and multiple airport authorities on aviation policies.

Throughout his career Dr. Ball has been an active member of INFORMS, the Institute for Operations Research and the Management Sciences. He recently stepped down as area editor for the journals Operations Research and is now associate editor for the journal, Operations Research and Transportation Science. In 2008, he was president of the INFORMS Transportation Science and Logistics Society. In 2004, he was named an INFORMS Fellow.

Dr. Ball received BES and MSE degrees from Johns Hopkins University in 1972 and a PhD in Operations Research from Cornell University in 1977.

Panel Hahn Hall

Challenges of Big Data in Urban Transportation Optimization

The workshop will feature a panel on “Challenges of Big Data in Urban Transportation Optimization”. The panel will be moderated by Bruce Golden and include a set of industry experts from different areas of urban transportation such as city logistics, public transport and shared mobility services.

- **Bruce Golden (Moderator, University of Maryland)**

  Bruce Golden is the France-Merrick Chair in Management Science in the Robert H. Smith School of Business at University of Maryland. He received his undergraduate degree in mathematics from the University of Pennsylvania and his masters and doctoral degrees from the Massachusetts Institute of Technology. His research interests include, but are not limited to, combinatorial optimization, network models, logistics, distribution, vehicle routing, data mining and applied operations research.

  Dr Golden has received numerous awards, including the Thomas L. Saaty Prize (1994 and 2005), the University of Maryland Distinguished Faculty Research Fellowship (1996) and Distinguished Scholar-Teacher Award (2000), the INFORMS Award for the Teaching of OR/MS Practice (2003), the INFORMS Computing Society Prize (2005), and the Harvey J. Greenberg Award for lifetime contributions to the INFORMS Computing Society. He was named an INFORMS Fellow in 2004 and was selected as one of 25 outstanding undergraduate mentors on campus in 2009.

- **Eileen Mandir (Moovel)**

  Eileen Mandir is the head of product at moovel GmbH, a Daimler subsidiary, since 2015. From 2013 to 2014, she worked with Daimler Mobility Services as the head of moovel software development for inter-modal routing. She joined Daimler as mobility innovations specialist in 2012, after receiving a PhD in transport planning and urban mobility from Stuttgart University in 2006. Her interest areas include designing connected multi-modal transport systems, human behaviour and decision making in transportation, the interdependency between urban life style and mobility patterns and disruptive change in mobility services enhanced by technology.

  Moovel GmbH, formerly Daimler Mobility Services GmbH, is a wholly owned subsidiary of Daimler AG and is assigned to Daimler Financial Services AG for organisational purposes. With services like car2go, car2go black, Park2gether, mytaxi and RideScout, moovel is already offering innovative solutions for getting from A to B the smart way.

• **Leendert Kok (ORTEC)**

Leendert Kok is a senior OR engineer at ORTEC and responsible for algorithmic research and development. Leendert received his PhD from the University of Twente in 2010, where he worked on “Congestion avoidance and break scheduling within vehicle routing“. During his academic work, he published several articles in peer-reviewed international journals. In a current project in cooperation with Free University Amsterdam, Leendert focuses on “Network planning and contract design for chain management in cash networks“. He is a member of the advisory board at the Free University of Amsterdam.

ORTEC is one of the largest providers of advanced planning and optimization solutions and services. ORTEC´s products and services result in optimized fleet routing and dispatch, vehicle and pallet loading, workforce scheduling, delivery forecasting, logistics network planning and warehouse control. The company`s mission mission is to support companies and public institutions in their strategic and operational decision making through the delivery of sophisticated planning and optimization software solutions, professional consulting and mathematical modeling services.

• **Michael Beck (INIT)**

Michael Beck has been working with initplan GmbH as Director of Development since 2008. He is responsible for the development of the planning system MOBILE-PLAN. The main focus is the usability of MOBILE-PLAN as well as the further development and provision of efficient optimization algorithms. Michael graduated in 1993 at University of Karlsruhe. Before changing to INIT AG, he worked at PTV AG, Karlsruhe for more than 20 years as head of department for the INTERPLAN planning system.

INIT is the worldwide leading supplier of integrated ITS, planning, dispatching and ticketing systems for buses and trains. For more than 30 years, INIT has been assisting transport companies in making public transport more attractive, faster and more efficient. More than 400 customers rely on INIT`s integrated solutions to support planning & dispatching, ticketing & fare management, operations control & real-time passenger information, as well as analyzing & optimizing.

Freie Universität Berlin

Public Transport

Included in the registration fee is a personalized **public transport ticket** for the city of Berlin (zones A&B). It is valid from Sun, 15:00 to Wed, 15:00 in all subways, buses, trams and regional trains within the city of Berlin. **Please have the ticket with you at all times** and show it to the bus driver when entering a bus. The ticket includes 15% discount on 40 tourist highlights.

How to get to…

[1] Welcome Reception at "Panoramapunkt" | Sunday, 17:30 – 19:30

Potsdamer Platz 1, 10785 Berlin

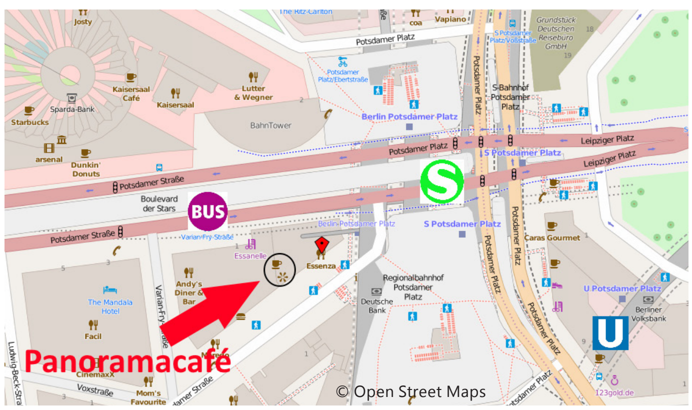
U 2, BUS 200 (and many more), stop **Potsdamer Platz**

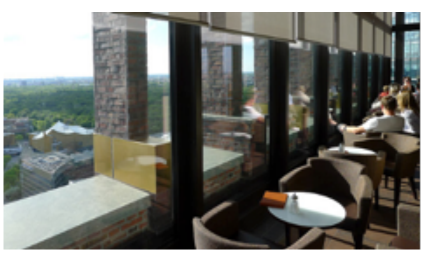
See the best views of Berlin, the fastest elevator in Europe, a multimedia open-air exhibition, and have a complementary drink at the Panoramacafé! Don't miss our welcome reception on the evening before the workshop.

We offer to walk you to the welcome reception. We will meet in the lobbies of Lindner hotel and Harnack House at 16:45.

From the Harnack house to the reception:
Take U 3, U 12 and U 2 to Potsdamer Platz via **Wittenbergplatz** and **Gleisdreieck**.

From the Lindner hotel to the reception:
Walk to stop **Bahnhof Zoo** (3 minutes) and take BUS 200 (leaves every 10 minutes).
Get off at **Varian-Fry-Straße** and enter the Panoramapunkt.





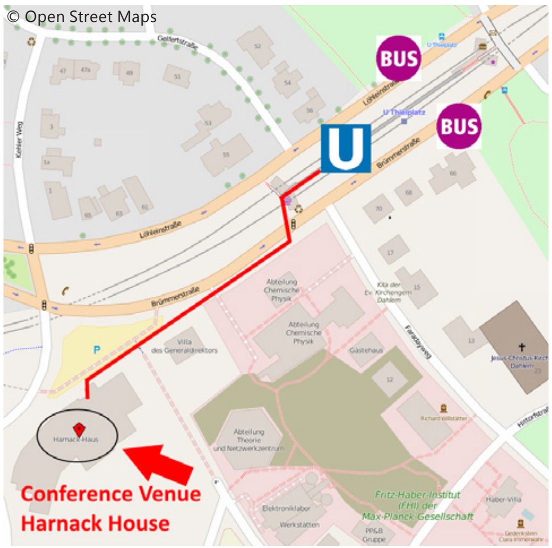
The welcome reception is not included in student tickets.

[2] Harnack House | Conference Venue

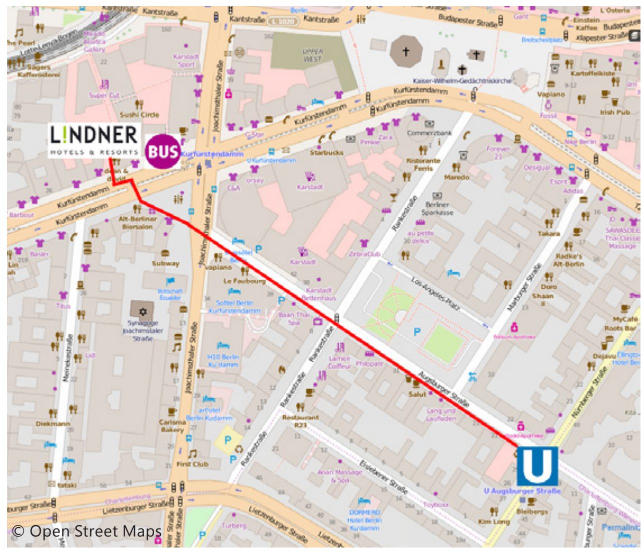
Ihnestraße 16–20, 14195 Berlin

U 3, BUS 110, stop **Thielplatz**

This is our workshop's venue. In the past, Nobel Prize winners and their students met here in social exchange and for academic discussion, holding lectures and colloquia. Today, the Harnack House offers all advantages of a modern workshop venue.



Harnack House surroundings



Lindner Hotel surroundings

From the Lindner hotel to the workshop:

Take BUS 110 leaving at stop **Kurfürstendamm** (in front of the hotel, departure 8:28, direction **Oskar-Helene-Heim**, leaves every 20 min.)

– alternatively –

Walk to subway station **Augsburger Straße**, take subway U 3 (direction **Krumme Lanke**, leaves every 5 minutes).

On Monday, we offer to walk you to the conference venue. We will meet in the lobby of Lindner hotel at 8:15.

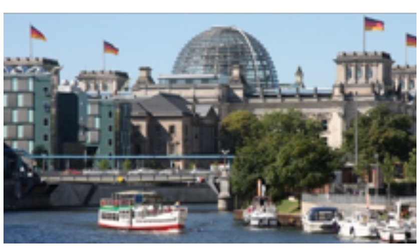
[3] Boat and City Tour | Tuesday, 14:30 – 18:30

Magnus-Hirschfeld-Ufer, 10557 Berlin

BUS 100, stop **Haus der Kulturen der Welt**

Join us for a boat tour through the city and a one-hour walking tour to see Berlin's most famous sights (Brandenburg Gate, Reichstag, Jewish Memorial).

We will walk you to the starting point of the tour. We will meet in front of the Harnack House at 14:30.



Boat & city tours are not included in student tickets.

[4] Conference Dinner Restaurant “Altes Zollhaus” | Tuesday, 19:30

Carl-Herz-Ufer 30, 10961 Berlin U 12, stop **Prinzenstraße**

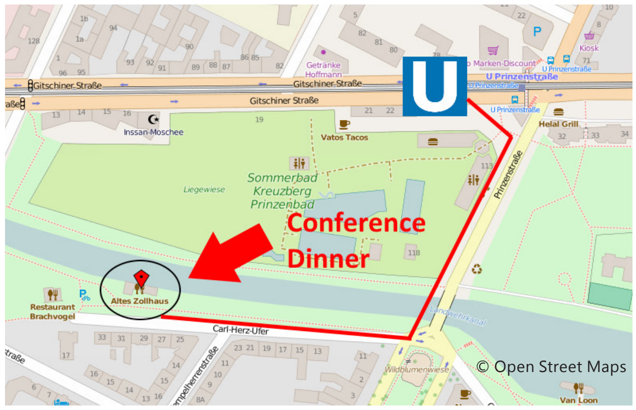
On behalf of our sponsor, we invite you to a reception and a traditional German 4-course dinner in the heart of Berlin, in the restaurant “Altes Zollhaus”.

To the conference dinner:

Take U 12 and leave at stop **Prinzenstraße**. Walk about 6 minutes to the restaurant “Altes Zollhaus“.

Travel back from the conference dinner to the Lindner hotel and Harnack House:

Walk back to subway U 12 (stop **Prinzenstraße**, direction **Olympia-Stadion**).
Leave at **Zoologischer Garten** for Lindner hotel.
For Harnack House, transfer at **Wittenbergplatz** to subway U 3.

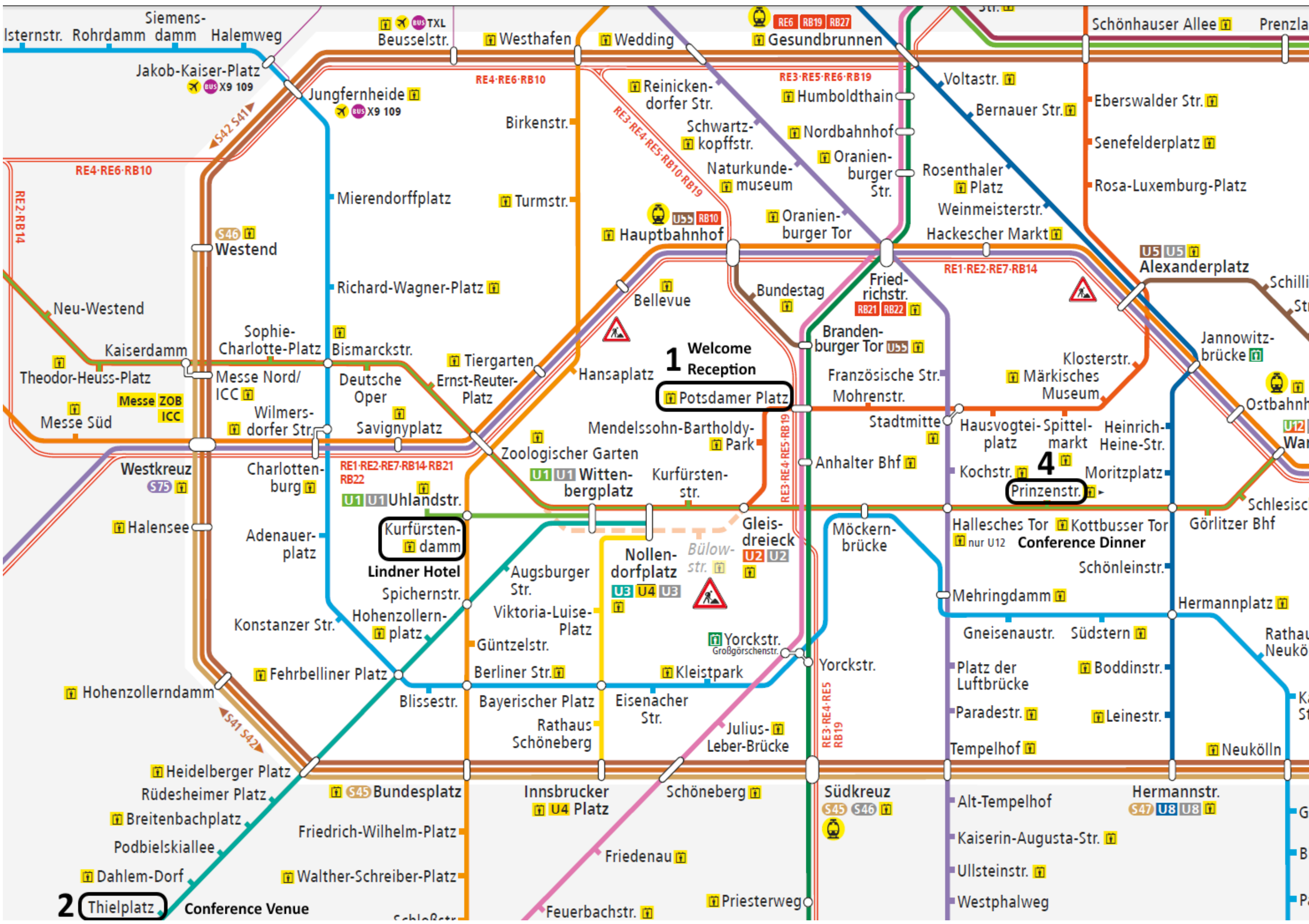


Registration and Wireless Internet

Registration is possible at the welcome reception on Sunday evening and in the Harnack house (conference venue) during the workshop.
In case of any questions, call the **registration hotline** at +49 30 5770 4725.
Wifi is available via Eduroam or get an access code at the reception.

For your notes…

Subway Map



Siemens-damm
Halemweg
Rohrdamm
Jakob-Kaiser-Platz
X9 109
Jungfernheide
Beusselstr.
TXL
Westhafen
Wedding
Gesundbrunnen
RE6 RB19 RB27
Schönhauser Allee
Reinicken-dorfer Str.
Birkenstr.
Schwartz-kopffstr.
Naturkunde-museum
Humboldthain
Nordbahnhof
Oranien-burger Str.
Voltastr.
Bernauer Str.
Rosenthaler Platz
Weinmeisterstr.
Hackescher Markt
Eberswalder Str.
Senefelderplatz
Rosa-Luxemburg-Platz
Alexanderplatz
Mierendorffplatz
Turmstr.
Hauptbahnhof
Oranien-burger Tor
Westend
Richard-Wagner-Platz
Neu-Westend
Bellevue
Bundestag
Fried-richstr.
Branden-burger Tor
Kaiserdamm
Sophie-Charlotte-Platz
Bismarckstr.
Theodor-Heuss-Platz
Messe Nord/ICC
Messe Süd
Deutsche Oper
Tiergarten
Ernst-Reuter-Platz
Hansaplatz
1 Welcome Reception
Potsdamer Platz
Französische Str.
Mohrenstr.
Stadtmitte
Klosterstr.
Märkisches Museum
Jannowitz-brücke
Hausvogtei-platz
Spittel-markt
Heinrich-Heine-Str.
Ostbahnhof
Wilmers-dorfer Str.
Savignyplatz
Mendelssohn-Bartholdy-Park
Zoologischer Garten
Westkreuz
Charlotten-burg
Witten-bergplatz
Kurfürsten-str.
Anhalter Bhf
Kochstr.
4 Prinzenstr.
Moritzplatz
Uhlandstr.
Halensee
Adenauer-platz
Kurfürsten-damm
Lindner Hotel
Gleis-dreieck
Möckern-brücke
Hallesches Tor
Kottbusser Tor
Conference Dinner
Görlitzer Bhf
Schönleinstr.
Spichernstr.
Augsburger Str.
Nollen-dorfplatz
Bülow-str.
Mehringdamm
Hermannplatz
Konstanzer Str.
Hohenzollern-platz
Viktoria-Luise-Platz
Güntzelstr.
Yorckstr.
Gneisenaustr.
Südstern
Fehrbelliner Platz
Berliner Str.
Kleistpark
Platz der Luftbrücke
Boddinstr.
Hohenzollerndamm
Blissestr.
Bayerischer Platz
Eisenacher Str.
Rathaus Schöneberg
Julius-Leber-Brücke
Paradestr.
Leinestr.
Tempelhof
Neukölln
Heidelberger Platz
Rüdesheimer Platz
Bundesplatz
Innsbrucker Platz
Schöneberg
Südkreuz
Alt-Tempelhof
Hermannstr.
Breitenbachplatz
Friedrich-Wilhelm-Platz
Podbielskiallee
Friedenau
Kaiserin-Augusta-Str.
Dahlem-Dorf
Walther-Schreiber-Platz
Ullsteinstr.
Priesterweg
2 Thielplatz
Conference Venue
Feuerbachstr.
Westphalweg

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- Optimizing Ridesharing Services – Complexity, Formulation and Solution Methods — Wei Lu & Luca Quadrifoglio
- Relocation and Balancing Strategies for Free-Floating Car Sharing Systems using Real-Time Data and Social Networking — Frederik Schulte & Stefan Voß
- Stochastic and Dynamic Inventory Routing in Bike Sharing Systems — **Dirk Mattfeld**, Viola Ricker & Marlin Ulmer

Session 3b Urban Delivery
13:30 – 15:30, Laue Hall

- Urban Distribution with Mobile Depots — Michael Schneider & Michael Drexl
- Some Recent Results on the Split Delivery Vehicle Routing Problem — Bruce Golden & Xingyin Wang
- Crowdsourced Same Day Delivery — Alp Arslan, Niels Agatz, Leo Kroon & Rob Zuidwijk
- Same-Day Delivery — **Barrett Thomas**, Stacy Voccia & Ann Campbell

Session chairs are shown in **bold**.

Robust Transit Network Design Based on Big Unrepresentative Data

C. Lee[a], G. McArdle[b], R. Nair[a]

[a]*IBM Research – Ireland*

[b]*National University of Ireland, Maynooth*

We investigate the extent to which systematic bias in source data can impact resource allocation decisions. This question arises in real-world applications of using opportunistically sensed data for transportation service design models. "Big" data available from telecommunication operators provide a rich and current estimate of travel demand at the disaggregate level, but likely suffer from systematic biases that depend on a range of factors, such as mobile phone market penetration rates, provider availability, ownership levels, usage patterns, costs and other factors. While optimization models leveraging such data benefit from high resolution data, the decisions are likely to lack equity on account of such systematic biases.

This question is addressed in the context of robust transit network design using origin-destination (OD) flows estimated from telecommunications data. The source data in this case is typically from call detail records (CDRs) from operators. A CDR is a disaggregate log of transactions (call or text) for each billed user of a mobile phone service provider. Taken as an aggregate, it provides sample sizes that are a few orders of magnitude larger than classical travel surveys. This high fidelity comes without representativeness guarantees however. Subsequent design models therefore are prone to inequity.

Past work by the authors have used a such data for line planning [1]. More recently, robust optimization methods where considered where demand is treated as a range estimate [2]. The key notion is the definition of an *uncertainty set* that considers all possible realizations and then optimizes for the worst-case realization. The resulting designs are conservative and hedges against uncertainty in demand estimates. The motivation behind having the uncertainty set is representativeness can be greatly improved by taking into account many possible outcomes rather than any single estimation of the world. In this paper, we address the extent to which such robust approaches can hedge against systematic biases, such as underrepresentation of key socio-demographic groups.

The examination of the representativeness question in the real-world has been previously hindered by the lack of global ground truth information on travel patterns. We exploit the unique Place of Work, School or College Census of Anonymised Records (POWSCAR) for Ireland. Unlike the Public Use Microsample Data (PUMS) in the US or the Sample of Anonymized Records (SAR) in the UK which were obtained from statistical sampling, the POWSCAR data was obtained via a national population census and provides socio-demographic and travel data for every worker or student in the country which is close to the ground truth. By systematically degrading observability over this baseline data, the impacts of design decisions and the value of robust optimization are studied.

We first present an urban sampling model that considers socio-demographic variables to yield specific subgroups, e.g. segments of the population that do not conform to dominant travel patterns, or subgroups with low probabilities of having digital signatures. Observability rates are then systematically considered for each market segment and range uncertainties are established. We focus on data for 2.7 million commuters and workers in Ireland.

The demand estimates along with their associated uncertainty from the urban sampling model are used in the robust transit network design model. Results from the partial observability cases are compared to the true demand process to study how under-represented groups are impacted by systematic biases.

Such representative considerations are critical in public sector applications, such as transit network design where equity is important. In growth market settings, opportunistic sensing is a key since classical surveys are prohibitively expensive and cities grow at a pace faster that the surveys can be conducted. African cities for example experience an annual growth of between 3-5% [3]. Design models implemented in these cases require careful real-world assessment where ground truth is available.

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Stochastic Service Network Design of Bike Sharing Systems

P. Vogel[a], A. Koberstein[b], D. C. Mattfeld[a]

[a]*Decision Support Group, Technische Universtität Braunschweig, Germany*

[b]*Chair in Business Informatics, European University Viadrina Frankfurt (Oder), Gemany*

This paper presents a stochastic programming approach to support the service network design of bike sharing systems. Bike sharing systems combine the advantages of public and private transportation to better exploit the given transportation infrastructure (DeMaio 2009). They enable sustainable means of shared mobility through automated rental stations. However, spatio-temporal variation of bike rentals in combination with one-way trips lead to imbalances in the distribution of bikes. Imbalances affect the service level, i.e., the successful provision of bikes and free bike racks when demanded. Due to limited capacity at stations, the fill level of bikes either prohibits rentals at empty stations or returns at full stations.

Ensuring the reliable provision of service is crucial for the viability of these systems. During the course of the day, the bike sharing operator relocates bikes in trucks from full to empty stations. Associated relocation services are described by pickup and return station, time period, and the number of relocated bikes. Operational planning of relocation usually involves vehicle routing models deciding on the assignment of relocation services to relocation vehicles and sequencing of relocation services in tours. Objectives for the optimization of relocation operations comprise e.g. minimizing the travel times or costs of relocation vehicles.

We aim at a tactical planning approach of service network design (Crainic 2000). Service network design supports the balancing of bikes to stations by determining target fill levels of bikes at stations in the course of day. Neglecting relocation in service network design will lead to suboptimal target fill level decisions since fill levels and relocation are directly interconnected. Poor target fill levels will induce high relocation effort whereas good target fill levels can alleviate relocation effort.

Thus, service network design of bike sharing systems requires the suitable anticipation of relocation. In order to formulate a computationally tractable model integrating decisions on fill levels and relocation, we refrain from using a computationally challenging vehicle routing model. Instead, operational relocation decisions are anticipated by a dynamic transportation model. The dynamic transportation model yields the set of relocation services required to maintain the target fill levels.

Implementation of target fill levels has to cover demand uncertainties. On the one hand side, trips follow typical traffic patterns in the course of day and week caused by e.g. commuter, leisure or tourist activities. On the other hand side, demand for trips is distorted by events, e.g. failure of bike stations, traffic jams or sport events, and weather effects such as seasonal temperature and sudden rain. As a result, robust fill levels are desired taking demand uncertainties into account.

In order to determine robust target fill levels, we present a stochastic service network design model. Similar to a recent approach in freight transportation (Bai et al. 2014), a two-stage linear program with recourse (Birge and Louveaux 2011) seems appropriate for our stochastic model formulation. The stochastic network design model aims at cost-efficient target fill levels given a predefined service level for uncertain bike demand. Uncertain demand is considered by means of scenarios representing different realizations of bike flows in the course of day. Each scenario is assigned a certain probability. In the first stage, target fill levels of bikes at stations are determined to satisfy a predefined service level. In the second stage, recourse actions are determined in the form of relocation services required for each scenario to maintain the target fill level. The objective is to minimize expected costs of relocation services. Output of the stochastic service network design model are robust time-dependent target fill levels at stations. In addition, sets of cost-efficient relocation services to facilitate these target fill levels for different demand scenarios are determined.

The two-stage model is solved by means of the parallelized nested L-shaped algorithm using dynamic sequencing and cut consolidation (Wolf and Koberstein 2013).

The proposed methodology is exemplified based on two years of operational data from Vienna's "Citybike Wien". Computational experiments show how to set robust target fill levels according to different scenarios of bike flows. Furthermore, spatio-temporal characteristics of relocation services are provided, which can support operators of bike sharing systems in the operational planning and implementation of relocation services.

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Optimizing Charging Station Locations for Urban Taxi Providers

M. Ruthmair, J. Asamer, M. Reinthaler, J. Puchinger

Mobility Department, Austrian Institute of Technology Vienna, Austria

Electric vehicles gain in importance and help to reduce dependency on oil, increase energy efficiency of transportation, reduce carbon emissions, and avoid tail pipe emissions. Major drawbacks of battery-only electric vehicles (BEVs) are higher acquisition costs and limited driving ranges due to limited energy storage capabilities. However, higher acquisition costs of BEVs compared to internal combustion engine vehicles (ICEVs) are compensated by lower operational costs. According to [3] the total cost of ownership (TCO) of a Smart Fortwo ICEV exceeds the TCO of a comparable BEV after approximately eight years, assuming an annual mileage of 10 000 km.

According to [2, 4, 5], taxi vehicles are ideal candidates for being replaced by BEVs, because of short driving distances, high mileages and intermediate waiting times, especially in urban areas. Trips can be accomplished without running out of electric energy, and intermediate waiting times can be used for charging. Although driving patterns of taxis are advantageous for introducing BEVs, there are some peculiarities which have to be considered. Many taxi vehicles are operated 24/7, meaning that several drivers share one vehicle over different shifts. Since nearly no time is left between two shifts, there is not sufficient time left for slow level I and II charging which usually takes several hours. Additionally, the number of charging operations should be kept as low as possible, because each time the driver has to search for a charging station (CS) and frequently plugging and unplugging to a CS is inconvenient. As shown in previous studies [2, 4, 5], the expected waiting time is below one hour implying that for level I and II CSs several charging operations are necessary and therefore not feasible. Fast level III chargers are more expensive and need more power but are able to charge the battery of an appropriate vehicle, e.g., the Nissan e-NV200, in about 30 minutes to 80% of its capacity. The Nissan e-NV200 has a maximum driving range of 170km and is a promising candidate for acting as taxi.

Prior to replacing taxis by BEVs, a suitable charging infrastructure has to be established. Sellmair and Hamacher [5] describe the optimization of CSs for taxi BEVs. They consider taxi stands as possible locations for CSs, where the demand for charging is identified by estimating the consumed electric energy for each trip. The analysis is based on GPS records of five taxis in Munich, Germany. The objective of the optimization was to gain an economic benefit for the entire system, meaning a cost-effective operation of CS.

Our study is based on operational data of a radio taxi provider in Vienna, Austria. We use positioning data of approximately 800 taxi vehicles (currently ICEVs) over one week. This period is representative since it contains a large number of trips ($> 60\,000$) from weekend, weekdays, day and night times. We aim to find locations for a limited number of CSs solely dedicated to taxis, while cost-efficiency for operating the CSs is not an objective. Instead of assuming taxi stands as the only possible locations for a CS, we focus on finding regions in which CSs should be placed. The exact location within an area is identified in a post-optimization phase, where environmental conditions, i.e., the capacity of the power network, availability of space, and legal issues, are considered. Such detailed information about specific locations might not be available in the planning phase. The investigated area is subdivided into uniform cells, i.e., hexagons, where each cell may contain at most one CS. The spatially distributed charging demand is aggregated, meaning that start and end locations of taxi trips within each cell were summed up. We assume that if a cell contains a CS it covers the charging demand of the corresponding cell, independent where exactly the CS is placed. This is only possible if travel times and distances within a cell are low. Therefore, the diameter of a cell was chosen to be one kilometre, which results in a maximum travel time of four minutes, given an average European urban travel speed of 15km/h [1]. A CS in a cell not only covers the demand of the same cell but also with a certain weight the demand of its neighbours.

Based on this data, an optimization problem – a set-covering problem – is defined as follows: Each

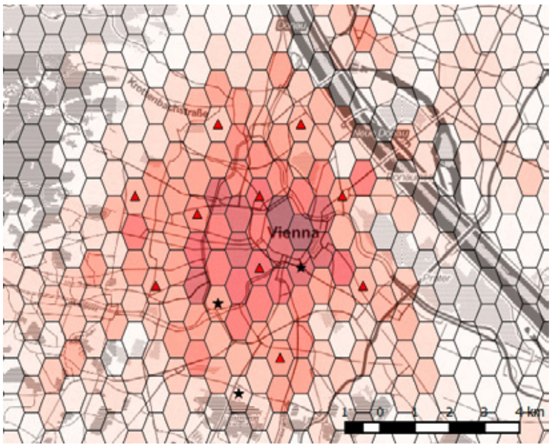

Figure 1: Hexagons with existing charging stations (stars) and recommended for placing a charging station (triangles). Weights $w_0 = w_1 = 1$.

hexagon in the considered region is assigned a value counting the taxi trips starting or ending in it. A hexagon is covered with some weight $w_0 \in [0, 1]$ if it is chosen as a location for a CS and with weight $w_1 \in [0, 1]$ if a neighboring hexagon contains a CS. We also consider already installed CSs here. The number of new CSs to be built is limited by R. The aim is to maximize the sum of covered trip counts, whereas (due to the weighting) a region can only be covered at most $M \geq 0$ times while using at most R CSs.

We formulate this problem as a mixed-integer linear program and solve it exactly by using the solver software IBM ILOG CPLEX 12.6. The optimization problem for the Vienna city region with about 1500 hexagons can be solved exactly within one second. We set $R = 10$ which is the number of budgeted CSs in the considered project. There are also two existing CS which are considered in the optimization. In Fig. 1 the corresponding solution is shown. Local authorities, power network operators, representatives of taxi driver guilds as well as radio taxi providers participated in the project and identified exact locations for CSs based on our suggested areas.

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A Bi-level Programming Model for the Workzone Scheduling Problem

D. Rey*, H. Bar-Gera, V. V. Dixit, S. T. Waller

* *Corresponding author, School of Civil and Environmental Engineering, University of New South Wales, Sydney, NSW 2052, Australia*

Major cities have dense road networks which require regular maintenance operations. Further, the organization of urban areas often relies on the road network to incorporate utility networks, such as electricity, telecommunications and water networks. As a result, lane or road closures—hereby referred to as workzones—are frequent and can lead to significant delays within the city if they are conducted without any coordination across the network. In this paper, we address the problem of determining an optimal schedule for the conduction of workzones in urban transportation networks. We propose a novel solution method for the Workzone Scheduling Problem (WSP) [1] that finds a schedule which maximizes the network performance while accounting for traffic prediction based on a forecasted travel demand.

Predicting and managing traffic flows in urban transportation networks is a complex modelling and planning problem that major cities confront on a daily basis. The prediction of traffic flows seeks to provide insight on the way travelers choose their route within a network and this step is known as the Traffic Assignment Problem (TAP) [2]. Such predictions are useful to evaluate the impact of transport planning policies concerned with the improvement of traffic conditions at a network level. The management of traffic flows is often focused on identifying the most suitable network design in order to reach a system optimum state, that is, to maximize the network performance. Among the available performance metrics, the Total System Travel Time (TSTT) is a well-studied objective function for traffic assignment based transportation models. Embedding the TAP into a Network Design Problem (NDP) has been widely studied in the field of transportation and this problem is generally represented as a bi-level programming where the upper level is the NDP and the lower level is the TAP [3].

To address the WSP, we propose a bi-level programming model with a scheduling problem that seeks to minimize the TSTT for the upper level and the TAP for the lower level. Specifically, the main decision variables of the upper level are the workzones start times and the main design constraints ensure that the workzones are completed within a given planning period. Each workzone is assumed to affect a given set of links in the network, for a specified duration; and the impact of workzones onto traffic conditions is represented by road capacity reductions. We use a link performance function to determine the travel time on a link according to its flow and its capacity. Travelers' route choice are represented using a static User Equilibrium (UE) model, which can be formulated as a convex optimization problem [4]. Due to the combinatorial nature of scheduling problem, the WSP problem is intractable for large instances and advanced search methods are required to efficiently find good solutions. We introduce a novel solution method for the WSP that uses the TAPAS algorithm [5] to solve the static TAP, which provides stable route flows under the assumption of proportionality. Our approach is based on a decomposition of the upper level search space where workzones schedules are evaluated according to their spatial (links affected) and temporal (workzone duration) characteristics. The model behavior is examined through tests conducted on benchmark traffic instances and we propose a heuristic approach to tackle larger instances. Further, we develop complexity metrics to classify instances for the WSP based on the spatial and temporal interaction between workzones. We show that the proposed model is competitive, even on difficult instances.

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Emerging Area in Urban Transportation System Research – Optimization and Analytics on Wireless Charging Electric Bus System

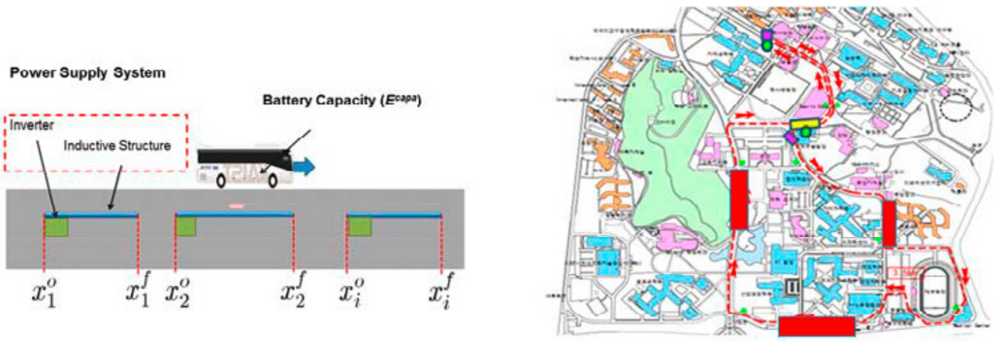
Y. J. Jang

Industrial and Systems Engineering, KAIST, South Korea

We introduce the innovative wireless charging electric vehicle which charges the battery wirelessly from the charging infrastructure installed under the road. The technology is innovative in that the vehicle is charged while it is even in motion. One example of the commercialized system is the Korea Advanced Institute of Science and Technology (KAIST) wireless charging EV shuttle, which is called Online Electric Vehicle (OLEV) currently operating in the KAIST campus.

As shown in Figure 1, the OLEV system comprises vehicle units and power supply systems. Note that although the name OLEV indicates a vehicle unit alone, it actually refers to a system comprising a vehicle or fleet of vehicles combined with a charging infrastructure that takes the form of a set of power supply systems buried in the road. A vehicle in the OLEV system has a pickup device that collects electric energy from the power supply systems. When the vehicle operates in the vicinity of a power supply system, the inductive cable sends electricity wirelessly to the pickup device. Because charging takes place while the vehicle is in motion, the system eliminates the major problem of conventional electric vehicles, the need to discontinue bus operation to charge the battery.

We introduce the optimization problem allocating the charging infrastructure of the wireless charging EVs. The problem is different from the conventional charging infrastructure allocation based on the facility location problem. Since the charging can be done while the vehicle is in motion, any place where the vehicle moves can be the candidate for allocating the charging infrastructure. We present a several optimization methods and algorithms developed and currently used in designing the commercial OLEV system. We also propose the new problems and research opportunities in wireless charging EVs to the OR/MS community.



(a) Decision Variables (Number of power transmitters, their locations, their lengths, and the battery size)

(b) Allocation of the power transmitters for the OLEV currently operating at KAIST campus

Figure 1 OLEV system

Optimal Deployment of Charging Lanes in Transportation Networks

Y. Yin[a], Z. Chen[a], F. He[b]

[a]*Department of Civil and Coastal Engineering, University of Florida, United States*

[b]*Department of Industrial Engineering, Tsinghua University, China*

Electric vehicles have been long recognized as a promising way to reduce traffic emissions locally and petroleum dependence. Early models of electric vehicles all came with limitations and costs that prevented them from competing with gas-fuelled cars. However, recent advances in battery technologies and expeditiously rising prices of crude oil have helped re-launch electric vehicles. Many governments also provide a variety of subsidies or incentives to promote the adoption of electric vehicles. With the deployment of charging or battery swapping stations and further improvement of battery technologies, a fast-growing adoption of electric vehicles can be expected.

This paper attempts to develop a mathematical model to optimally deploy in a large-scale highway network charging lanes that charge electric vehicles while they are on the move. Quite a number of technologies could enable charging lanes. Researchers at Volvo are testing two types of "conductive charging", the same technology used for trams and trains, to power electric vehicles on long-distance highway trips. One method charges via lines overhead and the other uses two metal bars in the road. Scania is also investigating a similar overhead charging technology to power heavy trucks and has a two kilometers of test track outside Berlin to field test the technology. On the other hand, remarkable progress has been made in the field of inductive charging. Recent research advances have enabled transferring power across large air gaps with high efficiency and signaled bright prospects that electric vehicles in motion can be charged wirelessly. The Energy Dynamics Laboratory at Utah State University has proved that enough power can be transferred wirelessly to safely and effectively charge electric vehicles. Future versions of their system are expected to wirelessly charge vehicles at a speed of 75mph. Companies such as Scania and

Qualcomm have been developing their own inductive charging technologies. 15 miles of charging lane has been constructed in Gumi, South Korea, which recharges a dozen of buses while in motion.

We envision in this paper that charging lanes can be deployed in regional or even urban road networks using either conductive or inductive charging technologies. With charging lanes deployed, drivers of electric vehicles will not fear any more running out of battery en route. This paper optimizes a deployment plan or design of charging lanes in a general road network. More specifically, given a limited budget, the model will determine the location and length of each charging lane to minimize total social cost that includes travel time and emissions. To achieve this goal, we first develop a new user equilibrium traffic assignment model that describes the network equilibrium flow distribution across the road network, given a particular deployment plan or design of charging lanes. It is assumed that drivers of electric vehicles, when traveling between their origins and destinations, select routes and decide battery recharging plans to minimize their trip times while making sure to complete their trips without running out of charge. A battery charging plan will dictate which charging lane to use and where to enter and leave the lane, and which speed to operate an electric vehicle. The speed will affect the recharging rate of electricity as well as the travel time. With the established user equilibrium conditions, we further formulate the design of charging lanes as a mathematical program with equilibrium constraints, which will be solved and demonstrated on a realistic network.

Time-Dependent Pollution-Routing Problems with Path Flexibility in Mega-City Logistics

Y. Huang[a*], L. Zhao[a†], T. Van Woensel[b‡], J.-P. Gross[a§]

[a]*Department of Industrial Engineering, Tsinghua University, China*

[b]*School of Industrial Engineering, Eindhoven University of Technology, Netherlands*

Freight transportation in urban areas of mega-cities has always been challenging. Congestion, which prolongs delivery time and causes more fuel consumption, is one of the major challenges for logistics companies in mega-cities. Smart routing under uncertain traffic condition requires the combination of planning in advance and decisions in real time. Fuel cost can account for over 46% of the total operation cost for a logistics company (China Federation of Logistics & Purchasing)[1]. It is critical to route its fleet of vehicles smartly to save fuel cost.

Bektaş and Laporte (2011) first introduced the pollution-routing problem (PRP) to take fuel cost and congestion into account. Franceschetti et al. (2013) further proposed the time-dependent pollution-routing problem (TDPRP) to consider the time dependency and spatial difference of traffic condition. Specifically, the travel time on each arc can be modeled as a piecewise linear function of the departure time at the origin node of the arc. Both models (implicitly) assume that an arc (which connects two customer locations) is mapped to one given path. However, it is possible that a vehicle may choose an alternative path to avoid the congestion, especially under time-dependent traffic condition. This paper focuses on TDPRP with Path Flexibility (TDPRP-PF) under both deterministic and stochastic traffic conditions, which highlights the importance of path flexibility in smart routing.

In this study, we emphasize the importance of decoupling two graphs in the time-dependent routing problem, the *customer graph* (with customer locations as nodes in the network) and the *geographical graph* (with intersections as nodes in the road network). Each arc in the customer graph corresponds to multiple paths in the geographical graph, which can be the distance-minimizing shortest path or the time-dependent time-minimizing shortest paths. These two types of paths can be generated in polynomial time. Assume that the travel speed of each road segment is a step function of the departure time at the starting node t, the total travel time on the road segment is a piecewise linear function of t. For a path containing finite road segments, the total travel time on this path is also a piecewise linear function of the departure time at the starting node of the path.

Under deterministic traffic condition, we formulate TDPRP-PF as a mixed integer program based on the two-index single-commodity flow model of the classical VRP (Gavish and Graves, 1981). The piecewise linear travel time function of each path can be modeled via integer programming techniques (Sridhar et al., 2013). Our model aims to minimize the total cost including fuel cost and distance-based (e.g., depreciation) cost. The fuel consumption is calculated via the Comprehensive Modal Emission Model (CMEM, Barth and Boriboonsomsin, 2009). Under stochastic traffic condition, the problem is modeled as a two-stage stochastic

*huangyx12@mails.tsinghua.edu.cn
†lzhao@tsinghua.edu.cn
‡T.v.Woensel@tue.nl
§jpgross@numericable.fr

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program, where in the first stage the offline routing decision is made in the customer graph and in the second stage the en route path selection is decided in the geographical graph. Note that the decoupling of the customer graph and the geographical graph enables the decoupling of offline routing decision and the en route path selection decision. The two-stage stochastic program has binary variables in both stages. We apply modified Benders' decomposition method (Carøe and Tind, 1998; Sherali and Fraticelli, 2002) to improve the solution efficiency.

We construct a case study based on the urban area of Beijing. The road segments in the geographical graph are classified into three categories: expressways, arterial roads, and small roads (Wang et al., 2008). The geographical graph contains of 409 nodes (road intersections) and 917 arcs (road segments) of expressways and arterial roads. Small roads are calculated using Manhattan distance. The customer set is composed of 54 hypermarkets (Carrefour, Wal-Mart, Auchan, Metro, and Beijing Hualian) in Beijing, which are representatives of the retail demand (also the delivery demand) in the city. For each instance, customer nodes in the customer graph are randomly selected from the customer set.

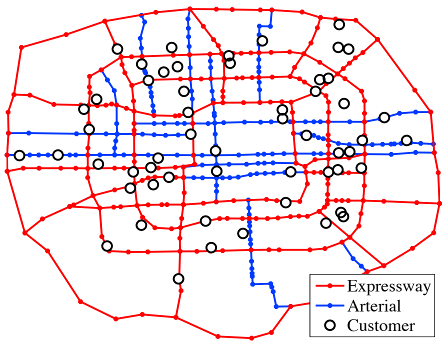

Figure 1: Road network and customer locations in Beijing

In the baseline instances, we assume the demand is equal at each customer site. Numerical results illustrate the importance of the path flexibility in TDPRP, under both deterministic and stochastic traffic conditions. Under deterministic traffic condition, TDPRP-PF saves 7.1% of the total cost on average comparing to distance-minimizing vehicle routing problem (CVRP), while TDPRP without path flexibility only saves 1.3% of the total cost. Similarly, under stochastic traffic condition, TDPRP-PF saves 7.3% of the total cost comparing to CVRP, while TDPRP without path flexibility only saves 1.3% of total cost. Moreover, we study the impact of key parameters on total cost savings and routing decisions, such as the demand/capacity ratios at customer sites, and the demand variation among customer sites. Furthermore, we study the impact of the flexibility of departure time at the depot and post-service waiting time at the customer sites.

Keywords: mega-city logistics; time-dependent vehicle routing problem; pollution-routing problem; path flexibility; geographical graph; uncertainty

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The Fleet Size and Mix Polluting-Routing Problem

C. Koc[a], T. Bektas[a], O. Jabali[b], G. Laporte[b]

[a]*CORMSIS and Southampton Management School, University of Southampton*

[b]*CIRRELT and HEC Montréal*

Many cities face significant challenges related to the pollution generated by the number of vehicles that need to travel within their areas. Urban freight transportation of goods is one of the primary sources of greenhouse gases (GHGs) emissions such as carbon dioxide (CO_2). This transportation activity is often captured by the Vehicle Routing Problem with Time Windows (VRPTW), which aims to design feasible routes for a homogeneous set of vehicles to meet customer demands within predetermined time windows. To account for environmental concerns Bektaş and Laporte (2011) introduced the pollution-routing problem (PRP) as an extension to the VRPTW. The PRP consists of routing a set of homogenous vehicles to serve a set of customers, and of determining their speed on each route segment to minimize a function comprising fuel cost, emissions and driver costs. However, in most real-world distribution problems, customer demands are met with heterogeneous vehicle fleets (Hoff et al., 2010). Therefore, the aim of this paper is to extend the pollution-routing problem by considering a heterogeneous vehicle fleet.

Using a heterogeneous fleet in VRPs was introduced by Golden et al. (1984) as the fleet size and mix vehicle routing problem, which works with an unlimited heterogeneous fleet. To our knowledge, the fleet size and mix vehicle routing problem combining time windows with the PRP objectives has not yet been investigated. We believe there is merit in analyzing and solving the fleet size and mix pollution-routing problem (FSMPRP), not only to quantify the benefits of using a flexible fleet with respect to fuel, emissions and the relevant costs, but also to overcome the necessary methodological challenges to solve the problem.

To estimate pollution resulting from goods transportation we use a simplified version of the emission and fuel consumption model proposed by Barth et al. (2005), Scora and Barth (2006) and Barth and Boriboonsomsin (2009). The simplified model assumes that in a vehicle trip all parameters will remain constant on a given arc, but load and speed may change from one arc to another. As such, the PRP model approximates the total amount of energy consumed on a given road segment, which directly translates into fuel consumption and further into GHG emissions. Furthermore, in our study, we consider the three main vehicle types of MAN (2014a) . These three vehicle types are TGL, TGM and TGX by MAN (2014a), which correspond to light duty, medium duty and heavy duty.

We develop a new hybrid evolutionary algorithm for the FSMPRP. This algorithm builds on the work of Koç et al. (2014), which is itself based on the principles put forward by Vidal et al. (2014). In this paper, we have additionally developed the heterogeneous adaptive large neighbourhood search which is used as main element in the algorithm. An adapted version of the Speed Optimization Algorithm (Norstad et al., 2010; Hvattum et al., 2013) is applied on a solution within the algorithm to optimize speeds between nodes.

The effectiveness of the algorithm was demonstrated through extensive computational experiments on realistic PRP and FSMPRP instances. These tests have enabled us to assess the effects of several algorithmic components and to measure the trade-offs between various cost indicators such as vehicle fixed cost, distance, fuel and emissions, driver cost and total cost. We have demonstrated the benefit of using a heterogeneous fleet over a homogeneous one. An interesting insight derived from this study is that using a heterogeneous fleet without speed optimization allows for a further reduction in total cost than using a homogeneous fleet with speed optimization. Furthermore, we have shown that using an adequate fixed speed yields results that are only slightly worse than optimizing the speed on each arc. This has a practical implication since it is easier to instruct drivers to hold a constant speed for their entire trip rather than change their speed on each segment.

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The Taxi Recourse Problem

N. Vodopivec[a], E. Miller-Hooks[b]

[a]*Applied Mathematics & Statistics, and Computation Program, University of Maryland*

[b]*Corresponding author: Civil & Enviromental Engineering Department, Unversity of Maryland and the National Science Foundation*

Dial-a-ride services are demand-responsive door-to-door ridesharing services. Their typical users are mobility-impaired passengers seeking rides to doctors' appointments and travelers accessing airports. Providers of such ridesharing services must negotiate between high customer expectations and rules set by planning agencies that fund such services. The Dial-A-Ride Problem considers efficient routes and schedules for these services. Although the problem is well researched, most models assume that exact travel times are known in advance. Even strategies that do plan for various uncertainties may not perform well in actual circumstances.

As a recourse measure and strategy for increasing operational efficiency, we consider dynamically reassigning customers to taxis when ridesharing vehicles fall behind schedule. We focus not on route development or revision, but on an effective strategy for calling taxis as backup to a vehicle deployed along a given route. We assume that operators must negotiate between two costs: the added fare for calling a taxi and a penalty for picking up a customer late. Moreover, if a taxi is called but does not arrive on time, the operator must pay both the added fare and the penalty.

As time passes, the vehicle approaches its destination and the operator knows with greater certainty whether calling a taxi is warranted. However, the more the decision is postponed, the greater the chance that a taxi, if called, will itself arrive late. We refer to the problem of determining if and when to call a taxi in this context as the Taxi Recourse Problem (TRP).

The decision to call a taxi is fundamentally different from the decision to continue with the vehicle—the first is irreversible and the second always contains a hidden opportunity for later recourse. In the language of investment, this implies that comparing the net present value of our options is not the optimal strategy. With this in mind, we model the TRP as an optimal stopping problem, in which the decision to stop and call a taxi can be made at any point on a continuous, finite interval of time. Along the open interval, the stopping cost is known a priori and increases linearly with time. If stopping has not occurred by the end of the horizon, the decision process is terminated and the terminal stopping cost is a binary value determined by whether the vehicle has reached its destination.

Model description, formulation and solution

We take as our decision horizon the interval $[0, T]$. Time 0 is the last moment that a taxi, if called, would be certain to arrive on time. (A rational decision maker would never call a taxi before this time.) Time T is the customer pickup deadline. In the proposed model, the vehicle adheres to its preplanned route. Its position along the route, $x(t)$, follows a Brownian motion with drift, $dx = \mu\, dt + \sigma\, dz$, where dz is the increment of a standard Wiener process. Drift rate μ is the mean velocity of the vehicle. The vehicle begins at initial position $x_0 = 0$ at time 0 and, if taken to the end, must reach position X by time T. If the vehicle is taken to the end and does not arrive by that time, that is, if $x_T < X$, the company incurs a cost of C_{late}.

Alternatively, at any point along the decision horizon, a taxi may be called for a fixed taxi fare of C_{fare}. The taxi's travel time to the pickup is uniformly distributed on the interval $[0, T]$. Because the taxi's position is exogenous to our model, we consider only its expected cost if called. This expected cost is a known, deterministic function of call time, which increases linearly from C_{fare} to $C_{\text{fare}} + C_{\text{late}}$ on $[0, T]$.

We define our stopping cost $\Omega(x, t)$ as follows:

$$\begin{aligned} \Omega(x,t) &= C_{\text{fare}} + C_{\text{late}} \cdot \frac{t}{T} \quad & 0 \le t < T \\ \Omega(x,T) &= \begin{cases} C_{\text{late}} & x < X \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

The first equation gives the stopping cost if the taxi is called and the second gives the terminal stopping cost if the vehicle is taken to the end.

We formulate our optimal stopping problem as a stochastic dynamic program (SDP) on the defined costs:

$$F(x,t) = \min\{\Omega(x,t), \mathrm{E}[F(x+dx, t+dt) \mid x]\}$$
$$F(x,T) = \Omega(x,T),$$

where $F(x,t)$ is a cost function that gives the operator's expected costs given that all future decisions are made optimally, and $F(x,T)$ is the terminal boundary condition.

We show that the optimal policy is a benchmark policy, characterized at each point in time by a single critical position that the vehicle must have reached in order to continue. More formally, for each t, there exists a unique $x^*(t)$ such that it is optimal to continue with the vehicle if $x(t) \ge x^*(t)$ and to call a taxi if $x(t) < x^*(t)$. In other words, over the interval $[0, T]$, $x^*(t)$ partitions the (x, t) space into two regions: one where it is optimal for the vehicle to continue and another where recourse should be taken.

By Ito's Lemma, our cost function $F(x,t)$ must satisfy the following partial differential equation in the continuation region above the free boundary $x^*(t)$:

$$\begin{aligned} \tfrac{1}{2}\sigma^2 F_{xx} + \mu F_x + F_t &= 0 && \text{(Kolmogorov backward equation)} \\ F(x,T) &= \Omega(x,T) && \text{(terminal boundary condition)} \\ F(x^*(t),t) &= \Omega(x^*(t),t) && \text{(value matching at free boundary)} \\ F_x(x^*(t),t) &= \Omega_x(x^*(t),t) = 0 && \text{(smooth pasting at free boundary)} \end{aligned}$$

We give a numerical approximation to the free boundary $x^*(t)$.

The 'wait-and-see' solution above accounts for the ability to take later recourse based on more accurate information. We compare this solution to a 'now-or-never' solution, which is chosen at each point based on a comparison of net present values of recourse and no recourse. We show that the benefits of the 'wait-and-see' solution are highest when we are most uncertain about our decision.

A Bilevel Model with Embedded SDP to Study Tradeoffs against Slack

With a reliable recourse plan, ridesharing service providers may be able to reduce unnecessary slack in the schedules when creating routes. The above SDP is embedded within a bilevel framework in which the upper level seeks an optimal use of slack in schedule planning given optimal taxi recourse decisions in response to actual circumstances at the lower level. An equilibrium is reached that balances added slack levied in the planning stage against late penalties and taxi fares imposed in the execution stage. We present numerical results to explore this point of equilibrium.

Relevance to Workshop Theme

This work addresses a dynamic ridesharing problem under real-time information. Up-to-the-minute travel-time forecasts and real-time location updates have been made widely available through mobile devices. The developed methodology exploits this information to make dynamic routing decisions in a stochastic environment. In an urban setting, where taxis are readily available, the proposed taxi recourse can help overcome existing challenges faced by shared mobility service providers.

Optimizing Ridesharing Services – Complexity, Formulation and Solution Methods

W. Lu, L. Quadrifoglio

Zachry Department of Civil Engineering, Texas A&M University, USA

Ridesharing services, which aim to bring together travelers with similar itineraries and compatible time schedules, may provide substantial societal and environmental benefits by reducing the use of private vehicles. When the operations of a ridesharing system is optimized, it can also save travelers significant amount of transportation cost. The economic benefits associated with ridesharing in turn attract more travelers to participate in ridesharing services and thereby improving the utilization of transportation infrastructure capacity. We study the most generalized setting of ridesharing problem – given a set of travelers and their origins/destinations, we aim to simultaneously make decisions on driver/rider role assignment, customer partition and route planning, with the goal of minimizing the system-wide total vehicle-miles.

Suppose we have n ridesharing participants $P = \{1, 2, \ldots, n\}$. Each of them has an origin location and a destination location. Denote the node set of origin and destination locations as V_O and V_D, respectively. Let node i be customer i's origin node ($1 \leq i \leq n$) and $i + n$ be his/her destination node, then we have $V_O = \{1, 2, \ldots, n\}$ and $V_D = \{n+1, n+2, \ldots, 2n\}$. Then we have a complete digraph $G = (V, A)$, where $V = V_O \cup V_D$ is the set of all nodes and $A = V \times V$ is the set of all arcs. Figure 1 provides an illustration showing two feasible solutions to ridesharing optimization problem on G. Note that the number in a node indicates its associated customer index. Nodes with a rectangular shape and a "+" label represent the destinations. Figure 1(a) is a solution that consists of individual trips (no ridesharing at all). On the other hand, in Figure 1(b) customers 1 and 2 form a ridesharing group and customers 4, 5 and 6 form a ridesharing group. Nodes in red belong to the customers that are assigned as drivers.

We show that the ridesharing optimization problem is NP-hard through a reduction from the set packing problem. A mixed-integer program (MIP) model is developed to solve the ridesharing optimization problem to optimality. Because the NP-hardness of the problem, the MIP model is not able to solve larger instances within a meaningful time. An insertion-based heuristic is developed to get approximate solutions to the ridesharing optimization problem. Parallel algorithm approaches are utilized to further improve the computational efficiency.

We conduct experiments to validate and evaluate the developed models and algorithms. All algorithms are implemented in Java with CPLEX 12.6 and the Concert library. The data set[1] we

[1] The data sets can be downloaded from `http://www.diku.dk/~sropke/`

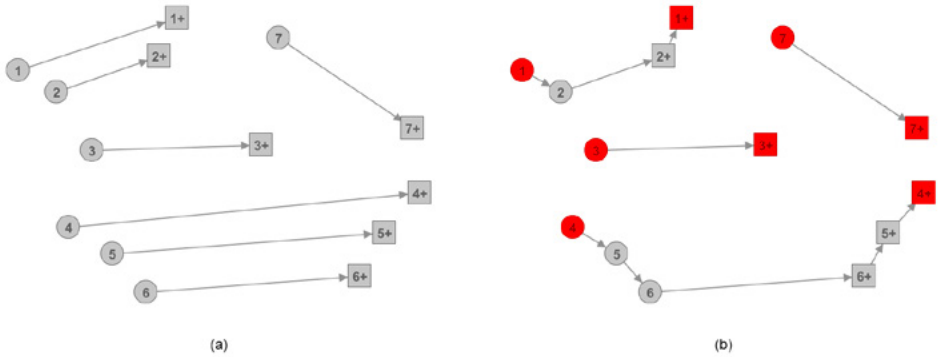

Figure 1 (a) Individual trips vs. (b) organized ridesharing trips

Table 1 Performance of algorithms

Problem size	Total cost				
	Solo	Match		Insertion	
5	2509.5	2264.5	(9.8%)	2225.9	(11.3%)
10	5325.9	4476.5	(15.9%)	4272.7	(19.8%)
15	7929.6	6654.7	(16.1%)	6499.7	(18.0%)
20	10561.8	8454.6	(19.9%)	8201.7	(22.4%)
25	12695.5	10430.8	(17.8%)	9826.4	(22.6%)
30	16490.1	12975.2	(21.3%)	12190.0	(26.1%)
35	18367.0	14327.1	(22.0%)	13576.6	(26.1%)

use in the experiments are selected from Dumitrescu et al. (2010). From a societal perspective, our ridesharing optimization model provides substantial system-wide travel cost saving (25%+) compared to the non-ridesharing situation. Evaluation of the heuristic solution method shows that the heuristic can solve the problem very fast and provide nearly optimal (98%) solutions. To further compare the solution qualities of insertion heuristic (Insertion) and optimal matching (Match) (see Wang 2013), the average solution values for each problem size are summarized in Table 1. The percentage in parenthesis for each solution method indicates the cost saving percentage compared to the non-ridesharing route plan (Solo). It can be seen that Insertion always outperforms Match, and can further save about 5 percent of the total travel cost – a non-trivial amount of mileage. In the future it will be interesting to see how our algorithms perform on the real-world data sets in which customer locations are more likely to be clustered than random.

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Relocation and Balancing Strategies for Free-Floating Car Sharing Systems using Real-Time Data and Social Networking

F. Schulte, S. Voß

Institute of Information Systems, University of Hamburg, Germany

Introduced in recent years free-floating car-sharing systems (FFCS) face a rapid growth, making car sharing an attractive alternative to a self-owned car and contributing significantly to the worldwide growth in car sharing (Shaheen and Cohen, 2013). Current studies indicate that FFCS can lead to a significant reduction of urban emissions (Firnkorn and Müller, 2011; Glotz-Richter, 2012). Previous work has furthermore demonstrated that, like in bike-sharing, FFCS tend to get imbalanced and system providers are challenged to reposition vehicles in an economic and eco-friendly fashion (Herrmann et al., 2014; Weikl and Bogenberger, 2012). To encourage app development and to enter social network (SN) communities, system providers, such as car2go, started to provide web based interfaces that offer comprehensive real-time data from their systems. This creates new opportunities for researchers to develop smart strategies and optimization algorithms to guide relocation and balancing attempts in car sharing (Herrmann et al., 2014). In addition, access to SNs enables new forms of sharing (Belk, 2014). In FFCS SN can, e.g., connect users, combine trips, help to share demand, and thus relieve high demand areas in car sharing systems.

Traditional car sharing operates stations where users have to pick-up and return cars. In contrast to these car sharing systems, free-floating systems define a geo-fence—an operating area around a city center—in which a user can hire and drop cars directly at or very close to his demand points without having to visit a station before or after the ride. This enables the user to simply search and book a car close to his current position using his smart phone. When a user decides to book a car, what matters most is the distance from his current position to the next available car (Herrmann et al., 2014). More generally, if a user frequently experiences that there are no available cars close to his demand points, he will probably not accept the system as a substitute to another, more reliable transportation mode. In car sharing, as well as in other vehicle sharing systems, e.g., in bike sharing, significant fluctuations in demand can be observed (Raviv et al., 2013). Depending on the day and the hour, certain areas in cities accumulate an extremely high demand, while others are not in the focus of the user. Thus, in certain areas there are a lot of empty or idle cars, while in other areas customers can hardly find a car close to their own position.

To address this problem relocation or repositioning of the cars has to be considered, granting that no potential short- and long-term customers are lost. In free-floating car sharing the vehicles are dispersed within different demand areas. In this way the FFCS relocation problem extends related problems named one-way or flexible car sharing, which allow the user to freely choose among multiple stations where to drop the shared car. For the FFCS relocation problem few strategies have been developed, and no strategies are yet applied in industry (Weikl and Bogenberger, 2012). Weikl and Bogenberger (2012) propose first user- and operator-based strategies for relocation in free-floating systems and point out a need for future development and evaluation of related strategies.

This paper aims to introduce an integrated approach for decision support in balancing FFCS and evaluate user-orientated relocation strategies based SNs. We propose a clustering approach to model car2go demand data and support effective relocation plans. Furthermore, we illustrate how demand forecasts and real-time data from the system provider can serve in an integrated decision support approach, controlling the application of relocation strategies. For the evaluation we have conducted a discrete-event simulation study, using booking and availability data from the car2go system in Hamburg, Germany. The results indicate that the proposed set of relocation strategies is significantly more economic and eco-friendly in terms of emissions than the classic relocation approach used in industry. This study includes a comprehensive literature review on FFCS, a new approach towards short term forecasting of FFCS demand, and integrated decision support approach relocation in FFCS with a quantitative analysis of costs and emissions for various relocation strategies using real-time data from car2go.

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Stochastic and Dynamic Inventory Routing in Bike Sharing Systems

V. Ricker, D. C. Mattfeld, M. W. Ulmer

Decision Support Group, Technische Universität Braunschweig, Germany

In order to encounter traffic congestion and environmental pollution, many cities established bike sharing as an addition to their local public transport [2]. Station-based bike sharing systems allow spontaneous rental and return of bikes at arbitrary stations. Depending on the locations of the stations, stochastic customer demand differs throughout a day. This leads to spatio temporal imbalances in the distribution of bikes [4]. If the demand cannot be fulfilled at a station, customers are forced to detour to a nearby station in order to rent or return bikes. To avoid these inconveniences, service providers reposition bikes. Thus, they decide about origin and destination and number of transported bikes and the routing of the transport vehicles. Customer demand and bike transports constitute fill levels of stations in analogy to inventory planning. This decision problem is a dynamic and stochastic case of the well known inventory routing problem (IRP) [1].The first objective is to reduce the customer inconveniences by minimizing the customer detours. The second is to minimize routing effort of the service provider. Thus we propose a weighted term of both objectives allowing a balanced consideration. Here anticipation of future customer demand has the potential to improve the decision making. This complex stochastic and dynamic IRP can be modeled as Markov decision process (MDP), depicted in (1). Given a time horizon $t = [0, T]$, let $k = 0, ..., K$ denote equidistant decision points. A state S_k contains information about fill levels at all stations $i = 1, ..., n$ at a particular time t_k as well as the position of the transport vehicles. The decision d includes fill levels, transports, and routing. Its instant costs represent the transport vehicles' effort $c_k^{tr}(d)$. The post decision state S_k^d contains the resulting fill levels and vehicle positions. The stochastic transition ω_k including all bike flows generated by customer actions leads to the next state S_{k+1}. Customer actions induce costs in terms of detours $c_k^{det}(d, \omega_k)$.

$$S_k \xrightarrow{d} S_k^d \xrightarrow{\omega_k} S_{k+1} \tag{1}$$

The size of the state space equals the number of all combinations of possible fill levels at the stations and every position of the vehicle fleet. The decision space consists of the fill level changes at the stations and every associated feasible routing plan. Due to the high dimensionality of real world instances a reduction of state and decision spaces is required to efficiently apply solution methods.

To reduce the decision space, we decompose the IRP into inventory planning and routing. Decisions about the inventory are made considering an estimation of the routing effort. The actual routing is applied subsequently.

For the inventory planning, we choose an anticipatory approximate dynamic programming (ADP) method [3]. ADP selects the decision minimizing the sum of instant and expected future costs. For the presented problem, the instant costs are given by an estimation of the routing effort $c_k^{tr}(d)$. The expected future costs, i.e. customer detours $c_k^{det}(d, \omega_k)$, are approximated by simulation. For a sufficient value approximation in reasonable time, we reduce the state space in two ways. First, the stations' post decision states $S_{ik}^{d_i}$ are considered individually. Second, we aggregate fill levels to coarse grained intervals. For routing we propose an adaption of a nearest neighbour heuristic.

We apply the decomposition to a real world case study, based on data of City-Bike in Vienna. We compare our anticipatory approach to two different myopic approaches regarding the overall time spent on customer detours and bike relocation. The first is a greedy method (*greedy*), which avoids any transportation actions because of its instant costs. The second approach uses inventory buffers (*buffer*). The results show that relocation is inevitable to achive an acceptable service level, as there is a huge amount of customer detours when we avoid any transportation costs. Compared to the *greedy* method, the *buffer* approach improves the solution quality, significantly reducing the customer detours. The *ADP* approach outruns both approaches, underlining the advantage of anticipation.

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Urban Distribution with Mobile Depots

M. Schneider[*], M. Drexl[†]

[*]*Logistics planning and Information Systems, TU Darmstadt, Germany*

[†]*Chair of Logistics Management, Gutenberg School of Management and Economics, Johannes Gutenberg University, Mainz, Germany*

The vehicle-routing problem with time windows and mobile depots (VRPTWMD) is a generic problem, which can be described as follows. We are given a set of delivery vehicles and a set of support vehicles, which are all positioned at a single depot and operate to visit a set of customers. Each customer is associated with a nonnegative demand, a service time, and a single, hard time window within which service at the customer has to start. With each ordered pair of locations, i.e., depot and customers, a travel time, and a fuel consumption are associated. Alternative to demand associated with the customers, demand can be associated with the links between locations.

The delivery vehicles are characterized by a restricted load capacity, fuel capacity, and time capacity (maximal route duration constraints). The respective capacities reduce depending on the following four consumption types until either the vehicle returns to the depot or the route becomes infeasible: i) load demands at customers, and ii) load demands on links between locations, iii) fuel demands on links between locations, and iv) time demands on links between locations.

Depending on the application context, a support vehicle can serve as mobile depot to restore either the load capacity for the load to be delivered, or the fuel capacity by serving as mobile refueling station, or the time capacity by serving as driver exchange. Note that we assume the "or" to be exclusive and that all support vehicles restore the same capacity type. To serve in one of the described ways, a support vehicle must meet with a delivery vehicle at a location, and both vehicles must stay at the location until the capacity transfer terminates. We assume that the respective capacity of a delivery vehicle is always fully restored upon meeting with a support vehicle. The possible meeting points are restricted to all customer locations and the transfer must occur while the delivery vehicle serves the respective customer. A transfer time is incurred if support vehicle and delivery vehicle meet. We further assume that the supply of a support vehicle is limited and that a maximal route duration applies for the operation of this vehicle type.

The problem is related to multi-echelon VRPs (Cuda et al. 2015) and to the truck-and-trailer routing problem (Drexl 2012). Application areas of the VRPTWMD are mainly found in the city logistics context where small vehicles are used to navigate narrow streets and deliver/collect goods or to collect waste, and a larger vehicle serves as mobile depot to replenish the good to be delivered or to take over the collected goods or waste. Access in urban centers may not only be restricted with respect to the dimensions of the vehicle but also due to regulations on emissions, which makes some areas only accessible for green vehicles such as, e.g., battery electric vehicles. The latter case is likely to play a major role in city distribution in the future. A further application area in the urban context is snow ploughing in city areas where the amount of snowfall forbids to simply move the snow to the side of the road. Similar use cases occur in street sweeping and bitumen delivery. In addition, the VRPTWMD lies at the heart of distribution/collection problems in a non-urban context like road painting, where the support vehicle refills the paint tanks of the painting vehicles. Another interesting future application may be the support of a company's fleet of battery electric vehicles by means of a support vehicle that serves as mobile recharging station or as battery swapping station. More generally, support vehicles may be reasonably employed as mobile fueling stations if alternative fuel vehicles are utilized in a region with sparse infrastructure.

We formally describe the VRPTWMD as a mixed integer program. We use a compact formulation with arc flow variables. The objective function is hierarchical, minimizing first the number of vehicles used and then the total traveled distance. The order in which a delivery vehicle performs the service at customer and the transfer with the support vehicle is a decision variable, but may in some cases be imposed by the customer time window, the maximal route duration, or a lack of capacity to deal with the customer demand. The VRPTWMD extends and generalizes existing models from the literature.

In the talk, we report on analyses of the features of the VRPTWMD and their interaction using the commercial solver Gurobi to solve small instances of the mixed integer program. Moreover, we present results obtained with an effective and efficient Adaptive Large Neighborhood Search (ALNS) tailored to the VRPTWMD. The ALNS includes a sophisticated local search improvement component. Its main algorithmic contribution is a local move evaluation procedure that adapts the time travel approach presented by Nagata et al. (2010) to synchronization.

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Some Recent Results on the Split Delivery Vehicle Routing Problem

B. Golden[a], X. Wang[b]

[a]*R.H. Smith School of Business, University of Maryland*

[b]*Department of Mathematics, University of Maryland*

The split delivery vehicle routing problem (SDVRP) is a relaxed version of the classic capacitated vehicle routing problem (CVRP). Customer demands are allowed to be split among several vehicles. This problem is computationally challenging and the state-of-the-art metaheuristics are often complicated to describe and to implement. Running times are usually large. These limitations hinder their application by practitioners to solve real-world vehicle routing problems. We propose an efficient, easy to implement, novel approach to the SDVRP using a priori customer demand splits. Our computational experiments on 82 benchmark instances demonstrate that our approach is very efficient and produces results that are nearly comparable to those from the metaheuristic approaches.

In related work, we compare the optimal solution to the CVRP with the solution to the SDVRP obtained using a priori splits with different split rules, from the worst-case point of view. This approach gives the analyst perfect control over how a customer demand is split (e.g., the number of splits per customer and the minimum delivery amount). The previous study shows the approach is computationally effective. In this study, we analyze the approach from a theoretical perspective.

A third project on split delivery vehicle routing is described next. The min-max split delivery multi-depot vehicle routing problem with minimum delivery amounts (min-max SDMDVRP-MDA) is a variant of the standard multi-depot VRP. The objective is to minimize the total duration of the most costly route taking into account the travel times and the customer service times. The service times of a customer can be split among several vehicles, provided that each visit serves a minimum fraction of the total service required. We develop a heuristic that produces high-quality results.

In our presentation in Berlin, we expect to discuss at least two of the three above-mentioned research projects.

Crowdsourced Same Day Delivery

A. M. Arslan, N. Agatz, L. Kroon, R. Zuidwijk

Rotterdam School of Management, Erasmus University, Rotterdam, The Netherlands

Online retailing continues to grow at a fast pace. Many traditional retailers such as Walmart, Target, and Ahold sell online in addition to their traditional sales channels. One of the main challenges of online retailing is to provide convenient home delivery services in a cost-efficient way. The trend towards shorter delivery lead-times and same-day delivery further increases the strain on transport efficiency. At the same time, internet and GPS-enabled smart phones give rise to new opportunities to organize the last-mile. One of those new opportunities is crowdsourced delivery. This concept entails obtaining transportation services from approved drivers and carrier companies with spare capacity rather than from traditional employees or suppliers. The key idea is to exploit existing transportation flows to save costs and additional vehicle miles. Several start-up companies, such as Deliv, Rideship, Hitch and Kanga, recently started offering platforms to facilitate crowdsourced delivery services. Besides the start-ups, large established corporations like DHL and Walmart are experimenting with these ideas. While DHL pilots a crowdsourcing platform for parcels, Walmart announced last year that it considers to invite their off-line store customers to deliver packages to their online customers on their route home from the store [3].

To be successful, a crowdsourced delivery system would have to overcome several legal and regulatory obstacles. Also, since *the crowd* will typically be less reliable than a traditional employee or service provider, crowd-shipping would generally be combined with the use of the company's own delivery vehicles. Thus, these service providers will have to synchronize the company's vehicle dispatching decisions with the assignment decisions of the delivery jobs to crowdshippers. These systems require sophisticated decision support to facilitate the matching of delivery requests and crowdshippers in real-time. In this study, we aim to develop optimization approaches with the objective to minimize the expected costs of deliveries while serving all delivery requests in time. We also aim to investigate under what circumstances it may be viable to implement a crowdsourced delivery system to support a same-day delivery service.

What makes crowdsourced delivery different from more traditional transportation settings is that both demand and supply is arriving dynamically over time. Also, since the crowdshippers are not employees, they are outside the direct control of the company. This makes the problem similar to dynamic ride-sharing, as studied by Agatz et al. [1], where people share trips to reach their destinations. While there are a lot of recent new developments in this area, the academic transportation community has only recently started to pay attention to the use of existing transportation flows to deliver packages. For example, [2] consider a setting in which they use taxi trips to transport packages. The model includes the taxi passengers' willingness since a passenger might refuse to pay the taxi fee if the taxi stops many times to pick up or drop packages. However, unlike our paper, they do not consider the interaction of company resources with crowdshipping. Based on an empirical study of GPS-data, [4] conclude that there are opportunities to route packages over a dynamic network of people.

In this study, we aim to investigate the opportunity of using in-store customers as an online retailer's last mile delivery couriers in a same-day delivery setting. In fact, crowdshippers cover a much more general set than just walk-in customers. Any approved driver can join the system. For instance, a taxi can stop at the store and collect a box while returning to the city from the airport. To illustrate this goal, we describe a setting in which an online retailer incorporates crowd-shipping into its transportation channels and propose a dynamic approach to match crowdshippers with online requests.

Our research approach is to model described environment as a matching problem. We propose a decision support mechanism for online retailers by implementing dynamic matching algorithm and rolling horizon methodology. In our other contribution, we explicitly incorporate future arrivals into our model. To evaluate different real-time matching strategies, we developed a simulation environment. We asses the following performance criteria to compare the different solution approaches:

1. Success rate: the relative number of delivery requests that is crowdshipped
2. Total last-mile delivery cost: the total costs of crowdshipping plus the dedicated transportation

Our simulation experiments also allow us to study the impact of different features on the performance of a crowsourced system. That is, what critical mass of crowdshippers is required to make this business model viable and which geographic characteristics are favorable to the success of such a system? The likelihood of visiting a store may be inversely related to the distance for the store customers but not for the online customers.

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Same-Day Delivery

B. W. Thomas, S. Voccia, A. M. Campbell

Department of Management Sciences, Tippie College of Business,
University of Iowa, Iowa, USA

Same-day delivery for online purchases is offered by a variety of established online retailers and tech companies including Amazon, eBay, and Google as well as a number of recent internet startups. Where instant gratification was once the largest advantage of brick-and-mortar stores over online retailers, same-day delivery now brings near instant gratification to online shoppers. While same-day delivery is currently being driven by companies looking to establish the market, Tom Allason, founder and chief executive of Shutl, a UK-based same-day delivery service that expanded to the U.S. and was purchased by eBay in 2013, predicts, "People dont need immediate delivery today, but they will need it tomorrow, because as soon as you know its available, you start expecting it and you start demanding it" (Clifford and Cain Miller 2013).

Same-day delivery is characterized by a fleet of vehicles that over the course of the day serve delivery requests. The requests arrive dynamically during the day, and the only information known about them before they are realized is probabilistic. Each request is associated with a unique order and a time constraint on the orders delivery. Requests can be served only by a vehicle first visiting a central depot (either a warehouse or brick-and-mortar store) where the order is loaded. A vehicle can carry more than one customer's order at a time. However, we assume that any loaded order must be delivered within its time constraint. Our objective is to maximize the number of orders that can be feasibly delivered. We call this problem the same-day delivery problem (SDDP).

While same-day delivery is focused in urban areas where there is sufficient customer density to support it, same-day delivery is a logistically complicated and expensive service to operate. With the expansion of same-day delivery services, there is a need for efficient routing strategies. In this talk, we will discuss a sample-scenario planning approach for the SDDP. While sample-scenario planning was first introduced by Bent and Van Hentenryck (2004), we introduce a new consensus function. The consensus function determines how sampled information is used to construct a near-term solution. Importantly, our consensus function allows for packages to be left at the depot in anticipation of future requests that allow for more efficient delivery of the packages left at the depot. We also introduce an analytical results that determines how long a vehicle can wait at the depot without impacting solution quality. We test our approach on a large set of instances characterized by differing geographies and by a variety of schemes for setting the delivery time constraints. We compare the solution approach to a myopic approach and also examine the computational trade-off between solution quality and runtime due to the number of samples and sampling-horizon length.

The talk will present the broad range of computational results. In summary, the results show that, for an eight-hour day, it is not necessary to sample the future all the way to the end of the day. Sampling only 30 minutes into the future improves solution quality over no sampling or a shorter horizon an performs well relative to longer horizons. In addition, 10 samples provides a good trade-off between computation time and solution quality.

From a managerial perspective, the results related to the time constraints are more interesting. First, anticipating the future has value only when there is the time deadlines offer sufficient flexibility in routing. Notably, for cases in which requests must be honored with two hours or in within a one-hour time window that begins one hour from the time of request, anticipating the future via sampling offers very little benefit (about 2%). This occurs because, in such situations, the vehicles must load requests and immediately leave the depot upon arrival back to the depot. The time constraints simply offer no opportunity to wait even a short time to try to find more beneficial routing opportunities. It is interesting to note that these results reflect an urban area in which travel to any particular customer is relatively short. As greater flexibility in the time constraints is allowed, the value of anticipating the future increases to around 10%.

Most similar to this work is the work of Azi et al. (2012) that addresses a same-day delivery problem with time windows. However, the objective is to maximize expected profits. Our objective is to maximize the number of requests served. Further, in Azi et al. (2012), the length of route segments are controlled by a fixed parameter. We allow the length to be determined explicitly through our consensus function while also determining when it may be beneficial to wait at the depot. In addition, we examine the construction of time windows and deadlines and the corresponding effects on the number of served requests.

Also related to this research are pick-up and delivery problems. The SDDP differs from most pick-up and delivery problems in two key ways. A majority of the pick-up and delivery problems in the literature have unique pick-up and delivery locations for each load (Sheridan et al. 2013, Ghiani et al. 2009, Vitoria and Laporte 2008).This is significant because a vehicle can drop-off a load at one location and pick-up a new load at a near-by location. In our problem, however, vehicles always have to make the return back to the depot to pick-up a new load. This makes it costly to serve demand that is far from the depot. Certain dial-a-ride problems in the literature do have a single location. An example is a hospital where patients are shuttled between their homes and the hospital. In such a situation, however, the priority is on patient satisfaction (Cordeau and Laporte 2007). In most situations, it would not be appropriate to pick-up some patients from the hospital, but leave others waiting for the next vehicle. In the same-day delivery problem, strategic loading decisions may mean that some orders are loaded onto another vehicle at a later time. Further, it is a non-trivial task to decide which orders should be loaded onto the departing vehicle.

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Freie Universität Berlin

Scientific Program – Tuesday, July 7th

Session 4a E-Mobility II
09:00 – 10:30, Hahn Hall

- Applying Floating Car Data to Aid the Transition to Electric Taxi Services — Michal Maciejewski & Joschka Bischoff
- Enabling Urban Parcel Pickup and Delivery Services using All-Electric Trucks — Nan Ding, Rajan Batta, Changhyun Kwon & June Dong
- Adaptive Routing and Recharging Policies for Electric Vehicles — **Irina Dolinskaya**, Timothy M. Sweda & Diego Klabjan

Session 4b Public Transport I
09:00 – 10:30, Laue Hall

- Time Choice Data for Public Transport Optimization — Paul Bouman, Clint Pennings, Jan van Dalen & Leo Kroon
- A Column Generation Approach for Crew Rostering Problems in Public Bus Transit — Lin Xie, Natalia Kliewer & Leena Suhl
- On-Demand Public Transportation — **M. Grazia Speranza**, Claudi Archetti & Dennis Weyland

Session 5a Vehicle Routing
11:00 – 12:00, Hahn Hall

- Value-Function-Approximation-Based Rollout Algorithms for a Vehicle Routing Problem with Stochastic Customer Requests — Marlin W. Ulmer, Justin C. Goodson, Dirk C. Mattfeld & Marco Henning
- A Scenario-Based Planning for the Pickup and Delivery Problem with Scheduled Lines and Stochastic Demands — **Tom van Woensel,** Veaceslav Ghilas & Emrah Demir

Session 5b Public Transport II
11:00 – 12:00, Laue Hall

- Robust Efficiency in Public Transport: Minimizing Delay Propagation in Cost-Efficient Resource Schedules — Bastian Amberg, Boris Amberg & Natalia Kliewer
- Tariff Zone Planning for Public Transport Companies — **Sven Müller** & Knut Haase

Session chairs are shown in **bold**.

Applying Floating Car Data to Aid the Transition to Electric Taxi Services

M. Maciejewski[ab], J. Bischoff[b]

[a]Division of Transport Systems, Poznan University of Technology

[b]Department of Transport System Planning and Telematics, TU Berlin

Because of the ecological concerns related to urban transport, the idea of substituting taxis with an internal combustion engine, generating a high amount of emissions per passenger in cities, with electric ones seems very appealing and promising. There have been already several successful attempts to introduce electric taxis in different cities around the globe, such as Shenzhen (800+ taxis), Amsterdam (160+ taxis serving mainly the airport), Bogota (40+), Tallinn (40+), Tokyo, New York, Paris or Brussels. Out of them, only Shenzhen with its fleet of 800+ electric taxis may be considered a large-scale initiative. However, the scale and speed of introducing Shenzhen's electric taxi fleet have resulted in a not adequately-developed charging infrastructure, which in turn, led to inefficient taxi dispatching and charging scheduling. To mitigate the risks related to launching electric taxi services on a large scale, a detailed design phase must be carried out to address many issues such as deployment of charging infrastructure, demand prediction, real-time taxi dispatching and scheduling of battery charging. This paper discusses the application of floating car data (FCD) collected by the taxi operator to aid in solving the problems mentioned above.

There have been several studies showing potential applications of taxi GPS trajectories. They have been used for estimating spatiotemporal taxi demand, analysing and/or optimizing taxi drivers' behaviour, calculating link travel times and shortest paths, analysing urban planning or determining land use.

This paper is based on the research on introducing electric taxis in Germany's capital city, Berlin, where FCD is collected by Taxi Berlin, the city's largest taxi association. More than 5700 vehicles may be dispatched by them, and GPS tracks of roughly 3000 vehicles have been made available to the authors. These taxis not only send their current location in a flexible interval (roughly every minute) to the operator, but also the current occupation status. During one week, almost 200000 taxi trips on average are registered this way. The data is anonymised, making it impossible to track drivers over a longer period.

There are numerous possible areas where FCD can be applied at different phases in the process of launching and operating a fleet of electric taxis. First of all, FCD is an invaluable source of information about patterns of taxi supply and demand, which, in general, tend to repeat over several weeks, with one demand peak on workday mornings around 9 o'clock and a second peak over a longer time but with a smaller absolute maximum of trips per hour in the afternoon. On weekends, the demand peaks shift towards the night. On the supply side, drivers seem to adapt to the demand peaks very efficiently, with fewer taxis being available at times of low demand, such as during middays.

The knowledge about the spatiotemporal distribution of demand and supply allows for detailed simulation of taxi services in order to assess the performance of online algorithms used for managing the fleet of taxis. By combining the microscopic level of detail (disaggregated requests and taxi vehicles embedded into traffic flow simulation) with a large scale (the city with the surrounding region), one can obtain a realistic picture of the taxi service. To simulate taxi services in Berlin, the MATSim simulation platform extended with the DVRP module were used. Simulation experiments carried out for the typical weekday demand and the non-electric taxi fleet have proved that the dispatching strategy used by the taxi company, consisting in dispatching the nearest idle vehicle to the first awaiting request, performs well. However, under heavy load, such as on Wednesday 15/10/2014, when Berlin's public transport company went on strike and the afternoon demand doubled, the algorithm is unable to serve all customers in a timely manner. Further experiments showed that a modified strategy that sends an idle vehicle not to the longest waiting request but to the nearest one, can handle a doubled or even tripled demand. Concerning the electric taxis, a small-scale simulation experiment was carried out for the city of Mielec, Poland, with about 50 taxis. Based on this research, a model of electric taxi services for Berlin is being developed at present. Here, dynamic optimization is not only about assigning taxis to requests but also about scheduling of battery re-charging. The analysis of FCD allows for spatiotemporal predictions of future demand, which is necessary for proactive movement of empty vehicles towards more attractive locations and spatiotemporal balancing of the charging infrastructure usage.

Apart from optimizing dynamically the usage of the existing charging stations, FCD may be exploited for the design of the charging infrastructure. In the ongoing research carried out for Taxi Berlin, the necessary amount of fast chargers is determined by taking the fleet's occupation (derived from the floating car data), the city's climate conditions and the general constraints of the Berlin taxi business into account. Next, using the floating car data, the demand for placing chargers, measured in vehicle-hours spent by idle vehicles, is calculated for each zone (the pickup and/or dropoff location statistics could serve as an alternative zone attractiveness measure). It is assumed that the more idle vehicles (both staying and cruising) are in the zone, the more attractive the zone is for placing a charger there.

To conclude, setting up efficient electric taxi services is a challenging, complex, multi-step problem that more and more cities and taxi companies are undertaking or will undertake in the near future. The experiences arising from the research on electrifying Taxi Berlin's fleet shows that in-depth analysis and processing of FCD collected by the existing non-electric taxis is an invaluable source of information to rely on when launching and running an electric taxi fleet.

Enabling Urban Parcel Pickup and Delivery Services using All-Electric Trucks

N. Ding[a], R. Batta[a], C. Kwon[a], J. Dong[b]

[a]*University at Buffalo (SUNY)*

[b]*SUNY at Oswego*

With the increasing interest of green logistics strategies and operations, all-electric truck adoption becomes one of the main addressees of green logistic activities, especially for urban parcel delivery, because of its positive effects on reducing greenhouse gas emission and promoting urban sustainability. Both the limited driving range of all-electric trucks which necessitates visits to charging stations and long charging time of these trucks which causes congestion and waiting at the charging station become the challenges to route these trucks. This research tackles the challenges by developing a mathematical optimization model with consideration of location and capacity of charging stations, electric vehicle routing, time window, and charging time.

This research has two closely related decision problems and corresponding objectives. One is a strategic decision problem that aims to determine the optimal charging-station locations and capacity with estimate of regular customers' locations. The other is an operational decision problem that focuses on daily routing schedules of all-electric delivery trucks with actual dynamic delivery locations but fixed charging stations.
The methodology of this project consists of following parts. The first is to consider a new Electric Vehicle Routing Problem (E-VRP) with incorporation of capacity of charging stations. The second is to formulate a strategic Location-Capacity-Routing problem and an operational vehicle routing problem based on E-VRP. We also develop a computational method to solve the problems and perform test using real data in the Buffalo metropolitan area.

We note that the current literature lacks this challenging issue of determining locations and capacities of charging stations for all-electric parcel delivery trucks. Depending on technology used, a full charging can take from 20 minutes to several hours. In a small scenario with 100 trucks and 5 dedicated charging stations, about 20 trucks will try to use the same charging station about the same time (in the middle of the day). This congestion and waiting at the charging station make vehicle routing very challenging.

Adaptive Routing and Recharging Policies for Electric Vehicles

T. M. Sweda[a], I. S. Dolinskaya[b], D. Klabjan[b]

[a]*Schneider, Inc.*

[b]*Northwestern University*

Battery operated electric vehicles (EVs) have become a practical and affordable alternative to conventional gasoline-powered vehicles. EVs are powered solely by electricity and connect directly to the electrical grid to recharge their batteries. There are a number of benefits associated with an electrical vehicle such as lower fuel costs, fewer greenhouse gas emissions, reduced dependence on foreign oil, and improved power systems management (e.g., vehicle-to-grid). Nevertheless, one of the main obstacles to mass adoption is range anxiety since the maximum range of an EV remains smaller than that of a traditional gasoline-powered vehicle. In addition, EV charging stations are scarce, and roadside assistance for EVs when they run out of charge is practically nonexistent. Planning a trip with an electric vehicle therefore requires consideration of the availability of charging infrastructure, and also of battery dynamics, which are unique to EVs. Recharging costs for an electric vehicle increase as the battery's charge level increases, and battery longevity is prolonged by recharging less frequently, at slower rates, and not too close to its maximum capacity. In the presented work, we study optimal recharging policies for an electric vehicle along a given path, and optimal adaptive routing and recharging policies for an electric vehicle in a network capturing charging stations uncertain availability. We develop and analyze a variety of models and solution methods that consider the amount and timing of information available to the EV driver while traveling.

An important aspect of our work is the inclusion of a realistic recharging model for electric vehicles. While most of the literature on vehicle refueling policies has focused primarily on the limited range of the vehicles, we show that the costs associated with battery overcharging can significantly influence recharging decisions, and thus, they should be taken into consideration when determining recharging policies for EVs. The simpler models of vehicle refueling used for conventional gasoline-powered vehicles are not suitable for EVs and require major enhancements before they can be used to improve our understanding of the various influences that battery dynamics have on EV recharging decisions.

Our work is the first to optimize recharging behavior specifically for EVs. We begin by identifying several properties of optimal recharging policies along a fixed path with deterministic travel costs and homogeneous charging stations. Using these properties, we develop efficient algorithms for finding an optimal recharging policy in the general case and in two specialized cases: when the vehicle can stop to recharge anywhere along the path (not just at prespecified nodes), and when the nodes with charging stations along the path are equidistant. We also describe two heuristic methods based on the properties of optimal paths that we use to obtain reasonable policies quickly, and we derive bounds on the quality of their solutions. To demonstrate the performance of these heuristics in practice, we implement them for highway and urban routes and conduct a numerical study to compare their solutions with those of optimal recharging policies. In addition, we formulate models that include stochastic travel costs and nonhomogeneous charging stations, and we provide detailed analyses and numerical experiments to illustrate how the solution approaches are affected. The main contributions of this part of our work are: (*i*) an efficient algorithm for obtaining an optimal recharging policy; (*ii*) closed-form optimal policies for instances in which either charging capability is available continuously along the path or charging stations are equidistantly spaced; (*iii*) two efficient and easy to implement heuristic methods, along with bounds on their solution quality.

The viability of any route requiring recharging is sensitive to the availability of charging stations along the way. Since each charging station can usually only recharge one or two vehicles at a time, and charge times can be on the order of hours, a driver who arrives at a fully occupied station may incur significant inconvenience (e.g., a long wait time) if no other nearby charging station is available. EV drivers therefore can benefit greatly from taking into account charging station availability and anticipating wait times at the stations while planning their routes. Thus, we also study the problem of finding an optimal adaptive routing and recharging policy for an electric vehicle in a grid network. The uncertainty of charging station availability and wait times within the network as well as the driver's ability to adaptively make routing and recharging decisions are unique and critical features of our problem. Furthermore, since the availability of each station may differ, the selection of stopping locations must be part of the routing decision. Our goal is to determine an adaptive routing and recharging policy that minimizes the sum of all traveling, waiting, and recharging costs. We assume that whenever the vehicle stops to recharge, it incurs a fixed stopping cost, a charging cost based on the total amount it recharges, and an additional cost when the battery becomes overcharged. Our work is the first in the literature to consider adaptive routing and recharging (or refueling) for range-constrained vehicles. It is also the first to implement two features together that are unique to EVs: overcharging costs and uncertain charging station availability. Thus, our main contributions here are: (*i*) properties of optimal adaptive and a priori recharging policies that consider EV overcharging characteristics and uncertain charging station availability; (*ii*) efficient solution procedures for obtaining a priori and adaptive routing and recharging policies in a grid network; and (*iii*) models capturing and analyzing various levels of adaptive decision making and information timing.

Time Choice Data for Public Transport Optimization

P. Bouman, C. Pennings, J. van Dalen, L. Kroon

Rotterdam School of Management, Erasmus University; Rotterdam, The Netherlands

As urbanization increases and working habits become more flexible, it is feared that demand for public transport becomes more difficult to model. Vehicle utilization is a complex issue to deal with for operators: having enough passengers in a vehicle makes a service profitable, but the resources necessary to cover the peak demand are typically not fully used outside the peak hours. Crowded vehicles clearly cause some discomfort for passengers, but it is not well understood at which point passengers will change their travel behavior in response to crowded vehicles. One way in which operators can deal with crowded situations is clever assignment of different vehicle types to optimize capacities. Another way is to adapt the frequency in which services are operated. In addition to scheduling based approaches, pricing incentives can seduce passengers to travel outside the peak hours. An even different angle is to provide information about the expected crowding level of each train service, e.g. via a smart-phone application, so passengers can replan their time of travel.

The difficulty with these approaches is that they will influence the behavior of passengers once implemented. Such a change in behavior will be observed by the operator, which may react by adapting one of the aforementioned measures. This can cause new changes in passenger behavior, and so forth. Ideally, such interaction effects should be taken into account by the operator during service design, but current demand and scheduling models do not take these effects into account. With the advent of smart card ticketing technologies, public transport operators have obtained a large amount of microscopic data on passenger journeys. It is tempting to think that one simply has to analyze this data to learn everything there is to know about passenger behavior and incorporate this knowledge into optimization models. Unfortunately, the smart card data misses important aspects of passenger behavior, such as any alternative options that have been considered by the passenger and the decisions that would have been made if different alternatives had been available.

In order to overcome this problem, we have conducted a survey experiment where we simulated a typical commuting scenario as it might occur within the public transport network of Dutch Railways. The collected data consists of time choice data, which can similarly be extracted from smart card datasets in a real life case study. In addition the data contains the satisfaction with the outcome of the selected choice, personality traits of the respondent and personal experience with public transport. Due to these additional observations, our dataset has a number of advantages over pure smart card data in the development of methodologies that take passenger behavior into account during public transport optimization. An example of an experiment where congestion dynamics were measured in road traffic is [5], but it is hard to make policy recommendations for public transport based on this study due to the different nature of road traffic.

Survey Experiment

We have conducted an experiment among more than 500 second year bachelor students, a relevant group in the Netherlands as they make intensive use of public transport. In this experiment, the respondents filled out a survey in which they were asked to choose a mode (train or car) and in case of the train a time of travel, all within a typical commuting scenario. These questions were repeated for two phases of twenty rounds each. After each choice, the students received feedback on their arrival time and the level of crowding in case of a journey by train. They were then asked how satisfied they were with the outcome. During the second phase of twenty rounds, the respondents were presented with crowding indicators, representing the predicted crowding of each train choice.

We applied three experimental manipulations, which yields a total of $2^3 = 8$ respondent groups. The first manipulation consists of the occurence of large disruptions. One group of respondents were incidentally confronted with a large disruption and the others only faced small delays. The second manipulation consists the quality of information during the second phase of the experiment. One group received accurate crowding level information and the others received random information. The third manipulation consists of the relation between the crowding level and the prior choice. One group experienced a purely random crowding level and for the others the crowding level was partly dependent on the previous choice.

The students were incentivized by the fact that the collected data would be part of an important assignment within the bachelor course. Furthermore, the students who took care in completing the survey could partake in a lottery where they could win a gift coupon that can be exchanged in many shops. The outcome of the lottery was not related to the answers given in the survey.

From Data to Optimization

Using the collected data, we aim to develop a microscopic behavioral model that can be used for the simulation of the interaction effects between passengers and the operator. We then propose to use this model in a simulation of the public transport system, in such a way that these complex interactions can be evaluated. Finally, we can let this model interact with the optimization models used by public transport operators.

We are particularly interested in including such a behavioral model within a simulation that resembles a repeated, interactive game. We have developed a stylized model [2] which captures the dynamics of the public transport system, by combining ideas from *Congestion Games* [4] and *Minority Games* (the El-Farol Bar Game [1] in particular). Our model can interact with an optimization model for rolling stock allocation [3], by using the output of the simulation model as demand data in the optimization model.

Conclusion

We propose that the development of behavioral models for the optimization of public transport is not a matter of simply plugging smart card data into optimization models. We have conducted an experiment, in which the collected data resembles smart card data, but also include many additional aspects relevant to behavioral modeling. Our preliminary results already provide promising first insights into switching behavior and we aim to extend our results to construct microscopic behavioral models for use in a simulation/optimization framework.

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A Column Generation Approach for Crew Rostering Problems in Public Bus Transit

L. Xie[a], N. Kliewer[b], L. Suhl[a]

[a]*University of Paderborn, Germany*

[b]*Freie Universität Berlin, Germany*

This paper presents a method for optimally solving the problem of constructing monthly, individual work schedules for each driver or for each group of drivers in public transportation companies. The generated work schedules are called *rosters*. In this problem, known as *crew rostering*, monthly crew schedules must be constructed by assigning duties, days off, and other activities to drivers, while taking the complex law and labor union rules into account, such as the minimum rest period between two duties or the maximum number of consecutive working days. A *duty* is a sequence of tasks within one day that is performed by a driver who leaves and returns to the same depot in accordance with the work regulations. Work regulations include maximum duration of a duty, minimal break times during a duty. Such duties are generated in the *crew scheduling problem*, which is the previous step of the crew rostering problem. Both problems are important and difficult problems for bus companies, since the expenses for the drivers and other personal represent a significant portion of bus operators' budgets (more than 50%). Moreover, complex regulations should be considered during the optimization. Therefore, it is common in the public bus transit literature to solve both problems one after the other, i.e., the crew rostering problem uses duties generated in the crew scheduling problem as input.

Compared to the crew scheduling problem, the crew rostering problem has received much less attention in academic literature, since most of the cost benefit can be achieved by minimizing the needed duties in the crew scheduling problem. However, the minimization of costs is still important in the crew rostering problem, and the preferences of drivers are considered during the optimization as well. The rosters which are generated by considering desires of drivers bring higher acceptance than rosters that ignore individual wishes (see Hanne et al. (2009)), which might cause less exchanges and less absence in operational days. Therefore, less recovery activities are expected, which implies lower operational costs, and better services are expected.

Because the crew rostering problem is complex, most methods proposed in the literature for solving the rostering problem rely on heuristics or metaheuristics, such as in Caprara et al. (1997), Caprara et al. (1999), Monfroglio (1996), Ernst et al. (1998), Lučić and Teodorović (1999), Hanne et al. (2009), El Moudani et al. (2001), Lee and Chen (2003), Lučić and Teodorović (2007), Maenhout and Vanhoucke (2010), Moz et al. (2009), Respício et al. (2007), and Xie et al. (2013). Besides that, a *column generation* approach is applied for solving set partitioning/covering-based rostering models in Gamache and Soumis (1998), Gamache et al. (1999), Medard and Sawhney (2007), Catanas and Paixão (1995), Pedrosa and Constantino (2001) in airline and railway sectors. Fewer publications discuss the application of column generation for solving the crew rostering problem in public bus transit, except in Yunes et al. (2005). Based on the multi-commodity network as well as mathematical models presented in Xie and Suhl (2015), this paper proposes a new solution approach, column generation, for solving the cyclic and non-cyclic crew rostering problems in public bus transit. The main differences between column generation implemented in this paper and the existing one in Yunes et al. (2005).

- We formulate the crew rostering problem as a multi-commodity flow network problem instead of a classic set-partitioning problem.
- We solve both CCR and NCCR problems with same column generation approach.
- We consider a more complex crew rostering problem, including components like multiple objectives, balanced workloads, feasibility checks from the previous period to the current one, fixed activities in the current planning period, personal requirements (not only the need for days off, but also considering the daily desired activities including a day off on each calendar day, etc.).
- We generate in each pricing problem a roster with the smallest negative reduce cost. The problem is formulated as an integer program instead of as a constraint satisfaction problem.

The tests for the proposed approach were conducted on problems from German bus companies. The results experimentally prove to outperform the exact solution approach in Xie and Suhl (2015), as well as different meta heuristics shown in Xie et al. (2013) in terms of solution quality.

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On-Demand Public Transportation

M. G. Speranza[a], C. Archetti[a], D. Weyland[b]

[a]*Department of Economics and Management, University of Brescia*

[b]*University of Lugano*

A recent analysis on modal split of inland passenger transport has revealed that in Europe 15-20% of the passengers' moves are satisfied by public transportation (motor coaches, buses, trolley buses and trains), while 80-85% are made through cars. With a moving population of more than 80 % of the total, this data implies that on a daily basis the number of cars on the roads exceeds half of the population.

Traffic congestion is a primary problem everywhere. The automobile has had a dramatic impact on the society during the last century. A crucial issue has become the sustainability of such a growing number of cars on the roads which has led to a renewed interest in alternative forms of transportation, especially in urban areas. This is witnessed by the wide diffusion of bicycle and car sharing systems, as well as car-pooling approaches. However, the main issue concerning the scarce use of public transportation means has not yet been properly addressed. Why is the public transportation system so unpopular? One of the main reasons that leads people to use their own private vehicle is the reduced flexibility of the public system. Mass mobility systems typically work on fixed schedules which in many situations cannot satisfy the dynamic demand of people who need to move. The frequency is often too low and the average travel time is higher than the one required by moving privately. A further issue related to the public transportation system is its inherent inefficiency: buses (or similar transportation vehicles) are too crowded during peak hours while they are almost empty in the remaining part of the day. This clearly has a high impact on the operational cost of the system, since it is impossible to operate almost empty buses in a sustainable way. Thus, there is the need to redesign the public transportation system in order to make it more suited to the users' needs and, also, to increase its efficiency in terms of operational costs.

Demand Responsive Transit (DRT) systems (also called dial-a-ride systems) have emerged in the last decades as an attempt to satisfy the dynamic nature of customer demands. They rely on flexible services able to provide almost `door-to-door' transport in small vehicles, with the possibility of pre-booking. DRT systems are nowadays mainly implemented as services for small groups (e.g. elderly or handicapped persons). On-line on-demand services are far from being considered as a possibility or an alternative to the conventional public transportation system. The literature is very limited too. The DRT systems can be classified as:

- with fixed itineraries and stops, where users must pre-book the service;
- with fixed itineraries and stops with possible detours;
- with services with unspecified itineraries along predefined stops;
- with unspecified itineraries and unspecified stops.

The purpose of this study is to evaluate, through global performance measures, the impact of an innovative large-scale on-demand service for the public transportation. The service we are proposing is based on the use of minibuses with unspecified itineraries and unspecified stops, thus fully flexible. It is an online service in the sense that users place their transportation requests and receive an answer in a very short time (within five minutes). The purpose is to keep travel time within a flexibility threshold in order to guarantee a high service level to users. However, the system differs from the shared-taxi system for the following reasons. There are no revenues for the drivers. This makes a big difference with respect to the shared-taxi system where typically one of the objectives while assigning service requests to drivers is to keep revenues balanced among drivers. Drivers are not traveling around the city looking for clients as it is typically done by taxi drivers while they are empty. The vehicles are minibuses with a higher capacity. The objectives we are interested in are different from the ones that are typically used to evaluate shared-taxi systems. Performance measures of shared-taxi systems are based on fares paid by the clients and revenues gained by the drivers. We are interested in the design of a public transport system that is able to attract a large portion of the people that travel every day with their own car in urban areas. This in order to reduce congestion and pollution, on one side, and to improve the efficiency of the public transport system, on the other side.

The goal of this paper is to present a preliminary simulation study of the on-demand public transport system. We will simulate the behavior of the system for different settings of the road network and of the customer requests. The purpose is to study the performance of the system in terms of average travel time of the customers, average distance traveled, fuel consumption and global system cost. The global system cost is measured as the sum of the cost for the drivers of the minibuses, cost for fuel and cost for the maintenance and insurance of vehicles (minibuses, buses and private cars). We do not include fares paid by the customers in this preliminary study and suppose that, if the service level provided by the public transport system satisfies the flexibility threshold of a customer, then the customer will use the public mean, otherwise will turn to a private car. We will simulate different scenarios and compare the performance of the different transportation modes. The results show that, although simple heuristics are used for the routing of vehicles, the on-demand system is very promising.

Value-Function-Approximation-Based Rollout Algorithms for a Vehicle Routing Problem with Stochastic Customer Request

M. W. Ulmer[a], J. C. Goodson[b], D. C. Mattfeld[a], M. Henning[a]

[a]*Technische Universität Braunschweig, Braunschweig, Germany*

[b]*Saint Louis University, Saint Lous, United States*

Vehicle routing problems with stochastic service requests underlie many operational challenges in logistics and supply chain management. These challenges are characterized by the need to design vehicle delivery routes to meet customer service requests arriving randomly over a given time horizon. For example, package express firms (e.g., local couriers and United Parcel Service) often begin a working day with a set of known service requests and may periodically adjust vehicle routes to accommodate additional service calls arriving throughout the day.

Leveraging increasing amounts of customer transaction data to quantify the numbers and locations of potential service requests, the last decade of routing literature demonstrates the value of anticipating and dynamically responding to customer calls. Recently, the value function approximations (VFAs) of Ulmer et al. (2014) identify computationally tractable procedures to estimate the optimal reward-to-go from a given state, thus making it possible to construct high-quality dynamic routing schemes based only on the time and slack components of the state variable. In contrast to the functional approximations of Ulmer et al. (2014), Ulmer et al. (2015) approximate rewards-to-go via a greedy heuristic, applied iteratively in a post-decision rollout algorithm (Goodson et al., 2014).

Our work seeks to improve upon existing dynamic routing methods by using rollout algorithms to enhance the performance of the VFAs of Ulmer et al. (2014). Specifically, we model as a Markov decision process the problem of dynamically routing a single vehicle across a finite time horizon with the objective of maximizing the expected number of confirmed service requests. At a decision epoch, we estimate the optimal reward-to-go from each post-decision state via the policy induced by the VFA. In each period, we dynamically accept or reject customer service requests by taking an action maximizing the sum of the current-period reward plus the corresponding estimate of the reward-to-go.

Preliminary computational results are encouraging. Notably, we demonstrate the combination of VFA and rollout algorithms improves upon the performance of myopic methods by as much as 28 percent and upon the VFA scheme in isolation by as much as four percent. Our investigation indicates improvement over the functional approximations is due to the explicit consideration of vehicle location in the rollout algorithm -- the VFA makes only temporal considerations, ignoring the spatial dimension of the state variable. Beyond our contribution to the routing literature, our work points to the potential benefit of using two different approximate dynamic programming techniques in tandem to enhance the performance of either method by itself.

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A Scenario-based Planning for the Pickup and Delivery Problem with Scheduled Lines and Stochastic Demands

V. Ghilas, E. Demir, T. Van Woensel*

Eindhoven University of Technology

1 Introduction

In the pickup and delivery problem with scheduled lines and stochastic demands (PDP-SLSD) a set of geographically spread requests need to be transported from origin to destination using a fleet of heterogeneous, limited-capacity pickup and delivery (PD) vehicles. Moreover, capacitated scheduled lined (SL) services, such as bus, train, etc., may be used as a part of the requests' journey. A characteristic of the problem is that every request may be transferred to an SL (i.e., picked up and dropped off twice by two PD vehicles). As a consequence, routing decisions become more complex due to possibility of inter-dependent PD-vehicle routes. In addition, the exact quantities demanded by each request are only learned upon the vehicle's arrival at the corresponding pickup locations. However, each request's demand is assumed to follow a known probability distribution. Demand uncertainty may impact the feasibility of the solution (PD and SL vehicles' capacity constraints) and therefore lead to the need of *recourse* actions that incur extra cost.

In this paper, a sample average aproximation (SAA) method is used to solve PDP-SLSD. The SAA is a scenario-based framework to solve stochastic discrete optimization problems ([1]). The basic idea of the method is as follows: *(i)* solve the sample average approximation problem given a restricted set of scenarios (a subset of a larger set of scenarios), *(ii)* evaluate the solution on a larger set of scenarios and approximate the expected value function by the sample average function, and *(iii)* iterate until stopping criteria is met.

Note that exact as well as heuristic algorithms can be used to solve the sample average approximation problem (step *(i)* in SAA). In this paper, we propose an enhanced adaptive large neighborhood search (ALNS) heuristic algorithm to solve PDP-SLSD for a given set of scenarios. Adapted and existing-in-the-literature destroy and insertion operators are described. Complex aspects such as the fixed lines' schedules and synchronization constraints are efficiently considered in the proposed algorithm.

The contributions of the paper are three-fold: *(i)* we describe the use of SAA framework to solve PDP-SLSD, *(ii)* we adapt the classical ALNS heuristic algorithm to solve PDP-SLSD, and *(iii)* we efficiently handle complex constraints (synchronization, schedules) within the proposed ALNS framework.

2 Problem description

The PDP-SLSD consists of routing and scheduling a set of heterogeneous (w.r.t. capacity) vehicles to transport a set of geographically spread requests from the corresponding origins to destinations. In addition, a set of capacity-limited scheduled lines operate according to pre-defined routes and schedules and each request may use them as a part of its journey. In other words, any request may be collected by one PD vehicle, transferred to a scheduled line and afterwards, delivered to its destination point after being re-collected by another PD vehicle. Furthermore, each request has to be served within its corresponding time windows.

In addition, the demand of each request is not known by the time of planning. The exact quantities demanded by each request are only learned upon the vehicle's arrival at the corresponding pickup locations. However, the demand of each request is assumed to follow a known distribution. The objective represents the minimization of the operating costs, such as routing (η) and SL costs (θ) and the recourse costs that are described below.

Due to aforementioned source of uncertainty, capacity constraints may be violated at any time, given an *a priori* route. More specifically, two types of capacity violations may happen. First, at a pickup or a transfer node, there may be insufficient capacity on the PD vehicle. In this case, we assume that the to-be-picked-up request will be serviced by an outsourced service at a cost (P_1) dependent on the direct distance from the point of failure to its destination. Second, there may be insufficient capacity on the scheduled line. In such case, it is assumed that scheduled line service provider is able to provide extra capacity (e.g., a towing) at a cost (P_2) per unit to be transported. Thus, such corrective actions are considered in order to recover feasibility.

2.1 Problem definition

We give a formal description of the PDP-SLSD. A solution to the problem is a routing plan for the PD vehicles, such that all requests are served. We now briefly describe the important features and assumptions of the PDP-SLSD.

- *Request.* A request r has an origin, o_r, and a destination, d_r. Each request is associated with two desired time windows, one for the origin ($[l_{o_r}, u_{o_r}]$), and one for the delivery point ($[l_{d_r}, u_{d_r}]$). The set of all requests is given as $\overline{\mathcal{P}}$, such that request r, has destination node $(o_r + n)$, where n shows the total number of requests. Furthermore, demand quantity h_r is represented by a probability distribution.
- *Vehicle.* A set of vehicles is given by $\mathcal{V}$. In addition, each vehicle v has the information of carrying capacity e_v and its origin g_v.
- *Time.* Travel and service times are known in advance and remain unchanged during the planning horizon. The travel time between nodes i and j is denoted by c_{ij} and service time at node i is represented as s_i.
- *Fixed line.* A set of all scheduled lines is given as $\mathcal{E}$, which is defined by the arc between start and end of the line (i, j). In addition, each scheduled line has a set of departure times $\mathcal{K}^{ij}$ from i (i.e., the start of scheduled line), such that the departure is given as p^w_{ij}, $\forall\, w \in \mathcal{K}^{ij}$, $(i, j) \in \mathcal{E}$. Note that each SL may have different frequencies than other lines, thus the size of the $\mathcal{K}^{ij}$ may differ. Furthermore, it is assumed that scheduled lined (SL) vehicles are designed to carry a limited amount of packages, thus implying a finite carrying capacity k_{ij}, $\forall\, (i, j) \in \mathcal{E}$.

We define a digraph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ represents a set of nodes and $\mathcal{A}$ represents a set of arcs. Each physical station-hub is replicated n times (n - the number of requests) as in Hall2009 and each replicated scheduled line is assigned a request. In particular, only the assigned request can use its corresponding replicated scheduled line. In addition, the following notations are used in the model formulation: d is the number of depots, τ - the number of replicated station-hubs. Moreover, a parameter f^r_i is equal to 1 if node i is the origin node of request r, to 0 if the node is intermediate node and finally to -1 if i is the destination of r. Furthermore, parameters θ is the weight in the objective function of PD routes, and η is the cost of shipping one package on a scheduled line, respectively.

The decision variables used to handle the routing of the PD vehicles are denoted as x^v_{ij}, which are binary variables equal to 1 if arc (i, j) is used by a PD vehicle v, 0 otherwise, $\forall\, (i, j) \in \mathcal{A}$, $v \in \mathcal{V}$. The scheduling of the PD vehicles is shown with α_v, continuous variables which indicate the time at which vehicle v returns to its depot, $\forall\, v \in \mathcal{V}$ and continuous variables β_i which indicate the departure time of a PD vehicle from node i, $\forall\, i \in \mathcal{N}$. The flow of the requests is given as y^r_{ij}, which are binary variables equal to 1 if arc (i, j)

is used by request r, 0 otherwise, $\forall\ i,\ j \in \mathcal{R}^3$, $r \in \overline{\mathcal{P}}$. The schedules of the requests are represented by the continuous variable γ_i^r that shows the time that request r departs from node i, $\forall\ i \in \mathcal{R}^3$, $r \in \overline{\mathcal{P}}$. Fixed line decisions are shown by q_{ij}^{rw}, that are binary variables equal to 1 if replicated scheduled line (i, j) is used by request r and departs from i at time p_{ij}^{w}, 0 otherwise, $\forall\ r \in \overline{\mathcal{P}}$, $(i, j) \in \mathcal{F}^r$, $w \in \mathcal{Z}^{ij}$.

The PDP-SLSD can be formulated as the following two-stage stochastic mixed-integer program.

2.2 Second-stage decisions

There is no simple way to formulate the computation of E[Q($\mathbf{x}$, ξ)] in terms of decision variables and linear constraints. However, given an a priori routing solution $\mathbf{x}$, the expected cost E[Q($\mathbf{x}$, ξ)] can be computed in two steps. In Step 1, capacity violation of the PD vehicles is evaluated. As a consequence, some requests (including transferable ones) may not be served due to given demand realizations and PD-vehicle capacity restrictions. Hence extra costs are incurred for outsourcing. Further in Step 2, given a restricted set of served requests, scheduled lines' capacity violations is verified.

3 Solution methodology

We provide details on the solution methodology used to solve the PDP-SLSD. As aforementioned, this method consists of a scenario-based framework combined with an ALNS algorithm. First, we describe the adaptations to the sampling method (SAA) used to reach good-quality stochastic solutions. Then we provide details on the ALNS to solve a scenario-based stochastic routing problem.

4 Results

Full results will be presented in the conference.

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Robust Efficiency in Public Transport: Minimizing Delay Propagation in Cost-Efficient Resource Schedules

B. Amberg[a], B. Amberg[b], N. Kliewer[a]

[a]*Freie Universität Berlin, Berlin, Germany*

[b]*FZI Forschungszentrum Informatik, Karlsruhe, Germany*

Introduction

In public bus transport disruptions and -in consequence- delays are unavoidable during execution of vehicle and crew schedules. As cost-efficient resource scheduling, including vehicle and driver scheduling, has become a highly relevant economic factor for public transportation companies, the scheduling process is increasingly supported by software tools, containing state-of-the-art optimization methods. However, using optimization methods to compute cost-optimal schedules usually results in tense schedules for both vehicles and crews without much idle or waiting time. As a consequence, delays cannot be absorbed and can propagate through the whole schedule. Delayed busses not only affect the vehicle schedule but also the associated crew schedule. Delayed drivers cause similar effects the other way round. As a result, planned schedules can become infeasible and the operations control has to initiate expensive recovery actions, thus making the previous schedule optimization useless.

In order to deal with disruptions, possible delays should already be considered offline in the planning phase. Schedules can be created that way that (minor) disruptions can be absorbed and delay propagation can be controlled, e.g. by inserting buffer times. However, the question is how to distribute buffer times appropriately between the scheduled tasks and how to connect the tasks of vehicles and crews efficiently such that the computed schedules minimize delay propagation and still remain cost-efficient?

Contributions

Firstly, in this work we examine the influence of different scheduling methods on robustness (delay-tolerance) and efficiency of vehicle and crew schedules. We propose approaches for sequential, partial-integrated and integrated scheduling which are able to consider the propagation of possible delays. In addition, the proposed approaches allow us to scale between robustness and cost-efficiency.

Secondly, by analyzing the computed schedules we investigate which of the following two factors exerts the stronger influence on delay propagation: compressing tasks which a driver has to serve consecutively on the same vehicle, or connecting different resources by scheduled vehicle changeovers of drivers.

Problem Definition

For a given set of timetabled trips the *vehicle scheduling problem* (VSP) can be stated as follows: Find an assignment of trips to vehicles such that each trip is assigned exactly once, each vehicle performs a feasible sequence of trips (called vehicle block), each sequence starts and ends at the same depot, constraints on the number/types of vehicles are satisfied, and the fleet size and operational costs are minimized.

Each vehicle activity corresponds to at least one task (a portion of work between two consecutive relief points) in the crew schedule. For a given set of tasks the *crew scheduling problem* (CSP) is defined as: Find a set of crew duties such that each task is covered by a duty, each duty satisfies constraints concerning federal laws and in-house agreements (e.g. break rules), and labor costs are minimized.

The *vehicle and crew scheduling problem* (VCSP) combines VSP and CSP: For a given set of timetabled trips, depots, and relief points, minimum costs sets of vehicle blocks and crew duties have to be found such that vehicle schedule and crew schedule are feasible and mutually compatible. Vehicle and crew schedules are compatible if each task derived from the vehicle schedule is covered by exactly one duty while all tasks not contained in the vehicle schedule are not part of any duty.

Schedules are called *robust* when effects of disruptions are less likely to be propagated into the future. There are different ways to measure robustness. Within this work we concentrate on the *delay-tolerance* of a schedule. The goal of increasing delay-tolerance within a schedule is to minimize the expected propagation of delays through the schedule.

Basic time-space-network model

In this work we use models for vehicle scheduling based on an aggregated time-space network (TSN) from Kliewer et al. (2006). The multi-depot vehicle scheduling problem is modeled as multi-commodity minimum-cost-flow problem in a TSN with one network layer for each depot-vehicle type combination. Each layer contains possible vehicle activities modeled as arcs between time-space nodes. The time-space nodes correspond to possible arrivals and departures at one station/depot. This modeling approach is adapted to the VCSP by constructing time-space networks also for duty generation (cf. Steinzen et al. (2010)). Due to the aggregated time-space network structure an optimal network flow solution represents a bundle of feasible, cost-optimal vehicle schedules.

Solution Approaches

In general, our proposed solution approaches are based on the approaches for vehicle and crew scheduling proposed by Gintner et al. (2008) and Steinzen et al. (2010). However, we extend the solution schemes in order to scale between cost-efficiency and robustness (delay-tolerance). We combine the network flow based formulation described above with path-based formulations. Cost-efficient and delay-tolerant resource schedules are computed by solving the corresponding models with column generation in combination with Lagrangian relaxation. The path-based formulations enable us to consider the possible propagation of delays between tasks correctly. In addition, we benefit from the underlying network model, as we obtain a bundle of feasible vehicle schedules, implicitly given by the solution flow. Depending on the scheduling method, the solution flow can be decomposed taking delay propagation and/or feasible crew duties into account. Thus, from a bundle of cost-efficient vehicle schedules we can obtain the one with the highest delay tolerances (in interaction with the crew schedule). In order to incorporate information about initial delays we use a set of different delay scenarios for each task during scheduling. The scenarios are derived from real world data or sampled from common delay distributions.

Evaluation and General Results

The proposed approaches are tested and compared on real-world instances from public transport companies in Germany. We use a delay propagation model for vehicle and crew tasks in combination with a Monte Carlo method to evaluate the expected delay propagation of the computed schedules.

Our results stress the relevance of incorporating the computation of possible delay propagation into scheduling. The expected delay propagation can be decreased drastically in resource schedules without additional costs compared to pure cost-efficient scheduling.

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Tariff Zone Planning for Public Transport Companies

S. Müller, K. Haase

University of Hamburg, Germany

In contrast to the representation in scientific literature we find the (spatial) design of tariff systems in public transportation to be very important in terms of managerial relevance: by appropriate design of the tariff system a public transport company is expected to increase its revenue remarkably (Borndörfer et al., 2012). The counting zones tariff system is the prevailing system in metropolitan areas, such as London, Boston, and Perth. For the counting zones tariff system, the corresponding tariff is determined by the product of the number of zones passed on the trip from origin to destination and the price per zone. The price per zone – denoted as fare – might be decreasing in the number of zones passed. Hamacher and Schöbel (2004) propose an approach to convert any given tariff system into a counting zone tariff. First, the fare is optimized given an exogenous zone partition. The objective function of the fare problem is to minimize the deviation from a given reference price. Second, they partition a given graph into as many node sets as given zones. Heuristic solution approaches are applied and evaluated. They assume an exogenously given, static customer demand with customers choosing the cheapest-path from origin to destination. Gattuso and Musolino (2007) present an approach for modeling an integrated fare and tariff zone system. The objective function is to minimize the increase of the fare compared to a reference price and hence to minimize expected revenue decline. They propose a system of simulation models to estimate the effects on users and on transit companies. Demand is assumed to be elastic with respect to the fare at modal and path choice dimensions. In this paper, we contribute to the scant literature on public transport tariff zone design by a new model for the tariff zone design problem. The objective is to maximize the expected total revenue (demand x tariff) taking into account contiguous tariff zones and discrete fare levels. The literature on public transport demand provides strong evidence that public transport customers are price sensitive. Demand – as a function of tariff (i.e., demand depends on the tariff to be paid) - is measured as the number of public transport trips between origin and destination. Customers are assumed to choose the time-shortest-path (which is confirmed by numerous empirical studies). For a given fare we compute the expected revenue for each origin-destination pair and the number of tariff zones passed. As a consequence we are able to model the original non-linear problem as a MIP. The problem has to be solved for each fare level separately. Contiguity is a complex task in spatial optimization. Here, contiguity is achieved by using primal and dual graph information. Therefore, we consider flow conservation constraints using the dual graph of the public transport graph. Our approach is general in the vein that demand can be determined by any arbitrarily chosen demand model (i.e., no assumptions about the functional form have to be made). We perform a series of numerical investigations using GAMS/CPLEX and artificial data to show the applicability of our approach. Further, we employ our approach to the San Francisco Bay Area, California using a simple version of the MTC Travel Model One as our demand model.

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Scientific Program – Wednesday, July 8th

Session 6a — City Logistics I — 09:00 – 10:30, Hahn Hall

- Static MILP Solutions and Adaptive Solutions for Hub Decisions in Very Large Scale Logistics Networks — Alexander Richter, Yann Disser, Wiebke Höhn & Sebastian Stiller
- Optimization Approaches for the Truck and Drone Delivery Problem — Niels Agatz, Paul Bouman & Marie Schmidt
- Optimizing Time-Dependent Arrival Rates for Truck Handling Operations — **Axel Franz** & Raik Stolletz

Session 6b — Uncertain Travel Times — 09:00 – 10:30, Laue Hall

- Disruption Management in Local Public Transport: Service Regularity Issues — Emanuele Tresoldi, Frederico Malucelli, Stefano Gualandi & Samuela Carosi
- Assessing Customer Service Reliability in Route Planning with Self-Imposed Time Windows and Uncertain Travel Times — Panagiotis Repoussis, Anastasios Varias & Christos Tarantilis
- Robust Scheduling of Urban Home Health Care Services Using Time-Dependent Public Transport — **Klaus-Dieter Rest** & Patrick Hirsch

Session 7a — City Logistics II — 11:00 – 12:30, Hahn Hall

- Handling Travel Time Uncertainly in City Logistics Systems — Utku Kunter, Cem Iyigun & Haldun Sural
- Freight Consolidation in Urban Networks With Transshipments — Wouter van Heeswijk, Martijn Mes & Marco Schutten
- Loading Bay Time Slot Allocation by Core-Selecting Package Auctions — **Paul Karaenke**, Martin Bichler & Stefan Minner

Session 7b — Urban Traffic — 11:00 – 12:30, Laue Hall

- City Monitoring with Dynamic UAV-Sensor-Based Sweep Coverage as a Stochastic Arc-Inventory Routing Policy — Joseph Chow & Xintao Liu
- A Metamodel Simulation-Based Optimization Approach for the Efficient Calibration Of Stochastic Traffic Simulators — Carolina Osorio, Gunnar Flötteröd & Chao Zhang
- Information and Traffic Incident Management — **Kalyan Talluri**, Dmitrii Tikhonenko & Gregory Fridman

Session chairs are shown in **bold**.

Static MILP Solutions and Adaptive Solutions for Hub Decisions in Very Large Scale Logistics Networks

Alexander Richter, Yann Disser, Wiebke Höhn, Sebastian Stiller

Technische Universität Berlin, Germany

Retail inside large cities is characterized by low storage and high locality. Major retailers consolidate a huge variety of goods close to the city for often more than daily deliveries to the stores. The resulting logistics networks from suppliers via several hub layers to stores are extremely large in practice. For such logistics networks, we study two approaches to select a set of hubs of fixed cardinality to minimize routing cost.

In the experience of our industry partner 4flow AG—a leading logistics software and consultancy company—some of these networks cannot even be loaded into standard planning software. For some of our case studies, even loading the raw network data consumes the majority of RAM on a standard laptop of, e.g., 8 GB RAM, thus leaving very little slack for advanced data structures and algorithms. Nevertheless, reducing cost is paramount in these networks. The cost crucially depends on a non-trivial consolidation effect. We seek a method applicable to such very large scale instances that can choose a set of hubs to rent, which allows for routing at low cost. In Europe rental contracts for hubs usually feature no fixed cost or opening cost. Still, the organizational overhead limits the number of hubs in practice. The final decision is best taken by an expert planner based on optimized solutions for different bounds on the number of hubs.

An additional planning aspect is the adaptivity of a solution. The realization of a priory uncertain demand data may require a different number of open hubs than initially planned. Planners in practice prefer to choose a set of hubs that can be adapted to a good solution with a smaller or larger hub number in case of decreasing or increasing demand values, respectively. A question we address in this context is about the *price* that we have to pay in order to have an *adaptable* hub set compared to a set of hubs which was optimized for a particular hub bound.

For optimizing for a particular hub bound, we design an involved Mixed Integer Linear Programming formulation based on column generation. In the adaptive setting, we propose a greedy framework that calls a black box routing routine. While the former approach is currently not able to handle very large instances, the latter approach is suitable for all instances for which fast routing algorithms exist. We evaluate our algorithms on anonymized real-world case studies which were provided by our project partner 4flow AG.

The model. We consider a logistics network which consists of source and sink nodes, potential hub nodes and transport relations. Moreover, there is set of commodities, each defined by its source and a sink node, and its *properties*—typically weight, volume and loading meter. Each commodity needs to be routed on a single path through the network.

Cost driver. The crucial optimization potential stems from the *consolidation* of different commodities with respect to different properties. Typical rates offered by European transportation companies depend on several properties. In our case studies, routing small heavy commodities together with bulky light-weight ones makes the difference between good and bad routings.

In this model, different tariff rates t—e.g., Full Truck Load (FTL) and Less Than Full Truck Load (LTL)—that may be available on edge e are modeled by affine linear functions that differ in their fix cost o_t (the initial jump point of the function) and in their cost rates m_{tp} for usage of property p. For a fixed multi-commodity flow f let $\alpha(f^e)$ be the corresponding *property vector*, its components $\alpha_p(f^e)$ specifying the usage of the respective property p of commodity flow f^e induced on e. The transportation cost on edge e is then given as

$$\min_t \left\{ o_t + \max_p m_{tp} \cdot \alpha_p(f^e) \right\}.$$

Network structure. Consolidation of commodity flow is only possible at hub nodes. Their usage incurs renting cost, depending on a hub's throughput but also organizational overhead faced by the trading company. Clearly a larger number of hubs allows more cost efficient consolidation. Optimizing the network structure is subject to finding a most cost efficient consolidation for an upper bound of hubs to open. As organizational overhead cannot be quantified adequately, we seek solutions for different hub bounds, and leave a final decision to the logistics expert.

Incremental hub solutions. In order to be robust against varying demands, so called *incremental hub solutions* are preferred in practice. Instead of independently deciding for each number of hubs which hubs to open—possibly resulting in completely different hub sets—one requires that the hub set chosen for $k < \ell$ hubs is contained in the hub set for bound ℓ. These nested hub sets imply a ranking of the hubs, and in case of k hubs to be opened, we choose the k hubs with highest rank. In practice, solutions of this kind allow to easily adapt to varying demands: One simply opens or closes the respective hubs according to the ranking.

Our Mix Integer Programming approach (MILP). This heuristic combines the solution of a suitable MILP with local search techniques. The MILP is based on a path formulation for the multi-commodity flow problem on the underlying graph. Transportation cost is modeled on each edge with binary variables deciding, which tariff rate applies to this edge. The tariff variables are thus linked to the binary path decision variables of commodity paths that contain this edge.

As the number of possible commodity paths grows exponentially with the network size, we use a column generation technique, which, given a solution to a restricted set of possible paths, finds new alternative paths for commodities, that reduce the cost of the current solution. The given network size also prohibits to include all tariff rates in the initial model. When carefully choosing the set of possible hub nodes that may be used by new paths, the pricing problem can be formulated as a linear program of solvable size.

We use this technique to solve the linear relaxation of the MILP and then branch on binary decision variables. We can observe that the linear formulation is strong and already yields near integral solutions. Finally, we apply a path-based local search to improve the multi-commodity flow of the solution, with the obtained hub set considered as fixed.

Our incremental greedy approach. We propose a generic framework for the incremental hub selection problem which is based on a black box routing algorithm and a hub evaluation function. Given a routing solution for all commodities, this function assigns a value to each hub; e.g., the total weight or volume shipped via the hub. The algorithm computes an incremental hub solution for a given list of hub numbers $k_1 < k_2 < \cdots < k_\ell$ as follows: Firstly, it computes a routing for the network in which all hubs are open, and it assesses the hubs according to the evaluation function. Next, all but the k_ℓ highest evaluated hubs are closed, and the routing is recomputed. We continue analogously for the next smaller hub number until we finally construct a solution for k_1 hubs.

In our computational study, we investigate different hub evaluation functions and different hub steps $k_{i+1} - k_i$. Currently, the routing is obtained by successively sending the commodities along a shortest path with respect to marginal transportation costs.

First results. We present preliminary experiments on real-world instances with approximately 400 sources, 20 sinks, 10000 commodities, and 85 possible hub locations and compare the incremental solution obtained by the greedy heuristic with the MILP heuristic for each hub bound. We observe that the incremental solutions incur only slightly higher cost (up to 1.5 %) for small bounds of used hubs (e.g., $3-6$). For larger numbers it is competitive with the non-incremental solution sometimes obtaining slightly better solutions. Our results suggest that the incremental greedy heuristic is a promising technique to be applied to even larger networks, where the MILP heuristic faces runtime and memory limitations. Currently, we have computed first incremental solutions for very large instances with roughly 300 sources, 14000 sinks, 48000 commodities, and 100 possible hub locations

Optimization Approaches for the Truck and Drone Delivery Problem

N. Agatz, P. Bouman, M. Schmidt

Rotterdam School of Management, Erasmus University, Rotterdam, The Netherlands

1 Introduction

In an effort to provide shorter delivery lead-times for goods ordered online, companies are looking for new technologies to bridge the last-mile to their customers. One technology-driven opportunity that has recently received much attention is the deployment of unmanned aerial vehicles or drones to support package delivery. An important advantage of a drone as compared to a regular delivery vehicle is that it can fly over congested roads without delay.

Several companies, including Amazon, Google, DHL, UPS en Fedex, are currently investigating the use of drones for deliveries [2]. Many of the recent tests involve multi-propeller drones that can carry packages of approximately 2 kilograms over a range of 20 kilometers. DHL Parcel recently announced a regular drone delivery service to deliver medications and other urgently needed goods to one of Germany's North Sea islands [1]. In this example, the drone flies automated but still has to be continuously monitored. Aeronautics experts expect that drones will be able to fly autonomously and safely in urban environments within the next few years, based on rapid advances in obstacle detection and avoidance technology.

While a drone is fast and relatively inexpensive in terms of costs per mile, there are also some inherent limitations to its use. The size of the drone puts an upper limit on the size of the packages it can carry. Since it is battery-powered, the range is likely to remain limited as compared to a regular (fuel-based) delivery vehicle. This means that a drone has to return to the depot after each delivery, which is not very efficient. One way to extend the effective range and capacity of a drone is to let it collaborate with a delivery vehicle. AMP Electric Vehicles is working with the University of Cincinnati Department of Aerospace Engineering on a drone that would be mounted on the top of its electric-powered trucks to help the truck driver with the deliveries [3].

In this setting, the delivery truck and the drone collaboratively serve all customers. While the delivery truck moves between different customers to make deliveries, the drone simultaneously serves another set of customers, one by one, returning to the truck after each delivery to pickup another package. The objective is to serve all customers while minimizing total costs, in which labor costs (i.e. time) is the most relevant cost factor. Even if we consider only one single truck, this problem involves both assignment decisions and routing decisions. Assignment decisions to determine which vehicle, drone or truck, will serve which customers, and routing decisions to determine in which sequence the customers on each vehicle are visited. Conceptually, the problem is related to the close enough traveling salesman problem [4] and falls in the class of vehicle routing problems that require synchronization between vehicles [5].

More formally, we model our depot and our customers as nodes in a graph $G = (V, E)$. Node v_0 represents the depot, the other nodes $v_1, \ldots, v_N$ represent the customers. The edges $e = \{v_i, v_j\}$ represent road connections between the nodes and the $c(e) = c(v_i, v_j)$ stands for the driving time that the truck needs to drive from v_i to v_j or vice versa. We assume that the drone is only allowed to fly above roads. It is faster than the truck by a factor $\frac{1}{\alpha}$, i.e., the time that the drone needs to fly from v_i to v_j is $\alpha \cdot c(v_i, v_j)$ for all $v_i, v_j \in V$. Note that the drone can transport one package at most. We make the simplifying assumption that recharging of the drone (if necessary) and pickup and delivery of packages is done instantaneously, i.e., it does not take time. Furthermore, we assume that the drone's battery power is sufficient to cover all involved distances and that the pickup of packages from the truck can only take place at nodes.

A *solution* to this problem is hence a truck route $\mathcal{R} = (r_1 = v_0, r_2, \ldots, r_n = v_0)$ from v_0 to v_0 together with a drone route $\mathcal{D} = (d_1 = v_0, d_2, \ldots, d_m = v_0)$. Note that the drone route describes the full path of the drone, i.e., not only the customers which are served by the drone but also all customers which are visited by both truck and drone. We will slightly abuse notation and identify the sequences $\mathcal{R}$ and $\mathcal{D}$ with the corresponding node sets, when convenient.

Since the drone has unit-capacity, it always has to return to a node visited by the truck before it can serve another customer. This means that $\mathcal{D}$ is a feasible drone route with respect to $\mathcal{R}$ if for each

$$d_i \notin \mathcal{R} \text{ implies } \exists j_1 \leq j_2 \text{ s.t. } d_{i-1} = r_{j_1}, d_{i+1} = r_{j_2}.$$

Note that this does not imply that the drone and the truck always meet up at the next node that is visited by the truck after the drone left. It could happen that the truck visits several customers before the drone catches up with it. Furthermore, we require that all nodes need to be visited either by the truck or by the drone, i.e. $\mathcal{R} \cup \mathcal{D} = V$.

Since the truck driver's wage is the most relevant cost factor, our objective is to minimize the total *time* $t(\mathcal{R}, \mathcal{D})$ needed to serve all customers. Since we allow waiting times for both the truck and the drone, this time is not simply the sum of the travel times of the truck and/ or drone. To compute the time, it is useful to consider the subsequence of nodes which is visited by both truck and drone. Let i_k and j_k for $k = 0, \ldots, l$ be the corresponding indices, i.e. $\mathcal{R} \cap \mathcal{D} = (r_{i_1} = v_0, r_{i_2}, \ldots, r_{i_l} = v_0) = (d_{j_1} = v_0, d_{j_2}, \ldots, d_{j_l} = v_0)$. The time it takes for the drone and the truck to arrive both at a node $r_{i_{k+1}} = d_{i_{k+1}}$ after they have departed (at the same time) from node $r_{i_k} = d_{i_k}$ depends on the routes of both the truck and drone to the meeting node. More precisely, it is given as

$$t(r_{i_k}, r_{i_{k+1}}) := \max\{ \sum_{a=i_k}^{a=i_{k+1}-1} c(r_a, r_{a+1}), \alpha \cdot \sum_{b=j_k}^{b=j_{k+1}-1} c(d_b, d_{b+1}) \}.$$

Hence, the overall time needed to distribute the packages is

$$t(\mathcal{R}, \mathcal{D}) := \sum_{l=1}^{k-1} t(r_{i_k}, r_{i_{k+1}}).$$

In this paper, we aim to contribute to the development of the truck and drone delivery concept by developing exact and heuristic solution approaches to the corresponding routing problem. We give quality bounds and conduct numerical experiments to investigate the efficiency of truck-paired drone deliveries for different realistic demand instances. In particular, we compare the costs of the truck-only solution to the solutions of the truck and drone problem under different cost assumptions.

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Optimizing Time-Dependent Arrival Rates for Truck Handling Operations

A. Franz[a], R. Stolletz[b]

[a]*Center for Doctoral Studies in Business, Graduate School of Economics & Social Sciences*
[b]*Chair of Production Management, Business School*
University of Mannheim, Germany

A variety of freight handling operations along the logistics chain is faced with fluctuating truck arrivals and consequently with long queues during peak times. In particular in urban areas, space for truck queues is very limited and emissions of idling truck engines are a major threat for air quality. Demand management mechanisms such as truck appointment systems aim at smoothing demand by shifting truck arrivals from peak to off-peak periods in order to improve the system's operational performance.

We provide a general, reliable, and fast methodology to evaluate and optimize the arrival pattern for the time-dependent queueing system of truck handling operations. Our optimization approach is based on the stationary backlog-carryover approach to analyze the system's performance. The time-dependent arrival rates serve as decision variables, i.e., changes in the original demand pattern are allowed and intentional. The objective of this non-linear optimization model is to minimize total waiting times while the corresponding change in the arrival pattern is limited. A numerical study compares the performance measures of original and optimized arrival patterns for truck handling operations of a distribution center. It shows that a significant reduction in waiting times can be reached even with minor shifts in time-dependent arrival rates.

Disruption Management in Local Public Transport: Service Regularity Issues

E. Tresoldi[a], F. Malucelli[a], S. Gualandi[b], S. Carosi[c]

[a]*DEIB – Politecnico di Milano*

[b]*AntOptima*

[c]*MAIOR*

In this paper, we elaborate, in the context of local public transport services, on the design and the development of optimization algorithms that can assist the operators in facing different types of disruptions with the ultimate objective of increasing the quality of service of public transportation or, at least, to limit the perception of inconvenience on passengers. As a case study, we will analyze the urban management of surface lines (buses, trolleybuses and trams) of Azienda Trasporti Milanese (ATM) of Milan.

After discussing about the various types of disruptions [CLLR10] that can be considered, we will focus on the way the regularity of the service can be assessed [BDFM13]. This is one of the most critical points since, from the service provider point of view and, also, from the municipality or the agency monitoring the service perspective, the regularity of the service should be measured in the simplest and most intuitive way. However, the measure should be also of help when actions, intended to recover the regularity or improve it in the presence of disruptions, must be taken and their definition demanded to a decision support system. In this regard, we present and analyze different types of functions that can be used to effectively evaluate the regularity of the service in a real-time environment.

Furthermore, we discuss the necessity of a simulation based evaluation system to automatically estimate the effect of detours and other changes on the regularity of the service. Such system can help the operations central officers in quickly and objectively assessing the impact of different alternative decisions taken to recover the regular service.

We analyze the mathematical aspects underlying the decision process required in defining the optimal curse of action to promptly react to short-term disruptions. In particular, a detailed description of the algorithms implemented to re-optimize on the fly both vehicles and drivers scheduling is given. The results obtained on real world case studies provided by ATM are reported and carefully analyzed.

Finally, we present a description of an integrated decision support system that includes in a uniform environment both the simulation and optimization aspects of the problem.

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Assessing Customer Service Reliability in Route Planning with Self-Imposed Time Windows and Uncertain Travel Times

P. P. Repoussis[a], A. D. Varias[b], C. D. Tarantilis[b]

[a]*Howe School of Technology Management, Stevens Institute of Technology, Castle Point on Hudson, USA*

[b]*School of Business, Athens University of Economics and Business, Athens, Greece*

Most studies in vehicle routing seek to minimize investment and operating costs, acknowledging only as side issues customer service aspects. This work focuses on how to incorporate service reliability in routing plans. It explores new models and solution frameworks for single-period problem settings with self-imposed time windows and stochastic travel times. For example, a logistics provider may want to quote time windows such that the expected costs incurred after routing are minimized. Promising a precise service time can be impossible or extremely costly to satisfy due to uncertainties. The goal is to generate robust vehicle routing plans that guarantee stable and reliable service despite unforeseeable disruption events.

Despite the fact that many distribution networks deal with endogenous time windows, most of the literature is devoted to the Vehicle Routing Problem with (exogenous) Time Windows, and the research on problem settings for assigning time windows is very poor. Spliet and Gabor (2014) introduced the so-called Time Window Assignment Vehicle Routing Problem (TWAVRP) with uncertain demand. The TWAVRP consists of finding a single time window assignment (before demand is known) and a vehicle routing schedule for each scenario (realization of the demand at each location) satisfying these time windows, such that the expected costs are minimized. A similar problem, namely the Vehicle Routing Problem with Self-Imposed Time Windows (VRP-SITW), is considered by Jabali et al. (2014). The main difference compared to the TWAVRP is that the demand is known deterministically beforehand; however, the travel time is uncertain.

This work presents two scenario-based frameworks for setting customer's time windows with stochastic travel times. The first framework generalizes in a number of ways the earlier work of Jabali et al. (2014). First, the length of the time windows can vary within a predefined lower and upper bound different for each customer. Second, the objective function is enhanced and consists of four components: (a) the routing cost; (b) the expected earliness and lateness penalty occurred at each customer for every possible disruption scenario that may happen at a previously routed customer, and all scenarios are taken into account for the disruption lengths at each disrupted customer; (c) the expected penalty caused if the maximum route duration is violated; and (d) the total penalty paid for the time window length. Third, in effort to further improve the robustness of the vehicle routing plans, a two-stage p-robust model formulation is also proposed.

At the first stage, time windows are endogenously imposed for each disruption realization, and we get the minimum cost of imposing a set of time windows to customers given the fact that one disruption scenario has occurred. In the second stage, the model takes into account all possible disruption scenarios, and imposes the time windows minimizing the expected cost of delay at each customer and the depot.

The second framework seeks to incorporate service reliability aspects. The main objective is to minimize the time window widths assigned to each customer, in the sense that the smaller the time windows, the better is the perceived customer service level. Assuming that we have discrete random travel times for each arc, a set of scenarios for all possible arrival times at customer's locations can be determined a priori. To that end, the goal is to find the time window for each customer, such that it is ensured that each customer will be served at the assigned time window with a given probability. For this purpose, chance constraints are added to guarantee a predefined level of service reliability.

A hierarchical solution approach has been developed for solving the above models. Initially, the master vehicle routing problem is solved, without considering any time window restrictions, to optimize the routing cost, and on this basis the subordinate time window assignment sub-problem is defined for every route, and solved so as to assign the time windows to the customers. An Iterated Local Search algorithm is employed for solving the master problem, while the time window assignment models are solved to optimality using Gurobi Optimizer 6.0. Various computational experiments has been performed to assess the performance of the proposed solution method as well as to value time window flexibility in a way that reflects the provider's tolerance for risk and ambiguity. Finally, the balance and the trade-off between robustness and routing cost is also examined.

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Robust Scheduling of Urban Home Health Care Services Using Time-Dependent Public Transport

K.-D. Rest & P. Hirsch

Institute of Production and Logistics, University of Natural Resources and Life Science, Vienna, Austria

1 Introduction

Home health care (HHC) services are of vital importance for today's society. With services ranging from qualified home nursing to assistance in leading the household and maintenance of social contacts, they allow old and frail people a self-determined living in their familiar environment. The current demographic and social developments induce a significant increase in demand for HHC services and further rises must be expected in many countries. Furthermore, HHC service providers are exposed to high cost pressure. Currently, the scheduling is usually done manually and because of its complexity, suitable decision support systems are highly welcomed. Optimization in the field of HHC is a rather young but quickly evolving research area. A recent comprehensive literature review on both daily and periodic HHC scheduling can be found in Trautsamwieser and Hirsch (2014) or Matta et al (2014).

We consider a real-world HHC problem, which is based on the demands of the Austrian Red Cross (ARC), one of the leading HHC service providers in Austria. It has a daily planning horizon, focuses on urban regions and can be summarized as follows: A certain number of heterogeneous nurses, with different qualification levels and working times, have to visit a set of clients at least once during a day. Various assignment constraints (e.g. language skills, declined nurses, etc.) and hard time windows of these visits are considered. In addition, maximum working times and mandatory breaks have to be observed. The objective is to minimize the total travel and waiting times of the nurses. In practice, nurses use either cars or public transport, depending on the geographical region and the efficiency of the public transport system. However, routing with public transport is still hardly considered in literature and we are not aware of any published work in this field, taking time-dependent travel times into account; with the exception of conference presentations of our working group (e.g. Rest and Hirsch, 2013).

In addition, many real-world problems are subject to dynamic and/or stochastic processes. In the case of HHC it may happen several times a day that the estimated service times for treating a client are exceeded as they depend for example on the physical condition of the client or the on-site situation. It may also happen that new clients show up who need last-minute services (e.g. due to dehospitalization) and thus, have to be inserted into the existing schedules. To the best of our knowledge, such aspects are still not taken into account in the routing of the nurses. Stochastic programming has only been applied to the HHC assignment problem (e.g. Carello and Lanzarone, 2014). This type of problem has a mid- to long-term perspective and aims at assigning clients to nurses based on their needs and skills. While the routing of the nurses is not considered, it usually addresses aspects like continuity of care or workload balancing. An overview of scientific work on stochastic and dynamic vehicle routing in general can be found in Pillac et al (2013).

2 Solution approach

The presented work builds upon our previous time-dependent and multimodal routing of the nurses and aims at computing robust schedules that are able to cope with small disturbances. In a first step we only consider the stochastic aspects of the HHC problem. More precisely, the service times for treating a client are assumed to follow a known probability distribution and to be independent from each other. From a modeling point of view, the presented problem can be seen as a time-dependent vehicle routing problem with stochastic service times and additional HHC-related constraints.

A discrete time approach has been chosen to model the the time-dependency. To efficiently compute time-dependent travel time matrices out of the timetables from the public transport service providers, a dynamic programming approach has been implemented. It considers walking to nearby stations as well as waiting for later connections and complies with the first in - first out (FIFO) property. To solve real-world sized instances within reasonable time a time-dependent Tabu Search (TS) based solution approach has been developed and implemented in the programming language C++. The algorithm is based on the ideas of the unified TS, as used in time-independent routing problems by Cordeau et al (2001) or Hirsch (2011). Thus, infeasible solutions are temporarily allowed and a dynamically adapted weighted objective function is used to guide the search process. To speed up the search the developed TS dynamically changes the size of its neighborhood.

In order to incorporate the stochastic service times and to compute robust schedules, a penalty formulation is used as in Mendoza et al (2013). Thus, the objective function is extended by the expected costs for recursive actions. Recursive actions are needed in case a route gets infeasible because of the prolonged service times. In such a case, HHC service providers send out floaters, who step in and take over a certain number of clients in order to sustain the services of the subsequent clients in the route.

The algorithm will be tested with real-world based data from the ARC in Vienna. Its solutions are compared with those obtained with deterministic service times, in order to evaluate the robustness of the computed schedules.

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Handling Travel Time Uncertainly in City Logistics Systems

U. Kunter, C. Iyigun, H. Sural

Institute of Production and Logistics, University of Natural Resources and Life Science, Vienna, Austria

City Logistics (CL) is a quickly developing area of research aiming to create the methods for designing efficient and effective freight distribution networks for cities. Consolidation and coordination are two approaches used in CL projects. Consolidation is combining shipments in order to make their deliveries possible with fewer vehicles. Such operations take place in facilities called City Distribution Centers (CDC). CDCs are typically located on the city boundaries in order to prevent large trucks from entering the city traffic. Coordination is establishing effective collaboration and communication between the stakeholders of the system.

There are three main decisions to be made in a CL system: determining the number of CDCs and their locations (strategic decisions), making the allocation decisions between customers and CDCs (tactical decisions), and determining the vehicle routes for customer service (operational decisions). Although these decision problems are well-studied separately in the literature, there are only a few studies that consider their integration with the features of CL systems. As CL projects become more popular, there is a growing demand for the methods dealing with such problems tailored for CL systems.

Decisions in CL systems are especially susceptible to uncertainty. For example, different realizations of uncertainty in demand, travel time, service time, etc. significantly affect the performance of decisions. Uncertainty in higher level decisions have even larger impact on the system performance. Due to their higher level nature, we consider CDC location and customer allocation decisions in the current study and we plan to incorporate routing decisions in a future research.

There are multiple ways of formulating location-allocation decisions together in a CL framework in the presence of uncertainty. We formulate the problem as a fixed charge capacitated facility location problem as it usually constitutes a basis of other formulations. To incorporate uncertainty, we prefer stochastic optimization to robust optimization. Focusing on the worst-case scenarios for robustness deteriorate the effectiveness of solutions. However, worst-case scenarios span only short intervals within our planning horizon and their consideration may not bring significant benefit. As the main goal in CL systems is to create distribution networks for the long-term, robust optimization would not be suitable with a strategic view of CL. With these points in mind, we make use of scenarios to represent solution environment and we apply stochastic optimization.

We use three types of models with respect to the different levels of incorporating uncertainty: deterministic, single-stage stochastic and two-stage stochastic models. Deterministic model is a simple facility location-allocation model. Single-stage stochastic model uses the expected value of uncertainty factors and both location and allocation decisions are made once, effective for all scenarios. Two-stage stochastic model attains different allocation decisions for each scenario while location decisions are made only once.

We compare the performance of solutions obtained from the three formulations within a value of information framework. Value of stochastic solution (VSS) and expected value of perfect information (EVPI) values are calculated to observe the tradeoff between the solution quality and the computational complexity of finding a solution. We have found that the two-stage stochastic model produces significantly better solutions than the single-stage stochastic model and that making both location and allocation decisions specifically for each scenario does not improve the objective function value significantly, compared to the two-stage stochastic model. Our understanding of these results is that the two-stage stochastic model should be the main decision-making tool for the location-allocation decisions of CL systems.

We consider several types of patterns (like clustered, unclustered, and mixed) and distributions (uniform and normal) for the customer locations. After applying value of information analysis on the instances generated for each type separately, we observed that patterns and distributions have a significant effect on VSS values. For instance, uniform distribution obtains lower VSS values than random distribution and clustered pattern obtains higher VSS values than unclustered pattern.

We repeat the same value of information analysis for the instances where candidate facilities are located inside the city (contrary to CDCs being located on the city boundaries). We observed that both VSS and EVPI values are significantly smaller in this case. We believe that these results demonstrate an important characteristic of location-allocation in CL systems.

Obtaining different allocation decisions for different scenarios brings up the need for coordination. We assume that any customer with varying allocation creates a coordination cost for the whole system. Therefore, a second tradeoff appears between solution performances with respect to the cost of serving customers and the cost of coordination. For a desirable solution according to the preferences of the decision maker, one can place a limit on the cost of coordination and investigate the possible solutions as alternatives.

While the methods described above can be applied for any kind of uncertainty, we made our experiments and analyses considering travel time uncertainty. The instances contain customers dispersed with different patterns and distributions. We generate a large number of scenarios for each instance using the Bureau of Public Roads function that models the travel time in a city. We identify several causes for traffic congestion and systematically construct our scenarios so that the effect of each cause is represented.

Considering the large number of customers that would be present in a CL system, we develop a solution method based on Benders Decomposition. For larger scale instances, Benders Decomposition finds feasible solutions with acceptable performance in short time. This method is makes it possible to decompose the problem with respect to scenarios as well as decision variables. By decomposing scenarios, we deal with a lot of small sized problems. However, the total solution time does not increase largely as the number of customers increases.

In the next steps of our study, we are planning to deal with routing decisions explicitly. Since the major model is already NP-hard even without routing decisions, our aim is to consider routing under an approximation framework.

Freight Consolidation in Urban Networks With Transshipments

W. van Heeswijk[a], M. Mes & M. Schutten

[a]*Department of Industrial Engineering and Business Information Systems, University of Twente*

1 Introduction

The demand for goods in urban areas has seen a sharp growth in the past years; this trend is expected to continue in years to come (Benjelloun and Crainic, 2009). As a result, urban areas experience an increase in inflow of trucks, contributing to problems such as congestion, air pollution, and noise hindrance. Often, these trucks carry only a relatively small volume of goods for a few destinations within the area. A possible solution to reduce the number of trucks in urban areas is the use of consolidation centers at the edge of these areas, where goods from incoming trucks are transshipped to dedicated urban delivery vehicles. These vehicles can subsequently make efficient tours within the urban area.

We study the dispatching decisions at an urban consolidation center with uncontrolled batch arrivals of Less-than-Truckload goods. The uncontrolled arrivals reflect the delivery of goods by independent carriers. A batch may well contain orders with, e.g., dispersed destinations and various delivery windows. Directly distributing an arriving batch may therefore render poor solutions. Instead, the hub operator could decide to hold some orders and wait for more incoming batches that allow for consolidation within the delivery vehicles. As such, more efficient routes can be taken. Various uncertainties affect the planning, such as the arrival time of new batches and the properties of the orders in a batch (e.g., size, volume, time-windows). Based on the available knowledge regarding current and future orders, the operator is able to make informed waiting decisions. This can be accomplished by deploying a waiting policy that provides shipping decisions given the information and beliefs of the operator. For this purpose, we propose an Approximate Dynamic Programming (ADP) approach, aimed at efficiently dispatching urban delivery vehicles. As such, we facilitate the need for operational planning at the urban distribution level, where the arrival process of goods at the consolidation center has a significant impact.

2 Problem description

We formulate the problem as a Stochastic Dynamic Program (SDP), where the goal of the hub operator is to minimize the total costs over a given planning horizon. We define stages as decision moments within this horizon, at which the hub operator can decide to ship orders available at the center. New orders may arrive at the consolidation center at every stage. Each order is characterized by its arrival time at the center, its destination in the urban area, its size, and its delivery window. We consider the latter as a soft constraint, allowing to violate delivery windows (up to a maximum deviation) in favor of more efficient dispatching. Every combination of attributes represents a unique order type. As delivery tours may take multiple stages, we also consider fleet availability during the planning horizon. The fleet is either owned by the hub operator or rented, resulting in distinct cost structures. We describe the state of the system as the amount of every order type available and the fleet availability. The action space is given by all possible combinations of orders to dispatch. The outcome space follows from the transition of inventory and fleet due to the action taken in combination with the new random arrivals. Costs are comprised of two elements. First, transportation costs are incurred according to a cost function based on travel distance and fill rate. Second, the operator incurs a financial penalty in case of violating the delivery windows. The operator aims to minimize total costs, and is therefore required to strike a balance between lateness and efficiency. The key difficulty in finding this balance lies in the uncertainty regarding future arrivals. New arriving batches may allow to combine orders and generate more efficient routes, but the waiting time increases the risk of lateness without the desired orders arriving.

3 Solution approach

The state space of the SDP increases exponentially with both the number of orders and the number of order types. Furthermore, the action space and outcome space quickly become very large. The SDP therefore becomes intractable for realistic instances. Following Powell et al. (2012), we develop an Approximate Dynamic Programming approach to (i) solve the decision problem for large instances, and (ii) obtain fitted value function approximations that allow for fast decision making in a practical setting.

To efficiently learn values of states, we define features that describe the state of the system, and determine the explanatory values of these features by applying linear regression on a small but representative instance of the corresponding SDP. We obtain a set of features that explain about 95% of the costs: the total number of orders available, the number of orders of every type, and fleet availability in the current stage. We introduce several exponents and cross-products as separate features to improve the fit. By considering the features instead of the full state description, we drastically reduce the computation effort. We learn the weights corresponding to specific features by simulating random arrivals and learn the values of specific actions. The result of the procedure is a value function, where inputting the batch properties and the corresponding weights directly yields an action.

4 Computational study

Inspired by a real-life case of urban distribution, we design a network and infer probability distributions for the order types. To assess the quality of the value function approximation, we first make use of toy-sized instances. For these small instances, we are able to compare the ADP results with the exact results of the SDP. To obtain insights into the behavior of the algorithm, we subsequently focus on large instances. We vary several of the real-life characteristics to obtain a broad insight into the behavior of the algorithm. Variables we assess are (i) transportation- and penalty costs, (ii) sources of uncertainty (batch arrival time and/or contents of the batch), (iii) frequency of incoming and departing batches, (iv) flexibility in delivery windows, and (v) sizes of batches and orders (order sizes, capacity of long-haul trucks and delivery trucks). For the large instances, we compare our approach with two greedy heuristics.

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Loading Bay Time Slot Allocation by Core-Selecting Package Auctions

P. Karaenke, M. Bichler, S. Minner

TU München

{karaenke, bichler}@in.tum.de, stefan.minner@tum.de

1 Introduction

Less stock-keeping at factories and retailers has increased the pressure on carriers to deliver on time. With more trucks, probabilities for congestions rise. These do not only occur on roads, but especially at warehouses. In urban areas, this problem is increased by inadequate loading facilities and parking space. Congestions at loading bays can cause severe delays in logistics processes and cause increasing bottlenecks for truck routes.

According to a survey among more than 500 transport companies in Germany, 18% of them have an average waiting time of more than two hours and 51% have an average waiting time between one to two hours at each warehouse [4]. Another problem is insufficient parking capacity for waiting trucks. The German Federal Office for Goods Transport has provided a special report on problems at loading bays [3]. The main reasons for waiting times include shortages of resources (staff and infrastructure) and uncoordinated arrivals of trucks, especially at peak times. These problems are interconnected, since uncoordinated arrival of trucks make appropriate staffing difficult. In addition, congestions can interfere with other processes due to a high number of trucks at the facility. Proposed remedies for these problems are time slot management, information sharing, and increased infrastructure capacities.

Capacity increases require rather high investments compared to improved coordination by information sharing or time slot management and are often even infeasible in urban areas. We have investigated the provision of information about the historical waiting times to the carriers in previous work. Carriers can utilize this information by changing their routes and schedules accordingly. Since waiting time information is the same for all carriers, there is a risk that they make similar decisions, e.g. delaying departure to avoid waiting times that occur in the morning, and therefore cause new congestion at another time of the day.

To mitigate congestions at loading bays, we propose the application of package (combinatorial) auctions to allocate time slots to trucks. The contributions of this research are a bidding language and a core-selecting package auction for loading bay coordination. Core-selecting payment rules have been applied in spectrum auctions and can avoid several drawbacks of the Vickrey–Clarke–Groves (VCG) mechanism with Clarke pivot rule, e.g., low perceived fairness of prices [2, 5, 6]. We evaluate our proposal by means of simulation and assess (i) the potential for waiting time reduction compared to uncoordinated arrivals as well as sharing of historical waiting times from previous work, (ii) the empirical complexity of the computational problem for scenarios of varying complexity, and (iii) the relation of VCG and bidder-Pareto-optimal core payments.

2 Loading bay time slot auction

We assume there is a set of carriers and warehouses, each having a specific location. Each of the carriers' trucks is given a tour that is a subset of the set of warehouses. Trucks start at and return to the depots. Warehouses can serve a number of carriers at the same time; this (un)loading capacity may vary for both different warehouses and different time slots. When a warehouse is fully occupied and/or reserved, other carriers have to line up and wait until the warehouse employees can serve them. Routes define ordered tours and thus paths in the transportation network graph. To build routes for tours, carriers have to order the locations. This can be done for example by solving a Traveling Salesman Problem (TSP).

The general problem setting is comparable with multiple instances of the time-dependent traveling salesman problem (TD-TSP) [1, 7, 8]. That is, for every truck, a TD-TSP has to be solved. In contrast to existing approaches, the problem addressed in this work also results from the constrained capacity of the *vertices* (as compared to edges) of the traveling graph. This means that the solutions interact with those of the other carriers and the resulting round trip times are therefore interdependent, i.e., carriers optimize at the same time and their optimizations impact each other.

The proposed auction allocates warehouse loading bay time slots to bidders and guarantees that a carrier either gets an entire bundle of time slots that fit a route or none. Different departure times and different routes can be realized by bidding for different bundles of time slots. The service capacity of warehouses (loading bays) is modeled as a multi-knapsack problem. In each time slot $t \in T$, each warehouse $k \in K$ has a capacity of c_{kt}. The carriers (bidders) i submit zero or more bids $j \in J_i$ as tuples (b_j, R^j), where R^j denotes a $|T| \times |K|$ reservation matrix and b_j the monetary bid on the reservations described by this matrix.

To maximize the social welfare, the objective is to maximize the sum of accepted monetary bids in the winner determination (WD) problem. Constraints ensures that the warehouse capacities are not exceeded for accepted bids and that at most one bid can be accepted per bidder (for alternative routes/departure times). Following Day and Raghavan [6], we calculate equitable bidder-Pareto optimal (EBPO) core payments iteratively as follows. (i) Determine winners and calculate VCG payments. (ii) Solve the core separation problem, which finds coalitions of bidders that block the current outcome (who "would pay more" than the current payments of winners). (iii) If there is a blocking coalition, add a constraint for the prices to be larger than the bids of the blocking coalition found. (iv) Re-calculate payments with the constraints found so far. This procedure is repeated from step (ii) until no further core constraint violation is found [6].

3 Results and conclusion

Our findings provide evidence that loading bay auctions can alleviate congestion substantially and that the core-pricing rule is well-suited to address the price fairness problem in this setting.

Building on previous work, we have proposed a method to further decrease the mean waiting time substantially in our simulations. This improvement, however, comes at the cost of computational complexity. Computational solver time substantially increases for scenarios of higher complexity, even for the rather small setting of ten bidders in our scenario. While the observed absolute numbers remain feasible in practice, the computational complexity has to be analyzed in detail for practical applications. For example, it may be required to restrict valid bids to a reduced number of time slots since this parameter has an essential impact on the computational complexity. The application of core-selecting payment rules requires WD and pricing problems to be solved exactly. If this is not feasible in practice since further restrictions on valid bids cannot be applied, approximation of these problems may be required. Then, additional problems can arise that mitigate the acceptance of the approach by participants. For example, when approximating WD, a bidder might win the auction who would not have won in the efficient, exact solution. We leave an application of approximation algorithms to our setting for future work.

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City Monitoring with Dynamic UAV-Sensor-Based Sweep Coverage as a Stochastic Arc-Inventory Routing Policy

J. Chow & X. Liu

Department of Civil Engineering, Ryerson University, Toronto, ON, Canada

With the rise of Big Data analytics and urban informatics, there is a rising interest to gather ever more real time data from a city's environment for real time traffic monitoring (Gerolimins and Daganzo, 2008) or travel momentum monitoring (Liu et al., 2014). Numerous monitoring sensor technologies exist for this purpose; some of the more promising among these are mobile sensors that can be deployed autonomously, such as unmanned aerial vehicles (i.e. drones). For example, UAVs have been demonstrated as feasible tools for gathering real traffic and transportation data (Srinivasan et al., 2004). UAVs can substitute traditional methods for a number of uses in transportation including measuring level of service, average annual daily traffic, intersection operations, parking utilization (Coifman et al., 2006); traffic management (Huiyuan et al., 2007); and origin-destination estimation (Braut et al., 2012).

Despite the benefits to city monitoring and humanitarian logistics, deployment of UAVs or other mobile sensors remains a challenge. Kinney et al. (2005) noted that current practice in planning the routes of UAVs typically involves manual calculations. More recent studies have sought to address the deployment problem in one of three ways. One group of studies tackled the need for periodic coverage and timing of mobile sensors over different areas (Cheng et al., 2011; Du et al., 2010), called "sweep coverage" (see Gage, 1992), which is not to be confused with sweep algorithms in vehicle routing. The second group of studies focused on the arc routing aspect of mobile sensors on infrastructure networks, ensuring that tours visit each critical link in a network like in a rural postman problem (Sipahioglu et al., 2010). Yazici et al. (2014) extended the arc routing to a dynamic deployment problem where incidents require updating the routes of the autonomous sensors in real time. However, there is a research gap in considering *dynamic/online* UAV sensor deployment that explicitly handles the periodic *sweep coverage*.

We address this gap by proposing an inventory routing variation of the dynamic UAV sensor deployment problem from Yazici et al. (2014) as a means to handle sweep coverage. Inventories in this problem setting are used to model the periodic constraint for revisiting a link in a network. This is accomplished by a new arc-inventory routing problem formulation where "customer demand" is located on links instead of nodes. The magnitude of the demand represents the degree of frequency desired for patrolling a particular link, and varies from link to link. The expected frequency requirement is related to factors for risk of an incident that requires significant surveillance (this would be the "stock-out" event). Factors include traffic flow densities, for example, if real time traffic surveillance was the objective, or population densities in the case of humanitarian logistics.

To maintain a dynamic problem under uncertainty with real time information, we consider the stochastic inventory routing problem (IRP) as defined in Bard et al. (1998), Jaillet et al. (2002), Bertazzi et al. (2013), Coelho et al. (2014), among others. Uncertainty in this problem setting may involve changing real time information pertaining to traffic densities or other data like weather conditions. The framework involves a look ahead to multiple periods to plan out which optional links to visit in the current period and which to defer, and then to execute only the portion of the plan until new information arises. Earlier studies have generally treated the random demand as a stationary variable. In our study we generalize it to a nonstationary process: a mean reverting process (see Chow and Regan, 2011a) from which the stationary process is a special case.

Three deployment policies are compared. The first is an adaptation of Bertazzi et al.'s (2013) rollout algorithm representing a state of the art method in solving the stochastic IRP. Rather than employing a deterministic IRP as the value approximation as they've done, the single period sensor deployment problem from Yazici et al. (2014) is substituted. Their method uses a generalized Voronoi diagram to construct the graph and solve by either a minimum perfect matching algorithm if all links need to be covered or with Frederickson's algorithm otherwise. The second policy is an adaptation of the real option-based network design and timing policy from Chow and Regan (2011b). Although Chow and Sayarshad (2015) showed that single period routing problems may not benefit much from such a policy that gains most of its value from timing, the IRP is essentially an optimal timing problem. The two policies are compared against a myopic reoptimization policy.

The three policies are compared in a series of numerical tests involving a simple 9 node grid network, a medium network of 24 nodes, and a larger, more realistic network setting extracted from the Toronto region.

To the best of our knowledge, there are no studies in the literature that consider dynamic stochastic inventory routing problems with nonstationary demand as mean reverting processes or as arc routing problems. There are also no studies that have dealt with dynamic sensor deployment with sweep coverage. Lastly, the proposed algorithm adapted from Chow and Regan (2011b) is the first such extension of a real option routing and timing policy for IRP.

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A Metamodel Simulation-Based Optimization Approach for the Efficient Calibration of Stochastic Traffic Simulators

C. Osorio[a], G. Flötteröd[b], C. Zhang[a]

[a]*Department of Civil & Environmental Engineering, Massachusetts Institute of Technology, Camebridge, USA, osorioc@mit.edu*

[b]*Department of Transport Science, KTH Royal Institute of Technology, Stockholm, Sweden, gunnar.floetteroed@abe.kth.se*

Introduction

A good calibration is usually a prerequisite for the simulator to reliably reproduce and predict traffic conditions. High-resolution stochastic traffic simulators enable detailed representations of reality, and as such they are built around data-intensive model systems. This renders the automatic calibration of high-resolution stochastic traffic simulators a difficult and practically relevant problem. A largely unsolved methodological challenge in this context is the formulation of tractable measurement equations that link available surveillance data from the real transport system to the model parameters one wishes to calibrate.

High-resolution stochastic traffic simulators usually do not satisfy strong model assumptions such as continuity, differentiability, and normality. Therefore, almost all existing approaches utilize black-box optimization routines that exploit problem structure hardly beyond numerical differentiation. Examples of computationally intensive strategies include simultaneous perturbation stochastic approximation (Spall (1)), unscented Kalman filter (Julier and Uhlmann (2)), and derivative-free search methods. See Antoniou, Balakrishna (3, 4) for examples, or Ben-Akiva et al. (5) for a comprehensive literature review. Recent contributions by Flötteröd et al. (6, 7, 8) approach the calibration problem efficiently by analytically approximating the gradient of the measurement equation.

This paper proposes a generalized calibration method for high-resolution stochastic traffic simulators. The problem is formulated as a simulation-based optimization (SO) problem whose framework was initially proposed by Osorio and Bierlaire (9).

Problem statement

Origin-destination (OD) pairs are trip production and attraction points connected by a set of routes in an urban network. A single OD pair is denoted by $s \in \mathcal{S}$ where $\mathcal{S}$ is the set of OD pairs. The set of routes for OD pair s is denoted by R_s. The total traffic demand between OD pair s is denoted by d_s. The probability that a traveler in OD pair s selects a route $r \in R_s$ is written as $P_s(r \mid \mathbf{x}, \boldsymbol{\theta})$ where $\mathbf{x}$ represents the route-associated network attributes (i.e., the travel times) and $\boldsymbol{\theta}$ is a vector of parameters that governs the route choice. Let δ_r^i be one if route r contains link i and zero otherwise. Assuming no losses, the expected link flow q on link i for parameter $\boldsymbol{\theta}$ is expressed as:

$$q_i(\boldsymbol{\theta}) = \sum_{s \in \mathcal{S}} d_s \sum_{r \in R_s} \delta_r^i P_s(r \mid \mathbf{x}, \boldsymbol{\theta}). \tag{1}$$

Since the network travel time contained in $\mathbf{x}$ depend in turn on the network flows, Equation (1) is circular and can in general only be solved iteratively. These iterations can be viewed as a learning process in high-resolution stochastic traffic simulations where users choose routes based on the recent network conditions $\mathbf{x}$, which updates the future network conditions.

Denoting the traffic count on link i by y_i, the problem of calibrating route choice behavioral parameters can be formulated as minimizing the sum of squared differences between the expected simulated flows $q_i(\boldsymbol{\theta})$ and the traffic counts:

$$\min_{\boldsymbol{\theta}} \sum_i (y_i - q_i(\boldsymbol{\theta}))^2 . \tag{2}$$

The problem is difficult because Equation (1) has no closed form expression and is represented only procedurally through the traffic simulation.

The objective of this paper is to address Problem (2) by embedding analytical approximation of Equation (1) which incorporates structural information from an analytical differentiable traffic model. The embedded analytical information is expected to enhance the computational efficiency, and further allows us to efficiently solve high-dimensional calibration problems.

At the outset, we concentrate on the calibration of the travel time coefficient in a logit route choice model where travel time is the sole explanatory variable and is denoted by a scalar θ.

Simulation-based optimization approach

Metamodel (or surrogate) method is used to derive an analytical approximation of Equation (1) that combines information from the high-resolution stochastic traffic simulation model and information from an computationally efficient macroscopic analytical traffic model. Ideas along these lines have been used to efficiently address large-scale urban traffic management problems while using inefficient yet detailed microsimulators (Osorio and Chong, Osorio and Nanduri, Chen et al. (10, 11, 12)).

A typical Metamodel SO iteration involves two main steps. Firstly, a metamodel is constructed based on a sample of simulated observations. Secondly, it is used to perform optimization and produces a trial point (calibration parameter value). The trial point is evaluated by the simulator and new simulation observations are obtained. The metamodel is improved with the availability of new simulation observations (step 1) and leads ultimately to better trial points (step 2). The general metamodel SO framework was proposed by Osorio and Bierlaire (9) who use the derivative-free trust region algorithm of Conn et al. (13).

The analytical traffic model used is based on Osorio and Bierlaire (14) and is complemented by multinomial logit model to make route choice endogenous. The high-resolution stochastic traffic simulator used is MATSim (Nagel et al. (15)) which is an agent-based mesoscopic traffic simulation model.

Results

Comparing to the benchmark approach using a linear polynomial metamodel, the performance of the proposed approach has been tested on a toy network. The 'real' traffic counts on links are generated by simulation.

Given the same fixed computational budget, 5 experiments for each approach are plotted respectively as the current iterate (the trial point value) vs. iteration in Figure 1 and 2. In both figures, the proposed metamodel is denoted by m while the benchmark metamodel is denoted by ϕ.

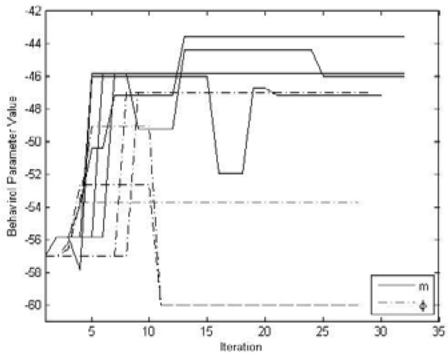

FIGURE 1 Initial point $\theta_0 = -57$; Optimal point $\theta^* = -42$. Simulated calibration parameter values across algorithmic iterations.

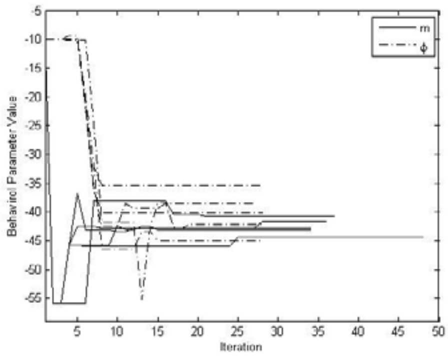

FIGURE 2 Initial point $\theta_0 = -10$; Optimal point $\theta^* = -42$. Simulated calibration parameter values across algorithmic iterations.

The figures suggests that the proposed metamodel outperforms the benchmark metamodel within a tight computational budget. To better understand the pros and cons of the proposed approach, more extensive experiments are currently being carried out.

The undergoing work is to evaluate the performance of this novel approach for a large-scale real network of the city of Berlin, Germany.

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Information and Traffic Incident Management

G. Fridman[a], K. Talluri[b], D. Tikhonenko[c]

[a]*Saint Petersburg State University of Economics, St. Petersburg, Russia*

[b]*Imperial College Business School, London, UK, kalyan.talluri@imperial.ac.uk*

[c]*Universitat Pompeu Farbra, Barcelona, Spain*

Traffic accidents or disruptions and the resulting traffic bottlenecks represent a huge drain on global productivity. New vehicular technologies enabling instantaneous direct communication with other vehicles as well as a central planner are soon on the way. However it is not clear how these technologies can be exploited. In this research work we consider a simple situation that represents a common traffic problem: In a two-lane highway, a vehicular incident (accident, breakdown) or maintenance work shuts down one lane at a certain point and traffic has to merge to the open lane to proceed. We set up an optimization model to determine the best solution if a central planner can control the vehicles. We then compare this solution against a number of behavioral and informational assumptions on the drivers. Our aim is to derive the best centralized and decentralized policies with selfish agents.

1 Traffic situation

A two-lane highway has one lane blocked due to some construction or an accident. The speed on

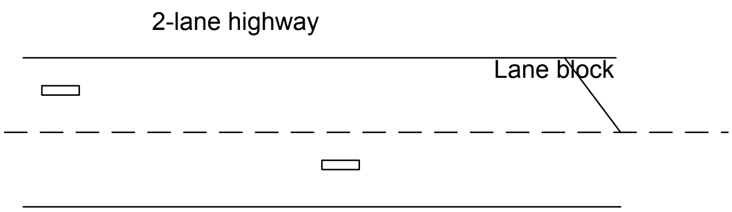

Figure 1: A two-lane highway with a blocked lane

the two lanes is given by some function

$$v_1 = f(M, \mu_1, \mu_{-1}, v_{-1})$$

where M is the maximum legal speed and μ_1 and μ_{-1} are the density of traffic (number of cars/km) on i and the other lane respectively, as well as the velocity of the other lane. Precise nature of this function has to be specified. It is for instance decreasing in both densities, but also decreasing if $\max(0, \mu_{-1} - \mu 1)$, that is if the other lane has a higher density there is a merging process that slows down the speed of lane 1. Likewise if the velocity of the other lane is slower, there is merging into lane 1 and again this effects lane 1 velocity.

In steady state $\mu_1 = \mu_{-1}$ and this is the maximum speed.

Now one of the lanes get blocked. We would like to compare the resulting process against a one lane highway

$$v_1^1 = f(M, 2\mu_1)$$

with a fully merged traffic.

Surprisingly very few papers that model and analyze merging behavior. Many simulations, cellular automata models that descriptively, and often without empirical justification, give rules of merging. Papers that marginally touch upon merging and game-theoretic analysis are the following. Daganzo [3], Hidas [6], Gipps [5], Chang and Y-M.Kao [2], Baykal-Gürsoy, Xiao, and Ozbay [1], Duret, Bouffier, and Buisson [4].

2 Research contribution

We first formulate a central planner's optimization problem to maximize throughput. The solution to this problem represents an equilibrium that may not be reached for lack of information or irrational behavior. We compare the solution with self-interested drivers who are either myopic or optimize based on local limited information. We study the role of information: equilibrium behavior when drivers are informed of the incident a distance $\hat{x}$ ahead of the incident but are under no obligation to merge right away. Each individual driver makes a decision on when to merge based on different informational assumptions. Our objective is to determine the optimal warning-ahead distance x^* if any, and study the Nash equilibrium.

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