Transportation Research Part C 144 (2022) 103912

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Stochastic service network design for a platooning service provider

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A R T I C L E I N F O

Keywords:
Stochastic service network design
Automated driving
Platooning

A B S T R A C T

Automated driving is expected to support a wide range of transportation applications in the near future. However, especially in urban environments, not all streets may be feasible for automated driving which restricts the operation of autonomous vehicles (AVs) to certain zones. Outside of these zones, AVs may be safely navigated by a leading vehicle that is operated by a human driver using the concept of platooning. In this paper, we consider the service network design problem of a service provider that offers platooning services to AV operators in an urban environment in exchange for monetary compensation. Tactical planning decisions comprise determining the fleet size and scheduling platooning services for a planning horizon such as a season. Those decisions are supported by the quoting of rates to potential customers that reflect their willingness to pay depending on the received service level. A second stage of decisions, made on each day of the planning horizon, comprises the acceptance or rejection of individual platooning requests and the routing of AVs through the platooning services. Since the platooning demand is assumed to be stochastic, we model the problem as a two-stage stochastic integer program. On a real-world based network, we perform computational experiments that indicate potential profits for a platooning service provider and considerable savings for AV operators with different demand characteristics. We further assess the value of considering uncertainty.

1. Introduction

Automated driving is expected to play a significant role in future urban transportation networks. Autonomous vehicles (AVs) that can operate without a human driver have been tested in various pilot projects (Bloomberg, 2020), with many companies currently preparing their roll-out beginning with long-haul transportation (Deloitte, 2021). Large fleet operators are expected to be among the first to deploy AVs in real-world environments as they are able to invest early on a large scale and profit from high levels of utilization (Mahmassani, 2016; Sindi and Woodman, 2021). We focus on the deployment of AVs in an urban environment where multiple service providers operate within the same area.

Presumably, AVs are not yet able to travel anywhere a human-guided vehicle can, i.e., they do not satisfy automation level 5 (SAE International, 2018). AVs in level 4 may be restricted to certain streets within “geofences” that provide the necessary conditions to enable automated driving (Hook, 2018). Whereas AVs may operate autonomously in such AV zones, traveling between disjunct

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https://doi.org/10.1016/j.trc.2022.103912
Received 4 April 2022; Received in revised form 24 September 2022; Accepted 25 September 2022
Available online 7 October 2022
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AV zones is prohibited. This yields a heterogeneous infrastructure that fleet operators need to consider when deploying AVs in an urban environment.

An approach to guide AVs safely outside of AV zones is platooning, a technology which has been extensively tested as an advanced driver-assistance system for human-guided vehicles over the last decades (Bergenhem et al., 2012). In a platoon, a group of vehicles is electronically coupled (Shladover et al., 2015) such that the vehicles follow each other with close headway. For pulling AVs outside of AV zones, a manually operated vehicle (MV) with a human driver must be the lead vehicle of a platoon. A number of AVs can follow this MV by replicating its driving actions such as accelerating, braking, and steering. The platoon capacity, i.e., the maximum number of AVs in a platoon, is typically predetermined by operational constraints or policy decisions by traffic authorities. Whereas early pilot studies have focused on highway traffic, the use of platooning in urban areas is increasingly investigated (e.g. Schindler et al., 2018; KIT, 2021). In general, platooning may be used as a bridge technology to accelerate the deployment of AVs in a variety of applications.

Planning is required to utilize the technology of platooning efficiently (Bhoopalam et al., 2018). The spatial and temporal synchronization of vehicles to form platoons poses challenges, particularly if vehicles are operated by multiple fleet operators. A widely applied optimization problem in various transportation applications with synchronization requirements is the service network design problem (Crainic, 2000). Scherr et al. (2019) consider the use of platooning in a service network design problem for a fleet of MVs and AVs that is owned and operated by a single service provider. This work has given evidence that effectively planning a mixed fleet can yield cost savings through reducing the number of drivers. Vehicle ownership or the interaction of multiple stakeholders have not been considered in this research.

In this paper, we presume a situation wherein multiple fleet operators fulfill transportation services using AVs in an urban environment. We specifically study the problem setting of a *platooning service provider (PSP)* that offers towing services between AV zones by means of platooning for independent AV operators. The PSP employs a fleet of MVs that perform movements on a regular basis, e.g., repeated every day of the planning horizon. On a tactical level of planning with a planning horizon of, e.g., a season, the PSP aims to maximize the profit determined by the revenue generated from platooning minus the costs for running the fleet. The MV fleet size, which is the main cost driver, and a repeatable schedule of MV movements must be determined in advance such that potential individual requests can be satisfied. However, if the operational costs exceed the revenue attained from fulfilling a request, individual requests may also be rejected.

While the potential customers, i.e., the AV operators requesting the platooning service for the planning horizon, may be known, their actual requests within the planning horizon are subject to variations. Nevertheless, the PSP wants to be able to offer a sufficient number of platooning spots and communicate rates to the individual AV operators. To perform the repeated MV movements for serving expected demand, the PSP must allocate a sufficient number of MVs for the planning horizon. Since the PSP must determine its schedule in advance of actual AV operator requests, those decisions are made under uncertainty. A repeatable schedule is needed to ensure operational stability of the PSP (e.g., in terms of driver routines) and reliability towards AV operators that may align their own operations.

The ratio of satisfied requests divided by posted requests determines the service level of an AV operator. Although AV operators pay on a per-unit-of-time, per-AV basis for satisfied requests, it is assumed that the fee the PSP can charge for these requests depends on the service level, reflecting the willingness to pay of an AV operator. Thus, a set of market-based rates is considered, each associating a service level with a fee. The quoting of rates allows the PSP to determine profitable service levels while keeping the fleet size within reasonable bounds. Additionally, it provides the PSP with a sense of what rates to offer potential customers when entering negotiations. In Fig. 1, we illustrate the dependencies of the PSP decisions (underlined) and their implications, with the signs (plus or minus) denoting their (positive or negative) impact.

For achieving a reliably profitable plan, we introduce a two-stage stochastic integer programming model that considers scenarios to depict stochastic platooning demand. The objective of the PSP is to maximize its profit from yielding revenue through serving platooning requests, deducting the costs for allocating and operating MVs. The first stage of the program considers the following decisions:

- choosing the rates customers should be charged;
- determining the MV fleet size;
- scheduling repeatable MV movements.

The second stage simulates the realization of the tactical plan with regard to consolidation and synchronization on a daily basis using scenarios. The following decisions are made for each scenario:

- accepting or rejecting individual platooning requests;
- routing the AVs of accepted requests through the scheduled service network.

While the schedule of MV movements is executed identically in every scenario, AVs may be routed through different paths as platoon followers of MV movements in each scenario.

Turning our attention to the literature on variants of the service network design problem, we note that the problems studied to date focus on only a subset of the decisions considered and modeled in this paper. Namely, scheduling repeatable vehicle (MVs in this paper) movements and routing shipments (analogous to AVs in this paper) given the network created by those vehicle movements. In these problems, the set of customers to serve has already been determined and the requests for service by those customers must be met. Fundamentally, these problems consider tactical decision-making.

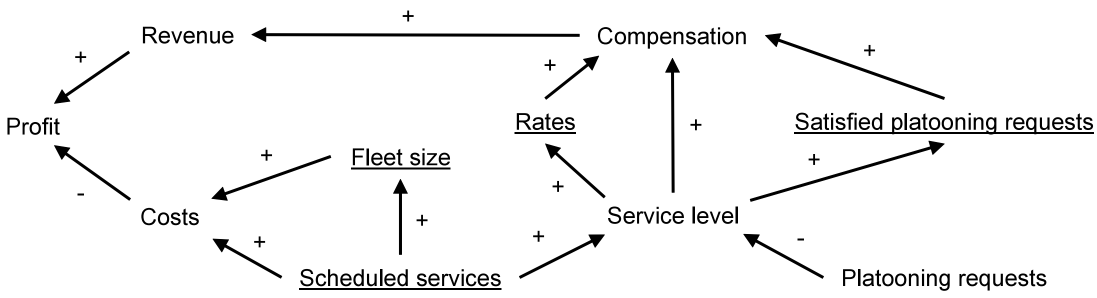


Fig. 1. Dependencies of PSP decisions and implications.

At a more strategic level, transportation service providers are often faced with the question of which additional customers they should serve to achieve or increase profitability. Measuring the profitability of doing so requires comparing the additional revenues gained from serving new customers with the costs incurred by increasing the fleet size to serve their requests. At the same time, in many transportation contexts, service providers are not obligated to serve every customer request. Instead, they seek to meet a service level quoted to a customer that represents the percentage of requests served. The rates customers pay typically depend on the service levels they can expect. Conversely, when negotiating rates and service levels with a current or potential customer, a service provider needs guidance regarding which will be profitable. The problem studied in this paper addresses these strategic and customer-focused decisions within a tactical transportation problem.

We provide the following contributions in this paper. We introduce a problem setting of a PSP that uses AV and platooning technology to achieve cooperation of multiple stakeholders in urban environments. We propose and investigate a rate-based scheme to depict the supply–demand interaction of a PSP with multiple AV operators considering their customer satisfaction. The proposed service network design problem considers a strategic level of decision-making that has not yet been considered in the service network design literature. In addition, it considers issues related to synchronizing heterogeneous vehicles and resource management, all while recognizing uncertainty in customer demands. We formulate a two-stage stochastic integer program for this problem and show that realistically-sized instances can be solved with an off-the-shelf solver.

By performing computational experiments on a real-world based network, we analyze the profitability for the PSP to offer such a service given different fees. The value of considering uncertainty in the PSP's planning is assessed by comparing stochastic solutions with mean-based deterministic solutions. Based on the obtained schedules, we analyze the cost savings and service fulfillment that AV operators with different demand characteristics can expect from using the service. The results indicate that a platooning service can be operated in a profitable way. The stochastic model produces solutions that are more robust and cost-efficient than deterministic solutions. AV operators can expect sufficient service fulfillment and significant cost savings compared to operating a fleet of MVs on their own, while the overall number of vehicles in the city is reduced.

The article is structured in the following way. Section 2 is dedicated to a literature review covering related work. We describe the problem setting in Section 3 and formulate the mathematical model in Section 4. In Section 5, we report the computational experiments and their results before discussing potential implications. Finally, we conclude and provide perspectives for future research in Section 6.

2. Literature review

We divide the overview on related literature into five streams: platooning, synchronization in transportation, cooperation in transportation, pricing in transportation, and service network design.

2.1. Platooning

Exploiting the benefits of platooning in real-world applications requires careful planning. The arising problem settings can be differentiated into a-priori assignment and ad-hoc matching of platoons. Thus, a variety of centralized and decentralized planning approaches have been explored in recent literature which we aim to briefly summarize in the following. For more extensive surveys on planning considerations for platooning, we refer to Bhoopalam et al. (2018) and Gazran et al. (2021).

Centralized approaches are mainly concerned with the planning of either the operations of a single service provider or of a coordinator that decides on the matching of vehicles by multiple service providers to form collaborative platoons. A centralized coordinator is considered in the vehicle platooning problem proposed by Larsson et al. (2015). The objective of this problem is to optimize the fuel savings by grouping trucks with an origin and a destination to form platoons. Larson et al. (2016) propose an improved formulation that allows to solve larger instances with time windows. Boysen et al. (2018) consider a similar problem setting with the restriction that all vehicles share an identical path. In Van De Hoef et al. (2017), a centralized coordinator determines routes and speed profiles of vehicles in platoons but the proposed formulation is limited to two vehicles in a platoon. All these works focus on exploiting the positive impact of platooning on fuel efficiency due to a reduction of aerodynamic drag.

Larsen et al. (2019) study a centralized coordinator that forms truck platoons at a single hub location using different static and dynamic dispatching strategies. They not only evaluate the impact on fuel efficiency but also potential savings by allowing drivers of the following trucks to rest while driving. Albiński et al. (2020) introduce the day-before truck platooning planning problem in which platoon-size limits, hard time windows, and driving time regulations are considered by a centralized coordinator. The implications on platoon planning given three different stages of automation are discussed.

As the above mentioned literature assumes that all vehicles in the platoon are still operated or at least monitored by human drivers, there are no restrictions to the infrastructure the vehicles are allowed to travel on. When considering levels of automation that allow safe autonomous driving under certain conditions, the infrastructure can be distinguished into feasible and infeasible zones for autonomous driving. In this case, significant cost savings can be observed due to a possible reduction of the number of drivers. The use of platooning as a transfer mode for AVs to travel outside of feasible zones is considered in Scherr et al. (2018, 2019, 2020) from the perspective of a city logistics service provider that operates a fleet of MVs and AVs.

Pourmohammad-Zia et al. (2020b) consider a similar problem setting that is concerned with transferring automated ground vehicles for container transportation on an infeasible road between ports and the hinterland. A multi-objective model minimizes time and cost of the system. In Pourmohammad-Zia et al. (2020a), a collaborative platooning platform is considered, in which the interaction between the platform provider and the individual carriers is modeled as a Stackelberg competition. In these works concerned with port-hinterland transportation, only one predetermined route is considered. This limitation prohibits a direct adaptation to urban environments with more complex road networks, in which the design of routes is required (Agatz et al., 2016).

In contrast to centralized approaches, which we consider in this paper, decentralized approaches have also been studied. These approaches are especially suitable for local and ad-hoc platoon matching among individual vehicles by multiple fleet operators without the need for a centralized coordinating instance. Maiti et al. (2017) provide a conceptual framework for ad-hoc platoon operations such as merging or splitting of vehicles. Johansson and Mårtensson (2019) study profit-sharing schemes among participating fleet operators based on game theory. Sebe et al. (2019) consider the grouping of cross-provider platoons in an urban environment and simulate the impact of platooning using a traffic model. Recently, Repoux et al. (2021) analyze an on-demand passenger transportation service based on platooning using simulation.

2.2. Synchronization in transportation

The problem we consider in this paper incorporates synchronization aspects which bear similarities to those found in related application areas. Transportation problems with synchronization requirements arise for different modes including road, rail, air, and maritime traffic. Although the problem we study in this paper focuses on road vehicles, it also shows considerable similarities with rail transportation, particularly regarding the coupling of trains and cars (Zhu et al., 2013). Similar problem settings can also be found in military applications such as the convoy movement problem, which Chardaire et al. (2005) model using time-expanded networks. Truck and trailer routing problems show similarities to platoon planning problems with regard to synchronization requirements (Derigs et al., 2013; Meisel and Kopfer, 2014). Synchronization requirements between vehicles have also been extensively studied in vehicle routing problems with regard to spatial, temporal, and load aspects. For an overview on their classification and on modeling approaches, we refer to Mankowska et al. (2011) and Drexl (2012). In Section 2.5, we review literature on service network design problems, in which synchronization generally plays an important role, in more detail.

2.3. Cooperation in transportation

Cooperation or collaboration in transportation is mainly considered to improve the utilization of resources by sharing them among groups of service providers. Cleophas et al. (2019) provide an overview on different types of collaboration in urban transportation. The emerging problem settings can be distinguished into horizontal and vertical cooperation, depending on the service providers' relationship to one another in a coalition. Vertical cooperation, in which the collaborating service providers act on different levels with few competing interests, can mainly be found in multi-tier distribution systems (Cattaruzza et al., 2017; Wang et al., 2018, 2021). Horizontal cooperation, in which service providers often compete over the same customers, can be found when service providers exchange requests, e.g., in less-than-truckload freight transportation (Wang and Kopfer, 2014) or collaborative vehicle routing (Gansterer and Hartl, 2018). A survey among logistics service providers by Cruijssen et al. (2007) identifies the search for a reliable coalition leader and the construction of a fair profit allocation mechanism as the crucial challenges to the success of horizontal cooperation in practice. Agent-based simulation provides further evidence that trust-related issues significantly affect the performance of cooperation (Serrano-Hernandez et al., 2018).

Audy et al. (2012) provide a comprehensive framework for the planning and implementation of logistics collaborations. The planning approaches to achieve efficient and fair coalitions can be distinguished into centralized and decentralized approaches (Gansterer and Hartl, 2020). In centralized approaches, typically a superordinate decision maker with full information about the participating service providers exists. In decentralized approaches, there is no such central authority and the individual service providers exchange requests between each other. Exchange mechanisms such as auctions can be installed to formalize the procedure of exchanging requests and allocating profits, but their large-scale deployment still faces practical burdens (Los et al., 2020).

2.4. Pricing in transportation

Revenue management, also known as yield management, with the objective of maximizing a company's revenue has been applied extensively in the transportation sector. First developed in the airline industry (Botimer, 1996), revenue management typically comprises forecasting, overbooking, seat inventory control, and pricing (McGill and Van Ryzin, 1999). In the recent decades, revenue management techniques have become more prevalent in other transportation sectors as well, including passenger but also freight transportation.

When designing and operating consolidation-based freight transportation systems, pricing decisions are particularly relevant to balance supply and demand. Thus, models have been developed that integrate pricing decisions into network design and operational planning. Powell et al. (1988) propose a network model for assigning drivers to truckloads that integrates load evaluation, pricing, marketing, and load solicitation decisions. For assisting with pricing decisions, demand forecasting approaches are considered, as e.g. Budak et al. (2017) propose for the truckload spot market. Carriers in freight transportation typically consider service-level agreements for differentiating pricing, measured e.g. by the on-time percentage of deliveries.

A popular modeling approach for integrating pricing is bilevel programming, in which an upper-level optimization problem with an embedded lower-level optimization problem is solved (Dempe, 2002). In bilevel network design and pricing problems in transportation, a leader, e.g., a transportation company, maximizes its revenue from providing services at a specific price and a follower, e.g., a passenger, pursues its own objective given the offered services. Gao et al. (2005) and Brotcorne et al. (2008) provide fundamental mathematical formulations and solution approaches. In rail transportation, multiple planning decisions typically need to be considered in parallel. Crevier et al. (2012) propose a bilevel mathematical formulation for integrating pricing decisions and network planning policies that include car-blocking, routing, train make-up, and scheduling.

2.5. Service network design

Tactical planning is used by transportation service providers to allocate resources in an efficient way (Crainic and Laporte, 1997). Service network design describes the specific optimization problem of determining the type and level of service that a service provider should offer over a medium-term time horizon to satisfy the expected demand (Crainic and Rousseau, 1986). Typically, the objective is to minimize the total costs that arise from providing the services, e.g., performing transportation moves between locations using vehicles, and satisfying the demand for them, e.g., transporting commodities on these vehicles. Service network design problems have been studied for diverse applications in the field of transportation, thus we refer to Crainic (2000), Wieberneit (2008), and Crainic and Hewitt (2021) for literature reviews. In the following, we point to some works that are closely related to our problem setting and modeling approach.

Scheduled service network design problems have been considered to account for time-dependent properties of tactical transportation planning problems, such as time windows of commodities, travel times of vehicles, or shift lengths. For this reason, services between locations are scheduled for specific dispatch times. This not only allows to depict the synchronization of commodities and resources but also the synchronization of multiple resources, e.g., when considering different vehicle types or vehicles and associated staff. Time-expanded networks are used to depict time attributes explicitly in the underlying network by replicating locations in discrete time periods. As Boland et al. (2019) note, the discretization of a time-expanded network is a crucial parameter to balance the trade-off between accurate solution quality and acceptable computational effort.

Service network design formulations have been enriched with asset or resource management considerations to ensure that services are designed in a way that leads to feasible paths or cycles for vehicles (Pedersen et al., 2009; Andersen et al., 2009; Crainic et al., 2016). Multiple types of resources are considered in Wang and Qi (2019). Also, rather strategic decisions such as the acquisition of resources have been introduced to service network design problems (Crainic et al., 2018). Crainic et al. (2020) consider coalitions of service providers that share their resources and information flows in a centralized tactical planning problem.

A more recent stream of literature aims to integrate the revenue-generating interaction with customers and their specific choices into service network design formulations. Bilegan et al. (2020) study a revenue-maximizing scheduled service network design problem for intermodal barge transportation that distinguishes between regular customers and potential customers on the spot market. Martin et al. (2021) integrate the design of a product portfolio that differentiates between prices and guaranteed delivery times into an express shipment service network design problem. Tawfik and Limbourg (2019) propose a bilevel service network design and pricing formulation that considers service frequencies instead of scheduled services.

Tactical plans are typically generated based on the expected demand within the time horizon in which the plan is repeatedly executed. Since, in most practical applications, this demand is not deterministic, models considering stochastic demand have been developed. Demand variations are depicted by considering multiple scenarios that each represent one deterministic demand realization. In two-stage formulations, the first stage determines a design of the services that holds for all scenarios and the second stage determines the commodity flow for each demand realization. In Lium et al. (2007) and Lium et al. (2009), the solutions to stochastic service network design formulations are analyzed for different demand correlations. The obtained service networks show structural differences compared to deterministic solutions and are robust against stochasticity due to enhanced consolidation opportunities. For solving larger instances of this problem, Hoff et al. (2010) propose a metaheuristic approach. Bai et al. (2014) expand the formulation to enable rerouting of vehicles in the second stage. A scheduled service network design problem with resource acquisition and management under uncertain demand is considered by Hewitt et al. (2019).

To our knowledge, the service network design problem with mixed autonomous fleets is the only service network design problem with resource management that considers platooning of vehicles (Scherr et al., 2019, 2020). The problem focuses on a logistics service provider operating a mixed fleet of MVs and AVs that aims to minimize the total costs. Sensitivity analyses have been conducted regarding the impact of different infrastructure, demand patterns, MV-to-AV cost ratio, and platoon capacity. In the paper at hand, we study a problem that considers the interests of two groups of companies: a PSP deploying MVs (platoon leaders) and fleet operators deploying AVs (platoon followers). The PSP aims to maximize the profit from offering this type of service. We introduce a stochastic modeling approach that recognizes uncertain demand to produce a robust scheduled service network. As the platoon synchronization is similar to the one considered in Scherr et al. (2019, 2020), insights regarding the impact of different parameters can be transferred from these works. Thus, we focus on the supply–demand interaction in the analyses in this paper. In contrast to existing literature on platoon planning, we consider a centralized tactical planning approach in which the PSP directly operates platoon-leading vehicles instead of only providing a platform for matching platoons. This enables horizontal cooperation of AV operators sharing the same platoon without the requirement of relying on competitors.

3. Problem description

We consider a transportation system that features a heterogeneous infrastructure in which multiple fleet operators deploy AVs that are only able to drive autonomously in dedicated AV zones. Satellites, i.e., dedicated locations distributed over the city, represent gates to enter or depart from AV zones. Outside of these zones, AVs need to be pulled by MVs using platooning, which we denote as platooning demand. Since the total length of a platoon may be prescribed by technical limitations or by traffic legislation, each MV has a platoon capacity to pull a limited number of AVs. The PSP aims to satisfy the demand from different AV operators over a medium-term planning horizon, such as a season, in a profitable way.

The platooning demand may be derived from forecasts or historic requests by AV operators. Those AV operators are each considered to have a stochastic demand that the PSP considers in the form of multiple requests. A single request consists of an origin satellite from which a quantity of AVs is picked up after an earliest departure time and a destination satellite to which they are platooned until a latest arrival time. The quantity of AVs associated with a request on a given day is assumed to be stochastic. Since a single operator's quantity of AVs requiring to move between the same origin–destination pair is expected to be small, we focus on the binary case, in which a quantity of one translates to a request demanded for a day and a quantity of zero to it not being demanded. When satisfying an individual request, the PSP accepts the request, routes the AV through its scheduled service network consisting of MV moves, and receives a monetary compensation from the respective AV operator. The compensation for a request is based on the travel duration between origin and destination, the quantity of AVs, and a fee.

Regarding pricing, the fee the PSP can charge is based on the AV operators' willingness to pay for a specific service level. The service level denotes the share of requests by an AV operator that are fulfilled by the PSP based on the total number of posted requests within the planning horizon. A service level of zero translates to the PSP turning down an AV operator as a customer. Depending on the demand fulfillment, a potential AV operator's regret due to a lower service level is expressed by a smaller willingness to pay, resulting in a smaller fee that the PSP could charge. Although the AV operator may still be able to adjust its AV movements if platooning is not possible, this may incur additional costs or delays. The PSP recognizes this interrelation by considering a set of rates, each associating a specific service level with a fee. These rates may be derived from negotiations with customers or observation of market dynamics. When designing the scheduled service network during tactical planning, the PSP quotes a single rate to each potential customer with the understanding that the customer expects the associated service level over the length of the planning horizon.

To satisfy platooning demand, the PSP uses a fleet of MVs. Each MV the PSP allocates for repeated use causes a fixed cost for acquisition, maintenance, and the driver's wage, all of which are amortized to a daily cost. All MVs are located at an external zone over night, acting as a depot location, where they depart from at the beginning of the day and return to at the end of the day. The PSP schedules platooning services, i.e., the movements between locations, for this fleet of MVs for a schedule length of one day. Platooning a number of AVs causes no cost for the PSP in addition to the costs that arise for traveling between locations. The MVs' services lead through satellites at which platoons can be (re)grouped by AVs merging or splitting. An AV can be platooned by different MVs on different services on its path from origin to destination.

Uncertainties in demand and the involvement of multiple stakeholders result in a complex supply–demand interaction between the PSP and AV operators. To ensure reliability both for AV operators and its own operations, the PSP employs a fleet of MVs that perform platooning services on a regular basis, e.g., repeated every day over a season. The PSP must determine the MV fleet size and the repeatable schedule ahead of the decisions of the individual AV operators. By doing so, the PSP is able to communicate capacities, i.e., available spots in the platoons, and prices, i.e., the fees associated with platooning AVs, to its potential customers in a profitable way. However, the tactical planning decisions regarding the fleet size and schedule must be made by the PSP under multiple sources of uncertainty. First, it is uncertain whether and how many AV operators choose the PSP's service for the planning horizon and under what conditions. Second, the actual platooning demand of an AV operator within the planning horizon is subject to shorter-term, e.g., daily, variations.

Overall, the objective of the PSP is to determine a tactical plan that maximizes the expected profit from collecting revenue while paying the total costs for allocating and operating the fleet. The planning decisions of the PSP are divided according to two different time points and levels of information about the demand. In a first stage of decisions, the PSP decides on the MV fleet size and the schedule of platooning services once for the whole planning horizon before knowing the actual demand. These decisions are based on statistical distributions of demand from AV operators to which the PSP quotes a rate consisting of a service level and fee.

The PSP considers a second stage of decisions that it makes after the demand is realized for any day of the planning horizon on which the schedule is executed. These second-stage decisions are composed of accepting or rejecting the individual platooning

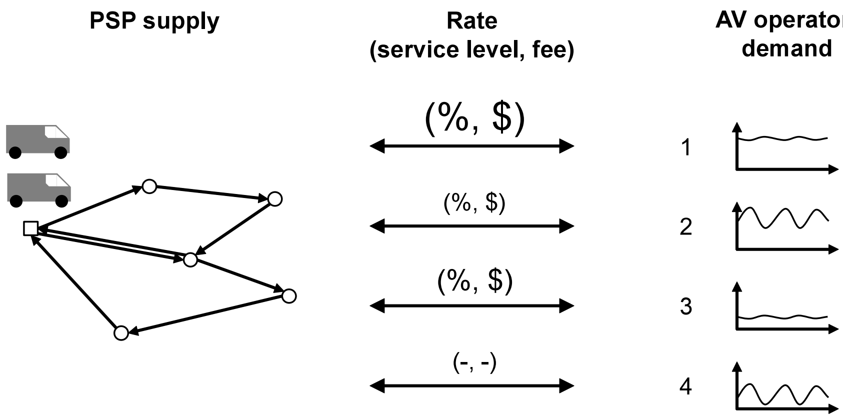


Fig. 2. Graphical example for the supply–demand interaction between PSP and AV operators.

requests and routing the AVs through the scheduled service network. The second-stage acceptance decisions follow the service levels, corresponding to the rates determined in the first stage, in expectation over the planning horizon. During tactical planning, the second-stage decisions are simulated for statistical distributions of demand, particularly to recognize the effects of consolidation and synchronization within the scheduled service network.

We illustrate the problem setting based on a graphical example in the following. For this reason, we first focus on the first-stage decisions in Fig. 2, depicting the supply–demand interaction between the PSP and AV operators. Then, the second-stage decisions are illustrated in Fig. 3 based on a spatial representation of a possible scheduled service network. Note that, while we divide the example into two separate visualizations for simplicity, we consider the decisions of both stages in an integrated problem setting that the PSP tackles.

In Fig. 2, the supply–demand interaction between the PSP and multiple AV operators is visualized. Ahead of the planning horizon, the PSP must determine an MV fleet size – of 2 MVs in this example – and a schedule of services, depicted as arrows here. This supply is based on the demand of multiple AV operators, each showing a stochastic distribution. We depict those demand distributions abstractly as graphs that show the demand volume over time, e.g., for each day of the planning horizon. Notice that the demand distribution of each of the 4 AV operators is different in terms of both overall volume and regularity over time. Along with the first-stage decisions of fleet sizing and scheduling, the PSP quotes rates to each of the potential customers, consisting of a service level (illustrated with the symbol %) and a fee ($). The size of the symbols indicates the respective extent of the rate for an AV operator that the PSP considers in its plan. Dashes replacing the symbols represent turning down an AV operator as a potential customer, which is the case for AV operator 4 here.

In Fig. 3, we illustrate a possible scheduled service network of the PSP using a spatial representation disregarding its temporal attributes. In this figure, AV zones are outlined as ellipses with dotted lines. Each AV zone contains a satellite depicted as a circle, while the external zone is illustrated as a square. As the demand for one day, we consider a single request of one AV from each of the AV operators introduced in Fig. 2, marked by the respective numbers in the AV symbols. The origin location of each request is depicted by an AV symbol in darker shade, whereas an AV symbol in lighter shade represents the respective destination location. The arrows depict scheduled services between locations conducted by the 2 MVs, with the associated MV and AV symbols representing the platoon configuration on them. In this example, the requests of AV operators 1, 2, and 3 are fulfilled, whereas the request of AV operator 4 is rejected as it could not be served with the scheduled services. Note that the PSP must respect the service levels determined for each AV operator in the first stage. Since the rate selection shown previously for this example does not warrant a service level to AV operator 4, the respective request can be rejected. Further note that platooning AV 2 from its origin to destination requires 2 MVs as platoon leaders based on this schedule. The AV needs to split from the first MV and merge to the second MV at an intermediate satellite between pick-up and drop-off.

4. Mathematical model

We formulate a two-stage stochastic integer programming model for this problem with the following notation. We consider a physical network $D_{ph} = (N_{ph}, A_{ph})$ as a directed network with the locations $i \in N_{ph}$. The set of locations can be distinguished into external zones ($N_E \subset N_{ph}$) and satellites ($N_S \subset N_{ph}$), with $N_E \cap N_S = \emptyset$. The arcs $(i, j) \in A_{ph}$ denote travel connections between those locations and feature a travel time τ_{ij} in minutes.

Based on this physical network, we derive a time-expanded network $D = (N, A)$ that spans over the schedule length t_{max}. The locations and arcs of the physical network are replicated in time intervals of the length Δ, which represents the discretization of the time-expanded network. Thus, the time-expanded network considers the time points $t \in T = \{0, \Delta, \dots, t_{max}\}$. Each location i is replicated for each time point t to yield a node $(i, t) \in N$. Analogously, a physical arc (i, j) is replicated to yield an arc $((i, t), (j, \bar{t})) \in A$. We further differentiate the set of arcs A into three disjunct types. Auxiliary arcs $A_\gamma \subset A$ for $i = j$ with $i, j \in N_E$ go back in time and

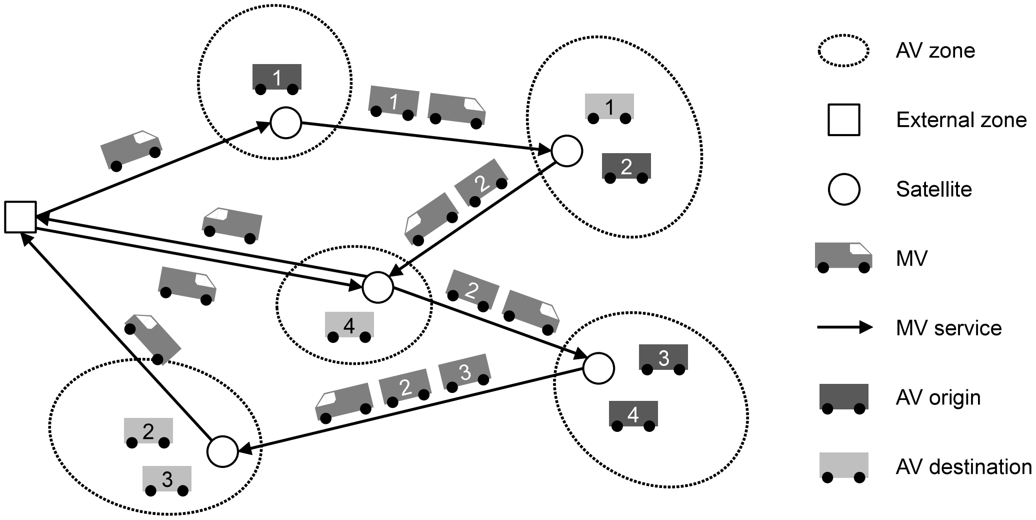


Fig. 3. Graphical example for the acceptance or rejection of platooning requests and AV routing based on MV schedule.

Table 1
Notation of the physical and time-expanded network.

Type	Notation	Description
Physical network D_{ph}	$i \in N_{ph}$	Location
	$i \in N_E$	External zone
	$i \in N_S$	Satellite
	$(i,j) \in A_{ph}$	Physical arc
	$\tau_{ij} \in \mathbb{N}$	Travel time on physical arc (i,j)
Time-expanded network D	$t \in T = \{0, \Delta, \dots, t_{max}\}$	Time point in schedule length
	$\Delta \in \mathbb{N}$	Time interval length
	$t_{max} \in \mathbb{N}$	Schedule length
	$(i,t) \in N$	Node
	$((i,t),(j,\bar{t})) \in A$	Arc
	$((i,t),(j,\bar{t})) \in A_\gamma$	Auxiliary arc to allocate MVs
	$((i,t),(j,\bar{t})) \in A_h$	Holding arc to idle at a location
	$((i,t),(j,\bar{t})) \in A_m$	Movement arc to travel between locations

connect the last ($t = t_{max}$) with the first ($\bar{t} = 0$) replication of an external zone. These arcs model the allocation of vehicles to the fleet and the cyclic nature of their services across the complete schedule length to ensure repeatability on every day. Holding arcs $A_h \subset A$ for $i = j$ with $i, j \in N_{ph}$ connect temporally consecutive nodes of the same location to model idling vehicles at a location from time point t to $\bar{t} = t + \Delta$. Movement arcs $A_m \subset A$ for $i \neq j$ with $i, j \in N_{ph}$ depict traveling between location i at time point t to a different location j at an arrival time point of $\bar{t} = t + \tau_{ij}$. The notation of the physical and time-expanded network is summarized in Table 1.

We consider a set of stochastic scenarios $s \in S$ for which the probability to occur is defined as $\omega_s \in [0,1]$, with $\sum_{s \in S} \omega_s = 1$. In each scenario, we consider AV platooning demand in the form $p \in P$. The set P contains subsets $P_c \in P$ depicting the platooning demand of each AV operator as the PSP customer $c \in C$. A single platooning request p in a scenario s represents a quantity of q_{sp} AVs, demanding to be platooned between an origin $o_p = (i_p^o, t_p^e)$ and a destination $d_p = (i_p^d, t_p^l)$. Note that $q_{sp} = 0$ if a request p does not occur in a scenario s. The origin is defined as a location i_p^o at which the AV is to be picked up after an earliest departure time t_p^e. The destination is defined as a location i_p^d at which the AV is to be dropped off before a latest arrival time t_p^l. We define l_p as the travel duration of a request p between its origin location i_p^o and destination location i_p^d.

We consider a set of rates Π. Each rate $\pi \in \Pi$ is composed of a service level Φ_π and a fee g_π. The service level denotes the share of the total platooning demand of a customer c that the PSP guarantees to serve in expectation over the course of the planning horizon. The fee g_π is a factor per AV per unit of travel time. Multiplied with the respective AV quantity q_{sp} and the travel duration l_p, the fee depicts the received compensation for satisfying a request p. While other pricing schemes, e.g., based on distance, may be suitable for certain settings, we consider the duration to be the factor that affects the operational costs of both the PSP and AV operators most.

The variables are defined as follows. We first describe the two types of decision variables in the first stage. The integer variables $m_{ij}^{t\bar{t}}$ denote the number of MV services operated on an arc $((i,t),(j,\bar{t})) \in A$. Using the same type of variables, the fleet size is determined by the total number of MV services installed on auxiliary arcs $((i,t),(j,\bar{t})) \in A_\gamma$. The binary variables $y_{c\pi}$ denote whether a customer c is assigned a rate π. The second stage contains the following decision variables. The binary variables z_{sp} denote whether a request p

is satisfied by the PSP in a scenario s. The auxiliary variables $x_{spc\pi}$ are linearization terms for modeling the product of the first-stage rate assignment variables $y_{c\pi}$ and the second-stage demand acceptance variables z_{sp}. Finally, the binary variables $a^{t\bar{t}}_{spij}$ denote for each scenario s if the AVs of request p flow on arc $((i,t),(j,\bar{t})) \in A$.

The objective function contains the following coefficients that are independent of the scenario. The amortized fixed cost for allocating an MV to the fleet for the schedule length is defined as f. Service costs k denote the cost for performing an MV service per minute of travel time τ_{ij} on any physical arc (i,j). Note that costs for idling MVs, that could be imposed through holding arcs A_h, are not considered, as fixed costs are already due per MV. The PSP receives a compensation in the form $g_\pi q_{sp} l_p$ for satisfying a request p, depending on the rate, the AV quantity, and the travel duration. The platoon capacity, that limits the number of AVs traveling in a platoon, is denoted as n. Note that this parameter can be easily modified to be n_{ij} to specify a different platoon capacity for each physical arc, including the case of $n_{ij} = 0$ which forbids platooning if it is not physically feasible on a street. The notation of the variables and parameters is summarized in Table 2.

The model we seek to solve is as follows:

$$\max \sum_{s\in S} \omega_s Q(m,y,s) - \sum_{((i,t),(j,\bar{t}))\in A_\gamma} f m^{t\bar{t}}_{ij} - \sum_{((i,t),(j,\bar{t}))\in A_m} k\tau_{ij} m^{t\bar{t}}_{ij} \tag{1}$$

subject to

$$\sum_{((j,\bar{t}),(i,t))\in A} m^{\bar{t}t}_{ji} = \sum_{((i,t),(j,\bar{t}))\in A} m^{t\bar{t}}_{ij} \qquad \forall (i,t)\in N, \tag{2}$$

$$m^{t\bar{t}}_{ij} \le 1 \qquad \forall ((i,t),(j,\bar{t}))\in A_m, \tag{3}$$

$$\sum_{\pi\in\Pi} y_{c\pi} = 1 \qquad \forall c\in C, \tag{4}$$

$$\sum_{\pi\in\Pi} y_{c\pi}\Phi_\pi \le \sum_{s\in S}\sum_{p\in P_c} z_{sp} \qquad \forall c\in C, \tag{5}$$

$$m^{t\bar{t}}_{ij} \in \mathbb{N} \qquad \forall ((i,t),(j,\bar{t}))\in A, \tag{6}$$

$$y_{c\pi} \in \{0,1\} \qquad \forall c\in C, \pi\in\Pi, \tag{7}$$

where

$$Q(m,y,s) = \max \sum_{p\in P}\sum_{c\in C}\sum_{\pi\in\Pi} x_{spc\pi} g_\pi q_{sp} l_p \qquad \forall s\in S, \tag{8}$$

$$\sum_{((j,\bar{t}),(i,t))\in A} a^{\bar{t}t}_{spji} - \sum_{((i,t),(j,\bar{t}))\in A} a^{t\bar{t}}_{spij} = \begin{cases} -z_{sp}, & (i^o_p, t^e_p) = o_p, \\ z_{sp}, & (i^d_p, t^l_p) = d_p, \\ 0, & (i,t) \ne o_p, d_p, \end{cases} \qquad \forall s\in S, p\in P, (i,t)\in N, \tag{9}$$

$$\sum_{p\in P} q_{sp} a^{t\bar{t}}_{spij} \le n m^{t\bar{t}}_{ij} \qquad \forall s\in S, ((i,t),(j,\bar{t}))\in A_m, \tag{10}$$

$$x_{spc\pi} \le y_{c\pi} \qquad \forall s\in S, p\in P, c\in C, \pi\in\Pi, \tag{11}$$

$$x_{spc\pi} \le z_{sp} \qquad \forall s\in S, p\in P, c\in C, \pi\in\Pi, \tag{12}$$

$$a^{t\bar{t}}_{spij} \in \{0,1\} \qquad \forall s\in S, p\in P, ((i,t),(j,\bar{t}))\in A, \tag{13}$$

$$z_{sp} \in \{0,1\} \qquad \forall s\in S, p\in P, \tag{14}$$

$$0 \le x_{spc\pi} \le 1 \qquad \forall s\in S, p\in P, c\in C, \pi\in\Pi. \tag{15}$$

The integer program is composed of two stages. While the first stage addresses the design of the MV services and the assignment of rates to customers over all scenarios, the second stage addresses the flow of AVs through this scheduled service network in each scenario. The objective function (1) maximizes the expected profit from the average sum of received revenue over all scenarios, deducting the fleet acquisition costs and the fleet operation costs that are the same for all scenarios.

In the first stage, Constraints (2) ensure design balance of the MV services, i.e., the outgoing number of services equals the incoming number of services in any node. Constraints (3) limit the number of MVs on every movement arc to one in order to prevent two platoons from traveling between the same locations at the same time. Constraints (4) ensure that exactly one rate is assigned to each customer. Constraints (5) ensure that the PSP fulfills the service level belonging to the rate of each AV operator based on its respective platooning requests in expectation over all scenarios. The integer domain of the MV service variables is defined in (6) and the binary domain of the rate assignment variables is defined in (7).

In the second stage, the objective function (8) maximizes the compensation received from satisfying platooning demand that occurs in each scenario. Constraints (9) ensure flow conservation for the AV flows considered to satisfy a platooning request. Constraints (10) restrict the number of AVs following an MV on a movement arc to the platoon capacity. Constraints (11) and (12) are used for linearizing the product of the first-stage rate assignment variables $y_{c\pi}$ with the second-stage demand acceptance variables z_{sp} using the auxiliary variables $x_{spc\pi}$. The domains of the binary variables for AV flow and demand acceptance are defined in (13) and (14), respectively. Finally, the auxiliary variables are bounded by Constraints (15). While these can be defined as continuous

Table 2
Notation of the variables and parameters.

Type	Notation	Description
Variables	$m_{ij}^{t\bar{t}} \in \mathbb{N}$	MV services on arc $((i,t),(j,\bar{t}))$
	$y_{c\pi} \in \{0,1\}$	Assignment of customer c to rate π
	$z_{sp} \in \{0,1\}$	Satisfying platooning request p in scenario s
	$a_{spij}^{t\bar{t}} \in \{0,1\}$	AV flow in scenario s for request p on arc $((i,t),(j,\bar{t}))$
	$x_{spc\pi} \in \mathbb{R}$	Auxiliary variables coupling the variables $y_{c\pi}$ and z_{sp}
Parameters	$f \in \mathbb{R}^+$	Amortized fixed cost for allocating an MV
	$k \in \mathbb{R}^+$	Service cost for MV service per minute of travel time
	$\pi \in \Pi$	Rate
	$\Phi_\pi \in [0,1]$	Service level of rate π
	$g_\pi \in \mathbb{R}^+$	Fee of rate π per AV and minute of travel time
	$s \in S$	Stochastic scenario
	$\omega_s \in [0,1]$	Probability of scenario s (with $\sum_{s\in S}\omega_s = 1$)
	$c \in C$	AV operator (customer of the PSP)
	$p \in P$	Platooning demand
	$q_{sp} \in \mathbb{N}$	Quantity of AVs for platooning request p in scenario s
	$o_p = (i_p^o, t_p^e) \in N$	Origin location and earliest departure time of request p
	$d_p = (i_p^d, t_p^l) \in N$	Destination location and latest arrival time of request p
	$l_p \in \mathbb{R}^+$	Travel duration between origin o_p and destination d_p of request p
	$n \in \mathbb{N}$	Platoon capacity in number of AVs

variables, in practice they only take on values of zero or one due to the coupling with binary variables in Constraints (11) and (12) in combination with the maximizing objective function.

In case a PSP would have to satisfy all platooning demand that occurs, the model can easily be adapted by setting $z_{sp} = 1, \forall s \in S, p \in P$. Then, the objective function essentially minimizes the total cost of satisfying all platooning requests.

5. Computational study

We perform a computational study to assess the value of a platooning service in an urban environment, both from the perspective of a PSP offering this service and from the perspective of AV operators using this service. We further assess the value of considering uncertainty. In this section, we first describe the experimental setup, then report the results, and finally discuss their implications.

5.1. Experimental setup

The instances are generated in the following way. We consider a physical network based on the city of Braunschweig, Germany, which has also been used as a case study for MV and AV platooning in a similar form in Scherr et al. (2020). In Fig. 4, we illustrate the locations and arcs of the physical network. The external zone is denoted as a square and the 12 satellite locations are denoted as circles. For the bidirectional arcs, denoted as black lines, we obtain estimated travel times from Google Maps. We consider a schedule length of 8 h, i.e., $t_{max} = 480$ min, corresponding to the typical length of a driver's shift. The time-expanded network covers this schedule length with a time interval length of $\Delta = 10$ min. Based on this discretization, we round up the actual travel times of the physical network to yield a conservative estimate that may provide small time buffers to account for delays, e.g., caused by congestion. This results in travel times of $\tau_{ij} = \{10, 20\}$ in the time-expanded network.

The fleet of the PSP is equipped with MVs that incur two types of cost, fixed costs and service costs. We set the fixed cost for allocating one MV to $f = 200$ cost units. The service costs are set to $k = 0.5$ cost units per minute of travel time. The platoon capacity is set to $n = 2$ in all experiments.

We generate platooning demand for an instance in the following way. Each demand instance comprises 60 randomly generated origin–destination pairs ($|P| = 60$). The origin and destination locations are uniformly distributed over the 12 satellites of the physical network. We define l_p as the shortest-path travel duration of a platooning request p between its origin location i_p^o and destination location i_p^d. The respective earliest departure times at the origins and the latest arrival times at the destinations are distributed uniformly over the respective feasible parts of the schedule length. We set the time difference between the departure and arrival time of a demand to correspond to the shortest-path travel duration between the origin and destination location plus a randomly assigned time buffer of 10 to 30 min length. The quantity of each request in a stochastic scenario is $q_{sp} = \{0, 1\}$, drawn from a binomial distribution with the baseline probability $\omega_q = 0.5$. We assume that the demand is uncorrelated as we consider different types of AV operators, which each serve heterogeneous customers themselves.

To determine an appropriate number of scenarios to be used in the computational study, we evaluate the in-sample and out-of-sample stability for different numbers of scenarios. In the Appendix, we describe this evaluation in more detail, based on which we decide to perform further experiments with $|S| = 60$ scenarios per instance. For the evaluation, we consider 10 demand instances that are randomly generated using the described procedure.

We consider a set of 8 AV operators as potential PSP customers ($|C| = 8$). Each platooning request p is associated with a single customer c to yield the sets of platooning demand of a customer P_c. We characterize the demand of each customer along two dimensions: volume and regularity. Combining them results in 4 customer buckets, to each of which 2 of the 8 modeled customers

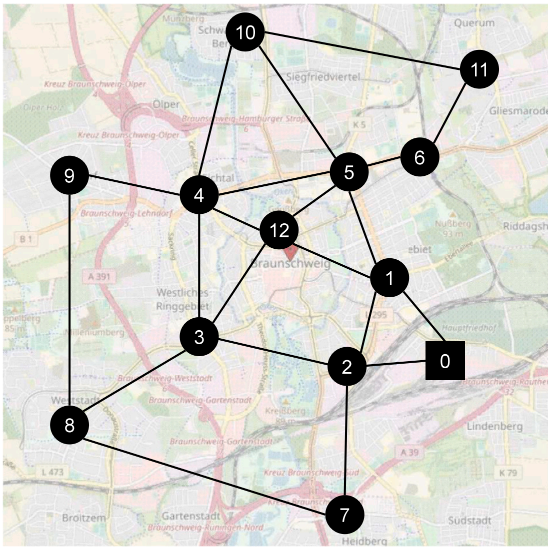


Fig. 4. Physical network based on the city of Braunschweig.

are assigned. We denote the customer buckets using the notation (volume — regularity) as follows: (high — regular), (high — irregular), (low — regular), (low — irregular).

Regarding volume, we distinguish customers between with high demand volume (C^{high}) and customers with low demand volume (C^{low}), with $C^{high} \cap C^{low} = \emptyset$. Considering a baseline probability $\omega_c = 1/|C|$ for every request being assigned to a customer, we modify this probability for all requests in a way that high-volume customers are assigned twice the number of requests as low-volume customers. In this way, the probability that a request is assigned to a high-volume customer $c \in C^{high}$ is set to $\omega_c^{high} = 4/3 * \omega_c$. Conversely, the probability that a request is assigned to a low-volume customer $c \in C^{low}$ is $\omega_c^{low} = 2/3 * \omega_c$. The probabilities for each request add up to $\sum_{c\in C} \omega_c = 1$ because the number of customers in each of the 4 buckets is equal. Regarding regularity, we distinguish between customers with regular demand ($C^{regular}$) and irregular demand ($C^{irregular}$), with $C^{regular} \cap C^{irregular} = \emptyset$. A baseline probability $\omega_q = 0.5$ is assumed for every request to occur in a scenario s, i.e., having a positive quantity q_{sp}, or not. We modify this probability for the requests assigned to regular-demand customers to be twice as high than for those assigned to irregular-demand customers. Thus, the probability that a request of a regular-demand customer $c \in C^{regular}$ occurs in a scenario s is set to $\omega_c^{regular} = 4/3 * \omega_q$. The probability that a request of an irregular-demand customer $c \in C^{irregular}$ occurs in a scenario s is set to $\omega_c^{irregular} = 2/3 * \omega_q$.

We depict those customers' willingness to pay by considering selected service levels and fees that the customer would accept for receiving the respective service. First, we assume a baseline fee g that represents a customer's willingness to pay if all of its platooning demand is satisfied by the PSP. This fee is paid for each minute of travel time required to serve a platooning request on its shortest path. In the experiments, we consider five different settings of the baseline fee of $g = \{2.5, 3.0, 3.5, 4.0, 4.5\}$ cost units. Considering the fleet acquisition costs ($f = 200$ per day) and fleet operation costs ($k = 0.5$ per minute), this translates to a range of 100 (for $g = 2.5$) to 50 (for $g = 4.5$) AV minutes that an MV needs to transport daily to break even.

To depict the sensitivity of a customer to platooning demand that is only partially satisfied by the PSP, we design four different rates $\pi \in \Pi$ that each comprise a guaranteed service level Φ_π and a respective fee g_π (dependent on the setting of the baseline fee g). The four rates, of which the first one represents rejection of the service, are as follows:

- $\pi = 0$: no service level ($\Phi_0 = 0.0$), no fee ($g_0 = 0$);
- $\pi = 1$: 80% service level ($\Phi_1 = 0.8$), 80% fee ($g_1 = 0.8g$);
- $\pi = 2$: 90% service level ($\Phi_2 = 0.9$), 90% fee ($g_2 = 0.9g$);
- $\pi = 3$: 100% service level ($\Phi_3 = 1.0$), full fee ($g_3 = g$).

We solve all instances in this computational study using the solver Gurobi in Version 9.1 called via the Python API on an AMD Ryzen Threadripper 2990WX machine. The number of threads used by Gurobi is limited to 16. Each run terminates either after an optimality gap of at most 1% is achieved or if the time limit of 5 h is reached. We note that the time limit was reached in the case of only two instances out of 380 instances solved in total.

5.2. Results

We analyze the experimental results in the following. First, the value of considering uncertainty during planning is assessed by comparing solutions of the stochastic model with those of a deterministic model. Then, we examine the profitability for the PSP by

Table 3
Value of the stochastic solution (VSS) with different fees.

Fee	$g = 2.5$	$g = 3.0$	$g = 3.5$	$g = 4.0$	$g = 4.5$
VSS	265.95	141.26	97.19	67.44	59.50
$VSS/\lvert obj_{mean}\rvert$	118.54%	85.58%	17.06%	6.90%	4.31%

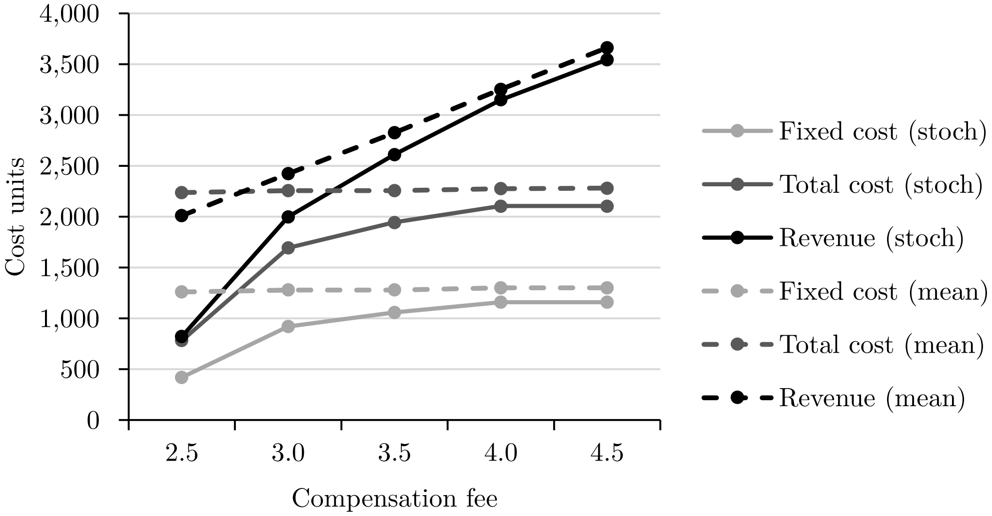


Fig. 5. Comparison of stochastic (stoch) and deterministic (mean) solutions regarding fixed cost, total cost, and revenue of the PSP for different fees.

investigating its tactical plans for different fleet sizes. Further, we investigate the value of such a platooning service for different types of AV operators. Finally, we analyze the supply–demand interaction by reporting the rates quoted by the PSP to different AV operators. Throughout these analyses, we report average values over the demand instances.

5.2.1. Value of considering uncertainty

As the results of this study are obtained using a stochastic model, we quantify the impact of considering uncertainty. To this end, we simulate the case in which a PSP would design its scheduled service network using a deterministic version of the model based on a single estimate of the platooning demand. In the deterministic model, we consider a single scenario s with mean quantities $\bar{q}_{sp}$ for each platooning request p, that we calculate using the quantities drawn for the stochastic scenarios of each respective instance. We solve this deterministic model to yield first-stage solutions. From those solutions, we fix the values of the MV service variables $m_{ij}^{t\bar{t}}$ and compute second-stage solutions based on the exact same scenarios used for the stochastic solutions. We denote the resulting objective function values as obj_{mean}, whereas the stochastic solutions are denoted as obj_{stoch}.

For measuring the value of considering uncertainty, we use the value of the stochastic solution (VSS) introduced by Birge (1982). The VSS measures the absolute difference in objective function value between the stochastic solution and the deterministic solution in the stochastic environment. Using our notation, we define $VSS = obj_{mean} - obj_{stoch}$. As another measure, we consider the VSS in relation to the objective value of the deterministic solution, i.e., $VSS/\lvert obj_{mean}\rvert$. In Table 3, we report the average values for those two measures for the experiments with fee settings ranging from $g = 2.5$ to $g = 4.5$.

We observe that the VSS is considerably high for all fee settings. Both the absolute and the relative VSS are larger with smaller fees. With the smallest setting of $g = 2.5$, the VSS is larger than the – in this case negative – objective function value of the deterministic solution. However, even with the largest fee setting of $g = 4.5$, the objective function values of the stochastic solutions are 4.31% larger than those of the deterministic solutions. To further investigate the reasons for the noticeably different VSS depending on the fee, we analyze the components of the objective function values in the following.

Thus, we depict in Fig. 5 the components of the stochastic solutions (solid lines) and the deterministic solutions based on mean demand (dashed lines) for the different fee settings. We report the fixed cost for allocating the fleet (light gray), the total cost (dark gray), and the revenue (black) in cost units.

We observe that the stochastic solutions adapt more flexibly to the potential revenues based on different fees than the deterministic solutions. In particular, the total costs can be reduced in the stochastic solutions by allocating fewer MVs and performing fewer services given lower fees. The deterministic solutions overestimate the mean-based revenue that can be generated in the second stage, which incurs higher costs, especially fixed costs, resulting from first-stage decisions. Regardless of the fee, the stochastic model produces solutions that are more cost-efficient than those of the deterministic model. In conclusion, considering a stochastic model mitigates the risk for the PSP to design a scheduled service network that is not profitable.

The results further show that, with increasing the fee, the PSP can achieve larger expected revenues. Since the costs grow to a minor degree only compared to the revenue, the potential profits of the PSP also grow with increasing the fee. In this way, the

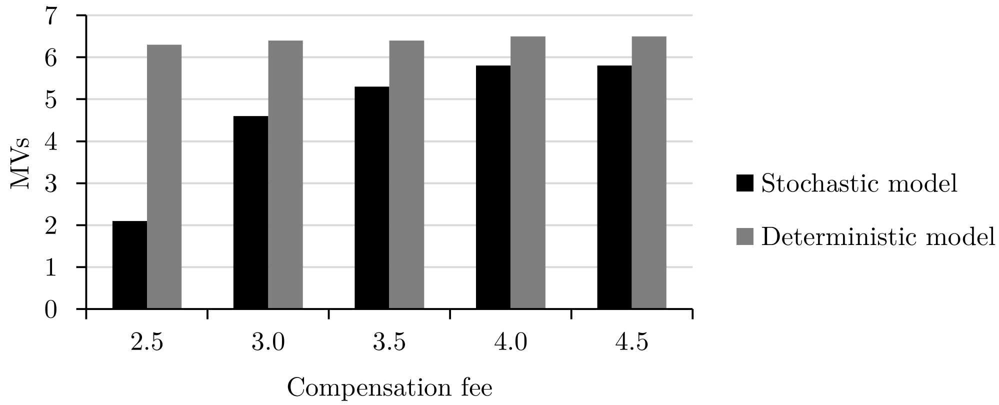


Fig. 6. Number of MVs allocated to the PSP's fleet for different fees according to the stochastic and the deterministic model.

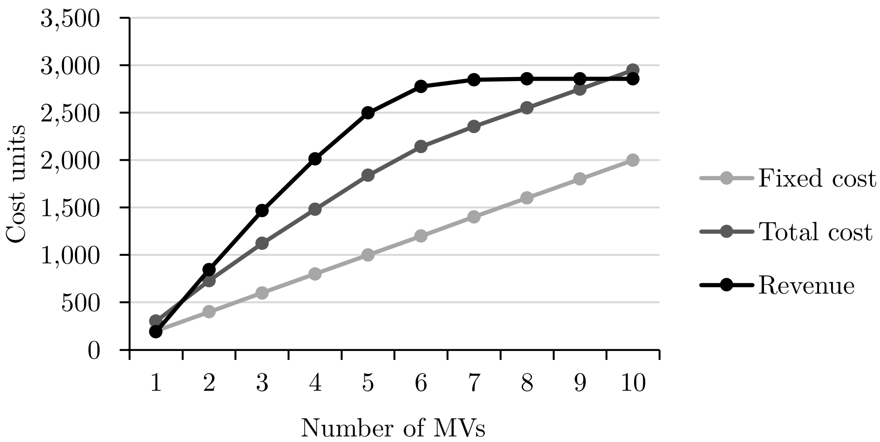


Fig. 7. Comparison of solutions regarding fixed cost, total cost, and revenue of the PSP for different fleet sizes.

expected profit margin ranges from around 5% with a fee of $g = 2.5$ to around 41% with $g = 4.5$. We further observe that a saturation point is reached with $g = 4.0$, such that the expected revenue increases with larger fees without incurring additional costs. In those results, more than half of the total costs are fixed costs for allocating MVs to the fleet.

Since there are two categories of decisions in the first stage, fleet sizing and service scheduling, we are interested in the impact of recognizing uncertainty in either category. For this reason, we report in Fig. 6 the average number of MVs allocated given the different fees according to the stochastic model (black bars) and the deterministic model (gray bars). As expected, the fleet size correlates with the fixed costs previously depicted in Fig. 5. Using the stochastic model, the number of allocated MVs steadily increases with higher fees until it reaches a point of saturation at a fee of around $g = 4.0$ with an average of 5.8 MVs. On the contrary, the deterministic model allocates a more or less steady number of 6.3 (for $g = 2.5$) to 6.5 (for $g = 4.5$) MVs. This overestimation of the fleet size leads to smaller profits, which has been shown in Fig. 7 for a single fee setting. Although recognizing uncertainty leads to better decisions in both first-stage categories, these results indicate a decisive impact of the fleet sizing decisions.

5.2.2. Profitability for the PSP

To gain a better understanding of the PSP's tactical planning decisions, we illustrate the interplay of the multiple components of a solution. For this reason, we fix one category of first-stage decision variables, i.e., those for determining the fleet size, and evaluate the impact of different values to those variables. By predetermining the fleet-sizing decision, the model decides in the first stage only on scheduling platooning services, choosing customers to serve, and quoting rates to those customers. For this evaluation, we set the compensation fee to a value of $g = 3.5$, i.e., the medium setting, and report average values over all demand instances. For the fleet size, integer values from 1 MV to 10 MVs are considered. The obtained solutions are analyzed with regard to the terms of the objective function. In Fig. 7, we report the fixed cost for fleet acquisition (light gray), the total cost (dark gray), and the revenue (black) in cost units.

The fixed cost increases steadily with the number of allocated MVs. By increasing the fleet size, a larger revenue can be generated through serving a larger share of requests. We also observe that, with a fleet of 8 MVs, the achieved revenue cannot be increased further. The curve for total cost, that includes costs for fleet acquisition and operation of scheduled services, has two intersections

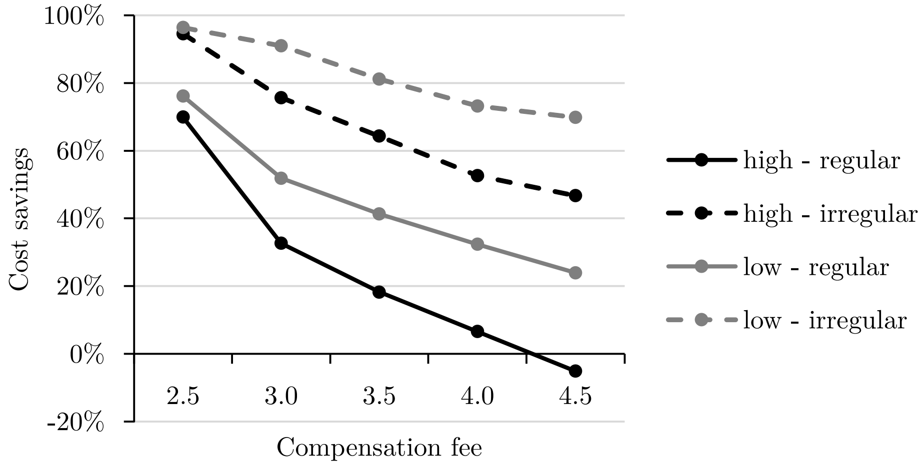


Fig. 8. Cost savings for AV operators in different PSP customer buckets with different fees compared to platooning AVs with an own fleet of MVs.

with the curve depicting revenue. For the considered instances, offering a platooning service with only 1 MV or with 10 or more MVs would not be profitable. In between, there exists a window in which the model yields profitable solutions. The decisions about which requests to serve and the design of the scheduled services adapt to the enforced fleet size such that the profit is maximized. After allowing the model to determine the fleet size, the best found solutions for each instance show an average fleet size of 5.3 MVs.

5.2.3. Value of a platooning service for AV operators

After reviewing the profitability of a platooning service for the supply side, we depict its value for the demand side in this section. For this reason, we analyze the cost savings and service levels that an AV operator can expect from using the platooning service. The characteristics of the platooning demand may differ between AV operators, depending on the volume and regularity of their demand. Thus, we distinguish between four customer buckets, each including AV operators with a specific demand characteristic, that the PSP considers in our experiments. Since the PSP decides on quoting a rate to each of its expected customers, the costs for compensation paid by an AV operator and the expected service level may differ between the different AV operators, particularly between customer buckets.

First, we compare each AV operator's costs for compensating the PSP with the costs that would be incurred by operating its own fleet of MVs to perform the necessary platooning services. The compensation payments can be derived from the solutions to the model solved by the PSP. The costs of AV operators for performing the platooning services on their own are obtained by solving a variation of this model from the perspective of each AV operator. It is presumed that the AV operators also use repeatable schedules to facilitate platoon synchronization and to coordinate supporting operations. Therefore, we consider the PSP model defined in Section 4 using the same coefficients as previously defined, but presume that the respective AV operator must fulfill all of its platooning demand (equal to a service level of 100%). Thus, we consider the demand set P_c of the respective AV operator c and set $z_{sp} = 1, \forall s \in S, p \in P_c$. As we can neglect the revenue term of the objective (thus disregarding the fees), we obtain an additional set of 80 instances based on the 8 AV operators and 10 demand instances. We solve these instances using the previously introduced setup.

Note that the latter results are all associated with a service level of 100%, whereas the service level in the former results is influenced by the PSP's decision of quoting rates. Thus, Fig. 8 must be viewed in the context of Fig. 9, showing the achieved service levels. In Fig. 8, we report the potential cost savings for AV operators as PSP customers in different buckets compared to platooning AVs with an own fleet of MVs. The cost savings in percentage values are calculated for each AV operator as the difference between the costs for operating its own fleet and the total compensation payments for using the PSP's service, divided by the costs for operating its own fleet. Results are reported for the average over the 2 AV operators in each customer bucket for different fee settings. Customer buckets with high demand volume are illustrated using black lines, those with low demand volume using gray lines. Solid lines represent customer buckets with regular demand, whereas dashed lines represent irregular demand.

We observe that AV operators with irregular demand can achieve larger cost savings than those with regular demand. Also, AV operators with low demand volumes can profit to a greater extent from using the PSP service than those with high volumes. Both of these observations can be explained by the large proportion of fixed costs required for allocating a dedicated fleet of MVs and operating them on a repeatable schedule. While high-volume, regular demand may enable an AV operator to achieve a sufficient level of consolidation on its own, low-volume and, particularly, irregular demand needs to be bundled with the demand from other AV operators. Overall, AV operators in all customer buckets can achieve cost savings, except for those with high-volume and regular demand in the case of fees higher than $g = 4.0$. The results also show that, as expected, the cost savings decrease with rising fees. However, lower fees are associated with lower service levels that the PSP can fulfill profitably, as we further investigate in the following.

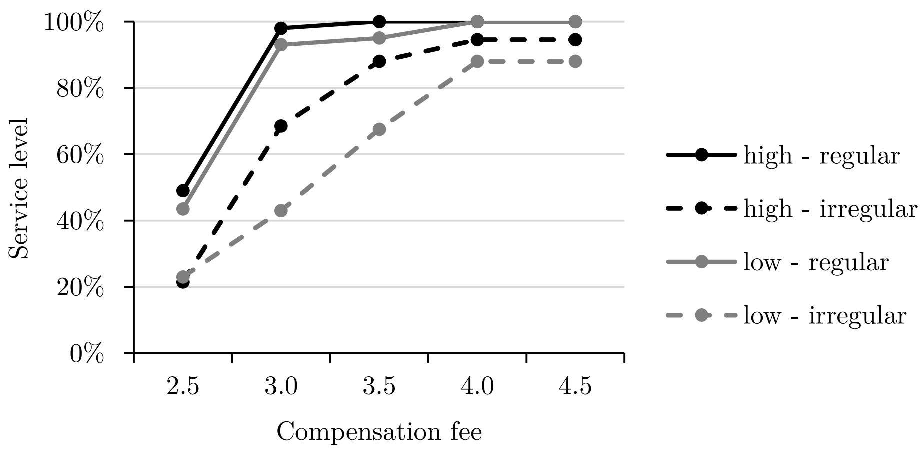


Fig. 9. Average service level fulfillment for AV operators in different PSP customer buckets with different fees.

In Fig. 9, we report the average service levels that the PSP considers to fulfill with its tactical plan for AV operators in different customer buckets. We use the same type of illustration as in the previous figure for distinguishing between the different customer buckets. It can be observed that with lower fees, especially with $g = 2.5$, the PSP is not able to provide sufficient levels of service. Increasing the fee to $g = 3.0$ already allows the PSP to offer AV operators with regular demand service levels of over 90% (93% with low volume, 98% with high volume). Raising the fee further contributes to ensuring 100% service levels to those AV operators. AV operators with irregular demand cannot expect service levels of the same quality. Still, the PSP can offer those AV operators with irregular demand acceptable service levels of 88% for low-volume demand and 95% for high-volume demand with a fee of at least around $g = 4.0$.

5.2.4. Supply–demand interaction

Since the average service levels result from the PSP's assignment of four discrete rates to the individual AV operators in each demand instance, we investigate the distribution of those assignments in more detail. In Fig. 10, we depict the share of service levels that are offered to AV operators in each of the four customer buckets. Those service levels must be fulfilled by the PSP. The 2×2-matrix of subfigures is organized to depict the demand volume along the y-axis and demand regularity along the x-axis. Each bar in a subfigure represents the distribution for a specific fee setting. The color of the bars indicates the offer of service level Φ_π to an AV operator in a demand instance with the values of $\Phi_\pi = \{0.0, 0.8, 0.9, 1.0\}$.

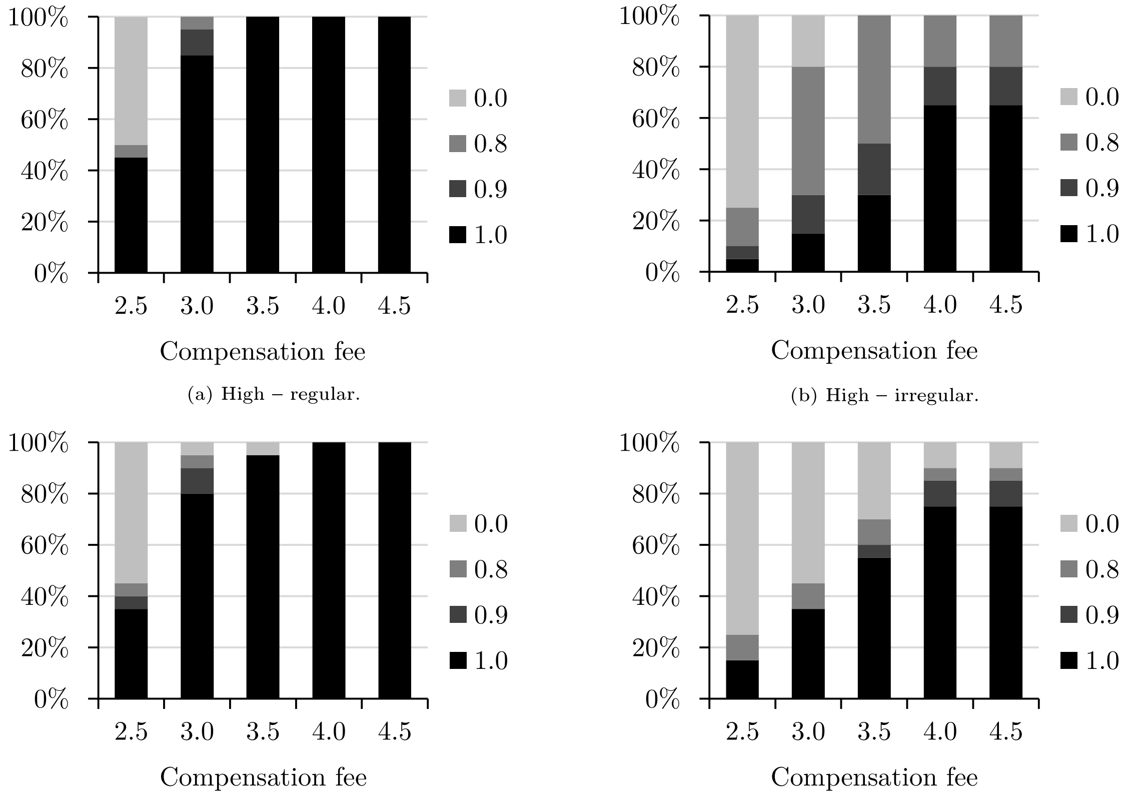
We observe more clearly now that AV operators with irregular demand are offered lower service levels than those with regular demand. Also, their service levels are impacted less by increases of the fee. AV operators with low demand volume are rejected to be served by the PSP ($\Phi_0 = 0$) more frequently than those with high demand volume. In fact, there are no rejections of high-volume AV operators with fees of $g = 3.5$ or more. The PSP rejects to serve AV operators in the bucket (low — irregular) in more than half of the instances with a fee of $g = 3.0$. After increasing the fee to $g = 4.0$, however, even the AV operators in this bucket can expect service levels of at least 90% in 85% of the instances. AV operators with regular demand, disregarding the volume, can expect service levels of 100% if the PSP can charge a fee of at least $g = 4.0$.

Finally, we note that the PSP requires a fleet of 5.8 MVs on average to fulfill those high service levels for all the considered AV operators with a fee of $g = 4.0$. With this fee, the PSP operates on a profit and each of the AV operators yields cost savings from using the PSP's platooning service, suggesting the cooperation is stable. The number of MVs required by those 8 AV operators to perform their individual platooning services on their own would add up to 17.9 MVs in total. In conclusion, the PSP contributes to reducing the number of MVs to around a third in our experiments.

5.3. Discussion

The experimental results show that a PSP can offer a platooning service in an urban environment profitably above a certain compensation fee. Even relatively high fees lead to considerable savings for AV operators with different demand characteristics. AV operators with regular demand, i.e., with similar requests every day of the planning horizon, can expect to be offered service levels of nearly 100%. AV operators with irregular demand, i.e., with larger volatility in their daily requests, can expect service levels of around 90%. But they can achieve large cost savings compared to operating an own fleet of MVs, relatively even more than those with regular demand. Overall, it becomes clear that a PSP needs to carefully balance which service levels to offer to different customers. In specific cases, this may require to disappoint individual customers to keep other customers satisfied and the PSP's operations profitable.

A comparison of the stochastic solutions with deterministic solutions based on mean demand quantities reveals that the PSP can benefit from considering uncertainty in demand during the planning phase. The value of stochastic solutions is most pronounced



(a) High – regular.

(b) High – irregular.

(c) Low – regular.

(d) Low – irregular.

Fig. 10. Service levels ($\Phi_\pi = \{0.0, 0.8, 0.9, 1.0\}$) offered to AV operators in different PSP customer buckets given different fee settings.

with small fees and relatively small expected profits. Using the proposed stochastic model especially mitigates the risk of determining a wrong fleet size.

This study's findings lead us to deriving the following practical implications. The differences in the service levels that a PSP offers to AV operators with different demand characteristics raise questions about the right design of the pricing scheme. AV operators may differ in their individual willingness to pay, e.g., based on their specific opportunity costs of performing platooning on their own. However, quoting different fees to different AV operators receiving equal service levels raises equality issues. Also, it is challenging for the PSP to reliably determine the individual willingness to pay ahead of the planning horizon when designing the scheduled service network.

In order to more flexibly and reliably move AVs between different zones in an urban environment, an AV operator may combine the use of own MVs as platoon leaders with outsourcing platooning requests to a PSP. This may especially be a suitable solution for AV operators with irregular demand. Multiple PSPs operating in the same environment may also contribute to more flexibility for the AV operators and, potentially, to lower prices due to competition. In the conducted experiments, we also found large potentials for the reduction of vehicles in the urban environment. This suggests that public authorities in cities have reasons to actively support the availability of a platooning service, e.g., with financial subsidies or infrastructural support, which may lower prices and further increase AV operators' service levels.

6. Conclusions and future research

In this article, we introduce a stochastic service network design problem of a platooning service provider. We propose a two-stage stochastic integer programming formulation that addresses fleet sizing, service scheduling, quoting of rates to customers, platooning request acceptance, and AV routing in an integrated model. We perform computational experiments on a real-world based network, in which we represent AV operators with different demand characteristics using stochastic scenarios. The results show that a PSP can operate a platooning service in a profitable way that provides AV operators with sufficient levels of service and significant cost savings. In conclusion, stochastic service network design can be viewed as a suitable tool for enabling the cooperation of fleet operators whenever synchronization plays a key role.

We identify the following perspectives for future research. While we apply time-dependent compensation fees, schemes based on distance or other metrics may be more suitable for other operational settings. A PSP may also apply more sophisticated pricing schemes to account for AV operators with different preferences. To reliably incorporate heterogeneous customer preferences within the PSP's planning decisions, further studies regarding the price elasticity in this novel problem setting are required. Further, approaches from revenue management other than pricing could be studied to balance supply and demand in this problem setting. For example, PSPs could overbook the capacities in platoons to being able to market higher service levels and prices to potential customers. In case the service levels promised to some customers cannot be fulfilled, the PSP would need to be penalized. Further analyses on specific operational settings of the problem may be conducted, evaluating the impact of technical or managerial parameters. For targeting larger instances in terms of, e.g., the network size or the number of requests, future research may develop or adapt more efficient solution approaches for this problem. Also, decentralized approaches should be further studied that enable the collaboration of multiple AV operators by sharing the leading and following roles in platoons.

The modeling approach proposed for the particular problem setting in this paper may also be relevant to other settings. For example, a similar business model is pursued by the US company Convoy (2021) that offers on-demand truck capacity to pull trailers of other companies. Another potential problem setting could occur if trucks are allowed to drive autonomously on dedicated AV lanes on highways. MVs may be required in this case for guiding traffic between exit ramps and ultimate locations. The proposed model can be easily adapted to related settings by modifying parameter settings such as those for the platoon capacity.

CRediT authorship contribution statement

Yannick Oskar Scherr: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Mike Hewitt:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Dirk Christian Mattfeld:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Acknowledgments

Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 227198829/GRK1931. This support is gratefully acknowledged.

Appendix. Stochastic scenarios

In the computational study presented in Section 5, we use scenarios to represent the stochastic platooning demand by considering a quantity $q_{sp} \in \{0,1\}$ for each platooning request p in a scenario s. We generate the scenarios by sampling the binary quantities according to a binomial distribution using the Monte Carlo simulation method. The scenarios chosen for an instance can also be considered as a scenario tree. Following the law of large numbers, a large scenario tree containing all possible scenarios would reproduce the distribution accurately, which generally enables the optimization to produce high-quality solutions. However, the number of scenarios that can be considered in an instance is typically restricted by the computational effort required to solve the optimization model. To achieve meaningful results for our problem within practically reasonable computation times, we assess in the following the number of scenarios that should be considered using our straightforward scenario generation approach.

Thus, we rely on the concept of evaluating the in-sample and out-of-sample stability of a scenario generation approach to ensure the reliability of the optimization results and their transferability to the implementation. In-sample stability provides evidence that the results of the optimization are sufficiently independent of the particular scenario tree that is generated by the approach using certain random elements. Out-of-sample stability shows that the objective value resulting from the optimization based on a scenario tree is sufficiently meaningful for any scenario occurring outside of this sample. A more detailed explanation of this concept is provided by Kaut and Wallace (2007). For the evaluation of the in-sample and out-of-sample stability of our scenario generation approach, we consider instances with the fee set to $g = 3.5$ and the platoon capacity set to $n = 2$.

Similar to the procedure outlined in Lium et al. (2007), we perform the in-sample stability test by randomly generating 20 different scenario trees for each evaluated number of scenarios. For each of those scenario trees, we solve the integer program stated in Eqs. (1)–(15) and compare the obtained objective function values. We choose the standard deviation as a measure of dispersion among the objective values for the scenario trees.

In Table A.4, we present optimization results for the different numbers of scenarios $|S| = \{20, 40, 60, 80\}$. We report the mean objective function values (μ_{obj}) and their standard deviation (σ_{obj}). To provide a problem-specific reference, we report the ratio between the standard deviation and the mean value of the compensation that must be paid for a single platooning request (σ_{obj}/μ_{comp}). For measuring the computational tractability, we report the share of instances solved to optimality and the average runtime in seconds. In case an instance could not be solved to optimality within the runtime limit of 5 h (18,000 s), we report the best found solution in the following.

We obtain from the results that – as expected – considering a larger number of scenarios improves the approximation quality but requires an increased computational effort. Considering at least 40 scenarios provides sufficiently accurate solutions for the instances considered in this evaluation. The standard deviation amounts to less than half of the average compensation. 30% of the instances with $|S| = 80$ could not be solved to optimality within the runtime limit. As a result, we note that achieving a relatively small improvement of the standard deviation from 45.09 to 41.34 by doubling the number of scenarios from 40 to 80 is accompanied by requiring more than five times of the runtime. As instances with 60 scenarios can be solved with reasonable computational effort and promise sufficiently accurate solutions, we assume that considering 60 scenarios in an instance provides in-sample stability.

Table A.4
Results of the in-sample stability test.

$\|S\|$	20	40	60	80
μ_{obj}	1177.05	1180.00	1176.05	1166.17
σ_{obj}	79.60	45.09	46.82	41.34
σ_{obj}/μ_{comp}	73.65%	42.41%	43.53%	38.51%
Solved to optimality	20/20	20/20	19/20	14/20
Runtime in seconds	675	2645	5699	13,501

To evaluate the out-of-sample stability, we consider a single scheduled service network, i.e., a first-stage solution, and fix all MV service variables, denoted by $\hat{m}_{ij}^{t\bar{t}}$. We do not fix the values of the other first-stage variables, the rate assignment variables $y_{c\pi}$, as the PSP would have no practical reasons for determining the customer rates irreversibly when designing the scheduled service network. We choose the solution with the smallest deviation from the mean objective value among the instances with 60 scenarios used for the in-sample stability evaluation. Then, we sample another set of 20 scenario trees, each containing $|S| = 1.000$ scenarios, and optimize the second stage given the fixed first-stage solution, i.e., Eqs. (8)–(15) with the objective function $Q(\hat{m}, y, s)$. Finally, we compare the objective function values obtained for each of the 20 scenario trees.

The results show that the standard deviation within this sample is 11.05. This corresponds to 0.33% of the mean objective function value of the second stage, representing the revenue part. Based on these results, we also conclude that out-of-sample stability is given and proceed with considering instances with $|S| = 60$ in the computational study.

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