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Service network design with mixed autonomous fleets

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ABSTRACT

We propose a service network design problem for the tactical planning of parcel delivery with autonomous vehicles in SAE level 4. We consider a heterogeneous infrastructure wherein such vehicles may only drive in feasible zones but need to be guided elsewhere by manually operated vehicles in platoons. Our model decides on the fleet size and mix as well as on the routing of vehicles and goods. We observe cost savings and show that the strategies to coordinate a fleet using platooning depend upon the infrastructure, demand, and fleet mix. We discuss our results and identify areas for future research.

1. Introduction

The rise of e-commerce has led to a parcel delivery market in which an increasing number of logistics service providers (LSPs) compete over market shares and customer satisfaction. Expectations for fast and reliable delivery times are growing in a way that more than half of LSPs are nowadays offering same-day and next-day delivery options to their customers (Saleh, 2017). However, small individual volumes and lacking opportunities for consolidation make it difficult for LSPs to operate efficiently and provide such services on a profitable basis. Moreover, a large share of demand for parcel delivery originates from densely populated urban areas, which are typically characterized by highly congested roads and scarce parking spaces. Therefore, municipal authorities promote city logistics concepts to reduce the impact on traffic and the environment (Savelsbergh and Van Woensel, 2016). The concept of two-tier city logistics introduces satellite locations in which consolidated transports from distribution centers outside of the city are transshipped to dedicated last-mile vehicles serving customers (Crainic et al., 2009).

A major challenge for LSPs is to implement innovative delivery options while meeting economic and service quality targets. In particular, they need to put emphasis on rationalizing delivery efforts to achieve the lowest shipment costs possible. This is becoming increasingly difficult as driver wages increase steadily, which is mainly due to a shortage of qualified drivers in logistics (Sen, 2018). The American Trucking Associations (ATA) project that the shortage could increase to 175,000 drivers by 2025 in the US alone (Hooper and Murray, 2017). Following this trend, LSPs struggle to operate a fleet of sufficient size to maintain the expected service quality.

With the aim of keeping ahead of the competition, LSPs are regularly adopting upcoming technologies to improve the parcel delivery process (Joerss et al., 2016). In particular, automated driving technologies promise to guide vehicles efficiently without a human driver and are expected to transform the logistics and mobility sector in the next years (Masoud and Jayakrishnan, 2017). For LSPs, autonomous vehicles (AVs) may significantly lower shipment costs by reducing driving staff expenses. Equipping a vehicle with the necessary hardware and software for automated driving, particularly sensor technology, comes at a one-time cost which is less

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than driver annual salaries in many regions. At launch, market prices for purchasing an AV are expected to be around 10,000 $ higher than a comparable vehicle without such technology (Mosquet et al., 2015). Due to the high utilization of their fleet, commercial fleet operators like LSPs may become early adopters in terms of AV deployment and profit from the technology first (Mahmassani, 2016).

Although automated driving technologies have already been used in controlled industrial environments successfully (Roodbergen and Vis, 2009; Heutger, 2014), their use on public roads still causes discussion of legal regulations to determine liability in traffic accidents (Parker et al., 2017). While fully autonomous driving, especially in cities, is not expected in the next few years, a more realistic scenario is that vehicles can drive autonomously under specific and carefully evaluated driving modes (CARMERA, 2018). This scenario would fall into level 4 of the SAE International's classification of driving automation where an autonomous driving system can react to fallbacks without human intervention (SAE International, 2018). Here, the automated system's ability to control a vehicle mainly depends on the infrastructure conditions surrounding it. This paper focuses on automation level 4 since fully autonomous driving (level 5) in arbitrary environments is still far away from being reached.

In addition to AV investment, an LSP depends on given conditions to operate AVs. Integrating AVs into a city environment may require costly infrastructure preconditions both to ensure traffic safety and to advise traffic flows in real time. Also, AVs rely on complex 3D maps to move on street networks. Since mapping may be difficult in specific areas of the network, "it will delay the deployment in certain geographies" (Hook, 2018). Rather, AVs in level 4 are "fully autonomous within a geofence, so within an area [with a] high definition map" (Crosbie, 2017). Therefore, we consider a heterogeneous infrastructure which comprises feasible streets for autonomous driving. In this paper, we call these feasible streets AV zones. Such AV zones may be characterized by having dedicated lanes, easy-to-handle junctions, certain speed limits or specific traffic rules (Coker, 2018). They are determined by planning authorities and traffic management within long-term strategic decision-making (Chen et al., 2017). The different stages of preparation for autonomous driving lead to a heterogeneous infrastructure which LSPs need to exploit to conduct an efficient delivery process.

For LSPs, one major challenge is to carry AVs to the AV zones where they can perform delivery operations and to bridge the gaps between AV zones. In other words, AVs require guidance on streets of the city network which are not feasible for automated driving. To this end, manually operated vehicles (MVs) with a human driver can navigate AVs in a platoon, a group of vehicles following each other closely. Vehicle-to-vehicle (V2V) communication is necessary to transfer the control signals which requires connected vehicles (Talebpour and Mahmassani, 2016). By simply replicating the driving tasks of the leading vehicle of a platoon, a limited number of vehicles can follow with considerably less control complexity. This difference can be crucial in providing easier conditions for an automated system to operate. After the feasibility of this approach was tested, e.g. by Englund et al. (2016) and Tiernan et al. (2017), several companies in the truck industry start deploying platooning in field tests recently (Volvo Trucks USA, 2018; Volkswagen AG, 2018; Scania Group, 2018). Following the recent trends of driver shortages and increasing driver wages, the prospect to operate a larger fleet with a similar number of drivers is promising.

Platooning is not only advantageous for LSPs but also for other traffic participants, which is an important aspect for city logistics applications. Benefits include the occupation of less road space in contrast to individual vehicles requiring larger headway between each other (Lioris et al., 2016). Additionally, experiments conducted by Lammert et al. (2014) show fuel savings of up to 9.7% for trailing vehicles in a platoon. For fleet operators, platooning can provide similar flexibility to truck-and-trailer combinations in long-haul transportation (Derigs et al., 2013; Regnier-Coudert et al., 2016) which can be configured to provide a certain transportation capacity. While trucks are active and trailers are passive means of transportation (Meisel and Kopfer, 2014), platooning introduces this flexibility to groups of vehicles all being able to actively drive. Present research on the planning of platooning focuses on long-distance traffic for which the reader is referred to the literature review by Bhoopalam et al. (2018).

We claim that operating a mixed fleet of MVs and AVs within a heterogeneous infrastructure will be a major opportunity for LSPs in the upcoming years. Tactical planning is concerned with scheduling shipment activities into regular services, as well as assigning resources and defining policies to operate these services. Service network design (SND) problems have been extensively used to determine which transportation services to offer and to coordinate the routing of vehicles and goods on an underlying network in a cost-efficient manner. SND problems produce an operations plan which satisfies expected demand for transporting goods at the lowest cost possible. First introduced by Crainic and Rousseau (1986), SND problems are applied in several fields (Wieberneit, 2008) from less-than-truckload (Crainic, 2000) to express shipment (Barnhart et al., 2002) and ferry (Lo et al., 2013) networks as well as in shared mobility systems (Neumann-Saavedra et al., 2016). In city logistics, tactical planning models are widely used by LSPs to enhance consolidation of transports (Crainic, 2008). Two-tier city logistics concepts particularly focus on serving satellites, transshipment terminals distributed within the city center, on a regular basis (Crainic and Sgalambro, 2014).

Tactical planning problems require appropriate modeling techniques that need to balance sufficient levels of detail with manageable amounts of information. For numerous problems in logistics, properties such as the origin and destination of commodities, travel times between locations or transshipment points contain a lot of temporal information. Service network design problems aim to capture such temporal information within medium-term planning horizons (Crainic, 2000). For this reason, they are usually modeled on time-expanded networks in which physical locations are replicated in discrete points in time (Andersen et al., 2009; Crainic et al., 2016; Boland et al., 2017). The length of these intervals determines the approximation quality compared to the continuous-time problem but also the size of the network and therefore computational tractability (Boland et al., 2018). The other commonly-used technique for modeling temporal information is to use continuous decision variables to represent dispatch times from locations and big-M constraints to ensure that those decision variables align with travel times between locations (Vigo and Toth, 2014). However, integer programs that include such big-M constraints have notoriously weak linear programming relaxations and thus are hard to solve, computationally-speaking (Vigo and Toth, 2014). By using a time-expanded network we obtain a static flow problem that can be solved by commercial solvers (Skutella, 2009).

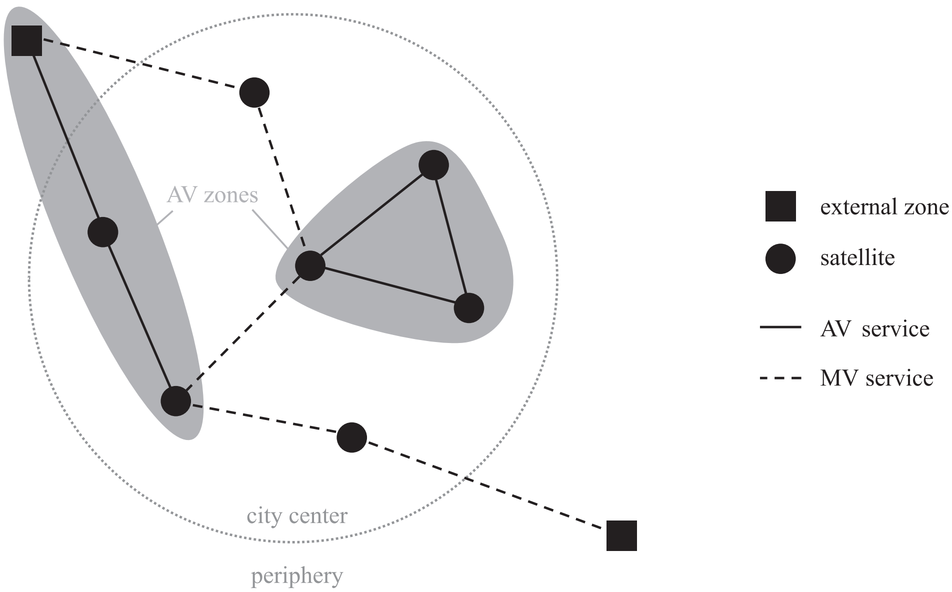


Fig. 1. Problem setting for the first tier of two-tier city logistics with a mixed autonomous fleet.

We are neither aware of any SND problem which considers mixed fleets with a group of vehicles relying on particular infrastructure conditions nor considers the synchronization of vehicles to form platoons. With this paper, we want to contribute to filling these gaps in present literature. We introduce an innovative SND problem with mixed autonomous fleets for tactical planning, which we apply to a two-tier city logistics setting without loss of generality. We present a generic model using an integer linear programming formulation on a time-expanded network that introduces platoon operations to prevailing formulations in literature. Our model decides on the number of MVs and AVs as well as on the routing of vehicles and goods. In a computational study, we analyze the cost sensitivity, the fleet size and mix as well as the infrastructure usage and the importance of platooning to derive managerial insights for LSPs. The results show that comparable transportation costs can be achieved with a fleet consisting of fewer MVs, and hence fewer drivers.

The remainder of this paper is organized as follows. In Section 2, we describe the examined problem in a city logistics setting. Section 3 formally describes our mathematical model as an integer linear program. We conduct a computational study and state results in Section 4. In Section 5, we discuss our findings before concluding with Section 6.

2. Problem description

In this section, we describe an SND problem for mixed autonomous fleets. The problem aims to determine the size and mix of the fleet as well as the routing of vehicles and goods on a given network. We follow the two-tier city logistics setting introduced by Crainic et al. (2009) and extend it by integrating autonomous driving and platooning into the parcel delivery process. After describing the general components of two-tier city logistics, we introduce the particular features of MVs and AVs, characterize heterogeneous infrastructure, and define platoon operations.

Fig. 1 displays an example for a two-tier city logistics problem setting. LSPs rely on a dedicated fleet of delivery vehicles to satisfy an expected demand which takes the form of goods with a specific volume defined in units. In the first tier, goods appear in external zones, i.e., distribution centers on the periphery of the city center, and are to be transported to spatially distributed satellites which are transshipment terminals within the city center. Goods need to reach their determined destination satellite but may be broken up in discrete units, e.g., pallets or bags, and transshipped between vehicles at any intermediate satellites to enhance consolidation. While external zones have warehousing capabilities, satellites do not. Thus, goods must be delivered to their destination satellite at a specific time that is determined a priori.

These predetermined arrival times at satellites ensure that goods can be transshipped from parking vehicles of the first tier to dedicated last-mile delivery vehicles of the second tier. The operational process of serving customers in proximity to the satellites within the second tier is not covered in the scope of our problem. We instead focus on the tactical problem of finding a repeatable schedule to fulfill recurring demand between external zones and satellites in the first tier. The objective is to minimize total cost for selecting the size and mix of the fleet as well as for routing the vehicles and goods.

Regarding costs, we consider a mixed fleet of MVs and AVs. Each vehicle is characterized by its type, speed, and transportation capacity. The LSP needs to select the number of vehicles from each type and assigns them to a specific external zone at the beginning of the day. With this selection, we associate a daily amortized cost for acquiring or leasing a vehicle. For each selected MV, we additionally consider the cost for hiring a driver for a day whereas AVs do not require human assistance inside the vehicle. All vehicles need to be parked at external zones at the end of the day. Since we aim at achieving a schedule which can be repeated every day of the week, each external zone must end a day with the same number of vehicles of each type that it begins with. With this assumption, we conform with the controlled urban-vehicle service network design problem which Crainic and Sgalambro (2014) formulate for a two-tier city logistics setting. Allowing vehicles and drivers to return to a different depot than they depart from provides LSPs with added flexibility which is why this assumption is widely applied in SND problems (Pedersen et al., 2009; Crainic et al., 2016).

By installing a service, a vehicle provides a transportation capacity for goods it can carry. To increase consolidation, these capacities are typically aimed to be exploited. However, empty services may be conducted to reposition vehicles. The two vehicle types, MVs and AVs, differ in their ability to travel on the network and therefore to perform services. While MVs are able to move everywhere on the network, AVs are only allowed to drive without guidance in AV zones, which may cover certain streets or areas of the city network. If an AV wants to move outside of these AV zones it must follow an MV via platooning. One MV can only guide a platoon with a limited number of AVs to not exceed the maximum length allowed for road vehicles.

The distribution of AV zones yields a heterogeneous infrastructure. Depending on different types of infrastructure, the LSP may pursue specific strategies for assigning vehicles to certain areas of the network and for using platooning. This is why we further characterize three different types of heterogeneous infrastructure: *corridor*, *artery*, and *nanny*. We describe these three heterogeneous infrastructure settings by means of examples in Section 4.1 in which we define the instances for our computational study.

Implementing platooning requires a high level of synchronization between MVs and AVs because the vehicles need to meet at a location at the same time to form platoons. To allow for such synchronization, we introduce a set of operations for depicting platooning activities. A first ontological framework for platoon operations is given by Maiti et al. (2017). In our problem, individual AVs can either *merge* to a platoon or *split* from a platoon. AVs are not designated to one specific MV as a platoon leader but can switch between different platoons over the course of the day. Further, we consider that platoons can also *transit* through locations, i.e., the formation of vehicles stays consistent between entering and leaving a location. This ensures that AVs are not left behind at a location they cannot depart from alone.

While such platoon operations could happen anywhere, we presume they only happen at external zones and satellites as these locations provide the necessary space. Executing the platoon operations does not induce any cost because vehicles in a platoon are only linked by communication technologies and there is no need for physical coupling in contrast to truck-and-trailer configurations. Naturally, these platoon operations can only be applied if vehicles not only meet at the same place but also at the same time. Vehicles can also accomplish synchronization by idling at a given location until they can form a platoon. At intermediate locations within the traffic network, roadside units would need to be installed to allow for platoon operations while driving due to the lack of space to park vehicles.

To fulfill demand on a given network, an LSP needs to coordinate a mixed fleet of MVs and AVs by choosing from platoon operations at given locations and points in time. In tactical planning, the LSP primarily determines the number of vehicles for particular services and specifies the size of the platoon. Further, platoon operations are planned for a specific location and time which need to be executed during the implementation. Operationally, a specific vehicle and driver would be assigned to conduct a service and the particular vehicles on site would execute the platoon operations. When implementing the tactical plan in real time, safety and efficiency considerations need to be taken into account that may impact the sequence of the vehicles in the platoon.

3. Mathematical model

In this section, we model our introduced SND problem with mixed autonomous fleets as an integer linear program. We first describe the general notation and then state the mathematical formulation. We use a time-expanded network formulation to capture

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

Type	Notation	Description
Physical network	$i \in N_{ph}$	Node in the physical network
	$i \in N_E$	External zone
	$i \in N_S$	Satellite
	$(i, j) \in A_{ph}$	Arc in the physical network
	$(i, j) \in A_M$	MV arc
	$(i, j) \in A_A$	AV arc
Time-expanded network	$t \in T = \{1, \ldots, T_{max}\}$	Time period in planning horizon T_{max}
	$(i, t) \in N$	Node in the time-expanded network
	$(\gamma, 0) \in N_\gamma$	Auxiliary node for each external zone
	$((i, t), (j, \bar{t})) \in A$	Arc in the time-expanded network
	$((i, t), (j, \bar{t})) \in A_\gamma$	Auxiliary arc to assign number of vehicles
	$((i, t), (j, \bar{t})) \in A_h$	Holding arc to idle at external zone
	$((i, t), (j, \bar{t})) \in A_w$	Waiting arc to idle at satellite
	$((i, t), (j, \bar{t})) \in A_m$	Movement arc to travel between locations

the time-dependent properties of the problem directly within the network. In our model, we particularly rely on these properties to synchronize vehicles in space and time. We further distinguish between the physical network and the time-expanded network. Table 1 aims to provide an overview for the notation of both networks we describe in the following.

The physical network $G_{ph} = (N_{ph}, A_{ph})$ consists of nodes $i \in N_{ph}$ representing locations and arcs $(i, j) \in A_{ph}$ representing the connections between the locations. Set N_{ph} contains subsets $N_E \subset N_{ph}$ for external zones and $N_S \subset N_{ph}$ for satellites. We distinguish between AV arcs $A_A \subset A_{ph}$ on which all vehicles are able to travel alone and MV arcs $A_M \subset A_{ph}$ on which AVs need guidance by MVs.

For the time-expanded network $G = (N, A)$, we replicate nodes $(i, t) \in N$ in discrete time steps $t \in T = \{1, ..., T_{max}\}$ to cover a given planning horizon T_{max}. The time-expanded network includes four types of arcs $((i, t), (j, \bar{t})) \in A$. Auxiliary arcs $A_\gamma \subset A$ connect the auxiliary nodes with the first ($t = 1$) and last ($t = T_{max}$) replication of the corresponding external zone. Holding and waiting arcs link the same logical representatives of locations in different time periods and allow for idling of vehicles. Holding arcs $A_h \subset A$ are applied in external zones and waiting arcs $A_w \subset A$ are applied in satellites. We use this distinguished notation because goods can only be stored in external zones for which holding arcs are used. Waiting arcs do not provide this capability for warehousing. Movement arcs $A_m \subset A$ allow for traveling between different physical nodes. Their length is determined by the respective travel time between the nodes in the physical network. Using this time-expanded network, goods $d \in D$ with volume $v(d)$ have to be transported from their assigned external zone $e(d) \in N_E$ to a given satellite $s(d) \in N_S$. Since synchronization with the second tier is required, delivery to satellites is enforced strictly for the time period requested.

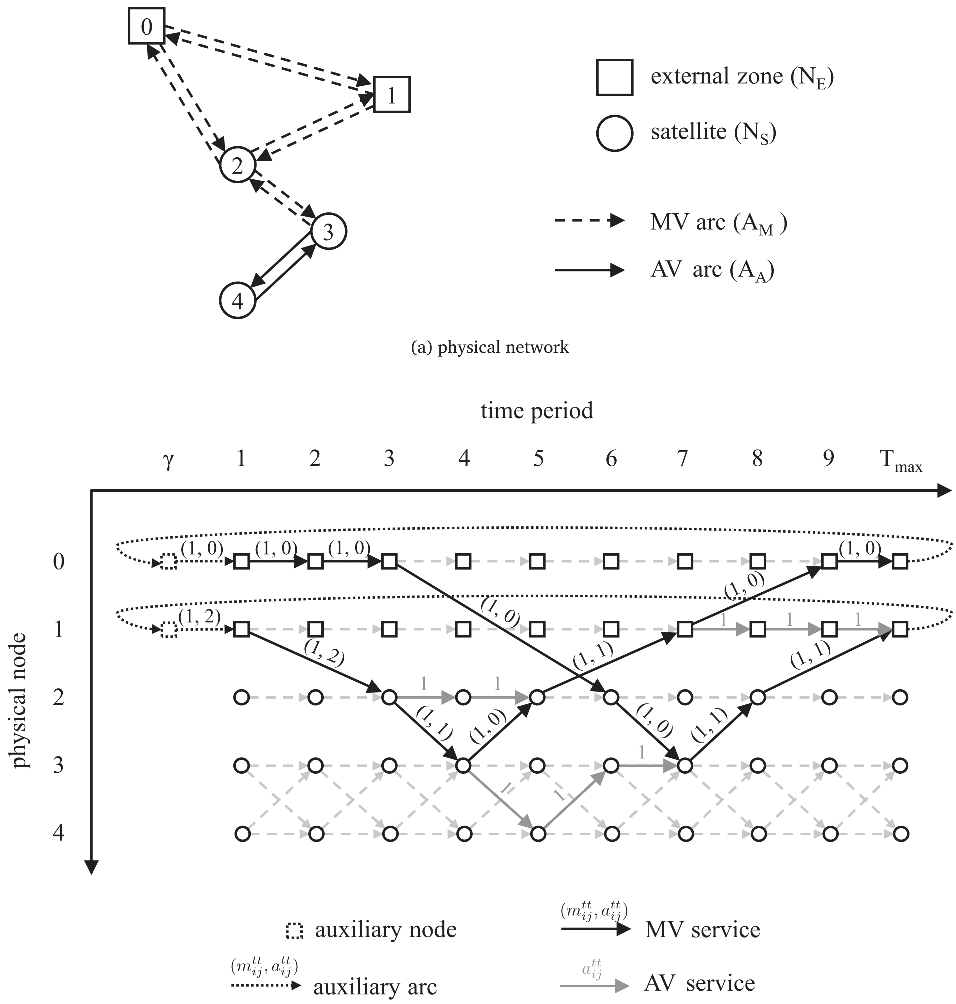
The mixed autonomous fleet consists of two different types of vehicles. Let $m_{ij}^{t\bar{t}}$ and $a_{ij}^{t\bar{t}}$ be integer variables indicating the number of services by MVs and AVs respectively using arc $((i, t), (j, \bar{t})) \in A$. MVs are driven by humans and can travel on all available arcs $(i, j) \in A_{ph}$ of the physical network. AVs do not contain a driver and can only move alone in specific AV zones that are distinguished by the subset of AV arcs $A_A \subset A_{ph}$. This includes all holding and waiting arcs, such that idling of AVs is permitted at any node. AVs are not allowed to move alone on arcs in the subset $A_M \subset A_{ph}$. On the time-expanded representatives of these arcs $((i, t), (j, \bar{t})) \in A$: $(i, j) \in A_M$, a limited number of AVs can be guided by an MV using platooning. Therefore, the involved vehicles have to synchronize in space and time by using the same arc of the time-expanded network. The flow of goods transported on an arc is denoted by the integer variable $x_{ij}^{dt\bar{t}}$ because we seek to model goods with discrete units. In some settings, it may be more appropriate for the flow variables to take on continuous values.

For selecting vehicles, there is one auxiliary node $(\gamma, 0) \in N_\gamma$ assigned to each external zone $i \in N_E$ using auxiliary arcs $((i, t), (j, \bar{t})) \in A_\gamma$. The fixed costs are assigned to the selected number of vehicles per type at the beginning of the planning horizon. Therefore, the flows $m_{\gamma i}^{0\bar{t}}$ and $a_{\gamma i}^{0\bar{t}}$ allow for the selection of vehicles by connecting each auxiliary node with the first replication of the external zone. Table 2 provides an overview on the variables and parameters used in the model.

We show the elements of the network formulations by means of an example in Fig. 2. We first display the underlying physical network in Fig. 2a which represents 2 external zones and 3 satellites. There is one AV zone which connects two satellites with each other using AV arcs. Outside of this AV zone, AVs can idle at any node or follow an MV via platooning. The time-expanded network in Fig. 2b replicates the physical nodes in 10 time periods and introduces auxiliary nodes for the external zones. For the sake of simplicity, we only display the used arcs as well as all arcs which AVs can possibly use when traveling alone. In the example, 2 MVs and 2 AVs are selected using the auxiliary arcs to perform services. Both MVs return to different external zones than the one they start at but the number of vehicles is balanced. For the interaction between platoons and AVs, several *split*, *merge*, and *transit* operations are performed. One of the AVs is solely used to extend transportation capacity and idles for 2 time periods at a satellite. The other AV travels alone on the AV arcs between satellites 3 and 4 but needs to wait for one time period before it is picked up by a platoon to return to the external zone.

Table 2
Notation of variables and parameters.

Type	Notation	Description
Variables	$m_{ij}^{t\bar{t}}$	MV services on arc $((i, t), (j, \bar{t})) \in A$
	$a_{ij}^{t\bar{t}}$	AV services on arc $((i, t), (j, \bar{t})) \in A$
	$x_{ij}^{dt\bar{t}}$	Flow of goods $d \in D$ on arc $((i, t), (j, \bar{t})) \in A$
Parameters	k_{ij}	Transportation cost per MV service on arc $(i, j) \in A_{ph}$
	l_{ij}	Transportation cost per AV service on arc $(i, j) \in A_{ph}$
	c_{ij}^d	Transportation cost per unit of goods $d \in D$ on arc $(i, j) \in A_{ph}$
	$d \in D$	Demand for goods
	$v(d)$	Volume in units of the demand for goods $d \in D$
	$e(d)$	Assigned external zone (origin) of the demand for goods $d \in D$
	$s(d)$	Assigned satellite (destination) of the demand for goods $d \in D$
	u_E	Warehousing capacity of external zones in volume units
	u_M	Transportation capacity of MVs in volume units
	u_A	Transportation capacity of AVs in volume units
	n_M	Maximum number of available MVs
	n_A	Maximum number of available AVs
	n_P	Platoon capacity, i.e., maximum number of following AVs in a platoon



(b) time–expanded network

Fig. 2. Network formulations for SND with mixed autonomous fleets.

With the given notation, the model we seek to solve is as follows:

$$\min \sum_{((i,t),(j,\bar{t}))\in A} \left[k_{ij} m_{ij}^{t\bar{t}} + l_{ij} a_{ij}^{t\bar{t}} + \sum_{d\in D} c_{ij}^{d} x_{ij}^{dt\bar{t}} \right] \tag{1}$$

s. t.

$$\sum_{((j,\bar{t}),(i,t))\in A} x_{ji}^{d\bar{t}t} - \sum_{((i,t),(j,\bar{t}))\in A} x_{ij}^{dt\bar{t}} = \begin{cases} v(d), & (i,\,t) = e(d), \\ -\,v(d), & (i,\,t) = s(d), \\ 0, & (i,\,t)\, \neq\, e(d),\, s(d), \end{cases} \qquad \forall\ d \in D,\ \ >(i,\,t>) \in N \tag{2}$$

$$\sum_{d\in D} x_{ij}^{dt\bar{t}} \leqslant u_E, \quad \forall\ ((i,\,t),\,(j,\,\bar{t})) \in A_h \tag{3}$$

$$\sum_{d\in D} x_{ij}^{dt\bar{t}} \leqslant m_{ij}^{t\bar{t}} u_M + a_{ij}^{t\bar{t}} u_A, \quad \forall\ ((i,\,t),\,(j,\,\bar{t})) \in A \backslash A_h \tag{4}$$

$$a_{ij}^{t\bar{t}} \leqslant n_P m_{ij}^{t\bar{t}}, \quad \forall\ ((i,\,t),\,(j,\,\bar{t})) \in A\colon (i,\,j) \in A_M \tag{5}$$

$$\sum_{((j,\bar{t}),(i,t))\in A} m_{ji}^{\bar{t}t} = \sum_{((i,t),(j,\bar{t}))\in A} m_{ij}^{t\bar{t}}, \quad \forall\ (i,\,t) \in N \tag{6}$$

$$\sum_{((j,\bar{t}),(i,t))\in A} a_{ji}^{\bar{t}t} = \sum_{((i,t),(j,\bar{t}))\in A} a_{ij}^{t\bar{t}}, \quad \forall\ (i,t)\in N \tag{7}$$

$$m_{ij}^{t\bar{t}},\ a_{ij}^{t\bar{t}},\ x_{ij}^{dt\bar{t}} \in \mathbb{N}, \quad \forall\ d\in D,\ ((i,t),(j,\bar{t}))\in A \tag{8}$$

The objective function (1) minimizes overall costs. Transportation costs k_{ij} are assigned to MV services $m_{ij}^{t\bar{t}}$ and l_{ij} to AV services $a_{ij}^{t\bar{t}}$. On the auxiliary arcs connected with the first ($t = 1$) replication of each external zone, transportation costs correspond to fixed costs $k_{\gamma i}$ for MVs and $l_{\gamma i}$ for AVs. Selecting a vehicle induces the fixed cost to utilize this vehicle for services during the whole planning horizon. Transporting a flow of goods $x_{ij}^{dt\bar{t}}$ on a service induces costs c_{ij}^{d}.

Constraints (2) ensure the flow balance of goods. Supply is assigned to external zones and demand to satellites for each good. Flows through transit nodes are conserved and transshipment of goods from one vehicle to another is allowed. Constraints (3) are applied to holding arcs $((i,t),(j,\bar{t}))\in A_h$ only and limit the storage capacity of each external zone to u_E. Transported goods have to satisfy the capacity constraints of vehicles on all arcs except for holding arcs due to constraints (4). MVs and AVs feature an available capacity u_M and u_A, respectively.

Since existing SND models do not yet consider platooning, we introduce particular platooning constraints (5). These constraints are applied to all movement arcs of the time-expanded network based on MV arcs of the physical network $((i,t),(j,\bar{t}))\in A$: $(i,j)\in A_M$. On such arcs, AV driving without guidance is prohibited and AVs can only travel on them by joining a platoon that is provided by a leading MV. Therefore, at least one MV service $m_{ij}^{t\bar{t}}$ needs to be installed for this particular arc. If this is the case, a limited number of AVs (n_P) can follow each MV. For AV arcs as well as for all holding and waiting arcs, this constraint is not applied.

Design-balance constraints (Andersen et al., 2009) balance the inflow and outflow of services in any node. Since we consider different vehicle types that rely on particular infrastructure conditions, we need to apply Eqs. (6) and (7) separately to MV and AV services. The constraints also apply to auxiliary arcs between the last and first time period of the planning horizon to assure the same number of vehicles per type in each external zone at the beginning and end of the planning horizon.

For enhanced fleet management considerations, we provide an optional set of constraints with (9) and (10). Similar to the resource bound constraints introduced by Crainic et al. (2016), these limit the maximum number of vehicles per type at the LSP's disposal to n_M and n_A, respectively. The restriction is imposed on the arcs between the auxiliary nodes $(\gamma,0)\in N_\gamma$ and the first replication of their corresponding external zone.

$$\sum_{(\gamma,0)\in N_\gamma} m_{\gamma i}^{0\bar{t}} \leqslant n_M, \tag{9}$$

$$\sum_{(\gamma,0)\in N_\gamma} a_{\gamma i}^{0\bar{t}} \leqslant n_A, \tag{10}$$

In addition to the generic model formulation we define within this section, we provide an alternative model formulation in Appendix A. This formulation allows for more control of the individual vehicles of the fleet which may be needed to incorporate several additional assumptions. As an LSP may want to ensure that drivers return to the same external zone every day, we specifically describe the case for MVs with a fixed external zone assignment.

4. Computational study

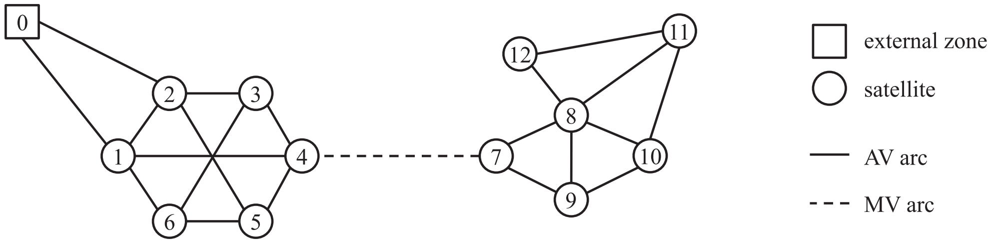
We conduct a set of computational experiments to investigate the model's functionality and to assess the value of considering AVs when designing the service network. To study the role of platooning in synchronizing a mixed autonomous fleet, we consider three infrastructure settings within the city logistics context, two demand patterns, and different fleet mixes by varying the fixed cost ratio between MVs and AVs.

4.1. Instances

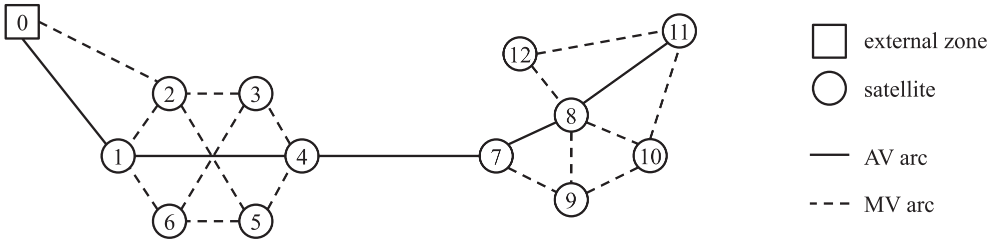
An individual problem instance is composed as a combination of heterogeneous infrastructure, demand setting, and fixed cost ratio. First, we generate problem instances according to the heterogeneous infrastructure mentioned in Section 2, *corridor*, *artery*, and *nanny*. Every infrastructure setting is based on one common underlying physical network consisting of one external zone, 12 satellites, and arcs connecting physical locations in both directions, see Fig. 3 for a simplified representation. The satellites are grouped into two clusters with 6 satellites each. These clusters are connected by one single arc between satellites 4 and 7. The external zone is connected with satellites 1 and 2 of the left cluster so vehicles must drive across the left cluster to reach the right cluster. Every arc is associated with a certain travel time which is equal for both directions.

We create instances to show the impact of different heterogeneous infrastructure. To this end, we restrict the example network to one external zone, which is not unusual in city logistics (Ehmke, 2012), enforcing vehicles to return to this external zone at the end of the planning horizon. From the underlying physical network, we define one problem instance for each infrastructure by defining AV arcs as part of the AV zone. As a benchmark, we use the *MV only* setting which resembles the conventional SND problem with a homogeneous fleet of MVs. Here, we prohibit the use of AVs by using constraint (10) with $n_A = 0$.

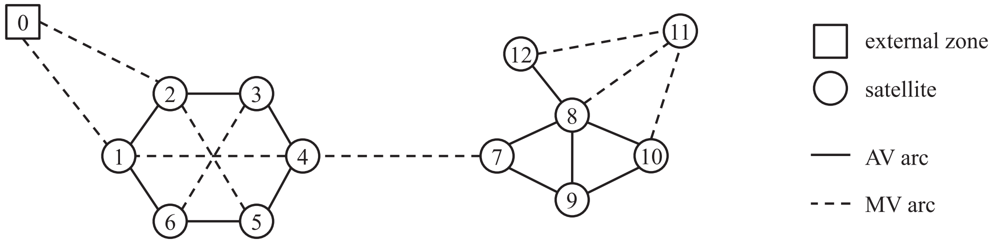
We define the three heterogeneous infrastructure settings as follows and use the representative network displayed in Fig. 3:



(a) corridor infrastructure



(b) artery infrastructure



(c) nanny infrastructure

Fig. 3. Heterogeneous infrastructure settings based on one common underlying physical network.

- The *corridor* infrastructure applies for cases in which several AV zones are separated from each other. This may be the case for industrial areas or parts of the network with low speed limits. On streets connecting the individual AV zones, AVs are not able to travel without guidance. Instead, they need to follow an MV by platooning. In this setting, MVs may fulfill the primary task to transfer AVs between AV zones. Fig. 3a displays the instance for the *corridor* infrastructure. In this infrastructure, the arc connecting the two clusters is the only MV arc. We thus expect that MVs will stay near the corridor to transfer AVs between clusters.
- In the *artery* infrastructure, AVs act as suppliers from external zones towards satellites in the city center using dedicated lanes on urban highways or arterial roads. Existing infrastructure for public transport such as tram lines or bus lanes could be utilized for this purpose. Alternatively, autonomous systems which use paint markings on the pavement for navigation are already practically feasible (Stopard et al., 2015; Coren, 2017). In the *artery* infrastructure, AVs are only allowed to travel on a so-called artery that leads through the network. Using this path, AVs can supply MVs with goods from the external zone and MVs deliver satellites outside of this path after transshipping the goods. The *artery* infrastructure is depicted in Fig. 3b. AVs are only allowed to travel on the artery that leads through the network. The artery leads from the external zone on the shortest path towards the furthermost satellite 11 and backwards, passing the corridor between the two clusters. This is why platooning is not especially encouraged in this infrastructure.
- In the *nanny* infrastructure, the network for AVs is fragmented and the routes of MVs and AVs need to be closely related to each other. An MV may carry a number of AVs which decouple over short time periods whenever parallel delivery is demanded. This behavior is reminiscent to truck-and-drone routing (Murray and Chu, 2015; Poikonen et al., 2017; Agatz et al., 2018), apart from widely different vehicle characteristics. In the *nanny* infrastructure, AVs can travel on large parts of the network, e.g., the outer ring of a city, but need to be guided in other parts. Fig. 3c shows the *nanny* infrastructure. AVs can travel on the outer ring of the left cluster or use platooning to travel on shortcuts. Bridging the corridor between the two clusters or reaching satellite 11 also requires guidance by an MV. In this infrastructure, there is no AV arc between the external zone and the satellites.

The physical network is transformed into a time-expanded network, considering time periods of 10 min. The arcs in the physical network are transformed into directed time-dependent arcs and distinguished between two subsets for each vehicle type. The length of the arcs is obtained by rounding up the ratio between the travel time and the time-period length of 10 min. We examine a planning horizon of 5 h, thus resulting in problem instances with a total of 30 time periods ($T_{max} = 30$) with 10 min length each.

We generate 5 demand allocations, in which 24 goods with a randomly assigned volume $v(d) = [1, 5] \in \mathbb{Z}$ in units need to be transported from the external zone $e(d)$ to a determined satellite $s(d)$. Each of the 12 satellites receives two deliveries within the planning horizon. The arrival time of each good at its terminating satellite is randomly chosen from the interval, in which all satellites can be reached within feasible travel time. The storage capacity of the external zone is not limited within the experiments.

We evaluate two different demand patterns that only vary based on the time the goods are available. One of them reproduces a conventional next-day delivery (NDD) approach, in which all of the supply appears in the external zone at the beginning of the planning horizon in $t = 1$. The same-day delivery (SDD) pattern represents supply appearing in the external zone within the course of the planning horizon. In our SDD instances, goods appear exactly 90 min ahead of their mandatory arrival time. The SDD pattern requires shorter delivery times and frequent returns to the external zone. After applying these 2 demand patterns to the 5 generated demand allocations, we investigate a total of 10 demand settings.

In all our experiments, the two available vehicle types have similar characteristics apart from the arcs they are able to move on. Both MVs and AVs have the same capacity of 10 volume units. Based on the maximum vehicle length of 15 m which is considered for crossings with traffic lights in Germany (Forschungsgesellschaft für Straßen- und Verkehrswesen, 2010), we allow for a maximum of two following AVs in a platoon, i.e., we set the platoon capacity $n_P = 2$. Both vehicle types induce the same amount of transportation cost per time traveled and per volume carried. Since we focus on a low-speed city logistics setting, platooning is assumed to not achieve any fuel savings, which means that vehicles induce the same transportation costs regardless of traveling in a platoon or not.

Fixed costs, on the other hand, are varied within the experiments. Since the fixed cost of an MV also includes hiring a driver, we investigate different fixed cost ratios between the two vehicle types. We define the fixed cost ratio $FCR = k_{\gamma i}/l_{\gamma i}$ by dividing the fixed cost of one MV ($k_{\gamma i}$) by the fixed cost of one AV ($l_{\gamma i}$). We subsequently increase the fixed cost ratio from $FCR = 1.0$ to $FCR = 2.0$ by increasing the MV fixed cost. The fleet size is not restricted within these experiments.

We consider 3 heterogeneous infrastructure settings as well as the conventional MV only setting, 2 demand patterns, 5 demand allocations, and 11 fixed cost ratios, amounting to a total number of 440 instances. Each instance contains over 4,000,000 variables and over 4,000,000 constraints. Due to Constraints (5) which relate to the number of MV arcs, the total number of constraints varies depending on the heterogeneous infrastructure.

4.2. Results

All experiments are conducted on a 32-core machine with 2.00 GHz Intel Xeon X7550 CPUs using the commercial solver CPLEX 12.8 (IBM, 2018) with Concert Technology for C++. Each run terminates if (a) a solution within the 1% optimality gap is found, or (b) the imposed CPU time limit of 400,000 s is reached. Our experiments reveal that instances of our SND problem with a mixed autonomous fleet are computationally challenging. In particular, these instances required on average more than 8 times the computing time than the MV only instances. 3% of all mixed-fleet instances reach the time limit with a maximum remaining gap of 5%. However, all MV only instances, which we use as a benchmark representing the conventional SND problem, were solved within 1% to optimality. We therefore underestimate the potential of considering AVs compared to the MV only problem setting. Please note that we report the mean values over all 5 demand allocations throughout this section.

4.2.1. Cost sensitivity

We first assess the impact of considering AVs in a heterogeneous infrastructure on the overall costs. As a benchmark, we use the MV only setting in which we prohibit the use of AVs but still increase the *FCR*. In Fig. 4, we report the average cost savings achieved by the three infrastructure settings compared to the MV only setting with the specific fixed cost ratios. Since the three infrastructure settings react differently depending on the demand pattern, we separately depict NDD in Fig. 4a and SDD in Fig. 4b.

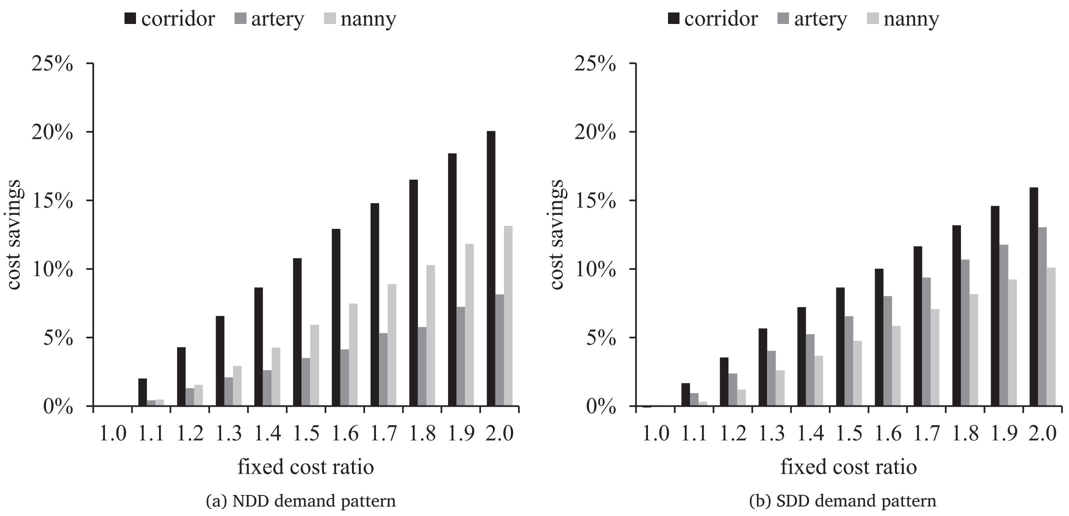
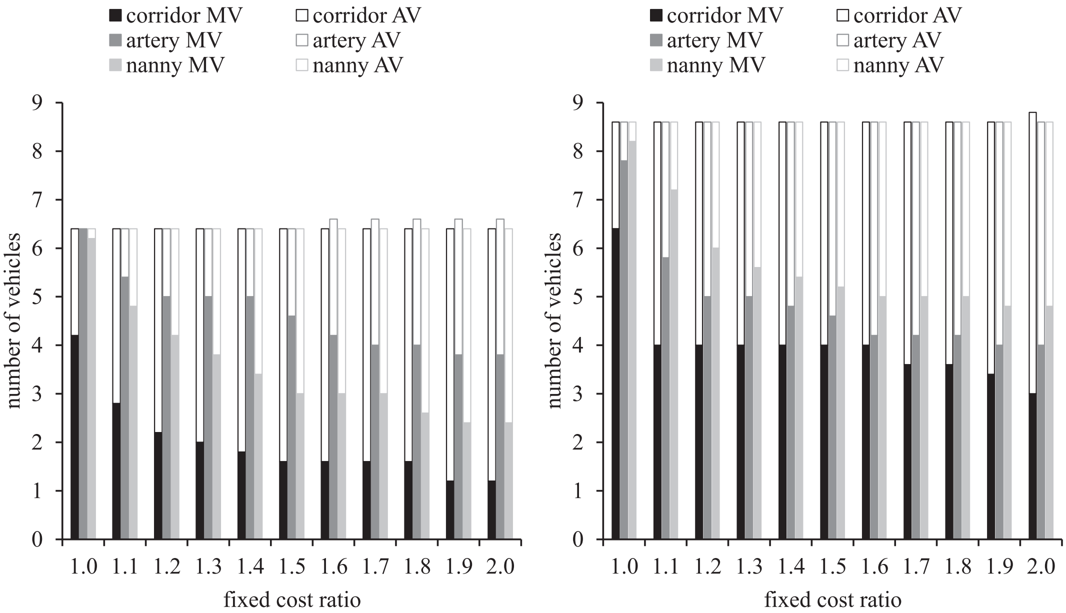


Fig. 4. Cost savings of different infrastructure compared to MV only setting.



(a) NDD demand pattern

(b) SDD demand pattern

Fig. 5. Number of MVs and total vehicles for different infrastructure and fixed cost ratios.

We note that average cost savings are obtained in every heterogeneous infrastructure setting, although it is not surprising that the overall costs rise for all settings by increasing the MV fixed costs. In all settings, we observe that cost savings monotonically grow by increasing the *FCR*. We also note that this growth of cost savings is in tendency higher for the NDD demand pattern than the SDD demand pattern. From this, we can infer that the larger the *FCR*, the more savings are obtained by substituting AVs for MVs. Later in Section 4.2.2, we investigate this concern in detail by investigating the fleet size and mix.

We observe that major cost savings are obtained for the corridor infrastructure. This is not surprising due to a large coverage of AV arcs in the network, including direct access to the external zone. Interestingly, the artery infrastructure leads to more cost savings than the nanny infrastructure for the SDD demand pattern, while the opposite occurs for the NDD demand pattern. Also, overall larger savings can be achieved in SDD than in NDD for the artery infrastructure, in contrast to the other two infrastructure settings. One reason for this is because the artery enables AVs to return to the external zone independently. This is beneficial for the SDD demand pattern in which goods arrive with shorter lead times demanding for more frequent returns to the external zone. The nanny infrastructure, on the other hand, is not as sensitive to different demand patterns, although larger cost savings are achieved for the NDD demand pattern.

4.2.2. Fleet size and mix

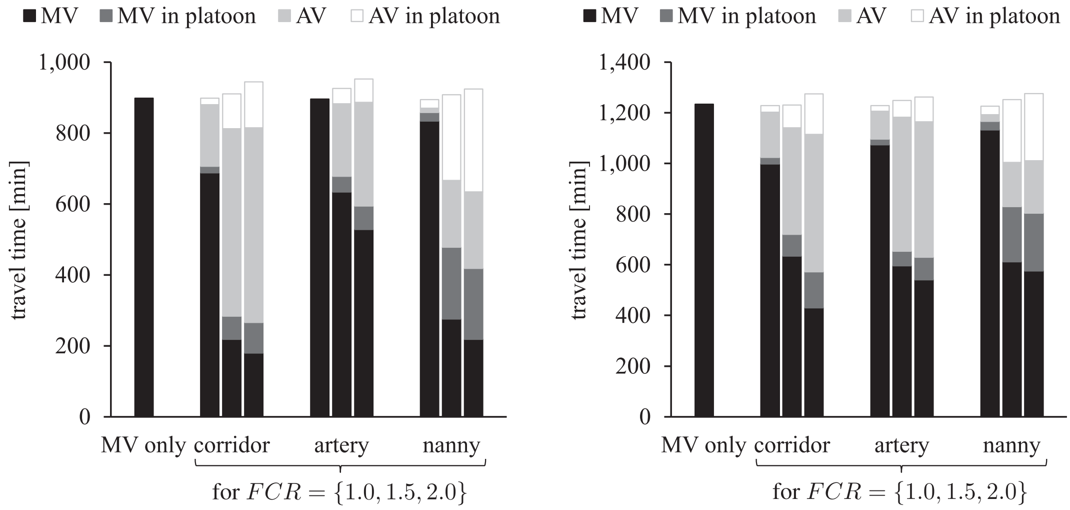
Now, we investigate the reasons behind the cost savings provided by the use of mixed autonomous fleets. To this end, we analyze the impact of the *FCR* on the number of MVs and AVs composing the mixed fleet. For $FCR = 1.0$, the model can have multiple solutions with equal quality because MVs and AVs do not differ in terms of fixed cost. Therefore, the particular infrastructure prescribes whether MVs have an advantage over AVs which cannot move freely within the network. For larger values of *FCR*, we encourage the substitution of MVs by AVs when designing the service network.

Fig. 5 displays the average number of MVs and AVs utilized for different infrastructure. Fig. 5a and b shows the results for the NDD and SDD demand pattern, respectively. In each graph, the total number of vehicles is depicted over the *FCR*. Each bar of the graph consists of two colors; one for the number of MVs and one for the number of AVs.

Over all infrastructure settings, the total number of vehicles, i.e., MVs and AVs taken together, stays nearly the same while varying the *FCR*. This total number is similar to the number of MVs obtained in the MV only setting which is not depicted in this figure. We observe that instances related to the SDD demand pattern require around a third more total vehicles than the ones related to the NDD demand pattern. As expected, by increasing the *FCR* a smaller number of MVs is chosen in all infrastructure settings which is substituted by a larger number of AVs. In general, cost savings are not caused by reducing the total number of vehicles, but the number of MVs when they are associated with large fixed costs.

Observing the results for the NDD demand pattern, we note that the smallest number of MVs is required for the corridor infrastructure. Furthermore, only around one MV is necessary if $FCR = 2.0$. In this case, the single MV focuses on transferring AVs between the two AV zones on the corridor. In the other infrastructure settings, the number of MVs cannot be reduced to the same extent. This is because in the corridor infrastructure, AVs can deliver goods to every satellite in the physical network while AV operations are more restricted in the nanny and artery infrastructure.

The results for the SDD demand pattern show similar behavior regarding the fleet mix. However, the total number of utilized



(a) NDD demand pattern (b) SDD demand pattern

Fig. 6. Travel time by vehicle type for different infrastructure with $FCR = \{1.0, 1.5, 2.0\}$.

vehicles is generally larger compared to the NDD demand pattern. The additional vehicles to cope with the shorter delivery times in SDD are mainly MVs in the corridor and nanny infrastructure. This observation is primarily regardless of the fixed cost ratio, although in the corridor infrastructure, the fleet mix sticks to a plateau between $FCR = 1.1$ and $FCR = 1.6$. As opposed to this, in the artery infrastructure, more AVs are utilized for the SDD instances. This explains the advantage of the artery infrastructure in terms of total costs as noted earlier.

4.2.3. Infrastructure usage and platooning

We further study the impact of platooning on the coordination of the mixed autonomous fleet. To this end, we analyze the number of services on movement arcs $((i, t), (j, \bar{t})) \in A_m$ which we call "moves" in this section. Thus, a move describes a vehicle driving between two locations. Since we assume idling at an external zone or satellite takes place within dedicated areas, moves are the only operations by an LSP which have an impact on traffic. We measure this impact by reporting the total travel time consumed by performing the moves.

To analyze the use of platooning, we count the number of moves which are done within a platoon for each vehicle type. Since we only have the integers $m_{ij}^{t\bar{t}}$ and $a_{ij}^{t\bar{t}}$ available in a solution, we need to first determine whether the service takes place within a platoon. For this reason, we introduce two measures for platoon moves: $m_{ij}^{t\bar{t}P} = min\{m_{ij}^{t\bar{t}}, \lceil a_{ij}^{t\bar{t}}/n_P \rceil\}$ defining MV moves for guiding a platoon and $a_{ij}^{t\bar{t}P} = min\{a_{ij}^{t\bar{t}}, m_{ij}^{t\bar{t}} n_P\}$ defining AV moves within a platoon. These platoon moves are defined for all movement arcs $((i, t), (j, \bar{t})) \in A_m$. MV-related moves thereby only count as platoon moves if they carry at least one AV within a platoon. We assume that each platoon aims to reach its maximum capacity given by n_P. AV moves count as platoon moves if MVs provide enough capacity to carry them on the particular arc.

In Fig. 6, we report the travel time consumed in minutes by MVs and AVs for each infrastructure setting with $FCR = \{1.0, 1.5, 2.0\}$. In this graph, the first bar of each infrastructure refers to $FCR = 1.0$, the second one to $FCR = 1.5$, and the third one to $FCR = 2.0$. We analyze this range of FCR values to also observe the effect of different fleet mixes. The individual vehicles traveling in platoons are depicted separately by vehicle type. For the MV only setting, we report the travel time of MV moves necessary in a conventional SND problem without AVs. Here, we display the results for $FCR = 2.0$ only because the FCR has no relevant effect on the travel time. Fig. 6a and b shows the results for the NDD and SDD demand pattern, respectively.

We observe that substituting MVs with AVs does not lead to a major increase of the total travel time. However, around one third more moves are required for the instances related to the SDD demand pattern with respect to the ones related to the NDD demand pattern. This is expected because in the SDD demand pattern vehicles need to pick up goods at different time periods from the external zone, whereas in the NDD demand pattern, vehicles only need to return there if they do not have enough capacity to pick up all goods at the beginning of the planning horizon. With increasing FCR values, we can observe that the coordination of the fleet adapts to the changing fleet mix and the total travel time increases marginally.

While the total travel time to fulfill demand is similar in each infrastructure setting, the distribution between MVs and AVs differs between settings. We observe that the corridor infrastructure requires the smallest number of MV moves with respect to the other infrastructure settings. This is because MVs are mostly dedicated to transfer AVs from one cluster to another, whereas AVs are able to deliver goods to the respective satellites. In the artery infrastructure, a minor flexibility for moving AVs leads to a major percentage of MV moves since only MVs can deliver goods to certain satellites. Although the same is true for the nanny infrastructure, we observe in this infrastructure setting the largest percentage of travel time accounting to AV moves in platoons. This is because AVs can save travel time when moving in platoons as they thus need to move across fewer arcs of the network to reach a location.

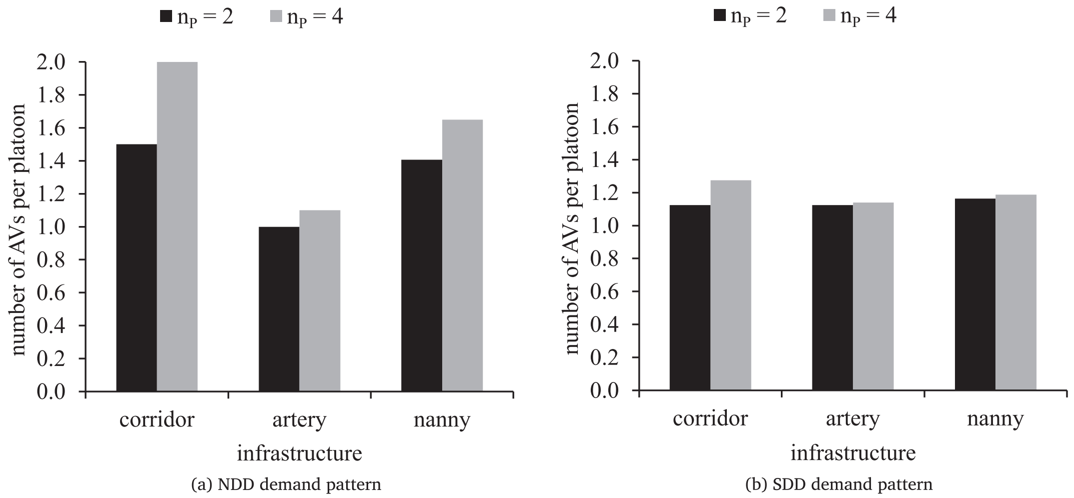


Fig. 7. Mean number of AVs per platoon for different platoon capacities n_P and infrastructure with $FCR = 2.0$.

To further investigate the coordination of the fleet, we study the moves of individual vehicles within platoons. In Fig. 7, we display the mean number of following AVs within platoons for the three infrastructure settings and the two demand patterns. This number is determined by dividing the total AV platoon moves $\sum_{((i,t),(j,\bar{t}))\in A_m} a_{ij}^{t\bar{t}P}$ by MV platoon moves $\sum_{((i,t),(j,\bar{t}))\in A_m} m_{ij}^{t\bar{t}P}$. We choose $FCR = 2.0$ because the small number of MVs induces more extensive use of platooning. There are large differences between the NDD demand pattern in Fig. 7a and the SDD demand pattern in Fig. 7b. In the corridor and nanny infrastructure, relatively more AVs are carried per MV within a platoon in the NDD demand pattern. In the SDD demand pattern, this ratio decreases in the corridor and nanny infrastructure, however, in the artery infrastructure it increases.

To examine whether the limit of maximum two following AVs in a platoon ($n_P = 2$) compromises platooning, we set the platoon capacity to $n_P = 4$ to allow for twice as many AVs per platoon. The results show that with the NDD demand pattern the MVs can utilize this additional capacity for platooning more than with the SDD demand pattern. With the NDD demand pattern, all three infrastructure settings utilize the increased platoon capacity. The corridor infrastructure induces the largest platoons but only locally on one corridor. For the SDD instances, barely more than one AV joins a platoon even for $n_P = 2$, which is why increasing the limit to $n_P = 4$ does not bring considerable advantages in the artery and nanny infrastructure. However, the corridor infrastructure benefits from the increased capacity which is due to the small number of MVs selected that can thereby carry more AVs.

5. Discussion

Our computational study validates the functionality of the proposed model to design a service network with a mixed autonomous fleet. The results provide evidence that significant cost savings can be achieved by substituting MVs with AVs in SAE level 4 while still fulfilling expected demand. This work is based on the assumption that acquiring an MV and hiring a human driver together costs much more than acquiring an AV. Based on this assumption, solutions of the SND problem show that AVs are preferably used as long as they can deliver goods to a certain satellite. Since AVs can only travel alone on specific arcs, the use of MVs is still essential to guide them to these arcs by means of platooning.

We tested our model on three carefully chosen heterogeneous infrastructure settings which differ in their number and distribution of available AV arcs. The results show that the different types of heterogeneous infrastructure as well as the number of MVs strongly impact the strategies to coordinate the fleet and to use platooning. While platooning was the only way to bring AVs to certain satellites in the corridor infrastructure, it was encouraged to reduce travel times of AVs in the nanny infrastructure. Finally, the artery infrastructure shows a case where AVs and MVs may transship goods at certain satellites for consolidation purposes. Another interesting find in this work is that the smaller the fleet of MVs, the more they exploit the capacity of platoons.

We further aim to analyze the practical implications of our study regarding the use of mixed autonomous fleets and platooning in a city logistics context. Different infrastructure settings show specific characteristics depending on the demand pattern and the configuration of the fleet. An LSP first needs to carefully evaluate the underlying infrastructure and the service requirements of its customer base before deploying a mixed autonomous fleet. Especially when offering short delivery times or same-day delivery, the location of AV zones may be crucial to enable deliveries with AVs. We further observed that the use of AVs would not increase the total network usage by the LSP's fleet considerably. This is an important aspect considering dense urban networks which are already stressed by heavy traffic. Platooning may additionally reduce the impact on the traffic network because less road space is used compared to individual vehicles.

We note that while LSPs may contribute to a significant part of traffic within a city, there are numerous other stakeholders involved. With this consideration in mind, LSPs are advised to cooperate with urban planners and traffic management. Public authorities take long-term decisions when building or modifying streets and regulating traffic. These measures influence the conditions for AV deployment and have a significant impact on the operations of LSPs. On the other hand, the operation of large mixed autonomous fleets can provide interesting insights into network usage. Urban planners can use this information from logistics and mobility fleet operators to decide about the installation of new AV zones.

Platooning in urban environments introduces additional complexity to street traffic which may prompt traffic management to take regulatory actions. Within the experiments, we consider a general limit for the number of following vehicles in a platoon. Such restrictions can also be imposed per individual street or time of the day with scattered platooning bans as a feasible option. Our results on the variation of this platoon capacity show that even punctured expansions, e.g., on corridors, can have a positive effect. Not only the LSP saves cost but also the urban environment benefits from less infrastructure usage and smaller impact on traffic. Regulations like these need to be considered to align with prevailing conditions. However, since a dominant direction regarding AV regulations is hard to predict at this point, involved players need to anticipate future developments.

Service providers in city logistics depend on public infrastructure and are not responsible for installing AV zones. However, they might choose the locations of external zones and satellites to adapt to the underlying road network with given AV zones. While installing warehousing facilities in external zones are strategic decisions with long-term effects, satellites without warehousing capabilities can be assigned with more flexibility. The LSP can choose parking spaces as satellites between the first and second tier of city logistics as part of tactical planning for a medium-term horizon. LSPs may also be advised to cooperate and distribute their profits (Wang et al., 2017a,b).

Scenarios in which only a small number of MVs is necessary raise the question whether an individual LSP can neglect MV services at all and focus on AVs only. However, without MVs, some areas cannot be reached in some heterogeneous infrastructure settings and customers cannot be served. In this case, third-party operators which offer platooning to bridge any AV through non-feasible zones may provide support. Especially smaller fleet operators or private AV owners could establish demand for platooning as a service. Furthermore, the cooperation between LSPs and mobility fleet operators by coordinating joint platoons may yield significant operational savings. Since cooperation in freight transportation nowadays usually requires some sort of shared resources, which a lot of companies shy away from, we specifically expect emerging business opportunities concerning shared platoons with owned vehicles.

6. Conclusion and future work

With this paper we introduced mixed autonomous fleets to SND problems. We specifically consider a two-tier city logistics application in which an LSP delivers goods to satellites within the city center. The two vehicle types, MVs and AVs, differ in their ability to travel on the underlying network. Since AVs are only allowed to drive within AV zones, platooning is used to guide AVs elsewhere. To model the problem, we develop a time-expanded network to introduce the notation and formulate an integer linear program. We validate functionality of the model with a computational study and discuss the results. After evaluating different heterogeneous infrastructure settings, demand patterns, and fixed cost ratios, we argue that LSPs need to take these factors into consideration before deploying a mixed autonomous fleet.

Altogether, using AVs in city logistics indicates positive effects, not only for LSPs and their customers but also for other traffic participants and the urban environment. This prospect is especially promising with increasing labor costs and driver shortages. Regulations regarding the large-scale deployment of automated driving and platooning technologies, however, are not defined conclusively at this point. Liability issues and changes of traffic rules need to be observed by logistics and mobility fleet operators in the next years. The concept we propose in this paper constitutes a first step towards differentiating between MVs and AVs not only from a technological but also a planning perspective.

As we consider an SND problem in this paper, the infrastructure is already given. For future work, the problem can be extended in several ways to incorporate network design aspects. For instance, the model may decide about installing roadside units at nodes so platooning operations can be performed. Even further, intermediate locations may be integrated for this purpose by creating additional nodes, resulting in a problem similar to Steiner tree problems. For an SND problem, the arcs on which AVs can travel alone are predetermined. By selecting these AV arcs within the model, decisions about infrastructure changes, such as installing AV lanes, may be integrated. Decisions about the infrastructure, however, are long-term and part of the strategic decision-making which is why uncertainty should be considered.

On the other hand, LSPs need to take the operability of their tactical plans into account to assure they can be implemented on an operational level. With an SND problem that considers platooning, LSPs particularly need to specify policies on how to perform platoon operations in an efficient and safe manner. Once we gain a more detailed understanding of the problem and particularly of the different vehicle types, the model should be continuously refined. In real-world applications, demand in SND problems usually follows repetitive patterns. However, even slight variations to the deterministic forecast can compromise the efficacy of an operations plan. This is why we consider the enhancement of the SND problem to manage stochastic demand and achieve robust solutions as an important direction for further research. Moreover, we learned that integrating mixed autonomous fleets adds complexity to the conventional SND problem. Developing or adapting a solution method requires further efforts to reduce computational runtimes and solve larger instances of the problem.

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Appendix A. Alternative model formulation for MVs with fixed external zone assignment

An LSP may want to consider additional assumptions or enforce particular policies that require enhanced control over the individual vehicles of the fleet. In this section, we present an alternative model formulation which particularly enforces each MV to return to the same external zone it departs from. For this alternative model formulation, we modify the generic model described in Section 3. To control individual MVs, we need to introduce an index $r \in R$ which is assigned to each individual MV. As a result, variables $m_{ijr}^{t\bar{t}}$ determine whether an individual MV performs a service and therefore only need to be binary as defined in (A.8). Since we have to set a magnitude $\|R\|$, set R restricts the fleet size similar to constraints (9). The model can be modified analogously with an index for each individual AV to consider the same assumption for AVs. The alternative model reads as follows:

$$\min \sum_{((i,t),(j,\bar{t}))\in A} \left[\sum_{r\in R} k_{ij} m_{ijr}^{t\bar{t}} + l_{ij} a_{ij}^{t\bar{t}} + \sum_{d\in D} c_{ij}^{d} x_{ij}^{dt\bar{t}}\right] \tag{A.1}$$

s. t.

$$\sum_{((j,\bar{t}),(i,t))\in A} x_{ji}^{d\bar{t}t} - \sum_{((i,t),(j,\bar{t}))\in A} x_{ij}^{dt\bar{t}} = \begin{cases} v(d), & (i,t) = e(d), \\ -v(d), & (i,t) = s(d), \\ 0, & (i,t) \neq e(d), s(d), \end{cases} \quad \forall\, d \in D,\ (i,t) \in N \tag{A.2}$$

$$\sum_{d\in D} x_{ij}^{dt\bar{t}} \leqslant u_E, \quad \forall\, ((i,t),(j,\bar{t})) \in A_h \tag{A.3}$$

$$\sum_{d\in D} x_{ij}^{dt\bar{t}} \leqslant \sum_{r\in R} m_{ijr}^{t\bar{t}} u_M + a_{ij}^{t\bar{t}} u_A, \quad \forall\, ((i,t),(j,\bar{t})) \in A\backslash A_h \tag{A.4}$$

$$a_{ij}^{t\bar{t}} \leqslant n_P \sum_{r\in R} m_{ijr}^{t\bar{t}}, \quad \forall\, ((i,t),(j,\bar{t})) \in A\colon (i,j) \in A_M \tag{A.5}$$

$$\sum_{((j,\bar{t}),(i,t))\in A} m_{jir}^{\bar{t}t} = \sum_{((i,t),(j,\bar{t}))\in A} m_{ijr}^{t\bar{t}}, \quad \forall\, (i,t) \in N,\ r \in R \tag{A.6}$$

$$\sum_{((j,\bar{t}),(i,t))\in A} a_{ji}^{\bar{t}t} = \sum_{((i,t),(j,\bar{t}))\in A} a_{ij}^{t\bar{t}}, \quad \forall\, (i,t) \in N \tag{A.7}$$

$$m_{ijr}^{t\bar{t}} \in \{0,1\}, \quad \forall\, ((i,t),(j,\bar{t})) \in A,\ r \in R \tag{A.8}$$

$$a_{ij}^{t\bar{t}},\ x_{ij}^{dt\bar{t}} \in \mathbb{N}, \quad \forall\, d \in D,\ ((i,t),(j,\bar{t})) \in A \tag{A.9}$$

The objective function (A.1) minimizes overall costs. Transportation costs k_{ij} are assigned to MV services $m_{ijr}^{t\bar{t}}$ and l_{ij} to AV services $a_{ij}^{t\bar{t}}$. On the auxiliary arcs transportation costs correspond to fixed costs $k_{\gamma i}$ for MVs and $l_{\gamma i}$ for AVs. Transporting a flow of goods $x_{ij}^{dt\bar{t}}$ on a service induces costs c_{ij}^{d}. Constraints (A.2) ensure the flow balance of goods. Constraints (A.3) are applied to holding arcs and limit the storage capacity of each external zone to u_E. Transportation capacity of vehicles is satisfied on all arcs except for holding arcs due to constraints (A.4). MVs and AVs feature an available capacity u_M and u_A, respectively.

Platooning constraints (A.5) are applied to all movement arcs of the time-expanded network based on MV arcs of the physical network. On such arcs, an MV service $m_{ijr}^{t\bar{t}}$ provides a capacity n_P for a number of AVs to follow. Design-balance constraints balance the inflow and outflow of services in any node and are applied to MVs (A.6) and AVs (A.7), respectively. The constraints also apply to auxiliary arcs between the last and first time period of the planning horizon to assure the same number of vehicles per type in each external zone at the beginning and end of the planning horizon. To ensure that each MV returns to the same external zone it departs from, we apply the design-balance constraints (A.6) to each MV. In all other constraints in the model, the sum over all MVs is considered.

Appendix B. Computational results for multiple external zones

In this section, we conduct a small computational study on the impact of multiple external zones. For this reason, we modify the instances described in Section 4.1 to include an additional external zone which is connected to the right cluster of satellites. Fig. B.8 shows the physical network with corridor infrastructure which we use for the experiments. We further use the same parameter setting as in the computational study in Section 4 and set $FCR = 1.5$. However, we modify both the 5 NDD and SDD demand allocations in a way that each satellite receives one delivery of goods originating from each external zone.

In Table B.3, we report the CPU time in seconds it takes CPLEX to solve the, in total, 10 demand allocations with a 1% optimality gap in columns “1% gap”. For instances that reach the runtime limit of 400,000 s, we report the remaining gap in %. Column “EZ 1” lists the results for the network with one external zone and “EZ 2” for the network with two external zones. The last column “fixed EZ

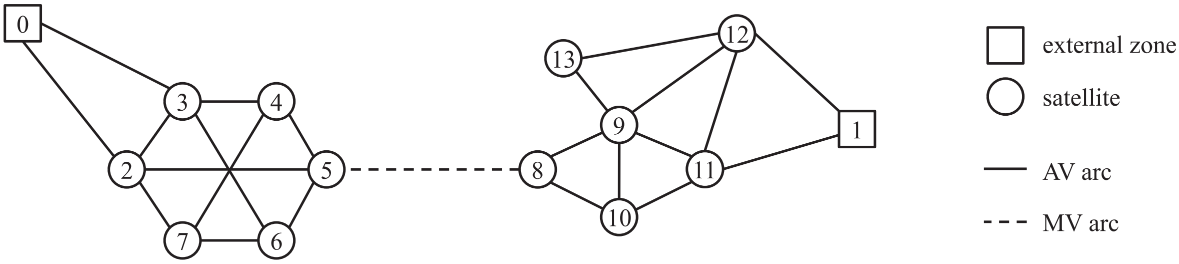

Fig. B.8. Physical network with corridor infrastructure for instance with additional external zone.

Table B.3
Runtime (s) or gap (%, after 400,000 s runtime limit) for multiple external zones.

Demand	EZ 1	EZ 2			Fixed EZ 2		
	1% gap	1% gap	Best primal	5% gap	1% gap	Best primal	5% gap
ndd_0	9,806 s	39,906 s	36,751 s	36,751 s	1.28%	241,658 s	185,865 s
ndd_1	61,406 s	4.21%	392,048 s	392,048 s	5.23%	301,291 s	5.23%
ndd_2	15,982 s	37,260 s	37,260 s	25,755 s	121,326 s	82,013 s	52,283 s
ndd_3	101,020 s	2.46%	59,284 s	59,284 s	3.93%	70,542 s	235,461 s
ndd_4	20,087 s	367,524 s	254,721 s	56,911 s	2.68%	374,602 s	82,265 s
sdd_0	675 s	1,707 s	1,707 s	1,707 s	10,279 s	10,279 s	7,556 s
sdd_1	15,596 s	125,168 s	2,969 s	5,431 s	2.82%	59,096 s	33,684 s
sdd_2	2,761 s	2,668 s	2,668 s	1,400 s	8,165 s	8,165 s	7,105 s
sdd_3	1,302 s	29,105 s	4,073 s	5,535 s	1.51%	6,797 s	19,517 s
sdd_4	1,803 s	5,092 s	1,091 s	5,092 s	7,767 s	4,684 s	2,228 s

2" displays the runtimes for the "EZ 2" network but the alternative model formulation we describe in Appendix A is applied. This model enforces each MV to return to the same external zone it departs from. We observe that the complexity generally increases for the larger instance. Moreover, the alternative model for MVs with fixed external zone assignment also leads to longer runtimes. We further analyze in columns "best primal" the time at which CPLEX found the best primal solution it ended up with. For a lot of the instances, this solution is found relatively early. In columns "5% gap", we additionally list the time at which the solver first reports an optimality gap smaller than 5%. In general, we can conclude that the solver obtains solutions of reasonable quality for all of the evaluated instances within the runtime limit.

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