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Parcel delivery systems for city logistics: a cost-based comparison between different transportation technologies

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ABSTRACT

Handling increasing volumes of parcel shipments in urban areas is one of the major challenges in city logistics. As the currently used conventional delivery by diesel vans is increasingly regarded critically by the public, alternative delivery concepts with cargo bikes, drones and robots have emerged in recent years. However, research studies that evaluate the benefits of such novel distribution systems usually investigate only one of them at a time. The contribution of this paper is to evaluate and compare the use of these alternative delivery options to identify efficient delivery systems for urban areas. To this end, a cost-oriented optimization model is presented in which, based on a two-echelon delivery system, parcel shipments are transported by comparably large vans from a depot outside of a city into the urban area to be distributed there by smaller vehicle types like cargo bikes or autonomous robots or drones. Thereby, the model enables both the integration of the first echelon vehicles into the final delivery, the transfer of parcels and smaller delivery vehicles within the urban area, the use of heterogeneous vehicles and the possibility to pickup further parcels during a tour. Computational studies are conducted for a real world city area to identify the benefits of using cargo bikes, robots, and drones in isolation or in combination under different parameter constellations such as population density of city segments, labor cost rates of the second echelon vehicles, and capacities of autonomous robots.

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KEYWORDS: City Logistics · Combined Delivery · Optimization Model · Cargo Bikes · Delivery Robots · Delivery Drones

1. INTRODUCTION

In 2020, an increase in shipment volumes of over 10 percent was observed in Germany [1]. By this, a volume of over 4 billion shipments per year has been reached for the first time, of which around 85 percent was generated by the parcel market. Driven by a continuing trend towards e-commerce, further increases might be expected for the coming years. Especially in urban areas, this development poses an enormous challenge for parcel service providers. Currently, over 77 percent of the population in Germany lives in cities [2]. Cities are therefore the place in which most deliveries have to be made. Next to a high population density, urban areas often have a historically grown infrastructure that cannot cope with today’s traffic load, resulting in congestion, noise and pollution. Attempts to reduce traffic volumes through consolidation, for example, have failed so far for a variety of reasons, as they require an institutional structure that can accommodate all of the stakeholders [3]. Parcel service providers face corresponding challenges in terms of access restrictions or non-existent loading zones. Deliverers may then be forced to stop in non-parking zones or on traffic lanes, or reach their customers only by quite long walking distances [4]. This is in contrast to the expectation of customers who still request a cheap, fast and reliable delivery. Last but not least, environmental and social impacts of urban transportation gain increasing public attention, where modern city logistics should not only be efficient but also cause as little negative externalities as possible [5]. These requirements can hardly be met by the currently used, widespread conventional delivery by diesel vans. Particularly in times of rising energy cost and under the call for carbon-neutral logistics, it is becoming more and more evident that this type of distribution is no viable option for the future. To counteract these challenges, alternative delivery concepts are being developed, tested, and implemented. In Germany, for example, a wide network of parcel lockers has already been established [6], distributing the delivery effort between the parcel service providers and the final customers. These facilities allow individual deliveries to be bundled at one place, which saves mileage and time for service providers [7]. However, even though parcel lockers are becoming more popular, both customer acceptance and the resulting savings for the parcel delivery company strongly depend on the availability and location of the lockers [8]. In addition, the majority of customers still want to be served by a direct delivery at home [9]. In areas with access restrictions or narrow streets, a suitable solution could be the use of cargo bikes, as they require only little parking space and can drive right up to the customers' front doors [10]. Electrically powered or assisted, they moreover cause no local emissions and noise and have low purchase and maintenance costs. However, compared with traditional vans, they only have limited capacity, and here again, the poorly developed infrastructure for replenishing cargo bikes might constitute a barrier [11, 12]. Even more innovative ideas include deliveries by autonomous drones or delivery robots. As no driver is required, they could turn out as a particularly cost-effective alternative. They also have the advantage of being independent of transport infrastructure, as drones are able to fly over ground-based traffic and robots use footpaths to get to their customers. However, the legal restrictions for their use are still far from being fully specified. In addition, they also suffer from low capacity and range and may be vulnerable to weather conditions [13, 14].

All those delivery concepts have already been well studied, as city logistics gained increasing attention in recent decades. Nevertheless, studies so far analyze one of these options in isolation and compare them to traditional delivery only. A direct comparison of all of these technologies, carried out in an identical delivery environment, is missing so far. Thus, the aim of this paper is to propose a methodological approach to identify the operational costs of different delivery concepts in order to compare them to each other. Based on the well-known two-echelon routing problem, a generic model for heterogeneous vehicles is presented here, which takes into account the specifics of classical and innovative delivery systems. Modifications are made to allow both direct delivery by vehicles serving the first echelon and repeated pickup of parcels at transfer locations. We also consider to carry smaller autonomous vehicles on the first echelon towards transfer locations from which they serve the final customers at the second echelon. Finally, the generic formulation not only allows to compare the use of different vehicle types but also to investigate various combinations of such delivery options as we consider the simultaneous use of heterogeneous vehicles.

Our paper is organized as follows. In Section 2, we review the relevant literature on urban delivery with cargo bikes, robots and drones. We also discuss several variants of the two-echelon vehicle routing problem. In Section 3, we present a formal problem description and our mathematical model formulation. Section 4 provides a case study for the city of Hamburg, Germany, to test and compare different delivery options based on exact computational results using the IBM ILOG CPLEX Optimizer. Section 5 concludes the paper.

2. RELATED LITERATURE

Since the 1990s, research started focusing on the solution of city logistics problems and last-mile delivery [15]. So far, numerous articles have been published that investigate the use of alternative delivery concepts in this context. In recent years, autonomous technologies have been included in this to an increasing extent. For comprehensive overviews of these developments, we refer to the review of Boysen et al. [16]. There, the delivery concepts of more than 100 studies on strategic planning, staffing and fleet scheduling, routing and scheduling are analysed and structured based on the investigated storage and transportation options. Further literature reviews are provided by Mangiaracina et al. [17], which mainly deal with innovative delivery concepts that are not yet fully established (e.g. crowd logistics, drones, robots, and trunk delivery), and Bosona [13], which takes a particular perspective at sustainability and environmental friendliness in the context of urban delivery. Since our study focuses on a cost-based comparison of alternative delivery systems, in the following we mainly concentrate on articles that involve a cost objective in the corresponding logistics planning.

As they are already being used or tested in many cities, cargo bikes are probably the most common alternative to vans in urban delivery. They come in several 2-wheeled or multi-wheeled model variants with different battery capacity, range and load volumes from 0.3 to 1.8 m^3 [18]. Since this means that they only have a relatively small capacity, cargo bikes are often used in combination with small inner-city depots (so-called satellites) that are available within the delivery area. There, parcels can be stored temporarily and be picked up repeatedly by the cargo bikes for final delivery [19]. The literature, however, is not clear about whether this type of delivery is a cost-effective alternative to traditional delivery, as there are both studies in which the cargo bike can achieve lower-cost delivery was well as those that evaluate bicycle delivery as more cost-intensive. For example, in a study based on real-world data from a South Korean courier service, Lee et al. [20] find cost savings of 5.7 to 26.9 percent for different fleet size ratios of vans to bikes compared with traditional delivery by van only. Yet, this study is based on large cargo bikes, which can carry about a third of the load of a van, while many other studies only assume about one tenth of a van's capacity [21]. In a simulation of typical delivery situations in downtown Seattle, Sheth et al. [22] observe that there are cost benefits in using cargo bikes only when a depot is in close proximity to customers and there are low volumes of shipments to be delivered in a densely populated area. Cost-efficient use of the bicycle is therefore only possible under limited conditions. Tipagornwong and Figliozzi [23] even show in a case study on the delivery of groceries and office supplies that delivery by van may be more cost efficient. Their sensitivity analysis shows that labor costs are an important factor of delivery costs by cargo bike. However, satellite utilisation rates, the quality of cycling infrastructure, and the potential travel speed also influence the cost of cargo bike delivery, as is shown in the literature review of Narayanan and Antoniou [24] on the main factors influencing the use of cargo bikes.

Due to the recent technical progress, autonomous vehicles also appear to be a useful delivery system for city logistics. They include, for example, delivery robots, which are already being tested in several cities especially for food deliveries [25]. Depending on the manufacturer, such robots may be equipped with several compartments for the simultaneous transportation of a corresponding number of shipments. Due to their moderate speed, they can use sidewalks for bringing deliveries to the customers [26, 27]. Like cargo bikes, they thus replace motorised road traffic but have a comparably short range only. Therefore, they are either used in combination with satellites or they need to be brought close to customer locations by a larger vehicle. This so-called mothership delivery can reduce total emissions of a delivery system (see e.g. [27]) and improve the service level (e.g. [28–30]) compared to traditional delivery. Significant savings can also be expected in terms of costs. For example, Ostermeier et al. [31] calculate a saving of almost 70 percent if satellites are available in the delivery area and used in combination with the mothership concept. However, these savings do not only refer to operational costs but also include delay costs, as the authors refer to a delivery situation where time windows of customers have to be respected. Similar results are reported by Bakach et al. [32]. They consider a delivery system with satellites, where vans are designated to transfer goods into the urban area and robots subsequently make the final delivery. Calculations with instance sizes of up to 300 customers show that, taking time windows into account, this distribution system can even achieve savings of almost 90 percent compared with traditional delivery. If no fixed delivery slots have to be met, the savings still amount to around 75 percent, depending on customer density. While the literature presented so far refers to robots that can deliver only one parcel at a time before returning to the satellite or mothership, Sonneberg et al. [33] investigate multi-compartment robots with different compartment sizes. They find that when using robots with a larger unit capacity, the operational cost can be almost halved. The greatest relative cost saving is achieved by using two compartments instead of one.

Another type of autonomous vehicle used for city logistics is drones that deliver parcels to customers through the air. Similar to robot-based systems, satellites or motherships are always integrated into drone-based delivery systems. This is necessary because only one parcel can be delivered by a typical drone at a time such that each drone needs to replenish each time it served a customer. Although this substantially increases the total distance travelled, Ha et al. [34] and Li et al. [35] find savings in operational costs in the range of 25 respectively 28 to 43 percent when van delivery is supported by drones. Considering the total costs of a drone-based delivery system, where multiple customers can be served in one flight, Dorling et al. [36] conclude that these mainly depend on the purchase costs of the drones. Further studies focus on the environmental friendliness or the service levels achieved by drone-based delivery systems, see the recent review of Benarbia and Kyamakya [37], which also lists several projects in which drones are being tested for delivery in practice.

As can be seen, all the delivery vehicles considered so far use satellites or are carried into the delivery area by larger vehicles, typically vans. In both cases, associated modelling is often based on the well-known two-echelon vehicle routing problem [38]. First introduced by Crainic et al. in 2009 [39], many variants of this distribution system have been studied to date. For an overview, the works of Cuda et al. [40] and Sluijk et al. [41] are recommended. While research has primarily focused on considering one type of vehicles per echelon, only few articles can be found that address heterogeneous vehicle fleets. For example Crainic et al. [42] distinguish different vehicles in the types of products that can be transported simultaneously and Kancharla and Ramadurai [43] and Bevilaqua et al. [44] use vehicles of different capacities and costs. Related to city logistics, Oliveira et al. [45] propose a combination of electric vehicles, cargo bikes and walking porters for final delivery. However, they do not present a model nor do they present comparative results. In addition, they assign fixed modes of transport to customers a priori. Accordingly, the individual vehicles must be mandatorily deployed if customer allocations have been made. A cost-based evaluation of the suitability of different delivery systems cannot be derived through this approach.

This pre-assignment of customers is also found in the sparsely studied variants with direct delivery to customers by the first echelon. For example, Anderluh et al. [46] consider a distribution system in which the delivery area is divided into two separate zones. Customers must necessarily be supplied by the second echelon if they are located in an access-restricted zone, while customers living outside of such a zone are exclusively delivered by the first echelon vehicle. Anderluh et al. [47] and Oliveira et al. [45] additionally introduce a third restricted zone in the area of which service providers may opt for delivery by either the first or the second echelon. To the best of the authors' knowledge, direct delivery to all customers only arises in the remotely related vehicle routing problem with intermediate facilities, as presented by Baldacci et al. [48]. However, the satellites and the responsibility for the subsequent final delivery are owned by third-party providers there.

Regarding the transfer of parcels from the first to the second echelon, Anderluh et al. [46, 47], Kancharla and Ramadurai [43], and Oliveira et al. [45] require perfect synchronization, where both vehicles have to meet at the exact same time. In reality, however, this type of synchronization is very vulnerable to disruptions, such that delivery plans must be adjusted in case of traffic jams or other delays, where long waiting times can occur for individual vehicles. We will therefore refer to the more flexible variant of the two-echelon vehicle routing problem, where it is necessary to ensure that the first echelon vehicles unload their parcels at an earlier time than vehicles of the second echelon are loaded, but storage at satellites is possible. Due to the narrowness in cities and the associated high costs of storage capacities, small satellites with a space requirement of 2-3 parking bays are conceivable here, such as proposed by Kania et al. [49]. However, constraint space conditions may imply that not all vehicles of the second echelon can be parked at the satellites. We therefore apply the concept of mothership delivery, as described above, and thereby allow a transfer of second echelon vehicles from the depot to the urban area. Such systems are often based on the two-echelon vehicle routing problem as well, although homogeneous vehicles are assumed in the so-far existing studies. Direct delivery to customers is possible in some models when drones or robots are dropped off at customer locations served by the mothership. These customer nodes then additionally serve as satellites without storage facilities, from which the small vehicles can serve additional customers, see e.g. [31, 34, 35].

As is shown by the literature overviews of Boysen et al. [16], Mangiaracina et al. [17], Sluijk et al. [41] and Li et al. [38] and the above discussion, research so far concentrated on studies that just evaluate a single type of novel distribution technology. These studies typically benchmark the new technology against the traditional delivery by vans. What is obviously missing in this research field is a systematic, comparative evaluation of innovative distribution systems. With this paper, we contribute to closing this gap by proposing a generic optimization model that can generate distribution plans for various types of vehicles such as vans, cargo bikes, robots, and drones, either in isolation or in combination. To this end, we present a variation of the two-echelon vehicle routing model that has not yet been formulated in this combination, see comparison in Table 1 of features covered by closely related studies. Thereby, we also include those features of two-echelon city logistics systems that are required to deploy the technologies (e.g., satellites, repeated replenishment at transfer locations, transfer of robots and drones by first echelon vans) and that contribute to the reduction of the overall cost of the system (e.g., direct service of customers also by first echelon vehicles). We then conduct computational experiments to evaluate under which circumstances which of those technologies appears most suitable with respect to the minimization of delivery cost.

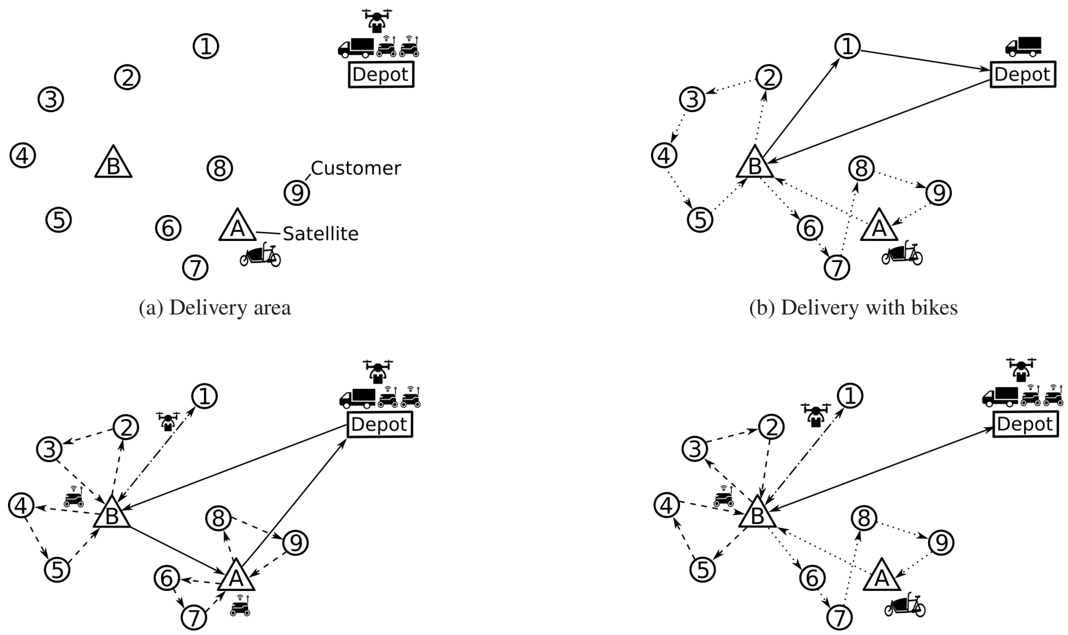
3. PROBLEM DESCRIPTION AND MODEL FORMULATION

3.1. Problem description

We consider a restricted urban area where a parcel service provider has to supply a set of customers each demanding one parcel. In order to identify the most cost-effective delivery option, various distribution systems are to be tested. The deliveries always originate from a depot on the outskirts of the city. However, as we assume, that a number of smaller transfer depots (satellites) have already been established in the delivery area, two-echelon distribution will be the main option

Table 1: Variants of two-echelon vehicle routing problems.

Reference	heterogeneous vehicles	direct delivery	storage at satellites	transfer of vehicles
Crainic et al. [42]	✓		✓	
Bevilaqua et al. [44]	✓		✓	
Kancharla and Ramadurai [43]	✓			
Oliveira et al. [45]	✓	part of customers		
Anderluh et al. [46]		part of customers		
Anderluh et al. [47]		part of customers		
Baldacci et al. [48]		all customers	✓	
Ha et al. [34]		if customers serve as satellites		✓
Li et al. [35]		if customers serve as satellites		✓
This article	✓	all customers	✓	✓



(a) Delivery area

(b) Delivery with bikes

(c) Delivery with robots and drones

(d) Combined delivery

Fig. 1: An illustrative example for various distribution options.

in addition to traditional direct delivery from the depot. In this case, the parcels are initially transferred to the satellites by larger vehicles (e.g. vans) on the fist echelon. From there, they are delivered to the customers by smaller vehicles (e.g. cargo bikes, robots or drones) on the second echelon.

In contrast to the classical two-echelon distribution system, we do not expect that all of the second echelon vehicles can be stored at the satellites. Instead, they will be divided into two groups: The *city-based vehicles*, which can be accommodated in one of the satellites, and the *depot-based vehicles*, which must be stored in the depot outside the city. Thus, we take into account, that logistic spaces in cities are often quite expensive and, therefore, of small size only. This implies that depot-vehicles must first be transferred to the city by the first echelon vehicles in advance of starting final delivery to customers. Consequently, however, depending on where they are dropped off, depot-vehicles can start their tour at any of the satellites, whereas the city-vehicles can only start their tour from the satellite they are stored at. A second difference to the classical two-echelon distribution system results from the characteristics of the second-echelon delivery vehicles. Due to their limited capacity, they can only serve a few customers before they have to return to a satellite. To mitigate this disadvantage, they should be allowed to pick up further parcels at any given satellite multiple times during their tour. Thus, depending on the location of the customer nodes, several trips can be carried out in succession by every second-echelon vehicle. Finally, in order to take into account any cost saving resulting from direct delivery (for example, if customers are located on a direct path between the depot and a satellite), the first echelon vehicles should be allowed to also conduct final delivery operations.

To illustrate the idea, an example is given in Figure 1. The basic situation shown in Figure 1a contains 9 customers (circles), that are to be supplied from one depot (rectangle). Two satellites A and B (triangles) are available as transfer locations. The first echelon supply is to be carried out by a van. For reasons of simplicity, we assume unlimited capacity for the van in this example. As one of the options for delivery on the second echelon, we consider a cargo bike with a capacity of four parcels that is initially stationed at satellite A. It is now to be decided which of the satellites are to be used for transferring parcels, which customers are to be supplied by which vehicle and which trips the individual vehicles have to make. A possible solution for this problem is depicted in Figure 1b. As only satellite B is served by the van (solid lines), the cargo bike (dotted lines) has to make an empty trip from A to B before starting its delivery of customers 2, 3, 4, and 5, but can pick up further parcels there for later serving customers 6, 7, 8 and 9 before returning to its starting point. Customer 1 cannot be included into bike-delivery in a cost-effective way because of the capacity-restriction and is therefore served by the first echelon van when returning to the depot. A quite different solution can result if delivery is to be carried out by depot-based vehicles only. For this, we assume that two robots (with a capacity of two parcels each) and a drone (with a capacity of one parcel) are available at the depot. Now, it must additionally be decided which vehicle will be dropped off at which satellite. In the possible solution shown in Figure 1c, all customers are served via the second echelon by first dropping of at satellite B one robot (serving customers 2, 3, 4, and 5 in two roundtrips) and the drone (serving customer 1). The second robot is brought to satellite A and serves customers 6, 7, 8, and 9 in two roundtrips. A possible solution for a combined delivery system with both, city-based and depot-based vehicles for the second echelon is shown in Figure 1d. Here, only satellite B is served by the first echelon van and all second echelon vehicles supply parcels from there. As before, the bike stationed in A must therefore first perform an empty trip to satellite B for picking up parcels. In this solution, however, the van can return directly to the depot, because customer 1 is served by the drone.

3.2. Model formulation

For the mathematical formulation of the considered problem, the following notation is used, which is also summarized in Table 2. Let C be the set of customers, o be the depot on the outskirt of the city, and S be the set of m satellites established in the delivery area. For modelling reasons, each of the satellites $s_r \in S$ is duplicated p times. Thus, multiple visits to the satellites can be ensured by successively visiting a satellite and its duplicates. The first $p-1$ clones of all satellites are subsumed in the set $\hat{S} = \{s_{11}, .., s_{1(p-1)}, ..., s_{m1}, .., s_{m(p-1)}\}$ and serve as transfer nodes for parcels. The set $\tilde{S} = S \cup \hat{S}$ describes all satellite nodes at which a transfer of parcels is possible. Furthermore, set $\dot{S} = \{s_{1p}, ..., s_{mp}\}$ contains all the last duplicated clones. These nodes are used only to ensure that each vehicle returns to its individual starting node and are therefore called end-of-trip clones. To carry out the delivery, we define a set of vehicles K^1 for the first echelon and K^2 for the second echelon, and a union $K = K^1 \cup K^2$. Each vehicle k out of the set of city-vehicles $K^C \subseteq K^2$ is assigned a unique satellite $s^k \in S$ representing its parking location. The depot-based vehicles in K^D do not get assigned a starting satellite ex ante as they can be dropped off by the first echelon vehicles at any of the satellites S. With this information, a directed graph can now be defined for each group of vehicles. Vehicles $k \in K^1$ can visit the depot, customers, satellites and their clones but are not supposed to visit the end-of-trip clones. The corresponding set of relevant arcs is thus specified by $A^k = (o \cup \tilde{S} \cup C) \times (o \cup \tilde{S} \cup C)$ for $k \in K^1$. It should be noted that by ensuring direct accessibility of all customers by the transporter, we are also able to reproduce the traditional delivery where there is no second echelon and the first echelon vans are responsible for completely serving all customers.

The vehicles of the second echelon must be distinguished as explained before, with the depot-vehicles being able to visit customers and transfer locations and to start and end at the satellites where they are dropped off. A city-vehicle $k \in K^C$ starts its tour at its designated satellite s^k, successively visits customers and satellite clones, and returns to the end-of-trip clone $s_p^k \in \dot{S}$ at the end of its tour. If a city-vehicle is based at a satellite that is not supplied by a first echelon vehicle, it has to make an empty trip to one of the other satellites for picking up parcels before starting delivery. Therefore, such a vehicle k can move from satellite s^k directly to a satellite clone $s \in \hat{S}$, but like the depot-based vehicles, it is not supposed to successively stop at two satellites or clones in any other case. The corresponding arc sets can then be defined as $A^k = [(s^k \cup \hat{S} \cup C) \times C] \cup [s^k \times \tilde{S}] \cup [C \times (\hat{S} \cup s_p^k)]$ for $k \in K^C$ and $A^k = [(S \cup \hat{S} \cup C) \times C] \cup [C \times (\hat{S} \cup \dot{S})]$ for $k \in K^D$. For better readability, the following notation is also introduced. $A_+^k(j) = \{i | (i, j, k) \in A^k\}$ is the set of nodes vehicle k can depart from for getting to node j, $A_-^k(i) = \{j | (i, j, k) \in A^k\}$ is the set of nodes that vehicle k can reach from node i, and sets $A_+^k = \bigcup_j \{i | (i, j, k) \in A^k\}$ and $A_-^k = \bigcup_i \{j | (i, j, k) \in A^k\}$ specify the entirety of entry and exit nodes of a vehicle, respectively. Since our intention is to investigate the use of different types of vehicles, they are considered to be heterogeneous. Therefore, a distance d_{ij}^k and a travel time t_{ij}^k are assigned to each arc (i, j) in the arc set A^k of vehicle $k \in K$. Similarly, each vehicle k gets assigned a distance-based cost rate c_d^k and a time-based cost rate c_t^k. An example of distance-based costs could be fuel and energy costs. Time-based costs can reflect wages if a driver is required for operating a vehicle. Other parameters that are given for each vehicle k are a maximum operation time T^k, which can be used, for example, to indicate the maximum working time of a driver when using cargo bikes or to specify the battery range when considering electrically powered vehicles. Likewise, the parameter w^k is defined as an individual service time for delivering or picking up a parcel at a node by vehicle k. At last, each vehicle has an individual capacity Q^k. As depot-based second echelon vehicles $k \in K^D$ need to be transferred to satellites, a capacity footprint L^k is assigned to them, which indicates their space consumption in the transfer vehicles of the first echelon. Note that despite the generic design, it is possible to assign the same parameters to the vehicles, e.g. if several bikes are of the same design.

Furthermore, we define as decision variables the binary variable $x_{ij}^k = 1$, if vehicle $k \in K$ directly travels from node $i \in A_+^k$ to node $j \in A_-^k(i)$ and continuous variables l_{ij}^k to specify the load carried by vehicle $k \in K$ on arc $(i, j) \in A^k$. The continuous variables f_s^k indicate the amount of parcels brought by vehicle $k \in K^1$ to the transfer location $s \in \tilde{S}$ and binary variables $e_s^{kv} = 1$ are used when first echelon vehicle $k \in K^1$ drops of depot-based second echelon vehicle $v \in K^D$ at satellite $s \in S$. To track the departure time of vehicle $k \in K$ at node $i \in A_+^k$, we define continuous variables a_i^k. Finally, we use binary variables $z_s = 1$ to indicate that transfer location $s \in \tilde{S}$ is used and binary variables $u_{is} = 1$ if customer $i \in C$ is served from the depot or a satellite $s \in \{o\} \cup \tilde{S}$. For simplification, we also introduce binary

Table 2: Notation used for the optimization model.

nodes and sets of nodes	
C	set of customers
o	first echelon depot
$S = \{s_1, ..., s_m\}$	satellites
$\hat{S} = \{s_{11}, .., s_{1(p-1)}, ..., s_{m1}, .., s_{m(p-1)}\}$	set of satellite clones used for transferring parcels
$\tilde{S} = S \cup \hat{S}$	all satellite locations
$\dot{S} = \{s_{1p}, .., s_{mp}\}$	subset of end-of-trip clones of satellites s_1 to s_m
$s^k \in \{s_1, .., s_m\}$	satellite $s \in S$ at which vehicle $k \in K^C$ is initially stationed
sets of vehicles	
K^1	set of first echelon vehicles
K^2	set of second echelon vehicles
$K = K^1 \cup K^2$	set of all vehicles
$K^C \subseteq K^2$	set of city-based second echelon vehicles (initially stationed at satellites)
$K^D \subseteq K^2$	set of depot-based second echelon vehicles (initially stationed in o)
parameters	
Q^k	capacity of vehicle $k \in K$
T^k	maximal operation time of vehicle $k \in K$
L^k	capacity needed for transferring vehicle $k \in K^D$ by a first echelon vehicle
d_{ij}^k	distance from node i to node j for vehicle $k \in K$
t_{ij}^k	travel time from node i to node j for vehicle $k \in K$
w^k	service time on each node for vehicle $k \in K$
c_d^k	distance-based cost rate for vehicle $k \in K$
c_t^k	time-based cost rate for vehicle $k \in K$

arc sets and node sets

$$A^k = \begin{cases} (o \cup \tilde{S} \cup C) \times (o \cup \tilde{S} \cup C) & k \in K^1 \\ [(s^k \cup \hat{S} \cup C) \times C] \;\cup\; [s^k \times \tilde{S}] \;\cup\; [C \times (\hat{S} \cup s_p^k)] & k \in K^C \\ [(S \cup \hat{S} \cup C) \times C] \;\cup\; [C \times (\hat{S} \cup \dot{S})] & k \in K^D \end{cases}$$

$A_+^k(j) = \{i | (i, j, k) \in A^k\}$ $\quad k \in K$

$A_-^k(i) = \{j | (i, j, k) \in A^k\}$ $\quad k \in K$

$A_+^k = \bigcup_j \{i | (i, j, k) \in A^k\}$ $\quad k \in K$

$A_-^k = \bigcup_i \{j | (i, j, k) \in A^k\}$ $\quad k \in K$

decision variables

x_{ij}^k = 1 if vehicle $k \in K$ travels on arc $(i, j) \in A^k$, 0 otherwise
y_i^k = 1 if vehicle $k \in K$ visits node $i \in A_+^k$, 0 otherwise
z_s = 1 if satellite location $s \in \tilde{S}$ is used, 0 otherwise
e_s^{kv} = 1 if vehicle $k \in K^1$ transfers vehicle $v \in K^2$ to satellite $s \in S$, 0 otherwise
u_{is} = 1 if customer $i \in C$ is assigned to depot or satellite location $s \in \{o\} \cup \tilde{S}$, 0 otherwise
a_i^k departure time of vehicle $k \in K$ at node $i \in A_+^k$
l_{ij}^k load carried by vehicle $k \in K$ on arc $(i, j) \in A^k$
f_s^k load transferred by vehicle $k \in K^1$ to satellite location $i \in \tilde{S}$

variables $y_i^k = \sum_{j\in A_-^k(i)} x_{ij}^k = 1$ to indicate that node i is visited by vehicle k.

Then, the formulation of the optimization model is as follows:

$$\min \sum_{k\in K} \sum_{(i,j)\in A^k} \left(c_d^k d_{ij}^k + c_t^k (t_{ij}^k + w^k)\right) x_{ij}^k \tag{1}$$

$$\begin{aligned}
\sum_{k\in K} y_i^k &= 1 && i \in C && (2)\\
\sum_{s\in\{o\}\cup\tilde{S}} u_{is} &= 1 && i \in C && (3)\\
u_{is} &\le z_s && i \in C, s \in \tilde{S} && (4)\\
\sum_{i\in C} u_{is} &\ge z_s && s \in \tilde{S} && (5)\\
z_s &\le \sum_{k\in K^\delta : s\in A_+^k} y_s^k && s \in \tilde{S}, \delta \in \{1,2\} && (6)\\
z_s &\ge y_s^k && k \in K^1 \cup K^D, s \in \tilde{S} && (7)\\
z_s &\ge y_s^k && k \in K^C, s \in \hat{S} && (8)\\
\sum_{(o,j)\in A^k} x_{oj}^k &\le 1 && k \in K^1 && (9)\\
\sum_{(i,j)\in A^k} x_{ij}^k &= \sum_{(j,i)\in A^k} x_{ji}^k && k \in K^1, j \in A_+^k \cap A_-^k && (10)\\
\sum_{(s^k,j)\in A^k} x_{s^k j}^k &\le 1 && k \in K^C && (11)\\
\sum_{s\in S\cap A_+^k} y_s^k &\le 1 && k \in K^D && (12)\\
\sum_{(s^k,j)\in A^k} x_{s^k j}^k &= \sum_{(j,s_p^k)\in A^k} x_{j s_p^k}^k && k \in K^2 && (13)\\
\sum_{(i,j)\in A^k} x_{ij}^k &= \sum_{(j,i)\in A^k} x_{ji}^k && k \in K^2, j \in A_+^k \cap A_-^k && (14)\\
1 - u_{is} &\ge y_i^k - y_s^k && i \in C, k \in K, s \in (\{o\}\cup\tilde{S}) \cap A_+^k && (15)\\
\sum_{(i,j)\in A^k} x_{ij}^k &= y_i^k && k \in K, i \in A_+^k && (16)\\
f_s^k &\le Q^k y_s^k && k \in K^1, s \in \tilde{S} && (17)\\
\sum_{k\in K^1} f_s^k &= \sum_{i\in C} u_{is} && s \in \tilde{S} && (18)\\
\sum_{(j,s)\in A^k} l_{js}^k - \sum_{(s,j)\in A^k} l_{sj}^k &= f_s^k && k \in K^1, s \in \tilde{S} && (19)\\
\sum_{(o,j)\in A^k} l_{oj}^k + \sum_{v\in K^D} L^v \cdot \sum_{s\in S} e_s^{kv} &\le Q^k && k \in K^1 && (20)\\
\sum_{(j,o)\in A^k} l_{jo}^k &= 0 && k \in K^1 && (21)\\
\sum_{(j,i)\in A^k} l_{ji}^k - \sum_{(i,j)\in A^k} l_{ij}^k &= y_i^k && k \in K, i \in C && (22)\\
\sum_{k\in K^2} \sum_{(s,j)\in A^k} l_{sj}^k &= \sum_{i\in C} u_{is} && s \in \tilde{S} && (23)
\end{aligned}$$

$$\sum_{(j,s)\in A^k} l_{js}^k = 0 \qquad k \in K^2, s \in \hat{S} \cup \dot{S} \tag{24}$$

$$l_{ij}^k \le Q^k x_{ij}^k \qquad k \in K, (i,j) \in A^k \tag{25}$$

$$e_s^{kv} \ge y_s^k + y_s^v - 1 \qquad k \in K^1, v \in K^D, s \in S \tag{26}$$

$$2e_s^{kv} \le y_s^k + y_s^v \qquad k \in K^1, v \in K^D, s \in S \tag{27}$$

$$a_o^k = 0 \qquad k \in K^1 \tag{28}$$

$$a_j^k \ge a_i^k + (t_{ij}^k + w^k)x_{ij}^k - T^k(1 - x_{ij}^k) \qquad k \in K^1, (i,j) \in A^k : j \ne o \tag{29}$$

$$a_j^k \ge a_i^k + (t_{ij}^k + w^k)x_{ij}^k - T^k(1 - x_{ij}^k) \qquad k \in K^2, (i,j) \in A^k \tag{30}$$

$$a_s^v \ge a_s^k + w^k - max(T^k, T^v)(2 - y_s^k - y_s^v) \qquad k \in K^1, v \in K^2, s \in (A_+^v \cap \tilde{S}) \tag{31}$$

$$a_i^k \ge a_s^k - T^k(2 - u_{is} - y_s^k) \qquad k \in K^1, i \in C, s \in o \cup \tilde{S} \tag{32}$$

$$a_i^k \ge a_s^k - T^k(2 - u_{is} - y_s^k) \qquad k \in K^2, i \in C, s \in (A_+^k \cap \tilde{S}) \tag{33}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall k \in K, (i,j) \in A^k \tag{34}$$

$$y_i^k \in \{0,1\} \qquad \forall k \in K, i \in A_+^k \tag{35}$$

$$z_s \in \{0,1\} \qquad \forall s \in \tilde{S} \tag{36}$$

$$e_s^{kv} \in \{0,1\} \qquad \forall k \in K^1, v \in K^D, s \in S \tag{37}$$

$$u_{is} \in \{0,1\} \qquad \forall i \in C, s \in \{o\} \cup \tilde{S} \tag{38}$$

$$a_i^k \in \mathbb{R}_+ \qquad \forall k \in K, i \in A_+^k \tag{39}$$

$$l_{ij}^k \in \mathbb{R}_+ \qquad \forall k \in K, (i,j) \in A^k \tag{40}$$

$$f_s^k \in \mathbb{R}_+ \qquad \forall k \in K^1, s \in \tilde{S} \tag{41}$$

Objective function (1) minimizes the total operational cost, which consists of the sum of distance- and time-based costs of all vehicles. Constraints (2)-(5) concern the allocation of customer demands to the individual satellite locations and regulate their opening. As split delivery is not an option for parcel distribution, Constraints (2) specify that each customer is served exactly once. The corresponding demand for this customer can be supplied either directly from the depot or via exactly one transfer location, which is determined by Constraints (3). According to Constraints (4) and (5), a satellite or clone is opened only if it is used for a delivery.

Constraints (6)-(16) are used for the vehicle routing. Constraints (6) specify that as soon as a satellite is used, both a vehicle from the first echelon ($\delta = 1$) and at least one from the second echelon ($\delta = 2$) must move to it. In turn, Constraints (7) prohibit the visit of first echelon vehicles and depot-based vehicles if a satellite is not used at all. Constraints (8) formulate this restriction for city-based vehicles. Note that these conditions are defined only for the satellite clones as a city-based vehicle must be allowed to launch from its own starting satellite s^k even if it is not used for a transfer of parcels. Constraints (9) and (10) ensure the connectivity of the first echelon routes by ensuring that each vehicle may only depart at most once from the depot and must subsequently leave each of the visited nodes. Similarly, city-based vehicles may only leave their starting satellite once and depot-based vehicles may only depart from one of the satellites, as is stated in Constraints (11) and (12). Like Constraints (9) and (10) for first echelon vehicles, Constraints (13) and (14) ensure the connectivity of the routes of second echelon vehicles by stating that each vehicle must end its tour at the end-of-tour clone associated with its individual starting satellite and in between must leave each visited node once. Constraints (15) ensure that a customer and the satellite location to which its parcel was transferred are visited by the same vehicle. Constraints (16) define the relation of the x- and y-variables.

The conditions that affect the vehicle load are specified in Constraints (17) to (27). Constraints (17) and (18) state, that the cargo delivered by a vehicle of the first echelon to a satellite location cannot exceed its capacity but corresponds exactly to the demand to be transferred there. The load of the first echelon vehicles is further regulated in the following constraints. Constraints (19) calculate the load when visiting satellite location s, (20) ensure that the transferred second echelon vehicles are included in the capacity when leaving the depot, and (21) guarantee that the van is empty when returning to the depot. Constraints (22) calculate the load for the first and second echelon vehicles at the customer nodes. Regulating the load of the second echelon vehicles, Constraints (23) determine that their load at the satellite locations is equal to the allocated demand, and (24) ensures that they arrive empty at each satellite clone and the end-of-trip clone. Constraints (25) specify that the maximum capacity of all vehicles must not be exceeded on any arc. Constraints (26) and (27) guarantee that a transfer of a second echelon vehicle only takes place if and only if both, a first echelon vehicle and a depot-based vehicle leave the same satellite.

The last section of the model concerns the departure times of all vehicles, where Constraints (28) specify that the vehicles of the first echelon start their tour at time 0. Constraints (29) and (30) calculate the departure times at all nodes visited by the vehicles of the first and second echelon, respectively. Constraints (31) ensure that in the case of a transfer of parcels, they have already been unloaded by a first echelon vehicle before the vehicles of the second echelon start their delivery from there. Constraints (32) and (33) enforce that a vehicle first visits the depot or transfer location to which a customer has been assigned before going to this customer. Constraints (34) to (41) define the domains of the decision variables.

4. COMPUTATIONAL EXPERIMENTS

In this section, we conduct computational experiments to evaluate the benefits of the diverse novel transport technologies in isolation and in comparison with each other. We do this by considering various vehicle scenarios for the distribution of parcels in the city of Hamburg, Germany. The next subsection describes the input data used in the experiments, followed by the presentation and analysis of the computational results.

4.1. Input data

In order to get a realistic comparison of different distribution systems, we consider nine adjacent map segments of the city of Hamburg, each of a size of 1x1km. The segments are referred to as S1 to S9 and shown in Figure 2. To build the instances, we derive for each segment the location of residential buildings via OSMnx 1.2.0 [50]. Assuming that each residential

Fig. 2: Considered map segments of city of Hamburg.

Table 3: Number of customers per segment.

density	segments	demand 1 %	demand 2 %	demand 3 %
low	S3, S6	4	8	12
medium	S2, S4, S5, S8, S9	7	14	21
high	S1, S7	10	20	30

Table 4: Vehicle scenarios and parameters.

			vehicle scenarios								parameters					
echelon	vehicles	parking space	V	B	R	D	BR	BD	RD	BRD	c_d^k (ct/km)	c_t^k (€/h)	Q^k	T^k (h)	w^k (min)	L^k
1st	van	depot	1	1	1	1	1	1	1	1	24	30	100	6	4.1	-
2nd	bike	city	0	1	0	0	1	1	0	1	0.5	25	10	6	2.5	-
2nd	robot	depot	0	0	5	0	5	0	5	5	1	-	2	2	2.05	2
2nd	drone	depot	0	0	0	10	0	10	10	10	2	-	1	0.5	1	1

building corresponds to a potential demand unit, we use this information to identify two segments (S3 and S6) as having low population density, five segments (S2, S4, S5, S8 and S9) of medium population density, and two segments (S1 and S7) of high population density. For each of these segments, we draw demands that correspond to approximately 1, 2 and 3 percent of the population reflecting varying daily loads. This results in 27 different combinations of a map segment and demand rate, the smallest ones with only 4 customers (low density segments with 1 percent demand), and up to a size of 30 customers (high density segments with 3 percent demand) as shown in Table 3. For each of them, 10 instances were generated by randomly drawing customer nodes from the residential addresses and locating two satellites within the segment. This leads to a total of 270 test instances, 30 for each of the map segments. For all instances, the depot is located about 19 km further south in an outskirt of Hamburg. We are aware that some of these instances are rather small but, due to the fact that this paper solves the optimization model by the MIP solver CPLEX, too large instances cannot be considered in the subsequent experiments. By relying on a real environment with corresponding infrastructure data, the present experiments nevertheless seem viable in order to compare the different technologies in reality and to draw initial conclusions regarding their suitability. We also conduct a broad range of sensitivity analysis to investigate the role of various kinds of parameters.

To each of the instances, we apply eight different vehicle scenarios that are specified in Table 4. They generally consist of one van serving the first echelon and diverse combinations of vehicles at the second echelon. Vehicle scenario ’V’ corresponds to traditional delivery with the van only and is used as a reference for the other delivery systems. Here, no vehicles are used on the second echelon meaning that all customers are served in direct delivery by the first echelon van. Three scenarios consider delivery with only one second echelon delivery vehicle type each. In vehicle scenario ’B’, a cargo bike is used for this purpose, scenario ’R’ provides five autonomous robots for this purpose, and in scenario ’D’ ten drones are available to serve the customers. The remaining four scenarios correspond to combinations of these individual delivery systems. Here, one bike and five robots (scenario ’BR’), one bike and ten drones (scenario ’BD’), five robots and ten drones (’RD’) and a combination of one bicycle, five robots and ten drones (’BRD’) are considered. A randomly chosen satellite in the inner-city was assumed as the parking space for the cargo bike, while all robots and drones are considered to be stored in the depot and brought to the delivery areas using the first echelon van.

The parameters used for the vehicle types are given in Table 4. Costs for the operational use of the vehicles are defined by distance-based cost rates c_d^k that reflect the fuel or energy consumption, whereas time-based cost rates c_t^k relate to the wages of the drivers. For the van, we assume a fuel consumption of 12 liters of diesel at a price of 2 €/liter. The vehicles of the second echelon are considered to be electrically powered. Their consumption rates are taken from the literature and set to 12 Wh/km for a cargo bike [24] and 24.7 Wh/km for a robot [27]. Since the energy consumption of drones differs enormously among various references, an average consumption of 50 Wh/km is chosen for the experiments [51]. The cost of one kWh of electricity is assumed to be 0.4 €. The labor cost per hour correspond to approximate gross wages for parcel and mail carriers according to a salary platform [52] and are adjusted using a personnel cost calculator [53]. Since robots and drones do not require drivers, no time-dependent costs are assumed for them for now. The remaining parameters are also taken from the literature. For example, the capacity T^k of a van is set to 100 parcels as suggested by Llorca and Moeckel [54] and to 10 parcels for cargo bikes as suggested by Arnold et al. [55]. Robots are assumed to be multi-compartment vehicles with a capacity of two parcels [26, 33]. As usual, drones are given a capacity of one parcel [56]. As a daily working time for bike and van operators, Arnold et al. [55] consider 2 hours for preparatory work and 6 hours for actual delivery work. Following this, we consider a maximum daily operation time of $T^k = 6$ hours for vans and bikes. Robots show a maximum travel time of 2 hours, which is half the operation time that a ZMP robot achieves under most favorable conditions [26]. For the drones, a value of 0.5 hours of operation time is assumed [51]. The service times w^k required at each node for pickup or delivery of a parcel are taken from Allen et al. [57] for vans, from Arnold et al. [55] for bikes, and from Chen et al. [30] and Murray and Raj [56] for robots and drones, respectively. The capacity footprint L^k for robots and drones is set to 2 and 1, reflecting their own capacity values. Assuming that these vehicles can already be loaded with parcels at the depot, they thus take up only little extra space in

Fig. 3: Infrastructure being available for different types of vehicles in map segment S5.

the van. As the first-echelon van has comparably high capacity for the instances under investigation, there is enough space to carry all autonomous vehicles, even if they take up slightly more room than the parcels themselves. Since the test instances are based on real world map segments, the underlying routing data takes into account real distances and travel times according to the individual traffic infrastructure that each vehicle can use. This information has been derived from OpenStreetMap [58] using the corresponding routing profiles for vans and bikes. For robots, the pedestrian profile is assumed to be suitable because the speed used there is just slightly below the maximum of the manufacturers' specifications for this vehicle type [26]. For the drones, geodetic distances have been calculated and an average speed of 43 km/h is assumed [56]. Figure 3 illustrates the infrastructure networks being available for the different types of vehicles at the example of segment S5.

For the computational experiments, the optimization model has been implemented in Python 3.7 and is solved on a CPU i7 with 4 x 2.5 GHZ and 32 GB RAM by using the Python API of CPLEX version 12.10.0. The runtime has been limited to 90 minutes per instance. If this time limit has been reached, the best integer feasible solution found so far was taken for the analysis of the results.

4.2. Computational results

In a first experiment, we analyze the solutions obtained for all map segments under each of the vehicle scenarios. Table 5 summarizes the corresponding results, where map segments are sorted according to their population density. For each segment and each vehicle scenario, the table reports the average solution costs (*obj*) in Euro for the 30 instances and the average relative *gap* for cases where CPLEX did not terminate within the given runtime limit. For a better comparison of the solutions, rows '*imp*' present the percentage improvement of operational costs resulting from the use of the respective vehicle scenario compared to the traditional vehicle scenario 'V' where only the van is used for serving the customers. Furthermore, rows '*n*' show in how many out of the 30 solutions to a segment-vehicle combination a particular type of vehicle is actually used for serving customers.

We first want to note that CPLEX can solve all instances for scenarios with low population density to optimality. For the medium population density, we observe a few exceptions but with very low gaps of between 0.1 % to 0.5 %. Instances for the segments with high population demand cannot be solved to optimality consistently, especially if combinations of vehicle types are considered in a scenario. Here, we observe average gaps of up to 9.9 %, which indicates that the optimal cost of the corresponding solutions might be somewhat lower compared to what is reported in the table.

From comparing the operational costs of the vehicle scenarios 'V' and 'B', it becomes apparent that using the cargo bike gives only little savings, even though it is the most widespread alternative delivery vehicle type to date. The lowest relative saving of *imp* = 2.0 % occurs for the low demand map segment S6. Here, the bike is used in only *n* = 15 out of the 30 instances. In the other 15 instances, the traditional delivery by van is the only type of vehicle used for serving customers. In the high demand segments S1 and S7, however, the cargo bike is used in almost all instances. This seems to suggest that their utilization becomes more effective as the number of customers increases. Still, the maximum cost saving achieved by delivering with cargo bikes next to the van is merely 7.2 % (segment S7).

The next two vehicle scenarios 'R' and 'D' either use robots or drones in addition to the van. We observe that these vehicles are used for final delivery in all instances and costs decrease significantly compared to the sole use of a delivery van. Thereby, the relative savings increase as customer demand increases. For low demand segments S3 and S6 the cost of delivery are reduced by about 33 %, no matter whether robots or drones are used. For medium demand segments, we observe cost improvements of 44.7 % to 47.5 %, again almost identically for robots and drones. If customer density is high, cost improvements increase up to 57 %, where drones give somewhat higher savings than robots. The autonomous second echelon vehicles are therefore clearly advantageous with respect to delivery cost compared to the use of vans or cargo bikes.

The results for vehicle scenarios combining cargo bikes with either robots or drones ('BR' and 'BD') show that the autonomous vehicles clearly displace the bikes. If robots or drones are available, the cargo bike is

Table 5: Computational results for all map segments and vehicle scenarios.

			vehicle scenario							
population density	segment	measure	V	B	R	D	BR	BD	RD	BRD
low	S3	*obj* (€)	56.75	54.03	37.82	37.91	37.82	37.91	37.14	37.14
		gap (%)	-	-	-	-	-	-	-	-
		imp (%)	-	4.8	33.4	33.2	33.4	33.2	34.6	34.6
		n	30	20	30	30	0|30	0|30	30|14	0|30|13
	S6	*obj* (€)	55.61	54.47	37.04	37.15	37.04	37.15	36.36	36.36
		gap (%)	-	-	-	-	-	-	-	-
		imp (%)	-	2.0	33.4	33.2	33.4	33.2	34.6	34.6
		n	30	15	30	30	0|30	0|30	30|13	0|30|13
medium	S2	*obj* (€)	70.63	67.12	38.26	38.51	38.25	38.51	36.91	36.91
		gap (%)	-	-	-	-	-	-	-	-
		imp (%)	-	5.0	45.8	45.5	45.8	45.5	47.7	47.7
		n	30	25	30	30	0|30	0|30	30|22	0|30|22
	S4	*obj* (€)	66.50	63.11	34.90	35.07	34.82	35.07	33.46	33.46
		gap (%)	-	-	0.3	-	-	-	-	-
		imp (%)	-	5.1	47.5	47.3	47.6	47.3	49.7	49.7
		n	30	22	30	30	0|30	0|30	30|20	0|30|20
	S5	*obj* (€)	68.92	64.70	36.63	36.77	36.71	36.76	35.14	35.14
		gap (%)	-	-	0.3	0.1	0.5	-	-	-
		imp	-	6.1	46.9	46.6	46.7	46.7	49.0	49.0
		n	30	26	30	30	0|30	0|30	30|20	0|30|20
	S8	*obj* (€)	64.85	61.53	34.30	34.49	34.22	34.49	32.87	32.87
		gap (%)	-	-	0.2	-	-	-	-	-
		imp (%)	-	5.1	47.1	46.8	47.2	46.8	49.3	49.3
		n	30	26	30	30	0|30	0|30	30|21	0|30|21
	S9	*obj* (€)	65.39	62.91	35.95	36.14	35.95	36.14	34.58	34.58
		gap (%)	-	-	-	-	-	-	-	-
		imp (%)	-	3.8	45.0	44.7	45.0	44.7	47.1	47.1
		n	30	20	30	30	0|30	0|30	30|21	0|30|21
high	S1	*obj* (€)	82.37	78.10	42.90	36.10	41.14	36.10	34.60	35.06
		gap (%)	-	1.9	9.9	-	9.3	-	0.5	1.3
		imp (%)	-	5.2	47.9	56.2	50.1	56.2	58.0	57.4
		n	30	29	30	30	0|30	0|30	30|23	3|30|23
	S7	*obj* (€)	77.91	72.77	37.76	33.47	35.27	33.47	31.98	31.79
		gap (%)	-	0.7	7.5	-	4.9	-	0.5	-
		imp (%)	-	7.2	51.5	57.0	54,7	57.0	59.0	59.2
		n	30	29	30	30	0|30	0|30	30|22	0|30|22

not used in a single solution. This shows that the labor cost associated with the cargo bikes constitutes a clear disadvantage when service operations are planned with respect to minimum cost. Due to this, the cost savings observed in scenarios ’BR’ and ’BD’ are identical to those of scenarios ’R’ and ’D’ in almost all cases with very slight differences only for those solutions where CPLEX did not reach optimality in the given time.

From combining both types of autonomous vehicles in vehicle scenario ’RD’, we observe that the robots are used in all solutions to all segments, whereas drones are only used in 13 (S6) to 23 (S1) out of 30 solutions. It seems that the robots are somewhat more advantageous due to the higher capacity and lower energy consumption. Finally, the findings with all three types of second echelon vehicles (scenario ’BRD’) are consistent with the previous observations as the additional availability of cargo bikes does not add any advantage next to the isolated usage of robots and drones. Solutions even become slightly worse for the high demand segment S1 which is, however, explained by the fact that CPLEX cannot solve these instances to optimality. In segment S3, one more drone is used in scenario BRD than in scenario RD. This is due to the fact that in one solution a single customer can be supplied by a drone at the same cost as by a robot.

Furthermore, we want to note that some of the solutions for low demand segments show even higher cost than for the high demand segments, see e.g. segments S3 and S7 under vehicle scenario ’D’. The explanation for this is that map segment S3 is further away from the van depot that is located in the southwest of the city than map segment S7. Due to this, there is an additional cost of having the first echelon van driving to a particular map segment and going back to the depot from there. As a consequence, comparing the solutions for different segments with each other is somewhat limited. Nevertheless, we at least observe that the usage of cargo bikes is more attractive the higher the population density is. Drones are used to a larger extent in map segments with medium and high population density when being combined with robots. For the latter, no such effects can be observed as they are used in all solutions for all map segments in the corresponding vehicle scenarios.

Since no drivers are required for robots and drones, we have not yet applied labor costs for them. However, it can be expected that even if the legal regulations on autonomous driving should enable the full use of these vehicles in the future, at least remote monitoring will be necessary for safety reasons. Employees will then be required for manual intervention and control in the event of unforeseen situations such as sensor errors or sudden obstacles. To account for this, our second experiment considers positive time-dependent costs c_t^R and c_t^D for robots and drones. Their amount is estimated by assuming that one employee is able to monitor five of the autonomous vehicles simultaneously. For initial calculations, the hourly wage of a van driver of 30 € is applied, resulting in time-dependent costs of $c_t^R = c_t^D = 6$ per robot or drone. We subsequently repeat the calculations with a doubled wage to account for the fact that better trained employees may be needed for monitoring.

The resulting operational delivery costs can be seen in Figure 4. For simplification, the costs for scenarios ’RD’ and ’BRD’ are combined in the diagram, since they have again proven to be identical except for a few cases in which CPLEX was unable to find an exact solution. Please note that in each case the best solution found within the given time limit is plotted. Especially in the segments with high population density S1 and S7 actual results can therefore be somewhat lower (like already noted in the analysis of Table 5). Since we obtained similar optimality gaps in all three labor cost variations, we have omitted their specification in the figure. The costs of the basic situation without time-dependent costs for the autonomous vehicles are shown at the top of Figure 4 for better comparability. As can be seen there, operational costs are only slightly reduced when using bicycles (scenario ’B’ – blue) instead of traditional delivery with vans (scenario ’V’ – red). By contrast, they drop significantly by using autonomous vehicles, even in combination, and then remain at an almost identical level. This finding already changes significantly when medium time-dependent monitoring

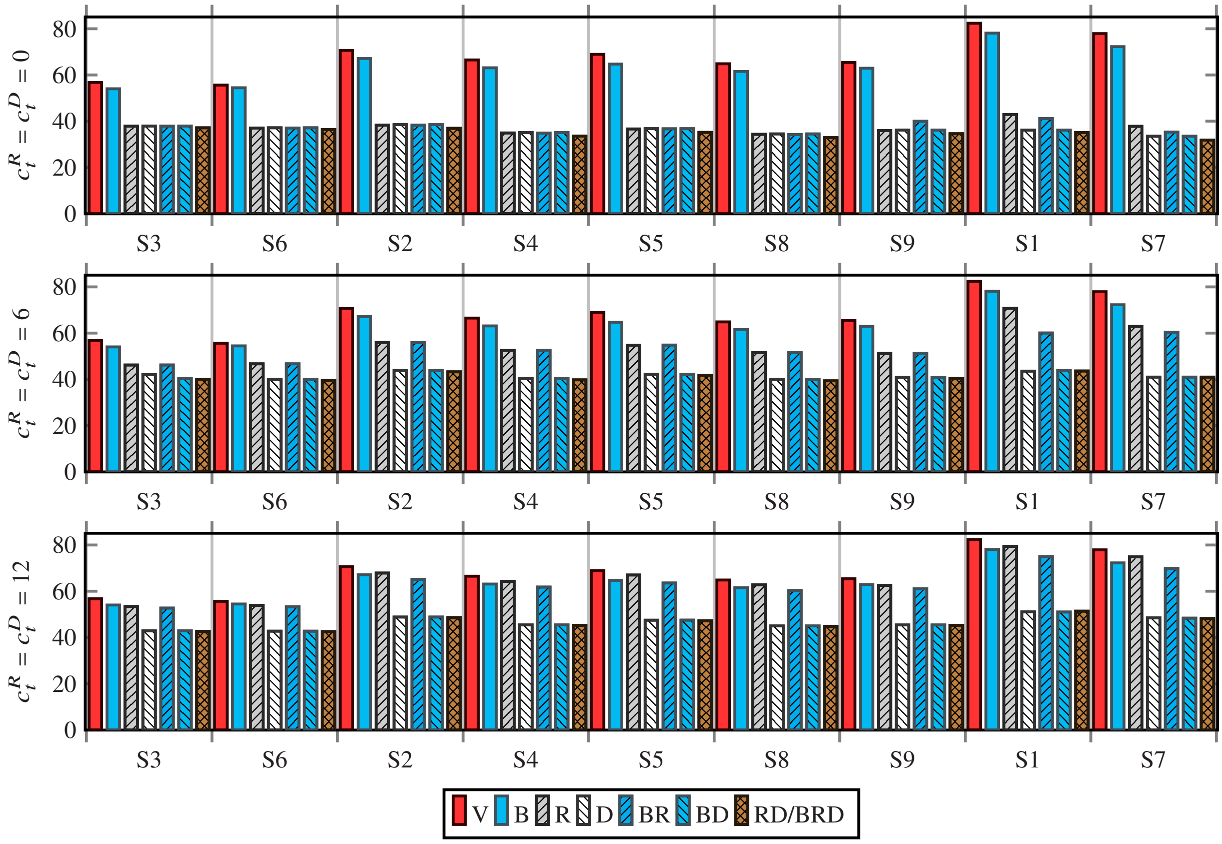


Fig. 4: Delivery costs under varied cost rates c_t^R and c_t^D for robots and drones.

costs $c_t^R = c_t^D = 6$ (center diagram) are included. The results for delivery in scenarios 'V' and 'B' of course remain unchanged, as no autonomous vehicles are involved. We therefore still have a slight advantage of the bike. However, when turning to delivery scenarios with robot deployment 'R' (gray, hatched upwards) and 'BR' (blue, hatched upwards), a fairly large increase in costs can be seen compared to the situation without monitoring costs. The savings over traditional delivery with van are are correspondingly lower, which is particularly noticeable in the segments with high population density S1 and S7. Regarding delivery scenarios with the involvement of drones 'D' (white, hatched downwards), 'BD' (blue, hatched downwards) and 'RD'/'BRD' (brown, crosshatched), significant cost savings are still evident compared to van delivery. This can be explained by the fact that drones are considerably faster compared to robots. Although they can only carry one parcel, little time is required for the actual delivery, which is why labor costs are likely to have a relatively low impact on operational costs. This is still the case even if wages for monitoring employees are raised to 12 €/h (bottom chart in the figure). In contrast, the robot delivery becomes even less favorable. As can be seen, the sole use of robots on the second echelon ('R') is even more expensive than bike delivery ('B') in almost all segments. Only in the low-population segments S3 and S6 as well as in segment S9 robot delivery is still slightly less expensive. The costs of combined delivery with bike and robot ('BR') now turn out to be almost as high as for bike-only delivery ('B'). This is also reflected in the utilization numbers of these vehicles (not shown in the figure). While robots are deployed in all instances in the basic variant without labor costs for autonomous vehicles in scenario 'BR', they are only used in about two-thirds of the instances with $c_t^R = c_t^D = 12$. The bike, on the other hand, which originally did not deliver any parcels, is now equally used in two-thirds of the instances. This ratio can also be seen in scenario 'RD', where without monitoring costs robots and drones are used in on average 30 and 17.7 instances per segment, respectively. With high labor costs, a shift occurs to 7.1 and 30 times in favor of the drone. Thus, it can be concluded that robots lose their advantage over other delivery vehicles when monitoring costs are high, especially when population density is high. Bike delivery is then preferred accordingly when considering a mixed delivery system. Since drones are assumed to be able to fly direct paths in this example and are able to move much faster, they are less affected by monitoring costs.

As we have just seen, labor costs for robots and drones affect both operational costs and the relative advantage of vehicles within a delivery system. Labor costs were also highlighted by Tipagornwong and Figliozzi [23] as an important factor in measuring delivery costs for cargo bikes. In the third experiment, we therefore vary the labor cost rate c_t^k of the cargo bike drivers to test their influence on operation costs and vehicle utilization. For this, we have chosen one segment of low (S3), medium (S2) and high population density (S1) and solved each of them once more with a reduced time dependent cost rate of $c_t^B = 20$ and $c_t^B = 13$ under each vehicle scenario that involves cargo bikes. Considering lower cost rates seems reasonable as the original rate reflected relatively high German labor payments whereas the gross minimum wage in Germany is just about 13 €/hour. Furthermore, also other economies often face lower labor cost levels compared to Germany. The results are shown in Table 6. For reasons of comparison, results for the original cost rate $c_t^B = 25$ are shown next to those for the

Table 6: Results under varied cost rate c_t^B for selected segments from each population density.

		vehicle scenario											
		B			BR			BD			BRD		
segment	measure	c_t^B=25	20	13	25	20	13	25	20	13	25	20	13
S3	*obj* (€)	54.03	51.39	46.96	37.82	37.80	37.82	37.89	37.91	37.91	37.14	37.14	37.14
	gap (%)	-	-	-	-	-	-	-	-	-	-	-	-
	imp (%)	4.8	9.4	13.1	33.4	33.4	33.0	33.2	33.2	29.87	34.6	34.6	31.3
	n	20	27	30	$0 \mid 30$	$0 \mid 30$	$4 \mid 30$	$0 \mid 30$	$0 \mid 30$	$4 \mid 30$	$0 \mid 30 \mid 13$	$0 \mid 30 \mid 12$	$0 \mid 30 \mid 13$
	δC (%)	75	87	98	$0 \mid 100$	$0 \mid 100$	$3 \mid 97$	$0 \mid 100$	$0 \mid 100$	$3 \mid 97$	$0 \mid 100 \mid 10$	$0 \mid 90 \mid 10$	$0 \mid 90 \mid 10$
S2	*obj* (€)	67.12	61.74	53.59	38.25	38.24	38.16	38.51	38.50	38.41	36.91	36.89	36.82
	gap (%)	-	-	-	-	-	0.1	-	-	-	-	-	-
	imp (%)	5.0	12.6	20.2	45.8	45.8	43.2	45.5	45.5	42.8	47.7	47.8	45.1
	n	25	30	30	$0 \mid 30$	$2 \mid 30$	$4 \mid 30$	$0 \mid 20$	$2 \mid 30$	$5 \mid 30$	$0 \mid 30 \mid 22$	$2 \mid 30 \mid 22$	$4 \mid 30 \mid 22$
	δC (%)	79	97	98	$0 \mid 99$	$<1 \mid 98$	$1 \mid 98$	$0 \mid 99$	$<1 \mid 99$	$1 \mid 98$	$0 \mid 88 \mid 12$	$0 \mid 83 \mid 17$	$1 \mid 78 \mid 21$
S1	*obj* (€)	78.10	68.06	58.70	41.14	39.93	42.33	36.10	36.10	36.10	36.06	34.78	34.94
	gap (%)	1.9	0.89	-	9.3	7.2	10.6	-	-	2.9	1.3	0.7	1.2
	imp (%)	5.2	17.4	24.9	50.5	52.5	45.8	56.2	56.2	53.8	57.4	57.8	55.3
	n	29	28	29	$0 \mid 30$	$1 \mid 30$	$4 \mid 30$	$0 \mid 30$	$0 \mid 30$	$0 \mid 30$	$0 \mid 30 \mid 23$	$0 \mid 30 \mid 23$	$2 \mid 30 \mid 23$
	δC (%)	81	90	96	$0 \mid 90$	$2 \mid 94$	$2 \mid 87$	$0 \mid 100$	$0 \mid 100$	$0 \mid 100$	$0 \mid 66 \mid 34$	$0 \mid 66 \mid 34$	$1 \mid 66 \mid 33$

reduced rates. In addition to those measures that were already introduced for Table 5, we also report in rows 'δC' the percentage of customers that is served by the respective vehicle type.

As expected, the costs of solutions in the vehicle scenario with bikes only ('B') decrease as the labor cost rate decreases. It can be seen that the bike is used in an increasing number of solutions as it becomes more competitive to the delivery van. In segments S3 and S2, the proportion of customers served by bike is strongly increasing from $\delta C = 75$ % and $\delta C = 79$ % to $\delta C = 98$ % when turning from an hourly wage of 25 € to the minimum wage of 13 €. The few remaining customers are served by the van, as we allow direct delivery in all cases. For the high population density segment S1, the share of customers served by bike is already at $\delta C = 81$ % even for the highest labor cost rate but still increases, even if not that strong, under the reduced cost rates.

When turning to the combined vehicle fleets ('BR', 'BD', 'BRD') for the low population density segment S3, we again observe that the cargo bike is most often completely displaced by the autonomous vehicles. Merely in scenarios 'BR' and 'BD', a few percent of the customers are served by bike under the lowest labor cost rate. The results for the medium population density segment S2 are somewhat different. Bikes are more relevant here with several solutions using them even under the medium cost rate of $c_t^B = 20$. Still, at most 5 solutions in an instance set involve the bike and at most one percent of customers is served by it in any scenario, which shows that the bike could also be completely removed in those cases at almost no additional cost. Furthermore, the actual cost of the solutions are hardly affected by the wage reduction. For the high population segment S1, the solutions under vehicle scenario 'BR' are limited in their meaningfulness as the solver cannot obtain the optimal solutions within the given runtime, and even fails in finding feasible solutions for two and one of the instances under cost rates $c_t^B = 20$ and $c_t^B = 13$, respectively. This becomes apparent from the observation that the cost of the solutions increase and the share of customers served by bike decreases when turning from 25 €/h to 20 €/h and 13 €/h. To conclude this experiment, cargo bikes can become more attractive due to lower labor cost, but only if no robots or drones are available in the delivery system. At the same time, reducing this cost rate makes solving the model more difficult for CPLEX as the bikes are no longer easily rejected in the solution process.

The final experiment investigates the role of the capacities of robots. As the proposed model supports multi-compartment robots, various capacities can be applied for these. Next to the already investigated capacity $Q^R = 2$, Table 7 also presents results for capacities of 1, 3, and 4 parcels per robot. The experiment again considers one map segment out of each population density, namely S3, S2, and S1, and each vehicle scenario that involves robots. For the low population density segment S3 and the vehicle scenarios with only robots ('R') and bikes and robots ('BR'), we observe that costs are somewhat higher if the robots have just one unit of capacity but only very slightly lower for capacities 3 and 4, which is in line with the findings of [33]. In the mixed vehicle scenarios with robots and drones ('RD') or all three second echelon vehicle type ('BRD'), we observe almost no change in cost under the different robot capacities. However, robots take over a larger share of the customer demand, the higher the capacity is, see rows n and δC. In the medium population density segment S2, cost reductions are somewhat higher and also occur when turning from $Q^R = 2$ to $Q^R = 3$. The results for the high population density segment S1 are again difficult to interpret as the problem cannot be solved to optimality especially for medium capacities of the robots. This effects that the non-optimal solutions for $Q^R = 3$ often show higher

Table 7: Results under varied robot capacity Q^R for selected segments from each population density.

<table>
<tr><th></th><th></th><th colspan="16">vehicle scenario</th></tr>
<tr><th></th><th></th><th colspan="4">R</th><th colspan="4">BR</th><th colspan="4">RD</th><th colspan="4">BRD</th></tr>
<tr><th>segment</th><th>measure</th><th>Q^R=1</th><th>2</th><th>3</th><th>4</th><th>1</th><th>2</th><th>3</th><th>4</th><th>1</th><th>2</th><th>3</th><th>4</th><th>1</th><th>2</th><th>3</th><th>4</th></tr>
<tr><td rowspan="5">S3</td><td>obj (€)</td><td>39.22</td><td>37.82</td><td>37.13</td><td>37.13</td><td>39.22</td><td>37.82</td><td>37.13</td><td>37.13</td><td>37.18</td><td>37.14</td><td>37.13</td><td>37.13</td><td>37.18</td><td>37.14</td><td>37.13</td><td>37.13</td></tr>
<tr><td>gap (%)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>imp (%)</td><td>30.9</td><td>33.4</td><td>34.6</td><td>34.6</td><td>30.9</td><td>33.4</td><td>34.6</td><td>34.6</td><td>34.5</td><td>34.6</td><td>34.6</td><td>34.6</td><td>34.5</td><td>34.6</td><td>34.6</td><td>34.6</td></tr>
<tr><td>n</td><td>30</td><td>30</td><td>30</td><td>30</td><td>0|30</td><td>0|30</td><td>0|30</td><td>0|30</td><td>30|22</td><td>30|14</td><td>30|5</td><td>30|1</td><td>0|30|23</td><td>0|30|13</td><td>0|30|5</td><td>0|30|1</td></tr>
<tr><td>δC (%)</td><td>100</td><td>100</td><td>100</td><td>100</td><td>0|100</td><td>0|100</td><td>0|100</td><td>0|100</td><td>56|44</td><td>90|10</td><td>98|2</td><td>100|0</td><td>0|56|44</td><td>0|90|10</td><td>0|98|2</td><td>0|100|0</td></tr>
<tr><td rowspan="5">S2</td><td>obj (€)</td><td>42.53</td><td>38.26</td><td>36.87</td><td>36.86</td><td>42.61</td><td>38.26</td><td>36.87</td><td>36.86</td><td>37.03</td><td>36.91</td><td>36.20</td><td>36.17</td><td>37.03</td><td>36.91</td><td>36.20</td><td>36.17</td></tr>
<tr><td>gap (%)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>imp (%)</td><td>39.8</td><td>5.8</td><td>47.8</td><td>47.8</td><td>39.7</td><td>45.8</td><td>47.8</td><td>47.8</td><td>47.6</td><td>47.7</td><td>48.7</td><td>48.8</td><td>47.6</td><td>47.7</td><td>48.7</td><td>48.8</td></tr>
<tr><td>n</td><td>30</td><td>30</td><td>30</td><td>30</td><td>1|30</td><td>0|30</td><td>0|30</td><td>0|30</td><td>30|30</td><td>30|22</td><td>30|11</td><td>30|12</td><td>0|30|30</td><td>0|30|22</td><td>0|30|11</td><td>0|30|12</td></tr>
<tr><td>δC (%)</td><td>99</td><td>99</td><td>100</td><td>98</td><td>1|97</td><td>0|99</td><td>0|100</td><td>0|98</td><td>48|52</td><td>87|13</td><td>85|15</td><td>97|3</td><td>0|48|52</td><td>0|88|12</td><td>0|85|15</td><td>0|97|3</td></tr>
<tr><td rowspan="5">S1</td><td>obj (€)</td><td>45.29</td><td>40.90</td><td>42.52</td><td>35.65</td><td>47.69</td><td>41.14</td><td>39.99</td><td>35.91</td><td>35.26</td><td>34.60</td><td>35.84</td><td>33.69</td><td>35.26</td><td>35.06</td><td>35.18</td><td>33.69</td></tr>
<tr><td>gap (%)</td><td>-</td><td>9.9</td><td>10.2</td><td>2.9</td><td>-</td><td>9.3</td><td>9.5</td><td>3.4</td><td>-</td><td>0.5</td><td>3.3</td><td>-</td><td>-</td><td>1.3</td><td>1.8</td><td>-</td></tr>
<tr><td>imp (%)</td><td>45.0</td><td>47.9</td><td>48.4</td><td>52.7</td><td>42.1</td><td>50.0</td><td>51.5</td><td>52.3</td><td>57.2</td><td>58.0</td><td>56.5</td><td>59.1</td><td>57.2</td><td>57.4</td><td>57.3</td><td>59.1</td></tr>
<tr><td>n</td><td>30</td><td>30</td><td>30</td><td>30</td><td>5|30</td><td>0|30</td><td>0|28</td><td>2|30</td><td>30|30</td><td>30|23</td><td>30|22</td><td>30|13</td><td>0|30|30</td><td>0|30|23</td><td>3|30|22</td><td>0|30|13</td></tr>
<tr><td>δC (%)</td><td>92</td><td>88</td><td>88</td><td>98</td><td>3|88</td><td>0|90</td><td>0|92</td><td>2|97</td><td>42|58</td><td>66|34</td><td>81|18</td><td>83|17</td><td>0|42|58</td><td>0|66|34</td><td>1|82|16</td><td>0|83|17</td></tr>
</table>

cost than for lower capacities. Still, the lowest cost are always observed for a robot capacity of $Q^R > 1$, which shows that multi-compartment robots can make a difference with respect to the cost efficiency of parcel delivery. In all these settings, robots are also used more frequently then drones, and drones are increasingly replaced by them, the higher the capacities of robots are.

5. CONCLUSIONS

In this paper, we have presented a generic optimization model that can be used for evaluating different delivery options in a two-echelon city logistics system for the delivery of parcels. The well-known 2-echelon vehicle routing problem was extended and adapted for this purpose to vehicle combinations not considered before. Our model allows both direct delivery and transfer of small vehicles by the first echelon, the use of heterogeneous vehicle fleets, and multiple load pickup by the second-echelon vehicles. Furthermore, the generic formulation makes it possible not only to simulate traditional delivery by vans, but also to investigate and compare the use of different fleet combinations on the second echelon.

In our real-world calculations simulating an urban setting, a traditional van is used for bringing parcels from a depot outside the city into the city center where it can also serve customers. Alternatively, cargo bikes that are stationed in the city can receive parcels at satellite locations and fulfill the delivery at the second echelon. Furthermore, autonomous robots and drones can be brought to the city by van and take over delivery of parcels at the second echelon. At the first echelon, a traditional van is used for bringing parcels from a depot outside the city into the city center where it can also serve customers. Alternatively, cargo bikes that are stationed in the city can receive parcels at satellite locations and fulfill the delivery at the second echelon. Furthermore, autonomous robots and drones can be brought into the city by the van and take over the delivery of parcels at the second echelon.

Our first experimental analysis of cost-oriented transport solutions has shown that cargo bikes are a useful supplement to the delivery vans. However, savings realized by their use were very small in our sample calculations. If robots or drones are available too, these means of transportation take over the largest share of deliveries as they are cheaper than the cargo bikes due to the absence of labor cost. Thereby, robots and drones are mostly substitutable with each other as they both have comparably low operational cost and similar capabilities. Only in direct comparison do robots seem to have a small advantage due to their ability to carry two parcels at a time. Further experiments considering monitoring costs for the autonomous vehicles have shown that time-dependent costs have a high impact on the cost efficiency of robots in particular. The cost of drone delivery, on the other hand, is hardly affected by increasing monitoring costs, presumably due to their speed and the ability to fly on a straight path to customers. The observation that labor costs constitute a significant factor in the cost-effectiveness of delivery vehicles was also shown by our third experiment, which evaluated different driver costs for cargo bikes. Furthermore, our last experiment has shown that the robots outperform the drones if they consist of multiple compartments such that each of them can carry several parcels at once.

Accordingly, the efficiency of delivery systems depends not only on the technical characteristics of the vehicles, such as their maximum capacity. In particular, it also depends on the labor costs to be observed in such systems. Regulatory requirements will certainly play a role here too, especially in the case of autonomous vehicles. When planning new delivery systems, parcel service providers will therefore have to pay very close attention to the particular configuration of the tranport system in each individual case, but also to the wages to be paid and regulations to be followed, to find a solution that cost-effectively replaces sole direct delivery by van.

We are aware that these results are based on a limited number of vehicles and customers in the experimental setting. As a standard solver like CPLEX already runs into its boundaries for these relatively small vehicle fleets and restricted urban areas of medium and high population density, our future research will be devoted to the development of a heuristic, which can then solve larger instances and further contribute to the validation of the results. Eventually, the use of two satellites within the relatively small section considered here could hinder the cost-effectiveness of such systems when construction and maintenance costs are taken into account too. Therefore, experiments for larger map segments and more diverse cities could be conducted to validate or extend the findings obtained in this study. Furthermore, an analysis from an environmental perspective could be a valuable area of future research.

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