AIRL-SCM
Association Internationale de Recherche
Logistique et Supply Chain Management

excelia
BUSINESS SCHOOL

Evaluating Cost and Design Implications of a Two-Stage Autonomous Urban Delivery System

Martin Kosch[a]*, Julian Maas[a] and Frank Straube[a]

[a]*Chair of Logistics, Berlin University of Technology, Berlin, Germany*

Correspondence:

*kosch@logistik.tu-berlin.de

maas@logistik.tu-berlin.de

frank.straube@tu-berlin.de

Evaluating Cost and Design Implications of a Two-Stage Autonomous Urban Delivery System

ARTICLE INFO

Keywords:
- Autonomous last mile delivery
- Autonomous fulfillment delivery concepts
- Last Mile logistics
- Van-and-Robot concept

ABSTRACT

Driven by trends as urbanization and innovative business models in online retailing, e-commerce is experiencing rapid growth. Paired with new customer expectations and increasing labor shortage as well as inefficient last-mile delivery, urban logistic concepts are in need for innovative solutions. Autonomous vehicles delivering shipments in a so-called Van-and-Robot (VnR) concept appear like a promising approach to tackle these hurdles, since limitations of delivery robots regarding speed and range can be compensated, while maintaining flexibility and the ability to bundle shipments. But since this concept was never implemented and requires the integration of two autonomous vehicles, it shows high implementation cost and uncertainties with regard to technical requirements. Therefore, this study aims to analyze the impact of the use of a VnR delivery concept on urban last mile delivery costs. Furthermore, the system-determining parameters with regard to these costs should be defined in order to design an efficient VnR concept usage. These implications should also serve as a guideline for practitioners to support an implementation.

Declaration of interests

This paper is based on the research conducted in the BeIntelli project, funded by the German Federal Ministry for Digital and Transport (BMDV) under the funding reference number 01MM20004.

Évaluation des Implications de Coût et de Conception d'un Système de Livraison Urbaine Autonome à Deux Étapes

INFO ARTICLE	RÉSUMÉ
Mots-clés : - Livraison autonome du dernier kilomètre - Concepts de livraison de commande autonome - Logistique du dernier kilomètre - Concept de camionnette et de robot	Stimulé par les tendances de l'urbanisation et les modèles d'affaires innovants dans le commerce en ligne, le e-commerce connaît une croissance rapide. Associée aux nouvelles attentes des clients et à la pénurie croissante de main-d'œuvre, les concepts logistiques urbains ont besoin de solutions innovantes. Les véhicules autonomes qui effectuent des livraisons dans le cadre d'un concept de camionnette et de robot apparaissent comme une approche prometteuse pour surmonter ces obstacles, étant donné les limitations des robots de livraison en ce qui concerne la vitesse et l'autonomie peuvent être compensées, tout en maintenant la flexibilité et la capacité de regrouper les envois. Cependant, comme ce concept n'a jamais été mis en œuvre et qu'il nécessite l'intégration de deux véhicules autonomes, il présente un coût de mise en œuvre élevé ainsi que de nombreuses incertitudes concernant les exigences techniques. Par conséquent, cette étude vise à analyser l'impact de l'utilisation d'un concept de livraison camionnette-et-robot sur les coûts de livraison du dernier kilomètre en milieu urbain. De plus, les paramètres déterminants du système en ce qui concerne ces coûts devraient être définis afin de concevoir une utilisation économique du concept camion-et-robot. Ces implications devraient également servir de lignes directrices pour les praticiens afin de soutenir une mise en œuvre.

Déclaration d'intérêts

Ce document est basé sur les recherches menées dans le cadre du projet BeIntelli, financé par le ministère fédéral allemand du numérique et des transports (BMDV) sous le numéro de référence 01MM20004

1 Introduction

Driven by trends in urbanization and evolving online retail models, e-commerce is experiencing rapid growth (Straube et al. 2021; World Economic Forum 2021; Jennings and Figliozzi 2019) doubling global sales to $5.7 trillion from 2017 to 2022. The increasing number of shipments pose challenges for urban logistics and transportation infrastructure (Jordan et al. 2020) resulting in more emissions, accidents, double-parking and congestions (Hu et al. 2019; Demir et al. 2015). Concurrently, rising customer expectations (Brabänder 2020) meet a growing driver shortage. These developments make new and innovative concepts for urban logistics indispensable (Fläming 2015; Schröder and Wegner 2019).

Autonomous deliveries in distributed AI based integrated connected mobility systems, being driverless and cost-effective, emerge as a potential solution. This enables greater flexibility for planning routes, delivery windows, fluctuating demand and deliveries at off-peak times of the day, avoiding periods of high traffic and increasing the likelihood of meeting customers (Mitteregger et al. 2021). For this particularly three concepts stand out: autonomous delivery vans, drones and robots (Schröder et al. 2018). Compared to drones, delivery robots boast higher capacity, lesser manufacturing costs, lower risks, and fewer regulatory challenges (Lee et al. 2016). However, the low speed and range is a major limitation of this technology. To compensate for this and simultaneously benefit from the advantages of delivery robots, the project BeIntelli aims to implement a Van-and-Robot (VnR) concept. Here, a delivery van acts as a "mother ship" to bring the delivery robots closer to the customers in a two-stage system functioning as a mobile depot to supply robots with parcels (Heimfarth et al. 2021). But since this concept was not implemented before and requires the integration of two vehicle types, it shows high implementation costs and a lot of uncertainties regarding technical requirements and the complex two staged routing. Therefore, research is needed to identify an optimal design setup of this concept to find the best fields of application and to optimize implementation costs (Jennings and Figliozzi 2019). In this way, initial technical and economic implications can be derived to support implementations in real environments, e.g. as in the BeIntelli project (BeIntelli 2024).

Consequently, the following two research questions arise:

- RQ1: How does the use of a VnR delivery concept affect the urban last mile delivery costs?
- RQ2: What are the critical design criteria for a VnR delivery concept?

Thus, this study seeks to obtain novel implications regarding cost advantages and the design of this concept. Therefore, existing optimization and cost models shall be used and more realistic restrictions shall be considered. A mixed integer problem (MIP) model is developed and computed using a variable neighborhood search (VNS) as a heuristic solution method to allow for less restrictions in a more complex model. The focus of the model is therefore on ensuring that the delivery robots can be collected again by the delivery van and are then available for subsequent deliveries. In addition, the delivery robots do not have to be collected at the same drop-off location, which can reduce waiting times for the delivery van and thus improve the performance of the concept. Accordingly, this study develops a mathematical route optimization with a heuristic solution approach of an autonomous two staged delivery process via different simulation experiments in order to identify main implications to design the process. Using this methodological approach limitations are primarily in static modeling of the environment by making simplifying assumptions. With this approach, deterministic solutions and thus reproducibility can be created in comparison to dynamic models such as used by Firdausiyah et al. (2019), which is necessary if the influence of various factors is to be determined in different experiments. Dynamic models are particularly suited to taking changes and time trends into account (Domschke et al. 2015).

The findings of this study enable more accurate cost predictions and the establishment of essential criteria for designing efficient delivery processes. By examining the effects of individual parameters, such as SADR speed and handover efficiency, this research offers valuable insights into optimizing these elements. Moreover, this study aims to lay a foundation for future research exploring more complex scenarios and broadening the application of the VnR concept to various urban settings. The implications derived here serve not only to guide further academic inquiry but also to provide practical guidelines for urban logistics practitioners looking to implement innovative delivery solutions. The investigation into cost-effective design and the operational impact of the VnR concept gives more sophisticated insights to address the challenges of urban delivery. By improving understanding and refining the deployment of autonomous delivery systems, this work contributes in the development of more sustainable, efficient, and customer-oriented delivery solutions.

2 Theoretical background

In this chapter, firstly, the scope of consideration is narrowed down and set in relation to existing literature in order to categorize this study thematically. Secondly, a detailed problem description of the delivery concept under consideration is provided, to which the model is applied.

2.1 Scope and related literature

The scope of this study focuses on last mile logistics as part of urban logistics. In relation to distribution logistics, the last mile of urban logistics can be defined as the final stage of parcel deliveries from the last transshipment point to the pick-up or destination point of a final recipient specifically for urban areas (Na et al. 2022). Aligned with the objectives of this study, the model can be applied at both the strategic and tactical levels to guide the design of the delivery concept. It also extends to operational aspects, particularly focusing on the routing of vehicles. This demonstrates the model's utility in shaping both overarching strategies and detailed operational tactics essential for optimizing delivery systems. Since the study primarily emphases the transportation process in the form of route planning and design information, transshipment and storage processes are therefore out of scope. In addition, the CEP sector and thus parcel shipments are specifically considered, as they make up the majority of shipments on the last mile in Germany (Bundesverband Paket und Expresslogistik e. V. (BIEK), KE-CONSULT Kurte&Esser GbR 2023).

The objective of urban logistics is among others to make urban freight transport efficient through measures such as the consolidation and coordination of freight flows, while at the same time reducing negative effects on the environment and society (Brabänder 2020). In order to achieve this objective, there is a multitude of new innovative delivery concept. One very promising seems to be a so-called VnR concept. In this, sidewalk autonomous delivery robots (SADR's) are combined with delivery vans to overcome limitations of the SADR's regarding delivery range and speed (Heimfarth et al. 2021). This enables fast and efficient delivery. Such a concept was presented by the Mercedes-Benz Group in collaboration with Starship Technologies under the project name "Vans and Robots" in 2016 (Mercedes-Benz Vans 2016). The system consists of a delivery van, which acts as a mobile depot for parcels and several SADR's. The delivery van´s task is to bring the SADR close to the recipient, load it with parcels and drop it off on the sidewalk. The SADR´s then make individual deliveries to the recipients using the sidewalk to then return to a meeting point with the delivery van and are collected there (Mercedes-Benz Vans 2016).

Thus, the concept is particularly favorable for CEP deliveries in urban areas, since it combines the flexibility of SADRs and the range and payload of delivery vans. Therefore, the high volume can be bundled in long tours. Simultaneously the tour is more consistent, since a single shipment can be delivered independently from the others (Maas et al. 2023). Due to these advantages, some research has already been carried out on this concept, which primarily focuses on the optimization of tours and routes. These routing problems can be generalized as heterogeneous vehicle routing problem (HVRP) (Taniguchi et al. 2023). A variety of different approaches address how the delivery van drops-off or supplies the SADRs. This also includes different infrastructure requirements such as separate depots where the SADRs are stored or loaded. An excerpt of these is shown in Table 1 to illustrate the different research approaches and to distinguish this study from the existing ones. In addition, one-stage approaches to route optimization with comparable variations of logistical constraints exist for mobile parcel lockers (Wang et al. 2024; Rabe et al. 2021).

Table 1: Related literature for VnR concepts

Authors	Concept	Focus
(Heimfarth et al. 2021)	VnR	Use of depots where the delivery robots drive to after delivery. Therefore, the delivery robots drop out of consideration of the model.
(Jennings and Figliozzi 2019)	VnR	Van drops of the robots and wait for a return on the same spot.
(Boysen et al. 2018)	VnR	Use of depots where the delivery robots drive to after. Therefore, the delivery robots drop out of consideration of the model.
(Mercedes-Benz Group AG 2017)	VnR	No route optimization. Focus on the introduction of the technical concept.
(Ostermeier et al. 2022)	VnR	Use of depots where the delivery robots drive to after delivery and drop out of consideration of the model Also the model considers delivery time windows.
(Simoni et al. 2020)	VnR	Delivery by van or robot with consideration of delivery time windows but the robot must return to the same van again. Robots can serve one or more consecutive deliveries.
(Kyriakakis et al. 2022)	Van-and-Drone	Delivery by drone minimizing energy consumption with focusing on the payload weight. Drones can carry multiple packages up to a certain weight limit.
(Di Puglia Pugliese et al. 2021)	Van-and-Drone	Delivery by van or drone with consideration of delivery time windows but the drone must land on the same van again.

In this paper, we introduce novel elements to autonomous urban delivery systems that set it apart from existing concepts. Our approach utilizes flexible pick-up points that adapt to varying logistics needs without requiring additional infrastructure. Additionally, we introduce an autonomous van equipped with automated material handling systems, serving as a mobile hub to enhance delivery efficiency.

2.2 Problem description

A specially converted or customized fully autonomous delivery van is required to carry out the VnR delivery. A possible design of such a vehicle is being developed and piloted in the BeIntelli project, as shown in Figure 1 (BeIntelli 2024).

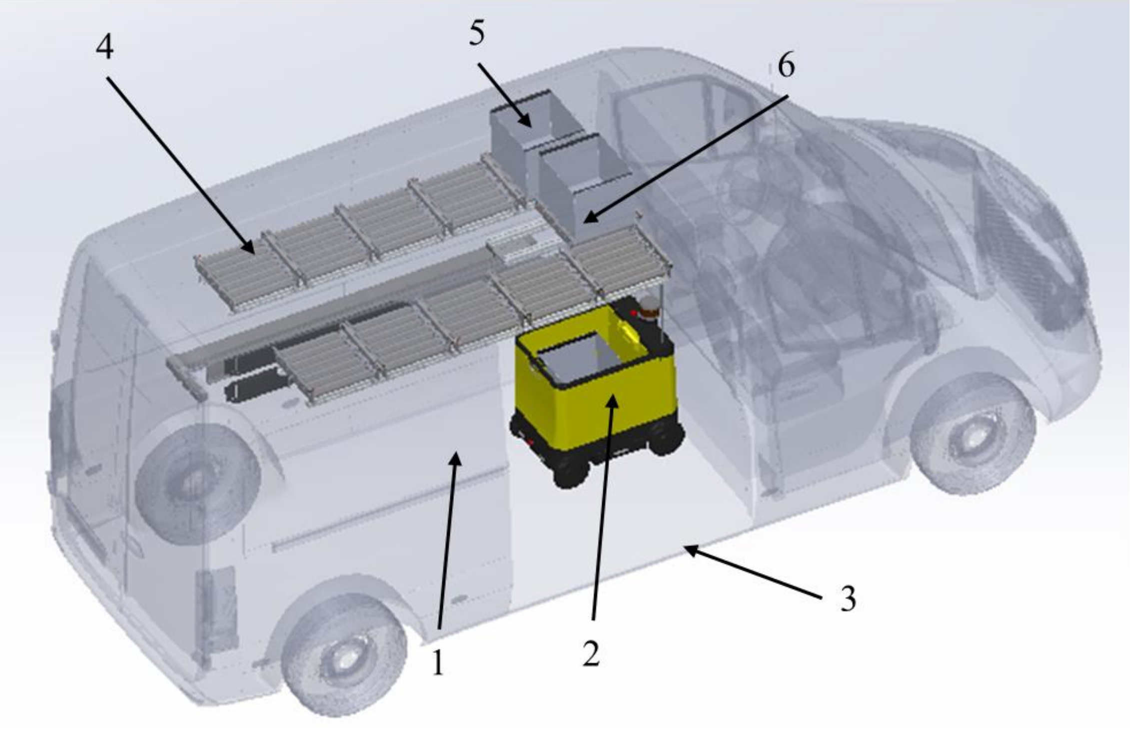

Figure 1: Specialized delivery van for VnR delivery

The vehicle has a loading space (1) in which the delivery robots (2) can drive in and out via a ramp or a lifting system (3). The loading space also contains charging interfaces for charging the robots' batteries. A freight storage area (4), in which the packages (5) are stored on several levels, is located above the loading area. With the help of a storage and retrieval unit (6), the parcels can be removed from the freight storage area and loaded into a delivery robot. In this specific concept, the loading capacity results from two levels in the freight storage area, each level containing two rows with five parcels each, as well as two rows in the loading area, each of which can accommodate two delivery robots. This results in a total capacity of 20 parcels and 4 SADR´s.

In addition to the delivery van, the BeIntelli (2024) project uses SADRs from Continental, which are equipped with four wheels and designed in such a way that they can negotiate curbs and are highly maneuverable on sidewalks. They have a cargo compartment measuring a volume of around 110 liters, which allows a maximum payload of 20 kilograms with a range of around 12 km. The robot's maximum speed is limited to 6 kilometers per hour, although the average driving speed is around 3 kilometers per hour due to pedestrians and obstacles on the sidewalk. An operator continuously monitors the robot to ensure additional safety.

It should be noted that the specific technical details and capacities may vary depending on implementation and further development. The figures given are only intended to illustrate the concept under consideration and should not be regarded as generally valid.

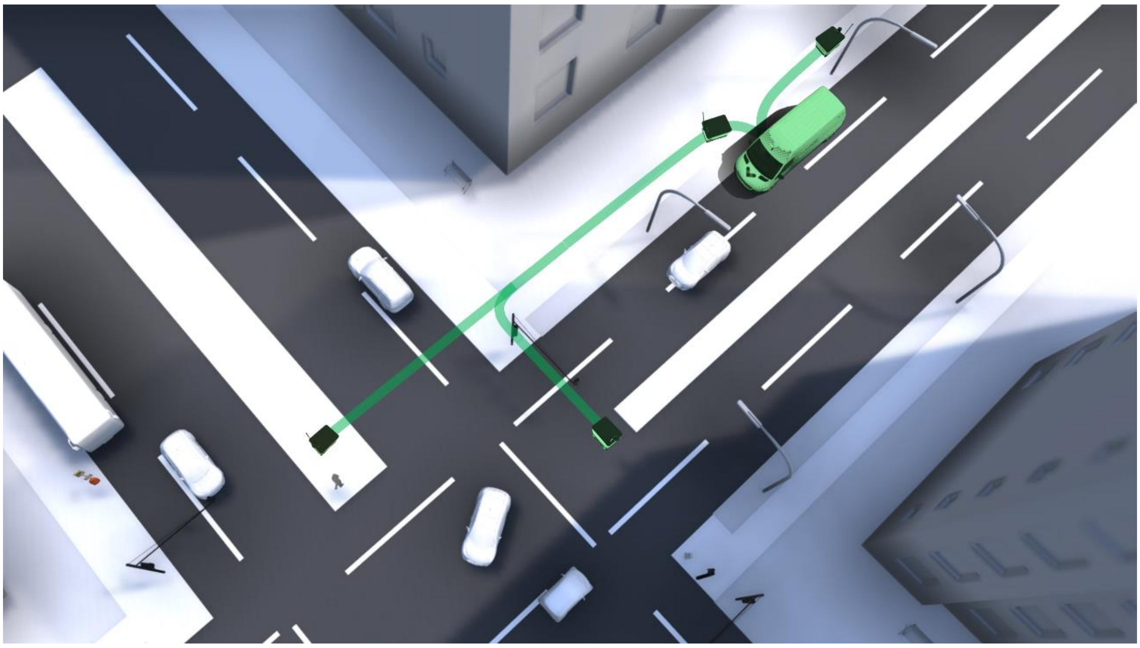

Figure 2: Exemplary VnR tour with flexible robot routes

The two vehicles are used together in a two-stage delivery route, which is shown as an exemplary model in Figure 2. This routing approach involves a tour where robots can be both dropped off and subsequently picked up, allowing for flexibility in pick-up locations that may differ from drop-off points. This method contrasts with other models where robots are retrieved in separate operational rounds.

The resulting problem to be modeled can be described according to this delivery concept. The resulting problem description is based on the model by Ostermeier et al. (2022) The notation has been adopted as far as possible for the sake of comparability.

The starting point of the problem are nodes that can be visited by the autonomous delivery van, along with a distinct set of SADR´s. The entities within this logistical framework are represented by the following sets:

- Set of customers C: This set encapsulates the locations of all customers expecting delivery within the specified planning horizon and area. Deliveries to these customers are exclusively conducted by the delivery robots.
- Set of drop-off locations D: This set encompasses all viable locations within the delivery area where the delivery van is authorized to stop. It's at these junctures that delivery robots are strategically loaded with parcels and subsequently deployed for delivery. Post-delivery, these locations also serve as pivotal points for the robots to be picked up.

- Set of delivery robots R: This set represents the ensemble of autonomous delivery robots (SADRs).

Deliveries are made using an autonomous delivery van loaded with parcels for customers from set C and autonomous SADRs $r, r \in R$. The number of SADRs loaded is limited by a maximum robot capacity K of the mother ship. The delivery van´s starting position γ is a hub in the delivery area at which it is fully loaded with robots $R = \{1, \dots, K\}$. The delivery van can potentially visit any drop-off location $i, i \in D \cup \{\gamma\}$ and reaches it at the arrival time t_i. It requires a travel time ϑ_{ij}^{t} to get from stop i to stop $j, i, j \in D \cup \{\gamma\}$. At each drop-off location, the delivery van can load any number of SADRs with a parcel and deploy them for delivery. Subsequently, the delivery van incurs a waiting time until it leaves the drop-off location $i \in D$ at the departure time q_i, strategically awaiting the return of the SADRs. Upon their return, the robots can either be reloaded with a new parcel for subsequent delivery missions or be transported to the next drop-off point. The final position of the delivery van corresponds to the starting position γ. Each dropped SADR $r \in R$ is sent from drop-off location $i \in D$ to exactly one customer $k, k \in C$. The robot requires a travel time ϑ_{ik}^{r} to reach customer $k \in C$ from drop-off location $i \in D$. After the delivery, the robot then navigates back to either the same drop-off location $j = i \in D$ or proceeds to the subsequent stop in the delivery van´s route $j \neq i \in D$ requiring a travel time ϑ_{kj}^{r} and readying itself for potential reassignment or relocation.

In addition, process times occur on arrival at each node, both for the delivery van, for example when dropping off a SADR at drop-off location $i \in D$, and for the SADRs, for example when handing over a parcel at the customer's location $k \in C$. For this reason, the process times can be added to the travel times $\vartheta_{ij}^{t}, \vartheta_{ik}^{r}$ and ϑ_{kj}^{r} and thus presented in a simplified form.

Various costs are incurred during the delivery process:

- Time-based costs for the delivery van: These costs incur due to the travel times between the drop-off location i and $j, i, j \in D \cup \{\gamma\}$, as well as process times and the waiting time for the robots to return. The cost rate for these time-based costs is defined as c^t per time unit.
- Time-based costs for the SADRs: These costs incur due to the travel times between the drop-off locations $i \in D \cup \{\gamma\}$ and the customers $k \in C$ as well as process times and the waiting time for the time window to start. The cost rate for these time-based costs is defined as c^r per time unit.

The described problem can be divided into two distinct yet interconnected sub-problems: a route planning problem for the delivery van and an assignment problem for the customers. (Boysen et al. 2018) The route planning problem is about determining an optimal sequence of drop-off locations $i \in D \cup \{\gamma\}$ which the delivery van visits. A solution to this problem can be represented by tuples of two drop-off locations i and $j, i, j \in D \cup \{\gamma\}$ if the delivery van travels from drop-off locations i to drop-off location j. The assignment problem is centered on determining the precise allocation for each customer $k \in C$, linking them to an initial drop-off location $i \in D$, and designating a corresponding pick-up location $j, j \in$ D, along with assigning a specific robot $r \in R$. The solution to this multifaceted problem is represented by a multi-dimensional matrix, where each entry delineates the combination of drop-off location, customer, pick-up location, and robot (Ostermeier et al. 2022). Crucially, the solution encapsulates an additional layer by establishing the order in which a customer k_1 is served before customer $k_2, k_1, k_2 \in C$ from the same location by the same robot. A solution can be represented by tuples of two customers.

The overall objective is to find a cost-efficient solution to the overall problem that considers both the route planning problem and the assignment problem. An optimal solution can only be found within the set of feasible solutions that fulfill all given restrictions.

3 Methodology – Mathematical optimization and Modeling of a VnR delivery

This section discusses the solution strategies specifically developed for our VnR problem. In Section 3.1, we lay out a Mixed Integer Programming (MIP) model that provides the foundational structure for our problem-solving approach. Moving forward, Section 3.2 introduces a Variable Neighborhood Search (VNS) technique, which is applied to determine an optimal assignment of customers under a predefined van route.

3.1 *Mathematical formulation*

Drawing from the problem delineated in Chapter 2.2, a MIP model has been developed, the details of which are outlined in the subsequent sections. Table 2 presents a comprehensive notation key for this model. The objective function, articulated in Function (1), is subject to the constraints enumerated from (2) through (18).

Table 2: Notation of the MIP model for VnR delivery

Index sets	
C	Set of customers
D	Set of distinct drop-off locations
R	Set of robots
Parameters	
γ	Starting position of the van $\gamma \in D \cup \{\gamma\}$
ϑ_{ij}^{t}	Van travel time from location i to location $j, i, j \in D \cup \{\gamma\}$
ϑ_{ik}^{r}	Robot travel time from location $i, i \in D$ to customer $k, k \in C$
Cost parameters	
c^t	Cost of van per time unit
c^r	Cost of robot per time unit
Decision variables	
s_{ij}	Binary: 1, if van goes from location i to location j; 0 otherwise
x_{ikjr}	Binary: 1, if customer k is supplied from location i by robot r and the robot returns to j; 0 otherwise
$y_{k_1k_2}$	Binary: 1, if customer k_1 is supplied before customer k_2 from the same location by the same robot; 0 otherwise
Auxiliary variables	
t_i	Arrival time of van at location $i, i \in D \cup \{\gamma\}$
q_i	Departure time of van at location $i, i \in D \cup \{\gamma\}$

q_{max}	Last departure time of van at location $i, i \in D$
a_{ir}	Arrival time of robot $r, r \in R$ at location $i, i \in D$

$$\text{Min } TC(S, X, q_{max}) = c^t \cdot q_{max} + \sum_{i \in D} c^t \cdot \vartheta_{i,\gamma}^t \cdot s_{i,\gamma} + \sum_{i \in D} \sum_{k \in C} \sum_{j \in D} \sum_{r \in R} c^r \cdot \vartheta_{i,k}^r \cdot x_{i,k,j,r} \tag{1}$$

subject to

$$\sum_{j \in D} s_{\gamma,j} \leq 1 \tag{2}$$

$$\sum_{i \in D \cup \{\gamma\}} s_{i,j} = \sum_{i \in D \cup \{\gamma\}} s_{j,i} \qquad \forall j \in D \cup \{\gamma\} \tag{3}$$

$$\sum_{i \in D} \sum_{j \in D} \sum_{r \in R} x_{i,k,j,r} = 1 \qquad \forall k \in C \tag{4}$$

$$\sum_{k \in C} \sum_{j \in D} \sum_{r \in R} x_{i,k,j,r} = M \cdot \sum_{j \in D \cup \{\gamma\}} s_{i,j} \qquad \forall i \in D \tag{5}$$

$$\sum_{k \in C} x_{i,k,j,r} \leq s_{i,j} \qquad \forall i \neq j \in D; r \in R \tag{6}$$

$$\sum_{j \in D} x_{i,k_1,j,r} + \sum_{j \in D} x_{i,k_2,j,r} \leq 1 + y_{k_1,k_2} + y_{k_2,k_1} \qquad \forall i \in D \cup \{\gamma\}; k_1 < k_2 \in C; r \in R \tag{7}$$

$$t_\gamma = 0 \tag{8}$$

$$t_j \geq q_i + \vartheta_{i,j}^t - M \cdot (1 - s_{i,j}) \qquad \forall j \in D; i \in D \cup \{\gamma\} \tag{9}$$

$$a_{j,r} \geq t_j \qquad \forall r \in R; j \in D \tag{10}$$

$$a_{j,r} \geq a_{i,r} + \sum_{k1 \in C} 2 \cdot \vartheta_{i,k1}^r \cdot y_{k1,k} + \vartheta_{i,k}^r + \vartheta_{k,j}^r - M \cdot (1 - x_{i,k,j,r}) \qquad \forall i \neq j \in D; k \in C; r \in R \tag{11}$$

$$q_j \geq a_{i,r} + \sum_{k1 \in C} 2 \cdot \vartheta_{i,k1}^r \cdot y_{k1,k} + (2 \cdot \vartheta_{i,k}^r \cdot x_{i,k,i,r}) \qquad \forall i, j \in D; r \in R; k \in C \tag{12}$$

$$q_{max} \geq q_i \qquad \forall i \in D \quad (13)$$

$$s_{ij} \in \{0,1\} \qquad \forall i \neq j \in D \cup \{\gamma\} \quad (14)$$

$$x_{ik} \in \{0,1\} \qquad \forall i \in D, k \in C \quad (15)$$

$$y_{k1,k2} \in \{0,1\} \qquad \forall k1 \in C, k2 \in C \setminus \{k1\} \quad (16)$$

$$t_i, q_i \geq 0 \qquad \forall i \in D \cup \{\gamma\} \quad (17)$$

$$a_{i,r} \geq 0 \qquad \forall i \in D; r \in R \quad (18)$$

The model's objective (1) is to minimize total costs, which includes the van travel costs, van waiting time costs at drop-off locations and robot travel costs. Constraint (2) ensures that only one van starts from the starting position γ. Constraint (3) ensures a van leaves a location it arrives at. Constraint (4) guarantees each customer is supplied by exactly one robot. Constraint (5) stipulates robots are dropped off only at van stops. Constraint (6) ensures that robots are picked up only from the same or a subsequent stop, while guaranteeing that each robot travels to another drop-off location at most once. Constraint (7) orders customer visits from the same location by the same robot.

Constraint (8) sets the initial time for the van at the starting position γ and Constraint (9) sets the van's arrival time at locations. Constraints (10) and (11) define the operation starting time of robots at stops, ensuring that the starting time is contingent upon the arrival time of either the van or the robot, whichever arrives later. Constraint (12) defines the van's departure time at every stop. Constraint (13) determines the latest departure time across all stops in the tour. Finally, Constraints (14) – (18) define the variables.

3.2 Solution approach

Since this is an NP-hard problem, most research on these problems use a heuristic method. Traditional optimization methods, including commercial solvers, have shown limitations. Despite attempts to solve the mathematical formulation above using commercial solvers, they failed to yield high-quality solutions even for moderate-size test instances within a reasonable timeframe. This situation underscores the complexity of the problem, prompting the need for a heuristic approach, such as Variable Neighborhood Search (VNS).

VNS is a metaheuristic optimization approach that systematically explores and adapts various neighborhood structures to escape local optima and find better solutions (Mladenović and Hansen 1997). Although VNS may not be the fastest approach for solution generation, its strength lies in its ability to produce high-quality solutions (Liu and Jiang 2022). The quality of solutions is crucial as it directly impacts the efficiency and reliability of the entire delivery system. In this study, we present a VNS approach, detailed in Algorithm 1.

3.2.1 General functioning of the algorithm

Table 3: Variable neighborhood search for VnR delivery

Algorithm 1. Variable neighborhood search for VnR delivery

```
Identify neighborhood structures set $N_k (k = 1, ..., k_{max})$
Initialize: Generate an initial solution $S, k \leftarrow 1, i \leftarrow 0, i_{max} \leftarrow n$
repeat
    Shake: generate a random point $S'$ from the neighborhood $N_k(S)$
    Local Search: use the local search starting from solution $S'$ to find a solution $S''$
    If $S''$ is better than $S$ then
        $S \leftarrow S'', k \leftarrow 1$ and $i \leftarrow 0$ (center the search around $S''$, search again in neighborhood 1 and reset counter)
    else
        $k \leftarrow k + 1$ (expand the neighborhood)
        $i \leftarrow i + 1$ (count runs without improvement)
until $i = i_{max}$ (terminate after $n$ runs without improvement)
```

At the onset, the algorithm establishes a set of neighborhood structures $N_k (k = 1, ..., k_{max})$ and an initial solution S. The algorithm commences its process with $k = 1$ and an iteration counter $i = 0$, which monitors the number of consecutive iterations without improvement. The *shake* function is the first stage of the algorithm, where a new solution S' is randomly generated from the current solution S using the k^{th} neighborhood structure N_k. Following this, the algorithm applies a *local search* improvement procedure to S'. This *local search*, utilizing the Gurobi optimizer, iteratively refines the tour. The procedure is repeated until a new incumbent solution S'' is discovered.

If S'' offers an improvement over S, the algorithm updates S to S'', resets k to 1, and resets the counter i to 0, marking the discovery of an improved solution. Conversely, if S'' fails to enhance S, the algorithm increments k to transition to the next neighborhood structure and increments i, indicating another iteration without improvement. This process of alternating between *shaking* and *local search* continues, with the counter i keeping track of the iterations. The algorithm incorporates a termination condition wherein it concludes its process when i reaches a predefined maximum number $i_{max} = n$ to ensure that the algorithm stops after a reasonable number of attempts, thus avoiding excessive computation time while still providing a solution of acceptable quality.

3.2.2 Construction of an initial solution

In tackling the two-stage Vehicle Routing Problem for VnR delivery, the problem is effectively divided into two interconnected segments: the routing problem for the van and the assignment problem for the delivery robots. This division is inherently advantageous for the application of the VNS method. In this approach, we capitalize on it by initially fixing the van route and systematically adjusting it, while concurrently optimizing the robot assignments.

The optimization process begins with the generation of an initial feasible solution. This plays a crucial role, not only in setting the stage for subsequent optimization but also in ensuring the feasibility of the model. This is achieved by adding each customer’s nearest drop-off point to the van tour in a random sequence. Following this, the robot assignment for each customer is optimized based on this preliminary van route.

3.2.3 Shake function and neighborhood structures

Table 4: Set of neighborhood structures for the VNS

Neighborhood	**Operator**
N_1	*Random removal*: A drop-off point is randomly removed from the van route.
N_2	*Random insertion*: A new drop-off point, not already on the route, is randomly inserted to the van route.
N_3	*Random swap*: Two drop-off points in the van route are randomly swapped.

In the Variable Neighborhood Search (VNS) framework, the neighborhood structures are pivotal for guiding the search process. These structures, denoted as $N_k(k = 1, \dots, k_{max})$, represent different ways in which the current solution can be modified to explore new potential solutions. In your VNS implementation, as encapsulated in the *shake* function, these neighborhood structures are defined by the operations of *random removal, random insertion*, and *random swap* (see Table 4). Each of these operations constitutes a distinct type of neighborhood structure within the VNS algorithm. The *shake* function randomly selects one of these operations to modify the current solution and thereby generates a new neighborhood to be explored. This approach allows the algorithm to methodically examine a wide range of possible configurations, moving beyond local optima and thoroughly searching the solution space for more efficient delivery tours.

4 Research Framework

The research framework for this study is structured into two main components. Initially, the study begins with a detailed problem description, which serves as the basis for the parametrization of the developed model. Subsequently, an experimental plan is devised, outlining a systematic approach to manipulating each parameter independently. This methodical alteration of parameters allows for a precise analysis of how each one impacts the overall system's performance.

4.1 Parameterization

Reflecting on the problem outlined in Chapter 2.2, this section presents a standard set of parameters for the model. These parameters are detailed in Table 5.

The cost model is based on the approaches of Boysen et al. (2018) and Ostermeier et al. (2022) and assumes that the costs for the use of autonomous vehicles can be represented by an hourly machine rate. In this case, interest costs are not considered, space costs are eliminated as the machines are used in public spaces and maintenance as well as energy costs are calculated as a simplified percentage factor. Therefore distance-based costs are not measured in an additional parameter.

If it is further assumed that there is no resale value due to the novelty of the vehicles, only the acquisition costs and the service life are considered as imputed depreciation and thus together with the time-related costs of the technical supervisor of the vehicle as machine-dependent costs. This results in the following hourly machine rates for the SADRs and the delivery van:

- Time-based costs for the SADRs: The robot costs amount to $c^r = 4{,}9\ €/h$. These costs include depreciation, maintenance, electrical energy and rent for the charging stations. A purchase price of 15,000€ is assumed for depreciation. The depreciation period is assumed as five years and 50 operating weeks per year, six days per week and 12 hours per day. The degree of utilization is estimated at a conservative 50%. A surcharge of 50% is added for maintenance, electricity and rent for the charging stations. As costs for the technical supervisor it is assumed, that the supervisor gets payed 24€ hourly and is able to supervise 10 robots at the same time. Accordingly, the robot costs are calculated as $c^r = \frac{15{,}000}{5*50*6*12*50\%\ (utilitisation)} * (1 + 50\%) + \frac{24}{10}$.
- Time-based costs for the delivery van: The Mercedes-Benz eSprinter is used as a reference vehicle. The costs for commercial customers amount to 54,000€. In a 2017 Wadud (2017) estimates the additional costs for such a fully autonomous vehicle compared to a conventional vehicle at 16,000€. This estimate is based on the evaluation of various sources and assumes the establishment of autonomous vehicles on the market and the associated mass production. The conversion costs for the special solution with

automatic material flow and automatic ramp are difficult to estimate but is presumed in the future without development expenses at 30,000€. Therefore, the total acquisition costs amount to 100,000€. As costs for the technical supervisor it is assumed, that the supervisor gets payed 24€ hourly and is able to supervise 5 vehicles at the same time. Equivalent to the robot costs, this results in time-based van costs of $c^t = 21{,}5€/h$ calculated by $c^t = \frac{100{,}000}{5*50*6*12*50\%\ (utilitisation)} * (1 + 50\%) + \frac{24}{5}$. It should be noted that such a procurement price cannot be achieved with an initial introduction of the VnR concept, but is only possible with an increasing production number of such vehicles.

The parameter values, such as prices or the vehicles to be supervised at the same time were gathered from discussions with vehicle manufacturers during on-site visits and at exhibitions, as well as from the project experience of BeIntelli (BeIntelli 2024). Looking ahead, vehicle costs are expected to decrease due to advancements in manufacturing and wider market adoption. Simultaneously, improvements in autonomous driving technology may allow a single supervisor to manage more vehicles, potentially reducing the overall operational costs as these technologies mature.

Table 5: Parameter values of the problem instance

Parameter	**Description**	**Value**
Size of the index sets		
$\lvert C\rvert$	Number of customers	10
$\lvert D\rvert$	Number of drop-off locations	9
$\lvert R\rvert$	Number of robots	4
Constraints		
μ_t	Fixed van processing time at every stop	60
μ_r	Fixed robot processing time at every stop	300
ω_t	Average van speed	30 km/h
ω_r	Average robot speed	3 km/h
Cost factors		
c^t	Time cost of van	21,50 €/h
c^r	Time cost of robots	4,90 €/h

Starting with a designated delivery area, a rectangle was set within the testing track of the BeIntelli research project. Within this defined area, there are 10 customers, denoted by $|C|$, all expecting to receive deliveries within the established planning horizon. The geographical positioning of these customers was randomly assigned using Open Street Maps – a freely accessible repository of cartographic and geospatial data. Potential drop-off points were identified through on-site surveys, with a focus on existing loading and delivery zones. Additionally, the headquarters of the BeIntelli project was designated as the hub, marking the delivery van´s point of departure. The computation of inter-location distances was conducted via the Open Source Routing Machine, a robust routing engine optimized for computing the shortest paths in road networks. Subsequently, these distances were divided by the respective travel speeds of the vehicles to derive travel times between each pair of locations for the different vehicle types.

4.2 Experiments

To examine the model's response to specific alterations, experiments are designed where parameter configurations are systematically varied, identifying these variables as "factors." A structured experimental plan facilitates the systematic recording of these configurations and their respective outcomes. Such a plan, often tabulated, details the configurations tested and the results obtained. In this study, parameters are adjusted following a standard parameterization to assess the impact of different factors. A what-if analysis is then conducted, setting specific parameter combinations to evaluate their influence on outcomes (Gutenschwager et al. 2017).

These factors are examined in isolation within the experiments, each assuming various states, independently of one another. This method resulted in the experimental plan detailed in Table 6, comprising 14 parameter configurations. The initial experiment employs the standard configuration, while subsequent experiments modify the factors across two different settings. The final experiment represents a best-case scenario, utilizing a combination of factors that positively influence the outcomes.

Table 6: Experiment plan for the Van-and-Robot model

ID	Parameter (factors)					
	Factor $\mu_r[s]$	*Factor* $\|R\|$	*Factor* $\omega_r[km/h]$	*Factor* $c^t[€/h]$	*Factor* $c^r[€/h]$	*Factor Teleoperator [# Van / # Robot]*
1	300	4	3	21,50	4,90	5 / 10
2	600	4	3	21,50	4,90	5 / 10
3	60	4	3	21,50	4,90	5 / 10
4	300	3	3	21,50	4,90	5 / 10
5	300	5	3	21,50	4,90	5 / 10
6	300	4	2	21,50	4,90	5 / 10
7	300	4	5	21,50	4,90	5 / 10

8	300	4	3	25,50	4,90	5 / 10
9	300	4	3	17,13	4,90	5 / 10
10	300	4	3	21,50	6,57	5 / 10
11	300	4	3	21,50	4,07	5 / 10
12	300	4	3	24,67	5,50	3 / 8
13	300	4	3	20,10	4,5	7 / 12
14	60	5	5	15,10x	3,67x	7 / 12

5 Results and Implications

This chapter outlines the findings, discusses their broader implications, and explores how individual factors influence the overall and specific types of delivery costs. For the purpose of these experiments, computational models were designed and implemented.

The models were programmed using Python version 3.12.1 in Visual Studio Code version 1.88.0, utilizing the 'gurobipy' extension. This extension offers extensive modeling capabilities and an interface for Gurobi, an advanced mathematical optimization software. The computational experiments were conducted on a PC running Windows 10 Education with an Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz, 8.00 GB of RAM, and a 64-bit operating system.

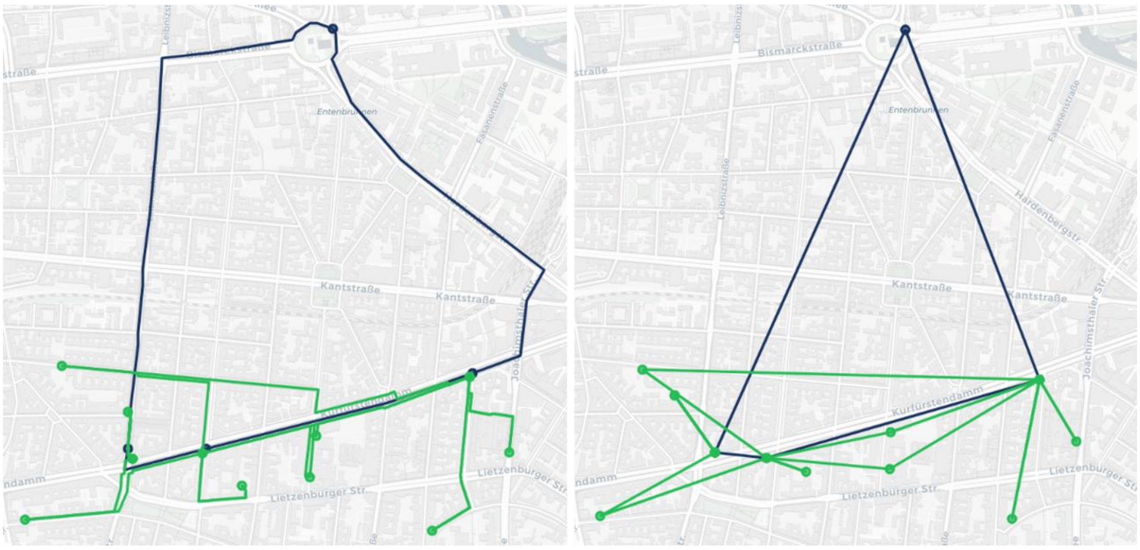

Figure 3: Routes with real-world road navigation (left) and geometric direct paths (right) as calculated in the standard parametrization

5.1 Cost analysis of the delivery concept

In this chapter, we present the results of 14 experiments, detailed in categorizing waiting times, vehicle costs, total times, and overall costs to evaluate different infrastructural impacts.

Table 7, categorizing waiting times, vehicle costs, total times, and overall costs to evaluate different infrastructural impacts.

Table 7: Experiment results

ID	Changed parameter	Ø Waiting time per stop [min]	Total tour time [min]	Waiting costs van	Driving costs van	Robot costs	Total costs	Change to standard parameter
1	Standard	27,98	98,23	30,09 €	5,11€	29,02€	*64,22 €*	-
2	Process time	34,33	116,7	36,91 €	4,91 €	38,81 €	*80,62 €*	**26%**
3		14,16	73	20,30 €	5,86€	21,19€	*47,36 €*	**-26%**
4		26	121	37,02 €	6,19 €	25,96 €	*69,17 €*	**8%**

5	Number of robots	16,26	81,6	23,32 €	5,92 €	27,26 €	*56,50 €*	**-12%**
6	Robot speed	28,5	130,5	40,85 €	5,92 €	35,79 €	*82,56 €*	**29%**
7		14,88	75,9	21,33 €	5,86 €	19,49 €	*46,68 €*	**-27%**
8	Costs of the van	20,15	95,28	34,25 €	6,25 €	29,66 €	*70,15 €*	**9%**
9		20,16	97,02	23,03 €	4,67 €	27,73 €	*55,42 €*	**-14%**
10	Costs of the robot	20,16	97,02	28,90 €	5,86 €	37,18 €	*71,93 €*	**12%**
11		20,16	97,02	28,90 €	5,86 €	23,03 €	*57,79 €*	**-10%**
12	Number of supervised vehicles	20,15	95,28	33,13 €	6,04 €	33,29 €	*72,46 €*	**13%**
13		20,16	97,02	27,02 €	5,48 €	25,46 €	*57,96 €*	**-10%**
14	Best Case	9,43	41,98	7,12 €	3,45 €	11,05 €	*21,61 €*	**-66%**

Under conservative standard settings, the costs per shipment are 6.42 €, which can be reduced to approximately 2.16 € per parcel in optimal scenarios. if the SADR speed is increased within the legal and technical framework conditions, handover times are reduced to a technical minimum, meaning that the receiver is already at the meeting position, more robots are used, purchase prices are reduced and more vehicles are supervised simultaneously. Conversely, costs may escalate to over 8.2 € per shipment if robot speeds decrease.

These findings suggest that significant reductions in shipment costs are feasible with advancements in autonomous driving technologies, even for small quantities. It should also be noted that the delivery van often experiences prolonged idle times at drop-off points, indicating potential for enhanced operational efficiency.

5.2 Effects of the factors on the result - Experiments

In this chapter, we examine the individual effects of specific factors on the overall results of our experiments, with the exception of the best-case scenario outlined in experiment 14. This allows for a clearer understanding of each factor's impact, leading to more grounded managerial implications.

Effects of the process time - experiments 2 and 3:

The handover process is a significant determinant of the overall delivery costs, with its optimization presenting substantial opportunities for reducing expenses. Our analysis reveals that prolonged handover times lead to increased operational costs, primarily due to extended robot activity and vehicle idling.

To optimize the handover process, advanced technologies that enable quicker loading and unloading operations are recommended. Implementing unattended home delivery systems could also streamline the process by allowing packages to be securely left at designated locations without needing direct recipient interaction, thus significantly cutting down on handover times.

Furthermore, proactive customer communication strategies, such as real-time notifications, can prepare customers for the arrival of their packages, minimizing any delays and further reducing robot idle time. Together, these improvements not only enhance service efficiency and customer satisfaction but also significantly improve resource utilization and overall cost-effectiveness of the delivery operations.

Effects of the robot capacity of the van - experiments 4 and 5:

Utilizing a greater number of robots in delivery operations has demonstrated a clear cost advantage, even when the volume of shipments is relatively low. The deployment of additional robots enables the parallel processing of deliveries, which significantly reduces both the time per delivery and the overall costs associated with delivery operations.

The efficiency gains from this parallelization could outweigh the initial investment in extra hardware. This benefit, however, is contingent upon the robots being employed consistently throughout their entire depreciation period. Ensuring full utilization maximizes the return on investment by spreading the cost of each robot over a greater number of deliveries.

Effects of the speed of the delivery robots - experiments 6 and 7:

The speed of delivery robots is a critical factor in optimizing cost-effectiveness of delivery operations. By reducing the time required for each delivery task, faster robot speeds directly lower overall operational costs. This improvement in speed enables the same number of deliveries to be completed in a shorter period, effectively optimizing the use of resources and significantly reducing the idle time of delivery vans.

By optimizing delivery schedules to avoid peak traffic times, utilizing data-driven routing to circumvent congested areas, and investing in improved autonomous navigation systems to allow for a more assertive navigation style, robot speed can be enhanced without compromising safety, leading to delivery cost reductions.

Effects of Hardware and accordingly of time-based costs- experiments 8 to 11 and effects of the number of simultaneously supervised vehicles - experiments 12 and 13:

In experiments 8 through 13, where we controlled for different cost factors without altering any technical or performance parameters, the optimal tour configurations remained consistent across various scenarios. This constancy reveals that the vehicle cost rates do not impact the structural design of delivery tours. Even when faced with significant fluctuations in cost factors, the chosen routes for deliveries remained unchanged. This outcome demonstrates that route planning is not sensitive to variations in vehicle costs and is instead influenced more significantly by logistical considerations and operational efficiency.

6 Final Remarks

In concluding our exploration into the VnR concept for autonomous urban delivery, this paper contributes a novel modeling approach that expands the operational flexibility for SADRs. Our research illuminates significant parameters influencing delivery efficiency and cost, specifically highlighting the profound impact of SADR speed and handover process efficiency.

Responding to our primary research questions, we have quantified the cost implications of the VnR delivery concept on urban last-mile delivery (RQ1) and delineated critical design criteria for its practical application (RQ2). The results from a series of parametric studies underscore the delicate balance between operational costs and system efficiency.

Next to influencing efficiency and costs, conclusions can also be drawn about sustainability. For instance, electric and, considering SADRs, lightweight vehicles are used. The concept in general reduces traffic on the road, but shifts it partially to the sidewalk. Above that it as shown that delivery vans have to wait a long time at drop-off points. However, these are often free parking spaces and, thanks to the mobility of the SADRs, no longer have to be directly in front of the delivery point, so that second-row parking can be reduced. Finally, the cost-efficient use of robots also offers the possibility of handling returns and thus potentially also using reusable packaging.

A key limitation of our study is the assumption of static environmental conditions. While the insights gained are tailored to the specific operational context of the BeIntelli project, generalizing these findings to other urban areas or delivery requirements necessitates a degree of caution. The model's dependence on current technology and operational standards means that rapid advancements in autonomous delivery systems could further optimize costs and performance.

For future research, a broader examination of varying urban settings, customer densities, and product-specific delivery needs is recommended. A more dynamic model, incorporating a fleet of vans with real-time customer order processing, could offer deeper insights into the design and cost efficiency of VnR systems.

The theoretical and practical implications provided herein aim to serve as guidelines for practitioners implementing autonomous delivery solutions, while also laying the groundwork for more advanced investigations into the VnR delivery concept.

7 Publication bibliography

BeIntelli (2024): KI für die Autonome Mobilität. Edited by DAI-Labor. Berlin. Available online at https://be-intelli.com/, checked on 4/4/2024.

Boysen, Nils; Schwerdfeger, Stefan; Weidinger, Felix (2018): Scheduling last-mile deliveries with truck-based autonomous robots. In *European Journal of Operational Research* 271 (3), pp. 1085–1099. DOI: 10.1016/j.ejor.2018.05.058.

Brabänder, Christian (2020): Die Letzte Meile. Wiesbaden: Springer Fachmedien Wiesbaden.

Bundesverband Paket und Expresslogistik e. V. (BIEK), KE-CONSULT Kurte&Esser GbR (2023): Impulsgeber mit Innovationskraft. KEP-Studie 2023 - Analyse des Marktes in Deutschland. Edited by Bundesverband Paket und Expresslogistik e. V. Berlin, Köln. Available online at https://www.biek.de/kep-branche/zahlen-und-fakten.html, updated on 6/13/2023.

Demir, Emrah; Huang, Yuan; Scholts, Sebastiaan; van Woensel, Tom (2015): A selected review on the negative externalities of the freight transportation: Modeling and pricing. In *Transportation Research Part E: Logistics and Transportation Review* 77, pp. 95–114. DOI: 10.1016/j.tre.2015.02.020.

Di Puglia Pugliese, Luigi; Macrina, Giusy; Guerriero, Francesca (2021): Trucks and drones cooperation in the last-mile delivery process. In *Networks.* 78 (4), pp. 371–399. DOI: 10.1002/net.22015.

Domschke, Wolfgang; Drexl, Andreas; Klein, Robert; Scholl, Armin (2015): Einführung in Operations Research: Springer Berlin Heidelberg.

Firdausiyah, N.; Taniguchi, E.; Qureshi, A. G. (2019): Modeling city logistics using adaptive dynamic programming based multi-agent simulation. In *Transportation Research Part E: Logistics and Transportation Review* 125, pp. 74–96. DOI: 10.1016/j.tre.2019.02.011.

Fläming, Heike (2015): Autonome Fahrzeuge und autonomes Fahren im Bereich des Gütertransportes. In Markus Maurer, J. Christian Gerdes, Barbara Lenz, Hermann Winner (Eds.): Autonomes Fahren. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 377–398.

Gutenschwager, Kai; Rabe, Markus; Spieckermann, Sven; Wenzel, Sigrid (2017): Simulation in Produktion und Logistik. Grundlagen und Anwendungen. Berlin, Heidelberg: Springer Berlin Heidelberg; Imprint: Springer Vieweg.

Heimfarth, Andreas; Ostermeier, Manuel; Hübner, Alexander (2021): A mixed truck and robot delivery approach for the daily supply of customers. In *SSRN Journal*. DOI: 10.2139/ssrn.3815759.

Hu, Wanjie; Dong, Jianjun; Hwang, Bon-gang; Ren, Rui; Chen, Zhilong (2019): A Scientometrics Review on City Logistics Literature: Research Trends, Advanced Theory and Practice. In *Sustainability* 11 (10), p. 2724. DOI: 10.3390/su11102724.

Jennings, Dylan; Figliozzi, Miguel (2019): Study of Sidewalk Autonomous Delivery Robots and Their Potential Impacts on Freight Efficiency and Travel. In *Transportation Research Record* 2673 (6), pp. 317–326. DOI: 10.1177/0361198119849398.

Jordan, Hanna; Kaden, Christian; Klauenberg, Jens; Kuchenbecker, Miachel; Rüdiger, Dag; Rybarczyk, Daniel et al. (2020): Die Veränderungen des gewerblichen Lieferverkehrs und dessen Auswirkungen auf die städtische Logistik. Edited by LNC LogisticNetwork Consultants GmbH, Fraunhofer-Institut für Materialfluss und Logistik IML. Available online at https://bmdv.bund.de/SharedDocs/DE/Anlage/G/staedtische-logistik-bericht-veraenderungen-lieferverkehr.pdf?__blob=publicationFile.

Kyriakakis, Nikolaos A.; Stamadianos, Themistoklis; Marinaki, Magdalene; Marinakis, Yannis (2022): The electric vehicle routing problem with drones: An energy minimization approach for aerial deliveries. In *Cleaner Logistics and Supply Chain* 4, p. 100041. DOI: 10.1016/j.clscn.2022.100041.

Lee, Hau L.; Chen, Yiwen; Gillai, Barchi; Rammohan, Sonali (2016): Technological disruption and innovation in last-mile delivery. Edited by Stanford Graduate School of Business. Stanford. Available online at https://www.gsb.stanford.edu/sites/default/files/publication-pdf/vcii-publication-technological-disruption-innovation-last-mile-delivery.pdf, checked on 5/4/2023.

Liu, Ran; Jiang, Shan (2022): A variable neighborhood search algorithm with constraint relaxation for the two-echelon vehicle routing problem with simultaneous delivery and pickup demands. In *Soft Comput* 26 (17), pp. 8879–8896. DOI: 10.1007/s00500-021-06692-3.

Maas, Julian; Nitsche, Benjamin; Straube, Frank (2023): Systematization of autonomous vehicles in last mile transportation processes – taxonomy development and clustering of existing concepts. In *International Journal of Logistics Research and Applications,* pp. 1–23. DOI: 10.1080/13675567.2023.2237454.

Mercedes-Benz Group AG (2017): Mercedes-Benz Vans invests in Starship Technologies, the world's leading manufacturer of delivery robots. Edited by Mercedes-Benz Group Media. Available online at https://group-media.mercedes-benz.com/marsMediaSite/en/instance/ko/Mercedes-Benz-Vans-invests-in-Starship-Technologies-the-worlds-leading-manufacturer-of-delivery-robots.xhtml?oid=15274799, checked on 2/10/2023.

Mercedes-Benz Vans (2016): Vans & Robots: Efficient delivery with the mothership concept. Available online at https://www.youtube.com/watch?v=yUMOLzCsifs, checked on 2/14/2023.

Mitteregger, Mathias; Bruck, Emilia M.; Soteropoulos, Aggelos; Stickler, Andrea; Berger, Martin; Dangschat, Jens S. et al. (2021): AVENUE21. Politische und planerische Aspekte der automatisierten Mobilität. Berlin, Heidelberg: Springer Berlin Heidelberg.

Mladenović, N.; Hansen, P. (1997): Variable neighborhood search. In *Computers & Operations Research* 24 (11), pp. 1097–1100. DOI: 10.1016/S0305-0548(97)00031-2.

Na, Hyeong Suk; Kweon, Sang Jin; Park, Kijung (2022): Characterization and Design for Last Mile Logistics: A Review of the State of the Art and Future Directions. In *Applied Sciences* 12 (1). DOI: 10.3390/app12010118.

Ostermeier, Manuel; Heimfarth, Andreas; Hübner, Alexander (2022): Cost-optimal truck-and-robot routing for last-mile delivery. In *Networks.* 79 (3), pp. 364–389. DOI: 10.1002/net.22030.

Rabe, Markus; Gonzalez-Feliu, Jesus; Chicaiza-Vaca, Jorge; Tordecilla, Rafael D. (2021): Simulation-Optimization Approach for Multi-Period Facility Location Problems with Forecasted and Random Demands in a Last-Mile Logistics Application. In *Algorithms* 14 (2), p. 41. DOI: 10.3390/a14020041.

Schröder, Jürgen; Heid, Bernd; Neuhaus, Florian; Kässer, Matthias; Klink Christoph; Tatomir, Simon (2018): Fast forwarding last-mile delivery. implications for the ecosystem. Edited by McKinsey & Company. Available online at https://www.mckinsey.com/~/media/mckinsey/industries/travel%20logistics%20and%20infrastructure/our%20insights/technology%20delivered%20implications%20for%20cost%20customers%20and%20competition%20in%20the%20last%20mile%20ecosystem/fast-forwarding-last-mile-delivery-implications-for-the-ecosystem.pdf.

Schröder, Meike; Wegner, Kirsten (2019): Logistik im Wandel der Zeit – Von der Produktionssteuerung zu vernetzten Supply Chains. Wiesbaden: Springer Fachmedien Wiesbaden.

Simoni, Michele D.; Kutanoglu, Erhan; Claudel, Christian G. (2020): Optimization and analysis of a robot-assisted last mile delivery system. In *Transportation Research Part E: Logistics and Transportation Review* 142, p. 102049. DOI: 10.1016/j.tre.2020.102049.

Straube, Frank; Grunow, Oliver; Ihlenburg, Stephanie; Sinn, Florian (2021): Konzeption und Implementierung von Mikro-City-Hubs als Baustein emissionsneutraler City-Logistik. In Dietmar Göhlich, Andreas F. Raab (Eds.): Mobility2Grid - Sektorenübergreifende Energie- und Verkehrswende. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 181–207.

Taniguchi, Eiichi; Thompson, Russell G.; Qureshi, Ali G. (2023): Urban Freight Analytics. Boca Raton: CRC Press.

Wadud, Zia (2017): Fully automated vehicles: A cost of ownership analysis to inform early adoption. In *Transportation Research Part A: Policy and Practice* 101, pp. 163–176. DOI: 10.1016/j.tra.2017.05.005.

Wang, Yang; Bi, Mengyu; Lai, Jianhui; Wang, Chenxi; Chen, Yanyan; Holguín-Veras, José (2024): Recourse strategy for the routing problem of mobile parcel lockers with time windows under uncertain demands. In *European Journal of Operational Research*. DOI: 10.1016/j.ejor.2024.02.034.

World Economic Forum (2021): Pandemic, Parcels and Public Vaccination. Envisioning the Next Normal for the Last-Mile Ecosystem. Available online at https://www3.weforum.org/docs/WEF_Pandemic_Parcels_and_Public_Vaccination_report_2021.pdf.