A Simulation Study on Electric Last Mile Delivery with Mobile Smart Cargo Boxes

Fabian Lorig*, Emil Johansson, Paul Davidsson, Jan A. Persson

Internet of Things and People Research Center, Department of Computer Science and Media Technology, Malmö University, Malmö, Sweden; *fabian.lorig@mau.se

SNE 32(3), 2022, 161-168, DOI: 10.11128/sne.32.tn.10616
Selected ASIM SPL 2021 Postconf. Publication: 2022-02-01;
Received English version: 2022-06-01; Accepted: 2022-06-03
SNE - Simulation Notes Europe, ARGESIM Publisher Vienna
ISSN Print 2305-9974, Online 2306-0271, www.sne-journal.org

Abstract. The increasing popularity of e-commerce requires efficient solutions for the provision of last mile logistics. There are different approaches for delivering parcels, e.g., home delivery, service points, or parcel lockers, which have different advantages and disadvantages for customers and logistics providers in terms of flexibility, accessibility, and operating costs. We have studied a novel transportation solution where electric vehicles dynamically set up smart cargo boxes, from which customers can fetch their delivery at any time of the day. This provides customers with a more flexible access to their packages and allows the service provider to deliver the parcels more efficiently. In this article, we present the results of a feasibility study conducted in Västra Hamnen, Malmö (Sweden). The developed simulation model shows that smart boxes not only are a viable approach for efficient last mile deliveries, but also result in considerably smaller travel distances compared to conventional package delivery system.

Introduction

Even before the beginning of the Covid-19 pandemic, business to consumer (B2C) e-commerce has experienced a steady growth. However, due to interventions for containing the pandemic such as movement restrictions and lockdowns as well as recommendations against visiting physical stores or even their closure, the importance and popularity of online shopping increased further (Elrhim & Elsayed 2020). A major challenge that arises from the growing trend towards online shopping is the effective realization of B2C last mile delivery, i.e., the delivery of the parcel from a regional depot to the customer (Mangiaracina et al. 2019).

There exists a great number of logistics service providers that pursue different last mile delivery approaches. Common last-mile solutions for B2C are to deliver the parcel to (i) the home address, (ii) service points where they are picked up by the customers, or (iii) stationary parcel lockers that are located at supermarkets or other frequented places, where customers can pick up their parcels. As outlined by Allen et al. (2007), these delivery alternatives provide customers but also service providers with different advantages and disadvantages regarding flexibility, accessibility, and effort of the pick-up process. Customers, for instance, experience shorter retrieval times and are not limited to opening hours when using parcel lockers compared to service point deliveries. However, compared to attended home deliveries, parcel lockers and service points do not require the customer to be present upon delivery and, thus, increase the customers' flexibility in terms of the delivery time window. Yet, pick-up points are limited in their opening hours and require each customer to travel there, which they might consider to be inconvenient.

From a logistics provider's perspective, these delivery options vary in efficiency. Compared to pick-up service points, home delivery results in increased delivery costs, a higher number of failed deliveries, and a significantly greater driving distance for delivery vehicles, which also might affect traffic congestion and exhaust emissions. Moreover, the delivery option with parcel lockers is more time-consuming for the driver as he or she needs to fill the lockers with new deliveries. For both parcel lockers and service point deliveries, it can be assumed that the cumulated customer travel distance is significantly higher in relation to the travel distance of the service provider. It is challenging to take all these, potentially conflicting, requirements into account and to find a balance between the requirements of the customer and logistics providers.

To address this issue, the Swedish start-up DiPP-R (www.dipp-r.com) develops a transportation solution to improve the efficiency of last mile delivery of e-commerce parcels. The idea is that electric vehicles dynamically set up smart cargo boxes at different locations in the city. These boxes can hold between 50 and 100 packages and are dynamically placed at, for instance, parking areas. This enables the customers to pick-up their deliveries at any time during the day. After all parcels were picked up by the customers or after a certain time, the boxes are collected by the vehicles, refilled at the depot, and placed at other locations. The aim is to reduce the handling of parcels outside the depot and to decrease the distance recipients must travel to fetch their parcels. This results in increased convenience and shorter total travel distance, ultimately reducing traffic congestion and environmental impact.

This article presents the results of a feasibility study that was conducted by Malmö University, the city of Malmö, and DiPP-R. As part of this study, a simulation model was developed to investigate the effects of this new delivery concept and how it can be realized. The simulation model allows for analysing the efficiency of different service designs in Västra Hamnen, a district in northern Malmö (Sweden). The simulation model also enables the comparison of this new approach with traditional delivery concepts, such as home delivery and central service points.

In summary, the simulation model can be used to answer research questions such as

- How does the new concept perform compared to existing delivery services in terms of, for instance, travelled distance, accessibility for customers, environmental and traffic impact?
- How shall smart cargo boxes be configured and how many compartments are required per box?
- How many setup locations are required to efficiently serve a particular area and where should they be located?
- Which pick-up and drop-off strategy is most efficient in terms of travel distance?
- How do variations in demand affect the service quality?

The paper is structured as follows: In Section 1, we provide a description of related work on last mile logistics and its simulation. We then describe the simulation model we developed, followed by a specification of the experiments and the results. After a discussion of the results, we provide conclusions and discuss future work.

1 State-of-the-Art

The use of simulation for analysing and comparing logistics processes is well established and studied (Manuj 2009). In transportation logistics, simulation is used to analyse, for instance, how transport tasks can be allocated to vehicles (Davidsson et al. 2005). According to Olsson et al. (2019), modelling and simulation is the leading methodology used in the emerging research area of last mile logistics. It is applied to investigate, e.g., the effects of different means of delivery such as electric vehicles and cargo-bikes but also the feasibility of crowdsourcing. This is, as simulation allows for creating digital copies (*digital twins*) of real-world systems, that can be used to efficiently investigate the system's behaviour under different circumstances, without influencing or jeopardizing the real-world system.

Grando & Gosso (2005) refer to the issue of identifying the optimal delivery solution as "*Last Mile Logistics Dilemma*" and present a reference model for comparing home delivery with pick-up points. To overcome this dilemma, Perboli et al. (2018) propose a multimodal simulation optimization framework for urban freight transportation of e-commerce deliveries, which allows for analysing different delivery modes in realistic scenarios. Besides such frameworks, there exists other studies for specific scenarios in last mile logistics. This includes, for instance, the use of robots for autonomous last mile deliveries, e.g., (Poeting et al. 2019), or for crowdsourced delivery, e.g., (Guo et al. 2019), where local non-professional couriers deliver the parcels to the customers' homes.

The use of cargo boxes has been mostly studied for scenarios with stationary boxes that are equipped to the customer's house or set up at fixes publicly accessible locations. To optimize the last mile in electronic grocery shopping, Punakivi et al. (2001) simulate the use of delivery and reception boxes for unattended delivery of groceries. Yetis & Karakose (2018) propose the use of smart cargo cabinets that are located within buildings and fed by unmanned aerial vehicles (drones). For a Polish city, a study has been conducted by Iwan et al. (2016). The results show that a reduction of the environmental impact of last mile delivery can only be achieved by alternative delivery concepts such as parcel lockers. A similar study has also been conducted in the Netherlands, which investigated the potential of cost reductions when shifting from home delivery to parcel lockers (Van Duin et al. 2020).

To our knowledge, there exists no simulation studies on smart cargo boxes that are dynamically placed at different locations in the city with the aim of optimizing delivery processes for both customers and logistic service provides.

2 Modelling Last Mile Delivery Options

We implemented an agent-based model (ABM) to investigate the effects of different last mile delivery options. The delivery vehicle, customers, deliveries, smart cargo boxes, potential locations of the boxes, and the depot are implemented as agents. Each day, a number of deliveries arrives to the depot each of which is designated for a specific customer in the simulated area. According to the customers' home addresses, the deliveries will be allocated to boxes such that the customers' travel distance for picking up their parcels is minimized. This includes the clustering of the deliveries for the allocation to the boxes as well as the identification of optimal setup locations for each box. A vehicle will then transport the boxes, one at a time, to their designated location. In case there is already a box standing at this location whose minimum setup time (e.g., after 24 hours) has been reached, it will be replaced, and the previous box is returned to the depot. Packages remaining in the returned box will then be allocated to new boxes in the same manner as newly arrived packages. The vehicle visits the box locations in an order prioritizing empty boxes and those that have exceeded their minimal setup time. Boxes that are placed at a location may not be completely filled with packages, however, the vehicle will never deliver empty boxes and will skip locations to which no packages are to be delivered. During hours with high volume of traffic (e.g., 6 a.m. – 9 a.m. and 3 p.m. – 6 p.m.) the vehicle will not leave the depot to reduce traffic congestion.

Each customer has a home address, from where he or she will pick up the parcel. Once a box with a parcel arrives at a pick-up location, there will be a random delay representing that the customers are occupied with other activities and that they pick up their deliveries at a later point in time. If the box with the package has not been returned to the depot by then, the customer walks to the location of the box, takes its package and walks back home. Otherwise, the customer will be informed when the delivery can be collected from another box.

In case the distance to the box is greater than a given threshold, the recipient will choose to take the car instead of walking.

Modelling of customer demand is challenging and requires data on where customers live as well as on their habits. For this study, each customer and delivery need to be assigned to a specific building to adequately simulate driving and walking distances to distribute and pick up parcels. Hence, address data is needed on where people live. This data is usually not openly available such that other data sources must be used to generate realistic artificial data on customer demand. OpenStreetMap (OSM; openstreetmap.org) data, for instance, can be used to geographically distribute customers in a realistic way. From OSM, positions of buildings can be extracted as well as their size and utilization. This allows us to identify the potential home addresses of customers and to estimate the likely number of residents. We do this by distributing the known number of inhabitants of the simulated area to the buildings we identified in OSM. Here, we use the floor area of the houses to estimate the number of residents by calculating the average floor area per resident. Due to a lack of data, the modelled population is homogenous in terms of their behaviour and habits, e.g., the threshold when they will use a car to fetch their delivery.

The model allows for comparing the new delivery concept to two traditional package delivery systems: deliveries to service points and home deliveries. For service point deliveries, different pick-up locations are defined, where the service points are located. Each time a customer fetches a package from a box, the walking distance from their home to one of the delivery locations and back is simulated as well. For home delivery, every time new packages are delivered to the depot, a route is iteratively planned such that packages are delivered to the recipient closest to the last one. This does not return the minimum distance required to deliver all packages but overestimates the delivery distance. Yet, we do not consider extra driving distances potentially caused by time windows for home delivery. Moreover, we assume that only one vehicle is in charge of all home deliveries.

For analysing different scenarios, the model provides the following parameters:

- The **number of packages delivered to the depot** each day. Each arriving package has an individual defined as its recipient.
- The **minimum set-up time of boxes** to stay at a location before it can be picked up or replaced by the vehicle.

- The **package capacity of the boxes**. Packages that do not fit in a box will be delivered with the next box to the same location or a suitable location close by.
- The **rate at which customers collect their packages** as the lambda parameter of the exponential function for determining waiting times of customers.
- The **maximum walking distance of recipients** before taking the car for fetching a delivery. We assume all individuals have access to a car.
- The **ratio of individuals fetching their packages combined with other activities.** If individuals fetch their package together with other activities, e.g., buying groceries, only the additional distance needed to fetch the package is considered. The customer will move from its home to the grocery store, to the box, and back home. In case the grocery store contains a delivery point, the additional distance is zero

The following outputs are provided for each run of the simulation model:

- The **total distance the delivery vehicle has travelled**.
- The **total time the vehicle is being active**.
- The **total distance of customers** to pick up their packages and to return home.
- The **distance of customers travelled by car** in case the distance to the box is above the car threshold. Driving distance can be longar than walking distance.
- The **number of deliveries that have been picked up** by the recipients.
- The **number of packages that have not been picked up by the customers** and thus were returned to the depot for a new delivery with another box.
- For *service point deliveries*:
  - The **total distance of customers** to fetch their packages and return home.
  - The **total distance of customers travelled by car**.
- For *home delivery*:
  - The **approximated total distance** travelled by the home delivery vehicle.
  - The **approximated total time** all deliveries will take.

3 Case Study: Smart Cargo Boxes in Västra Hamnen

The model was implemented using the AnyLogic simulation framework (www.anylogic.com). For this feasibility study, we have chosen the neighbourhood of Västra Hamnen in Malmö (Sweden) as the setting for our experiments. The potential locations of the boxes as well as for the depot can be chosen manually.

To generate more realistic results, we have chosen the location of the depot to be close to the depots of other existing logistics providers and identified suitable locations, e.g., parking areas, for setting up the boxes. For the simulation of both service point deliveries and grocery stores, two existing service point locations were chosen. AnyLogic includes built-in geographic information system (GIS) support with real-world road networks, which is used to create routings for vehicles and individuals. The user interface of the simulation is shown in Figure 1.

For the generation of customer address data and customer demand, we have used OSM data of Västra Hamnen in Malmö. According to the data, there are 298 buildings in this area. Buildings with a floor area over 2.000 m^2 were assumed to be industrials buildings and not considered as residence of customers. Buildings between 200 and 2.000 m^2 are assumed to be apartment buildings and below 200 m^2 as single-family house. In total, Västra Hamnen has 9 739 inhabitants, which were distributed to the existing buildings according to their floor area, resulting in 9 155 customers living in apartment buildings and 584 living in single-family houses. Each of the 9 739 customers was assigned an address according to this distribution.

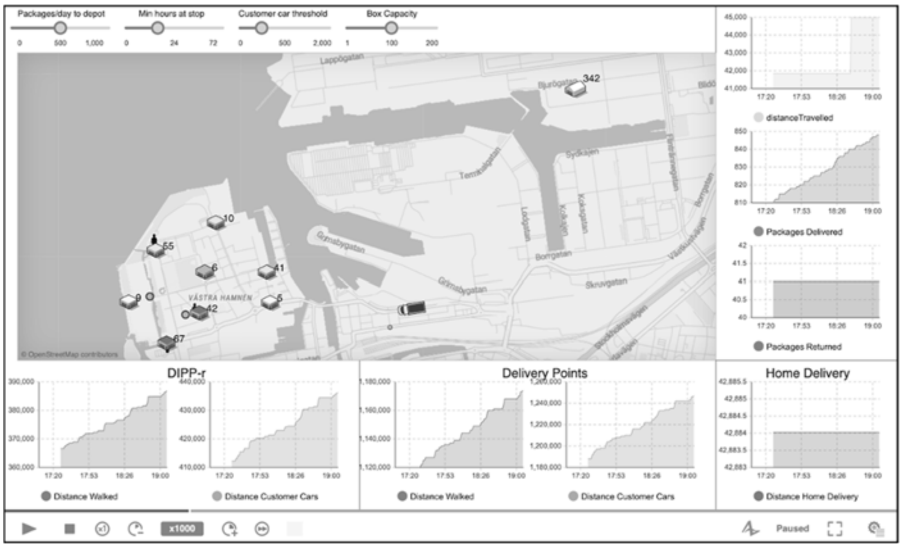

Figure 1: The user interface of the simulation model in AnyLogic.

4 Results of the Simulation Study

For the study, the simulation model was run using different combinations of input parameter values. The simulation starts at 8 a.m. and we simulate an entire week. The presented results were generated using 8 box locations, 9739 customers, and a single distribution vehicle. With respect to the comparability of the results, all simulations used a fixed random seed.

Figure 3 shows the distance travelled by vehicles for different delivery options and scenarios, i.e., thresholds when customers use their car to get their packages as well as packages per day. When customers chose not to use their car for picking up parcels if the distance is less than 1 km, the mobile smart boxes system results in considerably shorter driving distances compared to the delivery point system. Also, the distance is similar to the distance the home delivery vehicle has to drive, assuming it has a capacity of 100 parcels.

For the effectiveness of the service, it is not only relevant how many boxes are used but also where they are located. The placement of boxes and its effects on the distance customers must walk can also be explored using the model. For instance, in the two set-ups shown in Figure 2, the cumulated walking distance differs by 3.4%. Hence, the model can be used by decision makers to identify most suitable locations

The model also allows for varying the number of boxes and to investigate the effect this has on the service provision. We simulated the parallel set-up of 4, 6, 8, and 10 boxes with the locations of the boxes being determined using k-means clustering (see Figure 4). The results show a decreasing customers' travel distance and an increasing distance driven by the delivery vehicle, when the number of parallelly used cargo boxes increases. As shown in Table 1, increasing the number of boxes from 4 to 6 results in a 13.9% decrease of the customers' walking distance and 23.2% decrease of the distance driven by car (in total -18.8%) whereas the travel distance of the delivery vehicle increases by 48.8%.

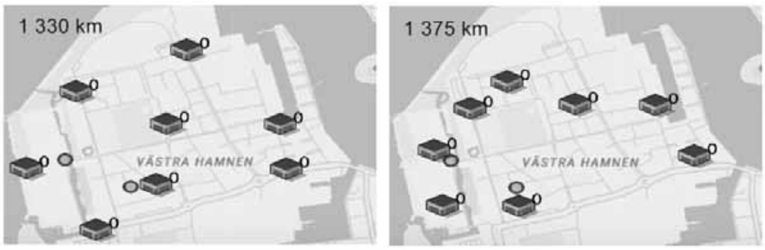

Figure 2: Total customers' walking distance for two different placements of boxes.

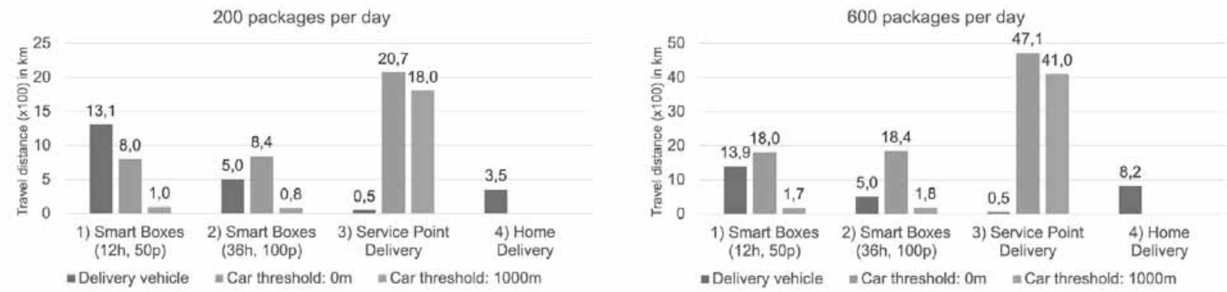

Figure 3: The distance (in km) travelled by the delivery vehicle and by customers using cars at thresholds of 0km and 1km for four scenarios: 1) Boxes, with a capacity of 50 packages waiting for 12 hours at stops; 2) Boxes, with a capacity of 100 packages waiting for 36 hours at stops; 3) Service point delivery; 4) Home delivery. The depot received 200 resp. 600 packages per day.

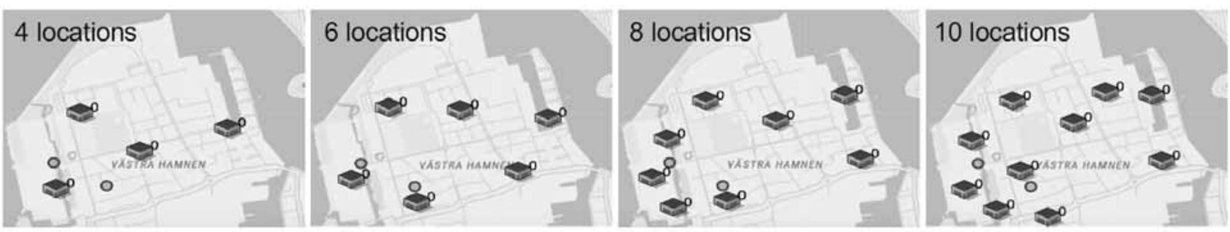

Figure 4: Different number and placement of set-up locations for smart boxes.

Number of cargo boxes	Distance walked by customers (km)	Distance driven by customers (km)	Distance delivery vehicle (km)
4	1717	1974	180
6	1478	1516	268
8	1453	1319	345
10	1346	1083	451

Table 1: Traveling distance of customers and delivery vehicle for different number of stops assuming that customers will walk in case the distance is less than 1km.

When increasing the number of boxes from 6 to 8, the total decrease in customers' travel distance is only 7.5% whereas the distance of the delivery vehicle almost doubles (+91.7%)

It can be assumed that some customers will combine the collection of their delivery with other activities such as grocery shopping, as service points often are located at grocery stores.

Figure 5 shows how the percent of individuals fetching their package combined with another activity affects the additional distance travelled by private car for both mobile smart boxes and delivery points. More people combining fetching their package with grocery shopping leads to smaller additional distances travelled. More interestingly, the smart boxes system is shown to lead to smaller distances travelled than the delivery point system for almost all scenarios.

An estimate of the cumulative time it takes to distribute the mobile smart boxes and to make all home deliveries is shown in Figure 6. For home delivery, each delivery is assumed to take one minute per address, the vehicle's movement speed is 15 km/h, and the capacity is 100 parcels.

The figure shows that the time the smart box delivery vehicle is active correlates with the frequency at which boxes are delivered and returned to the depot. Yet, it is largely unaffected by the number of packages being delivered. This is not true for the home delivery vehicle.

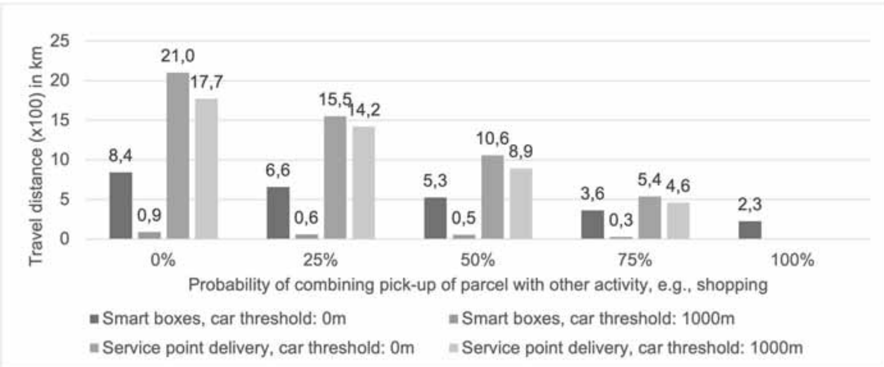

Figure 5: The distance (in km) travelled by customers by private car for different probability of combining the fetching of parcels with other trips, e.g., shopping.

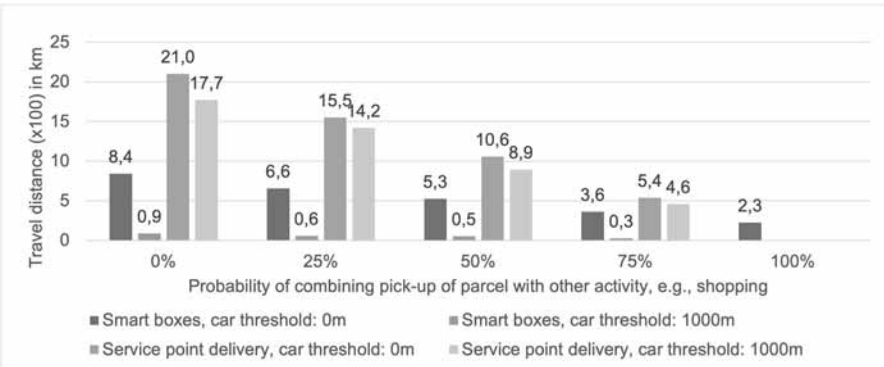

Figure 6: The cumulative time the delivery takes for smart boxes with a capacity of 50 packages being replaced after 12 hours, smart boxes with a capacity of 100 packages being replaced after 36 hours, and home delivery.

5 Conclusions

In this article, we have presented an agent-based simulation model for comparing a delivery solution with mobile smart cargo boxes to existing systems for last-mile delivery. The simulation explores the effects of different smart box service designs and results show that smart boxes are not only feasible as a delivery solution, but significantly decrease the distance customers must travel to fetch their packages and the total distance driven by vehicles compared to service point deliveries. For a car threshold of 1 km, the total vehicle distance is similar to the one of home delivery.

Yet, existing delivery systems have limitations that have not been included in this study. For instance, home delivery might require the recipient to be at home and service points usually have opening hours. With smart boxes solution, however, customers can fetch their packages whenever they desire during the day, allowing for increased flexibility. Moreover, the service provider can set up and collect boxes all day through, which increases the utilization of the vehicles.

There is a trade-off concerning the time boxes stay out before being returned to the depot. A shorter setup time reduces the time packages stay at the depot before being distributed. Recipients, however, have a smaller time window for fetching their packages. This, as well as the fact that not all individuals fetch their packages right away, increases the load at the depot and requires the use of more boxes. Also, reducing the time packages are available for pickup is less convenient to customers.

Examples of simplifications made in the model are the homogeneity of individuals and their habits, the assumption of a static threshold for fetching a parcel by car, and the exclusion of workplaces and other venues than grocery stores and service points. There is also no consideration of exhaust emissions of vehicles, which might be relevant for cities with low-emission zones. Another assumption is that only one delivery vehicle is used for all home deliveries. An extension of the model requires, e.g., data on the capacity of home delivery vehicles and the time to deliver packages

Besides the design of the service, local regulations and policies might affect the feasibility and viability of deliveries using mobile smart cargo boxes. This includes, for instance, parking regulations that might limit potential locations for setting up boxes and how long they can stand at a location.

Moreover, it is uncertain how different configurations of the service, e.g., the minimum setup time, affect customer acceptance and satisfaction. Yet, the proposed simulation model can be used to investigate different scenarios and to identify potential challenges and opportunities.

With respect to future trends, it is planned to use electric vehicles for the distribution of the boxes. To this end, the effect the battery capacity of the vehicles has on the service needs to be investigated as well as the approaches for charging the vehicles. It can also be assumed that many customers will combine the pick-up of their parcels with, for instance, their work trip. This might affect the optimal placement of the boxes as the location closest to the home might not be most convenient.

Acknowledgement

This work was partially funded by VINNOVA through the project Smarta Offentliga Miljöer (Smart Public Environments), a part of the strategic innovation program for the Internet of Things (IoT Sverige), and partially by the Knowledge Foundation through the Internet of Things and People Research Profile.

References

[1] Allen J, Thorne G, Browne M: BESTUFS – Good Practice Guide on Urban Freight Transport (2007). URL: http://www.bestufs.net/gp_guide.html

[2] Davidsson P, Henesey L, Ramstedt L, Törnquist J, Wernstedt F. An analysis of agent-based approaches to transport logistics. Transportation Research part C: Emerging technologies, 13 (2005) 4, pp. 255-271.

[3] Guo X, Jaramillo YJ L, Bloemhof-Ruwaard J, Claassen, GDH. On integrating crowdsourced delivery in last-mile logistics: A simulation study to quantify its feasibility. Journal of Cleaner Production, 241 (2019), 118365.

[4] Iwan S, Kijewska K, Lemke J. Analysis of parcel lockers' efficiency as the last mile delivery solution – the results of the research in Poland. Transportation Research Procedia, 12 (2016), pp. 644-655.

[5] Manuj I, Mentzer JTM, Bowers MR. Improving the rigor of discrete-event simulation in logistics and supply chain research. International Journal of Physical Distribution & Logistics Management, 39 (2009) 3, pp. 172-201.

[6] Olsson J, Hellström D, Pålsson H: Framework of last mile logistics research: A systematic review of the literature. Sustainability, 11 (2019) 24, 7131.

[7] Perboli G, Rosano M, Saint-Guillain M, Rizzo P. Simulation-optimisation framework for City Logistics: An application on multimodal last-mile delivery. IET Intelligent Transport Systems, 12 (2018) 4, pp. 262-269.

[8] Poeting M, Schaudt S, Clausen U. Simulation of an optimized last-mile parcel delivery network involving delivery robots. In: Clausen U, Langkau S, Kreuz F, Eds. Interdisciplinary Conference on Production, Logistics and Traffic, Springer, Cham, 2019, pp. 1-19.

[9] Punakivi M, Yrjölä H, Holmström J. Solving the last mile issue: reception box or delivery box? International Journal of Physical Distribution & Logistics Management, 31 (2001) 6, pp. 427-439.

[10] Van Duin JHR, Wiegmans BW, van Arem B, van Amstel, Y. From home delivery to parcel lockers: A case study in Amsterdam. Transportation Research Procedia, 46 (2020), pp. 37-44.