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A COMPREHENSIVE CASE STUDY IN LAST-MILE DELIVERY CONCEPTS FOR PARCEL ROBOTS

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ABSTRACT

This study was designed to evaluate innovative last-mile delivery concepts involving autonomous parcel robots with simulation and optimization. In the proposed concept, the last mile of parcel delivery is split into a two-tiered system, where parcels are first transported to a transfer point by conventional trucks and then delivered with parcel robots on customer demand. The purpose of this publication is to compare different time slot selection options for customers, namely due window and on demand selection, in the context of city logistics measures such as access regulations and driving bans for city centers. An agent-based simulation model is used, including a Geographic Information System environment and optimization algorithms for allocation and scheduling of delivery robots. The concept is tested in a comprehensive case study located in the city center of Cologne (Germany) based on real data from the parcel delivery company Hermes.

1 INTRODUCTION

With urbanization as an ongoing global trend, increasing economic and transport activities are observable in cities world-wide. More than half of the population in Germany lives in cities. The four biggest ones alone – Berlin, Munich, Hamburg, and Cologne – account for 10 % whereby there is only one person living in almost half of the households (Statistisches Bundesamt 2018). Consequences of urbanization are an increasing shortage of space, competition regarding utilization, and bottlenecks in the capacity of the road network. A still growing e-commerce keeps driving up the number of parcels to be delivered, especially in the B2C segment. Thus, the logistics industry is seeking new ways to increase efficiency and investigates new technologies for last-mile delivery. In addition, cities in all over Western Europe want to become more environmentally friendly and limit the exposure of population created by traffic. Therefore, cities either plan to establish or already established low emission zones (ADAC 2019a; ADAC 2019b). To overcome both, the increase in parcel volumes and the access restrictions, the parcel industry is seeking for new innovative concepts such as drones, autonomous vehicles, sharing economy, deliveries to the trunk of a car, and parcel robots (Gester and Bogdanski 2017). Field tests for parcel delivery robots have been carried out by the manufacturer Starship Technologies in cooperation with the parcel delivery company Hermes in Hamburg. Customers were able to choose an arrival time slot of 15 minutes. In total, the robots completed 600 tours and traveled 3,500 kilometers (Bertram 2017). However, there are also other companies exploring this and other automated delivery solutions including Amazon, Deutsche Post DHL, Domino's Pizza, or Swiss Post. Apparently, the application field of delivery robots on the last mile represents a promising field of research, not only for logistics but also for mathematical optimization and simulation.

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The outline of this paper is as follows: In Section 2, we briefly discuss the related literature on simulation and optimization of urban delivery and parcel robots. In Section 3, a detailed problem description of the delivery process with parcel robots and the delivery concepts of our case study is given. The optimization algorithms that are used to schedule deliveries and allocate robots to the micro-depots are described in Section 4. In Section 5, we present our simulation model on urban parcel delivery and the connection to the optimization. Section 6 describes the studied case and the experimental setup. Furthermore, the results of the investigated scenarios are discussed. Finally, Section 7 concludes and provides an outlook on future research.

2 RELATED LITERATURE

In the context of urban logistics, simulation is an important tool for decision support and widely used by several works that focus on urban distribution (e.g., the distribution of food, consumer goods, or waste collection) using conventional trucks, electric vehicles, or cargo bikes.

Rabe et al. (2018) used supply chain simulation in order to determine the performance of freight delivery in an urban environment. In this context, the application of urban consolidation centers (UCC) and collaboration between different actors are evaluated within a supply chain. The simulation approach uses real application data from companies in Athens (Greece). However, the model uses approximated distances without consideration of the actual urban infrastructure. In the contribution of Elbert and Friedrich (2018) the topic of urban transportation from a legal perspective is examined. An agent-based simulation is used to assess the impact of urban access regulations on the cost-attractiveness of UCCs for carriers. A case study for the Frankfurt Rhine-Main area (Germany) is presented that compares deliveries of a group of carriers with and without an UCC under various urban access scenarios.

In addition to contributions dealing with conventional vehicles, there are simulation case studies that investigate alternative means of transport. One of these case studies is presented by Fikar et al. (2018), where orders are delivered from micro-hubs using both conventional vehicles and cargo-bikes. They use AnyLogic to generate and select vehicle routes and transshipment points. The model is based on an architecture that integrates Geographic Information System (GIS) information with dynamic vehicle routing. Hofmann et al. (2017) combine simulation with tour planning algorithms for cargo-bikes in a GIS-based environment using AnyLogic. The tool is applied to evaluate the potentials of UCCs at the city edge of Grenoble (France).

Besides simulation also mathematical optimization is used to evaluate the potential of alternative concepts for the last mile. Kafle et al. (2017) use the principle of Simulated Annealing to solve a two-tiered crowd-sourced delivery system, which suggests that a set of cyclists and pedestrians, called crowd-sources, deliver parcels from a delivery truck to customers living in the same neighborhood. A set of carrier trucks transport parcels to intermediate transfer points (first-tier) and then potential crowd-sources perform the final leg of last-mile delivery. In the contribution of Boysen et al. (2018) an optimization model involving truck-based delivery robots is conducted. In this model, autonomous robots are launched from trucks to deliver shipments towards customers. Their objective is to minimize the weighted number of late deliveries. An integer programming formulation and a multi-start local search heuristic is presented.

Delivering parcels with autonomous robots is a relatively new topic and not yet considered widely in research. A combined simulation and optimization involving autonomous parcel robots was first introduced by Poeting et al. (2019). A Simulation framework based on AnyLogic is used to create a data-driven model for the last mile parcel delivery involving delivery robots. Decisions of the simulation model are supported by optimization, where variants of the Traveling Salesperson problem are solved. In their case study, delivery vans are used to serve the complete area of Cologne (Germany). In addition to conventional trucking, a small percentage of all parcels is delivered by autonomous robots.

This contribution addresses the further development of the approach presented by Poeting et al. (2019). In particular, it includes a more detailed model for the urban level as well as the implementation of innovative delivery concepts, i.e., due windows and on-demand delivery.

3 PROBLEM DESCRIPTION

Due to upcoming driving bans in city centers throughout Europe, alternative solutions for parcel delivery companies gain interest. Therefore, we investigate the effects of substituting traditional truck deliveries by autonomous robots in a city center. A two-tiered delivery system is observed, in which parcels are not directly delivered by conventional trucking. On the first tier, a single truck transports all parcels from a hub to a set of micro-depots, which are located in the neighborhood of the customers, and from there a set of autonomous robots perform the last leg of the last mile. We assume that each robot has a one-unit capacity and drives at walking speed on sidewalks. The two-tiered delivery structure is represented in Figure 1.

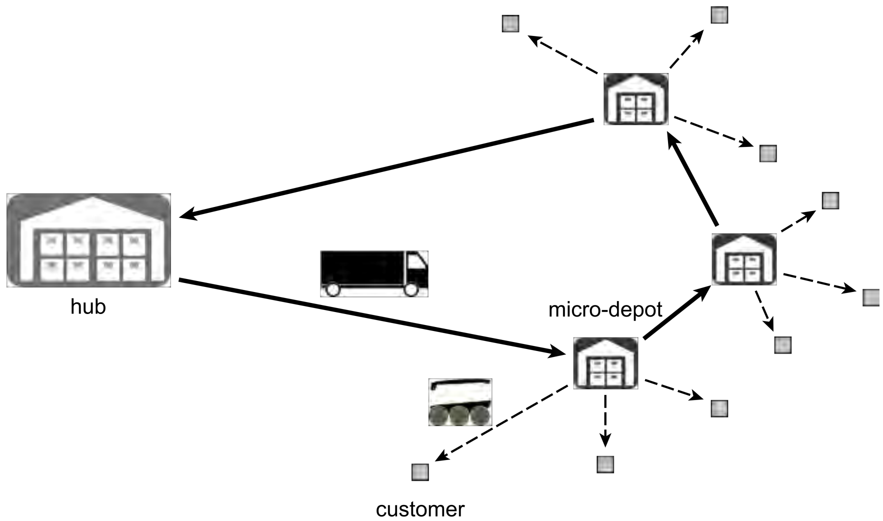

Figure 1: Two-tiered delivery system.

Formally described, we simulate and optimize several consecutive days of parcel delivery from a hub to a set of customers. Since each simulation day is structured in the same way, we describe a single day. Given a set of N customers, whereas each customer has ordered a single parcel. Starting at a hub, all parcels are loaded on a single truck and distributed over a set of D micro-depots. We assume that the capacity of the truck is sufficient to transport all parcels. At the same time as the vehicle gets loaded, the delivery robots are allowed to change their assigned micro-depot. This reassignment is only done at the beginning of the day. From the set of micro-depots the parcels get delivered with the delivery robots. A delivery robot can only operate during the opening hours of the micro-depots. It is assumed that the opening hours of all micro-depots are the same. If a parcel can not be delivered within the opening hours, it gets collected by the customer at the micro-depot. Two different concepts of customer time slot selection are compared. In the first case, all customers select their slot in advance. This selected slot will be called due window in the following. In the second case, customers trigger their start of delivery on demand, which leads to a lack of information for the planner. This concept of time slot selection can also be represented by a due window. However, the due window does not start immediately after the customer announced his request. But, rather is the due window shifted by an additional buffer time, which corresponds to the average transport time. We assume that all time slots have equal lengths and a customer can not be served early. If the customer is served outside the selected time slot, a penalty occurs. A description of the penalty function is given in the upcoming section. In both cases, a simulated annealing heuristic, which is described in the following, is used to build an assignment between all three: parcels, micro-depots, and delivery robots.

4 OPTIMIZATION

In the following, the optimization algorithms that are used to improve the solution quality of the simulation are explained, starting with the tour of the conventional truck. The goal is to find a tour of minimal distance, which starts at the hub, visits all micro-depots and goes back to the hub, as shown in Figure 1. A solution to this problem is calculated by solving an integer programming formulation of the well known Traveling Salesperson problem (see Miller et al. 1960).

The other algorithms focus on the reassignment, allocation, and scheduling of delivery robots. Since robots can change their assigned micro-depot once a day, we calculate an exchange matrix $E^{D \times D}$, whereas $E_{i,j}$ corresponds to the number of delivery robots changing from micro-depot i to j. This matrix should reassign the robots to minimize the total distance travelled. The calculation of this matrix can be done by solving a Transshipment problem (see Garg and Prakash 1985). In this Transshipment problem, all micro-depots are duplicated and represent an origin and a destination at the same time.

The allocation and scheduling of delivery robots is calculated with a Simulated Annealing heuristic. The adaptations of the heuristic for the on-demand case and the due-window case are explained in the following. In the on-demand case, we distribute the delivery robots to the micro-depots and – based on this distribution – we assign parcels to minimize the maximal workload over all delivery robots. The workload corresponds to the sum of all traveling times plus service times at a simulation day. In the case of due windows, robots are also distributed over the micro-depots, but with the information given, we are able to build a schedule involving all parcels and delivery robots. A schedule is rated according to the weighted sum of all customers that are supplied late. Suppose a customer $i \in N$ has chosen due window $[l_i, u_i]$ and a delivery robot arrives at a_i, if a_i is smaller or equal to u_i no penalty occurs, otherwise a penalty of $(\frac{u_i - a_i}{u_i - l_i})^2$ is added to the sum. The pseudo code of the Simulated Annealing heuristic is presented in the following.

Algorithm 1 Simulated Annealing

Input: $\{S, \lambda, k_{max}, i_{max}, T_1\}$ //start solution S is obtained with a primal heuristic
Output: S^*
$S', S^* \leftarrow S$
for $1 \leq k \leq k_{max}$ **do**
  for $1 \leq i \leq i_{max}$ **do**
    $S \leftarrow N(S)$ //neighborhood of solution S
    if $cost(S) \leq cost(S^*)$ **then**
      $S', S^* \leftarrow S$
      $i \leftarrow 1$
    else if $cost(S) \leq cost(S')$ **then**
      $S' \leftarrow S$
    else
      $\Delta \leftarrow (Cost(S) - Cost(S'))$
      $S' \leftarrow S$ with probability $e^{-\Delta / T_k}$
    end if
  end for
  $T_{k+1} \leftarrow \lambda T_k$ //update temperature
end for

For both cases, the heuristic is initialized with parameters: $T_1 = 400, \lambda = 0.7, i_{max} = 500, k_{max} = 500$. A neighborhood $N(S)$ is the best solution obtained from the following three local search operations: change the depot of a robot (swap), change two customers between two robots (swap), move a customer from a robot to another robot (insertion). An input solution is generated with a random heuristic that generates 10,000 random solutions for the on-demand case and 1,000 random solutions for the due-window case.

5 SIMULATION MODEL

In this section, the simulation model is presented. Our conceptional model was first introduced by Poeting et al. (2019). The model is implemented in *AnyLogic 8.2.0* and features different agent types for hubs, micro-depots, customers, tours, and vehicles. Based on the agent types and the underlying data model, the simulation model is automatically generated from database entries.

For the allocation of customers and vehicle routing, we use a GIS environment that is provided by AnyLogic and uses open data from OpenStreetMaps (OSM). The optimization algorithms are calculated during the simulation with the mixed integer programming solver *Gurobi 7.0.2*. To generate a realistic distribution of parcels within the urban area, we created an address generator that maps shipment volumes to the actual locations for each district. The data for this generator are provided from the municipality of Cologne. We chose a data-driven modeling approach where parcels and customers are generated automatically based on parcel volume information from a database. This includes the name of the district in OSM and the relative share of parcels that are allocated to the area. Furthermore, the addresses of hub and micro-depot locations are stored in a database table and generated when the simulation model is initialized. Thus, we are able to generate simulation models for different urban environments based on the provided data (Poeting et al. 2019).

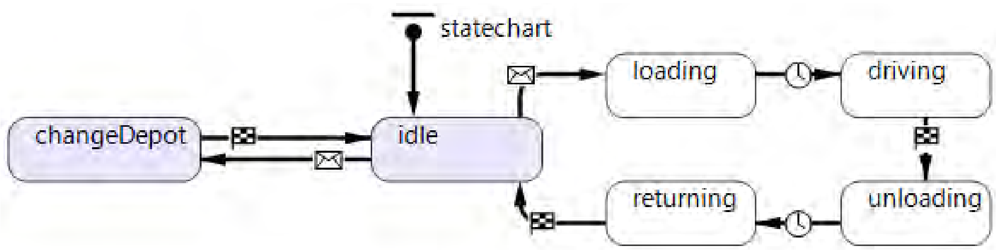

Figure 2: State chart of a parcel robot.

Figure 2 shows the state chart of a parcel robot in the simulation model. Each robot is represented by an independent agent that is able to travel from micro-depots to customers or from one micro-depot to another. The default state of a robot is ”idle”. When the robot receives a message from outside, it is activated and begins its job depending on the message.

At the beginning of a delivery day, robots are able to change their micro-depot according to the allocation of the optimization results. In this case, a robot receives a new micro-depot reference and a ”change” message. The robot changes in the ”changeDepot” state and begins to travel to its new micro-depot. After arrival, the robot changes back to the ”idle” state and is available for parcel deliveries. Generally, the robot receives messages from his assigned micro-depot when a parcel is scheduled for delivery. Then, the robot changes into the ”loading” state for a predetermined loading time, delivers the parcel to the customer, changes into the ”unloading” state similar to the loading and returns to his micro-depot afterwards. During the simulation we evaluate the duration of each trip and calculate the individual and total delay in order to determine the service level for each scenario.

6 EXPERIMENTATION AND RESULTS

In the present model, we investigate the effects of substituting traditional truck deliveries by autonomous robots in a city center. The city center under consideration is the historical center of Cologne (Germany) with an extension of 3 miles from north to south and 1.4 miles from east to west. The parcel robots travel at walking speed (around 2.2 mph) and have a maximum range of 3.7 miles per trip (Swiss Post 2017).

Two scenarios with different micro-depot locations are compared in the following. In the first scenario, we consider the effects of a complete driving ban for vehicles in the city center. Thus, we choose micro-depots that are located at the edge of the historical center. In the second scenario, delivery vans are allowed to enter the city center in the morning hours to supply the micro-depots. In both scenarios, the number of parcels as well as the location of micro-depots refer to real data from the delivery company Hermes (Hermes 2018). The number of parcels per year delivered by Hermes in this area of Cologne was 194,651 in 2017. The number of available micro-depots is in both scenarios seven. All micro-depots have the same opening hours from 8:00AM to 11:00PM and robot deliveries are only possible within these hours. If a parcel can not be delivered by a robot, because the shop has closed, it is assumed that the customer has to pick up the parcel at the micro-depot the next day. As mentioned in Section 3, two cases of time slot selection are considered. In the first case, customers choose a due window (DW) of 30 minutes, starting every half hour between 9:00AM and 9:00PM. For the on-demand (OD) case, the customer can trigger the delivery of his order at any time between 8:30AM and 8:00PM. The created due window is then shifted, assuming an average driving time of 30 minutes. Of course, these two procedures are not fully equivalent, but it enables a basic comparison of the two concepts. In both cases, a shipment is delayed if the robot arrives outside the due window. The amount and time of delayed shipments are measured.

First, we determined the number of robots required to serve 95 % of all customers within their due window, which is called level of service in the following. Several simulation runs with common random numbers for each of the scenarios with a variation of 10 to 40 robots are performed. A total of 15 days were assessed for all simulation experiments. Figure 3 shows the resulting service level of delivery for different amounts of delivery robots in each scenario.

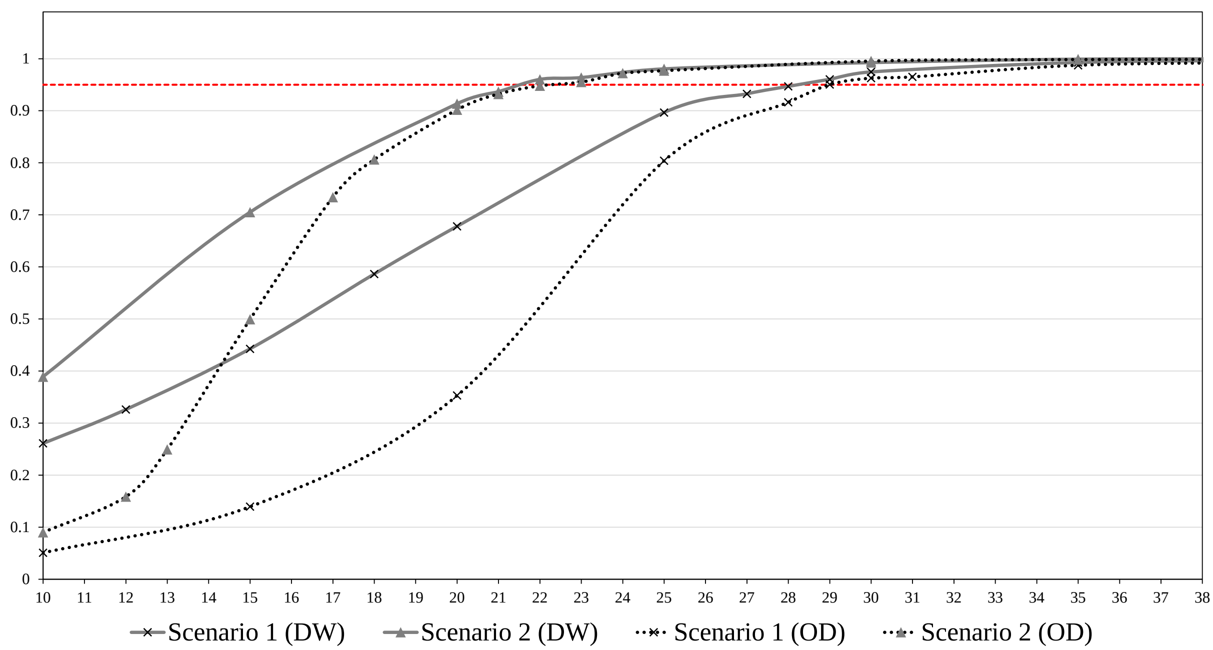

Figure 3: Comparison of customer service level with different amounts of robots and experiments.

In the first scenario, where the micro-depots are located at the city ring road, more robots are required to reach a service level of 95 % compared to scenario 2. Therefore, a total number of 29 robots is required for scenario 1 and 22 robots for scenario 2.

Comparing the delivery concepts DW and OD, the experiments highlight the benefits of system knowledge in the optimization: In the first scenario, the two cases lead to the same number of 29 robots needed to achieve a 95 % level of service. In the second scenario, the 95 % goal is achieved with an amount of 22 robots for the DW and 23 for the OD case. However, the DW case is performing slightly better and the graph clearly shows that the differences are even more pronounced when the number of robots is reduced.

Figure 4 gives an overview of scenario 1 and 2 with DW and the previously determined number of robots. For each micro-depot we display the relative share of parcels assigned to the micro-depot by the optimization algorithm and the average number of robots assigned to the micro-depot. In addition, the share of parcels is displayed by a circle with corresponding size.

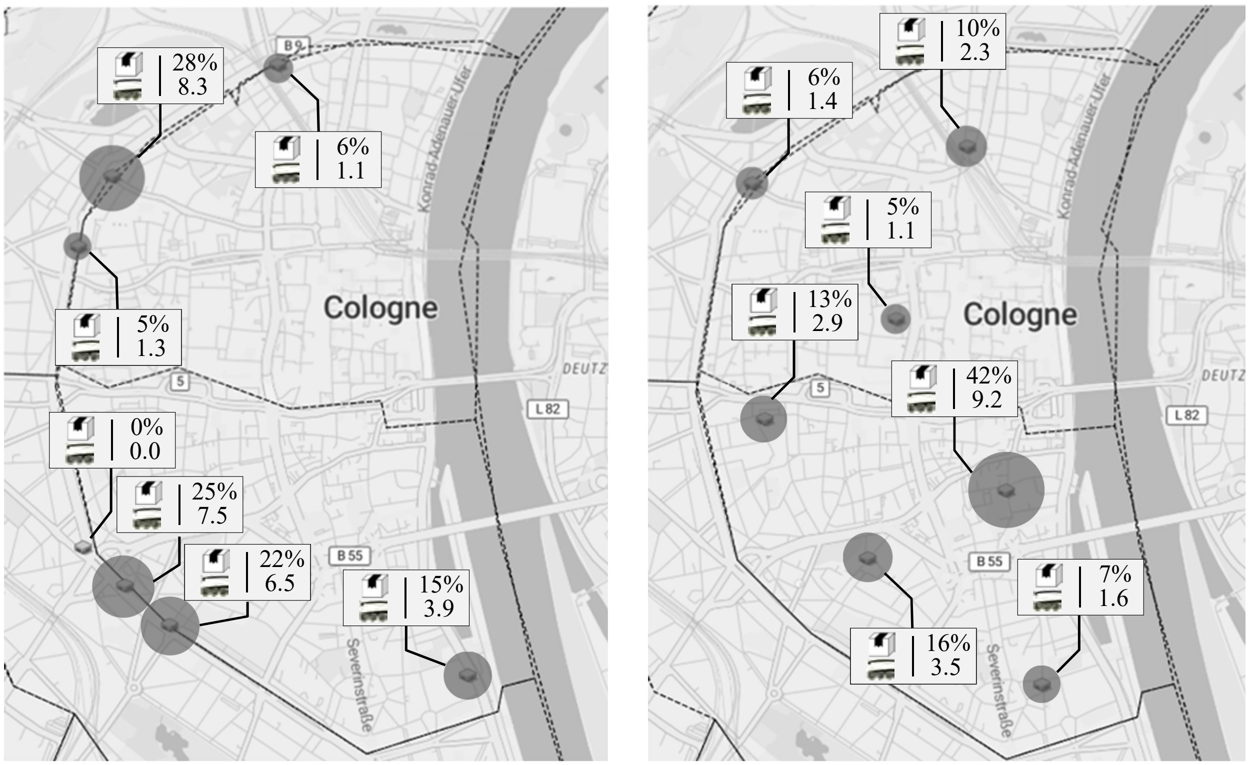

Figure 4: Comparison of scenario 1 with due windows and 29 robots (left) and scenario 2 with due windows and 22 robots (right).

At the left side, we see the first scenario where customers within the city center are supplied from micro-depots located at the inner city ring and conventional trucks are restricted from entering the center. It can be seen that the optimization distributed a large part of parcels on four micro-depots. Two of the depots have a minor share and one depot was not used at all. The average number of robots per depot reflects this distribution well. Furthermore, it is noticeable that the majority of deliveries is performed from a depot in the southern area of the city center. Although the input data reflect that the southern area has a slightly higher parcel volume (53 % vs. 47 %), the optimization decided to start 62 % of the deliveries from a micro-depot in the south. This is due to the specific infrastructure, which is realistically represented by the GIS information and allows for calculating the actual distances using sidewalks in the city.

The right side shows the second scenario, where delivery vans are allowed to enter the city center during the morning hours and parcels are dropped at micro-depots inside the city center. In contrast to scenario 1, every micro-depot is used. Particularly noteworthy is that one micro-depot at the center of the southern area takes over a large part of the deliveries (42 %). Therefore, an average of 9.2 robots are operating the deliveries from this location. Overall, the position of the micro-depots is significantly more advantageous than in scenario 1. In the following, we further analyze the results for both scenarios using the previously determined amount of robots with respect to transport distances and delays.

6.1 Scenario 1

For the first scenario, we further examine the concept of DW delivery. In the DW case it needs 29 robots to achieve the 95 % service level goal. Merely 204 of 5,155 deliveries are delayed. The average delay was 15.2 minutes, the median 9.4 minutes, and the maximum 1.3 hours. However, every parcel was delivered successfully before the micro-depots closed on 10PM. A total of 7,707.5 miles (12,404 km) were travelled by robots in the 15 days of observation – this corresponds to 513.8 miles (826.9 km) per day. The average CO_2 emissions for new light commercial vehicle fleet (delivery vans) in the EU-28 in 2017 were 156.1 g CO_2/km (European Environment Agency 2018). Accordingly, the electric parcel robots are able to take over transports in which conventional vehicles emit an equivalent of 39.1 tons CO_2 per year. Furthermore, the absence of vehicles prevents noise, nitrogen oxides, and particulate matter from being produced in city centers.

In the OD case, 29 robots are used as well. The number of delayed parcels is slightly higher (265/5,155) compared with the DW case. The average delay was 16.8 minutes (+10.5 %), the median 10.4 (+10.6 %) minutes, and the maximum 1.97 hours (+51.2%). Every parcel was delivered on the scheduled day. The total travelled distance is 7,584.5 miles (12,206 km, -1.6 %).

6.2 Scenario 2

First, we examine the DW case for scenario 2. Due to the significantly more favourable location of the micro-depots, it needs only 22 robots to achieve the same service level as 29 robots in scenario 1 (204 of 5,155 parcels delayed). The total traveled distance of robots is 5,622.8 miles (9,049.0 km) which is a 27.0 % reduction compared to the DW case in scenario 1. The average delay was 22.8 minutes, the median 12.8 minutes, and the maximum 2.8 hours. This shows that fewer robots achieve the same level of service compared with scenario 1, but peak hours are not well absorbed and higher delays can occur. Increasing the amount of robots to 23 already shows comparable results according to the delays (average 16.6 min, median 11.9 min, maximum 1.6 hrs) and the service level (96.3 %).

Finally, the results of the OD case in scenario 2 are analyzed. Compared with the first scenario the results of the two concepts are closer to one another: The total distance: 5,160.6 miles (8,305.2 km). The service level is 95.5 % (231/5,155 parcels) with an average delay of 12.9 minutes, the median 8.9 minutes, and the maximum delay 1.0 hours.

7 CONCLUSION

This contribution presents a simulation model that investigates autonomous robots for parcel delivery in the urban area. We introduced and implemented optimization algorithms for tour- and route-planning as well as job-scheduling for parcel delivery with due windows and on-demand delivery. Furthermore, two scenarios were simulated in a case study that investigates parcel delivery in the historical city center of Cologne (Germany). For each of the scenarios we determined the required number of parcel robots for the two application cases of due windows and on-demand delivery. The results for each of the scenarios highlight that the position of the micro-depots within the urban environment is the most crucial factor for delivery performance. In the first scenario with a complete ban on driving into the city center, the driven distances for the DW case are 37 % longer than in the second scenario DW case. This is also reflected in the number of robots needed to fulfill a 95 % service level, which is 32 % higher in scenario 1 when comparing the DW cases. Both concepts have proven to be variable concepts for parcel delivery on the last mile. However, the advanced system knowledge in the DW case is useful for the allocation and scheduling of the delivery robots. This is reflected in higher service levels and lower delay times.

Future research will focus on the implementation of more-realistic parameters when it comes to driving regulations and access scenarios as well as customer behaviour and seasonal effects. This includes dynamic ordering behaviour (weekly course and seasonal fluctuation). We assume that innovative concepts such as the on-demand delivery and due windows will play a major part in future logistics.

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