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The Electric Scooter Collection Problem: A Case Study in the City of Vienna

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Abstract: The urban population has been growing rapidly, especially in the European Union. The trend of urbanization has led to an increased demand for mobility, through both passenger and goods transportation. One of latest trends in passenger transportation is electric scooters, which have been offered under a framework of shared mobility since 2017. This paper addresses an optimization problem emerging from the process of collecting e-scooters from the streets of Vienna during the night. One of the major planning issues for rental companies is the uncertainty of service times, i.e., the time needed to locate and load the e-scooters onto the vans. We formulated the e-scooter collection problem as an extension of the vehicle routing problem with the goal of minimizing the number of vans needed to collect the scooters and the distance traveled by vans, as well as penalizing belated collection. We proposed a solution method based on a large neighborhood search and solved problem instances generated based on real-world data. We then evaluated the impact of the service time uncertainty on the total system costs through a scenario analysis. Furthermore, we proposed a dynamic re-optimization policy that made use of real-time information on service times. We showed that the dynamic policy outperformed the static policy by 4–17% and could lead to reductions in delays of 49–54%, depending on the standard deviation.

Keywords: vehicle routing problem; electric scooters; dynamic policies; shared mobility; heuristic solution method

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1. Introduction

The global population in urban areas is growing yearly, from 43% in 1990 to 56% in 2021, with an upward trend. Even higher numbers have been reported in the European Union: the urban population grew from 69% in 1990 to 75% in 2021 (see [1]). With the increase in the urban population, more vehicles are needed for transportation, for the movement of both freight and people. Mobility in cities is essential to sustain life; however, it has a high impact on the environment. Road transportation is the sector with the highest CO_2 emissions (26%) in the European Union. Since 1990, the CO_2 emissions from this sector have increased by 7% [2].

1.1. Motivation and Goals

As cities move towards greener and more sustainable solutions for transportation, there is an increase in the demand for more environmentally friendly transportation modes. One of the newest trends in passenger transportation is electric scooters (e-scooters)—collapsible kick-scooters, which utilize a small electric motor in order to move forward [3]. When powered by sustainable fuel, e-scooters constitute an environmentally friendly transportation option for short trips within cities [4]. E-scooter rental companies use the concept of shared mobility and a free-floating sharing system. They provide their e-scooters for a specified price to anybody for the period during which they need transportation. As e-scooters are relatively light-weight and small, they can be made available in many more places around a city than other forms of transportation (e.g., bicycles). Recent studies show that e-scooters are a competitive transportation mode in urban areas (see [5]), as was especially evident during the COVID-19 pandemic with its associated mobility restrictions (see [6]).

Although e-scooters are a very efficient and economical transportation mode, they have a major drawback, i.e., their short operating period due to the limitation of their battery charge. Furthermore, the recharging process of the battery is quite time-consuming and can take anywhere between 6 and 10 h [7]. One of the solutions for the recharging problem could be to equip the e-scooter with a swappable battery. A depleted battery can be replaced with a fully charged one, so there would be no need to bring the e-scooter back to the depot for recharging. However, several issues and concerns come with swappable batteries. As swappable batteries are designed to be easily removable, they must be accessible to everyone. Thus, they are more exposed to theft, vandalism, and damage. E-scooters are powered by energy-dense lithium-ion batteries. Although providers emphasize that these industrial-grade high-quality devices are highly endurable and safe for daily use, there are still reports worldwide of fire incidents, electrical faults, and self-ignition [8,9]. Therefore, several operators, e.g., LINK, Kiwi, and Bird, mistrust swappable batteries and do not plan to use them as long as the safety standards are not completely fulfilled.

The companies that do not use swappable batteries typically collect their e-scooters from the streets late in the evening and charge them at a central depot during the night. A fleet of vans is assigned to collect the scooters from the street and bring them to the depot at a certain time. The same vehicle fleet is in charge of distributing fully charged e-scooters at designated locations early in the morning. All these processes follow very tight policies: the e-scooters have to be collected after the operating hours end, which is typically around 10pm, and distributed again in the streets at 7 a.m.

Discussions with practitioners have shown that the collection policies in major cities, e.g., Vienna, are typically static. This can, however, lead to sub-optimal solutions, as the service times needed to locate e-scooters on the streets and load them onto vehicles are uncertain. Furthermore, the predicted time windows for the collection of e-scooters are quite tight, as the e-scooters need to be recharged at the depot for a long time. Therefore, any delay in the collection process can lead to delays in e-scooter distribution in the morning, which would result in high costs and lost sales.

In this paper, we propose an e-scooter collection problem that takes into account the uncertainty of service times. We formulated the problem as a vehicle routing problem (VRP) and proposed a solution method based on a large neighborhood search heuristic. The goal of the model was to minimize delays and resulting costs. We addressed both a static and dynamic policy for the collection of e-scooters. A simulation of real-world service times measured the impact of real-time information on the re-optimization and compared the costs of the dynamic solution with the static solution.

1.2. Related Literature

The usage of (electric) scooters for short-distance transportation in urban settings pertains to the field of micro-mobility solutions. Micro-mobility includes transportation with smaller vehicles, such as bicycles, scooters, skateboards, segways, and hoverboards. For a recent review of the literature on micro-mobility solutions for urban transport, see [10].

The business concept of e-scooter rental companies is based on shared mobility. This principle is based on the idea of a sharing economy, wherein users pay a specific price and rent a product or service for a defined time frame. Sharing is typically achieved via online platforms (see [11]). Shared mobility includes the transportation of people via carsharing, bikesharing, moped or scooter sharing, ridesharing, public transit services, and on-demand ride services [12]. For a recent review of vehicle-sharing systems, see [13–16].

This paper deals with an optimization problem emerging within e-scooter rental companies. However, the majority of the literature on e-scooters is not related to the field of optimization and vehicle routing. In [17], a data-driven demand model was used to compare different electric-scooter-sharing designs. The authors evaluated the impact of the charging costs and the number of e-scooters on real-world demand in Minneapolis and Louisville. In [18], the travel times of different micro-mobility solutions were analyzed and compared with car travel times. The authors showed that, in urban settings, e-scooters and bikes take noticeably less time for journeys than passenger cars. In [19], GIS hotspot spatial analysis and negative binomial regression models were used to analyze the spatio-temporal travel patterns of rental e-scooters in two US cities. The authors identified the factors that influenced demand for e-scooters, such as topography, infrastructure, and local uniqueness. The authors of [20] conducted a similar study in the city of Indianapolis, and those of [21] in the city of Belgrade.

In [22], a demand prediction model for shared e-scooters based on deep learning was presented. The authors of [23] conducted a study to investigate the impact of pricing packages on demand in e-car and e-scooter sharing. However, the conjoint analysis showed that users still prefer e-cars over e-scooters. In [24], a literature review on the laws, trends, prices, and environmental impact related to e-scooters was presented. The authors showed that regulations for rental e-scooters varied from city to city. Furthermore, they conducted a study and showed that typical users of rental e-scooters are young males. In [25], focus groups were used to analyze user attitudes towards rental e-scooters in the city of Riga. The results showed that young people (18-35 years) see e-scooters as a sustainable mode of transportation and use them as a substitute for taxis, private cars, and public transport. The authors of [26] argued that rental e-scooters might not be a sustainable solution for urban transportation at all, due to their short life cycle.

A handful of optimization problems related to battery charging have been addressed in the literature. In [27], the best locations for e-scooter battery swapping stations were determined. The authors formulated the problem as a mixed-integer program and solve it with a large neighborhood search. The authors of [28] discussed the factors that influenced customers' willingness to use battery swapping stations, such as availability, design, and user-friendliness.

Another problem faced by e-scooter providers is the mismatch in the demand and supply of e-scooters throughout the day: scooters are distributed at designated locations in the morning; however, according to the usage levels throughout the day, the number of available scooters at certain locations either surpasses or does not meet the demand. A solution to this problem is the repositioning of the scooters from the locations with high supply and low demand to locations with low supply. In [29,30], the problem of relocating e-scooters with the additional task of relocating inappropriately parked vehicles was presented. The authors formulated the problem as a mixed-integer linear program and proposed a matheuristic based on a genetic algorithm as a solution method. The authors of [31] discussed the problem of the on-board charging of e-scooters while they are being transported or relocated in a van. They solved an inventory routing problem for a real-world dataset with the help of a heuristic solution method. For a recent survey on further optimization problems and methods emerging in shared mobility, see [32].

Our problem belongs to the field of dynamic vehicle routing problems (DVRPs). The vehicle routing problem was first introduced in [33] as a truck dispatching problem, wherein a set of vehicles had to be assigned to deliver goods to a set of customers in a cost-minimizing way. Typically, the input data for such problems are known in advance. However, in real-world scenarios, this is often not the case, and the data may vary. In the late 1970s, researchers were already aware of the impact of data uncertainty and availability on the quality of the solution (see [34]). The authors of [35] addressed the issue of uncertainty in travel and service times. They pointed out that the skills of drivers as well as the characteristics of the parking or loading bay play an important role in the estimation of service times. In [36], the authors stated that the uncertainty of arrival times for delivery vans had a high impact on customer satisfaction. They analyzed different scenarios to find the trade-off between the total carrier costs and the customer service levels.

The literature distinguishes between four different categories of problems based on whether data are available and certain (see [37]). Hence, problems are defined as:

(i) deterministic and static, (ii) deterministic and dynamic, (iii) stochastic and static, and (iv) stochastic and dynamic. Our problem belongs to the deterministic and dynamic group. For reviews on dynamic problems, see [37–43]. The authors of [43] showed that, of the literature on DVRPs in the last seven years, 35% dealt with deterministic and dynamic problems. Furthermore, 17.5% was dedicated to the transport of people, and (meta)heuristics dominated as solution methods.

2. E-Scooters in the City of Vienna

This section provides some insight into the current state of the market for rental e-scooters in the city of Vienna, as well as on the regulations that have been issued by the city administration to manage the vehicle fleets on the streets.

2.1. State of the Viennese E-Scooter Rental Market

Table 1 shows an overview of the e-scooter rental companies that have entered the Viennese market, together with their status as of December 2022 and numbers of permits issued for e-scooters. The first providers, Bird and Lime, entered the Viennese ridesharing market in September 2018, followed by Tier and Wind in November of the same year. New competitors such as Flash/Circ, Hive, and Kiwi joined in the next year, increasing the Viennese total fleet size from 600 to 6000 e-scooters [44]. The presence of and increasing interest in this transport mode turned out to be fatal for some e-bike rental companies.

In 2019, the first rental companies started leaving the Viennese market. During the harsh winter conditions of 2018/2019, Wind left the market. High competition and new strict regulations were some of the reasons for Hive leaving the market by the end of 2019. During 2020, Max Motion and Holmi/Rollmi, Austrian-based start-ups, left Vienna to focus on smaller Austrian cities. Furthermore, Bird took over Circ. In April 2021, Link joined the market and managed to establish a large user base rather quickly, mainly due to their offering of free rides in association with COVID-19 vaccines (see [45]).

Table 1. State of the Viennese E-Scooter Rental Market, as of December 2022.

	Company	Market Entry Date	Market Exit Date	No. Permits Issued	Status
1	**Lime**	**18 September**	**-**	**1500**	**active**
2	**Bird**	**18 September**	**-**	**1500**	**active**
3	**Tier**	**18 November**	**-**	**1500**	**active**
4	Wind/Byke	18 November	19 August	574	left
5	Flash/Circ	19 March	21 January	1500	left
6	Hive	19 April	20 February	790	left
7	**Kiwi**	**19 July**	**-**	**1500**	**active**
8	Holmi/Rollmi	19 August	20 February	30	left
9	MaxMotion	19 October	20 June	130	left
10	**Link**	**21 April**	**-**	**1500**	**active**

2.2. Regulatory Work in the City of Vienna

As citizens and users were not accustomed to e-scooters in Vienna when they were introduced, several issues arose for safe urban transport. First, the lack of knowledge and information on where and how to park the scooters after riding caused blockages in the normal traffic flow. Scooters carelessly discarded on sidewalks or even on streets endanger the safety of all traffic participants. Secondly, the lack of skills in handling the vehicles on the road resulted in numerous traffic accidents, which led to a clear disapproval of e-scooters among Viennese residents.

The Vienna City Administration saw the need to issue regulations concerning rental e-scooters in 2018 [46]. The first set of regulations included the following municipality rules:

- Each rental scooter company, including their subsidiaries, is allowed up to 1500 scooters.
- Improperly parked scooters have to be relocated within 4 h on weekdays and within 12 h on weekends. Otherwise, a fine of EUR 700 will be issued.
- All rental scooters need to have a permit issued and an official identification tag.
- The municipal waste management division of the city of Vienna is responsible for the proper disposal of all vandalized or irreparable scooters.

Though these municipality rules brought some improvement in the regulation of e-scooter fleets on the streets of Vienna, there were still no legal consequences for the improper usage of the scooters. The national parliament saw the need to change this and, as of 1 June 2019, e-scooters were brought under regulation with the 31st Amendment of the Road Traffic Regulations Act. Legally, e-scooters became defined as motorized two-wheeled vehicles that fall under the same regulations as bicycles in traffic. The legal regulations also brought some changes to the design of e-scooters. The maximum motor capacity was set to a limit of 600 watts. Though previous designs allowed for speeds of over 35 km/h, the new regulations limited the speed of e-scooters to 25 km/h.

To ensure road safety for all participants, e-scooter legal regulations are equivalent to those of bicycles [46]. The main rules are:

- The use of bicycle lanes or zones where cycling is permitted is mandatory.
- The use of sidewalks is prohibited.
- The maximum allowed speed is 25 km/h, and the actual speed has to be adjusted to traffic situations.
- The use of mobile phones or listening to music is prohibited.
- The alcohol limit is set to 0.8.
- The minimum age requirement for users is 12 years. Younger users can still book a ride; the ride then has to be supervised by a person over 16 years old.
- Head protection is recommended for everyone and mandatory for users under the age of 13.
- The use of scooters by two or more riders at the same time is prohibited.
- The safety protocol must be checked before each ride.

In the summer of 2020, it became evident that the concentration of e-scooters throughout the city was not balanced. Therefore, the Vienna City Administration issued amended guidelines to balance the e-scooter distribution and, in particular, to make sure that enough e-scooters were available in the outskirt districts of the city of Vienna [46]. The previous guidelines for rental e-scooter providers were updated with additional rules:

- The 1st, 2nd, 9th, and 20th districts can hold up to 500 vehicles at most.
- In districts 10–22, a minimum of 500 scooters has to be provided.
- Improperly parked scooters have to be relocated within 2 h on weekdays.
- Operations teams in charge of collecting the e-scooters at night are not allowed to use acoustic tracking signals.
- Scooter rental companies have to report the locations of the distributed scooters each morning before 7 a.m.
- Scooters cannot be parked on a sidewalk narrower than 4 m.
- Adherence to the law will be checked by the City Administration.

The Vienna City Administration planned stricter regulations by the summer of 2021, which eventually ended in a round-table discussion between the Austrian Chamber of Commerce and e-scooter rental companies. Both the city's and the companies' aims were to provide a sustainable last/first-mile transport solution and make sure that e-scooters were used and parked in a safe way and did not interfere with other traffic. They agreed on the stricter supervision of the riding and parking of e-scooters by users. A pilot project of 'scooter sheriffs', who were responsible for reporting violations, took place until September of 2021.

For 2023, new, stricter regulations for e-scooters are being proposed by the Vienna City Administration [46]. The new regulations will include the following:

- The number of e-scooters in the inner districts will be further reduced to balance the oversupply.
- Parking on sidewalks will no longer be permitted. Scooters should be parked in the designated fixed parking areas or in the parking lane.
- A digital dashboard will make it possible to check the location of every single scooter at any time—even retrospectively—and thus enable consistent penalties for illegally parked scooters.
- Rental companies must ensure that scooters are properly parked; otherwise, penalties will be imposed. The successful scooter sheriff project will be reinstalled, and they will also monitor compliance with the rules on site.
- Certain places will become restricted to scooters. Geo-fencing will be used to prohibit driving into restricted areas.

3. E-Scooter Collection Problem

In this paper, we address the problem of e-scooter collection by vans during the night. Furthermore, we evaluate the impact of the uncertainty of service times on the problem. We propose static and dynamic solution policies to solve the problem and evaluate them using a simulation of service times.

3.1. Problem Description

The problem was inspired by an interview with a rental e-scooter company based in the city of Vienna. The company employs an operations team responsible for collecting the e-scooters in the night, recharging them at the depot, and distributing them to designated locations early in the morning. According to the interviewed operations team, the collection of e-scooters from the streets is a challenging task, as all planning and the routing of the vans is carried out manually, which can lead to sub-optimal solutions. One of the biggest problems is the estimation of the service time needed to load the e-scooters onto the van. The team reports that approximately 2–4 min are needed to find a parking spot, locate the e-scooter, and secure it in the van. However, these times may vary depending on the location of the scooter: if the scooter is damaged, parked in an inaccessible area, or parked in an area restricted for vans, the service times can be much longer. The typical policy of the company is that, if a scooter cannot be found within 15 min, the driver should proceed to the next location. The data are collected from the GPS coordinates of the vans responsible for collecting the e-scooters.

An additional problem is the long charging times of e-scooters. Depending on the model of e-scooter, the charging process can take between 6 and 10 h [7]. The recharging time is crucial, especially when the vehicles are collected during the night and redistributed to designated locations in the morning. If the e-scooters are not fully charged in the morning, this can lead to delays in the supply.

This paper investigates the problem of collecting e-scooters during the night. The goal was to generate a routing plan for the vans that minimized the total operational costs of e-scooter collection—the number of vans needed for collection, the costs for the total kilometers driven, and delays in supply. An additional task was to design a dynamic collection policy to re-optimize the van routes after real-time information on service times is disclosed. If one driver needs longer than planned to collect the e-scooters assigned to his route, the remainder of his route might be assigned to another driver. In this way, delays can be reduced or even prevented. Within this paper, we evaluate the effect of the re-optimization by comparing the total delays and costs in the cases with and without re-optimization. Unfortunately, we did not obtain any data regarding the real-world costs and delays; therefore, a comparison with the current company's policy was not possible.

3.2. Mathematical Model

The mathematical model was based on the capacitated vehicle routing problem with time windows (see [47,48]). Table 2 provides an overview of the sets, parameters, and decision variables used in the model.

Table 2. Notation of sets, input parameters, and decision variables used herein.

Notation	Description
Sets and nodes	
0	Depot
n	Number of locations of e-scooters
m	Number of vehicles
$N = \{1, \ldots, n\}$	Set of locations of e-scooters
$K = \{1, \ldots, m\}$	Set of vehicles
Parameters	
C_{f}	Fixed costs per vehicle used
C_{v}	Variable costs per kilometer traveled
C_{p}	Penalty costs per minute delay
dt_{ij}	Distance traveled between locations i and j
tt_{ij}	Time taken to travel between locations i and j
s_i	Service time at location i
E_i	The end of the time widow at location i
Q	Maximum number of e-scooters transported per vehicle
$D_{\max}$	Maximum allowed delay
Decision variables	
y_{ik}	Binary variable equal to 1 if vehicle k is used for collection of e-scooter at location i, and 0 otherwise
x_{ijk}	Binary flow variable equal to 1 if vehicle k travels from node i to node j, and 0 otherwise
a_i	Arrival time at location i
d_i	Delay at location i

Let $N = \{1, \ldots, n\}$ be the set of locations of e-scooters that have to be collected by a set of vehicles $K = \{1, \ldots, m\}$. Furthermore, let 0 denote the location of the depot. The homogeneous vehicle fleet consists of vans equipped to transport e-scooters, which can all carry the same number of e-scooters, Q. For each vehicle used, fixed costs of C_{fix} have to be paid. Additionally, C_{var} denotes the costs per kilometer traveled. The distance traveled and travel times between nodes i and j are denoted by dt_{ij} and tt_{ij}, respectively. The service time needed to locate the e-scooters at each location i and load them onto the van is denoted by s_i. E-scooters should be located within the given time frame; otherwise, a penalty has to be paid. Let E_i denote the end of the time widow at location i and $C_{penalty}$ the costs that have to be paid per minute delay. The maximum allowed delay is denoted by $D_{\max}$.

Binary variable y_{ik} indicates whether vehicle k is used for the collection of e-scooters at location i or not. Binary flow variable x_{ijk} is equal to 1 if vehicle k travels from node i to node j, and 0 otherwise. a_i denotes the arrival time at location i, and d_i denotes delays.

The e-scooter collection problem can be formulated as follows:

$$\min \sum_{k \in K} y_{0k} C_{\text{f}} + \sum_{i \in N \cup 0} \sum_{j \in N \cup 0} \sum_{k \in K} x_{ijk} dt_{ij} C_{\text{v}} + \sum_{i \in N} d_i C_{\text{p}}$$

subject to

$$\sum_{i \in N} y_{ik} \leq Q \qquad \forall\, k \in K \tag{1}$$
$$\sum_{j \in N} x_{ijk} = \sum_{j \in N} x_{jik} = y_{ik} \qquad \forall\, i \in N \cup 0, k \in K \tag{2}$$
$$\sum_{k \in K} y_{ik} = 1 \qquad \forall\, i \in N \tag{3}$$
$$a_i + s_i + tt_{ij} \leq a_j + (1 - x_{ijk})M \qquad \forall\, i, j \in N \cup 0, k \in K \tag{4}$$
$$a_i \leq E_i + d_i \qquad \forall\, i \in N \tag{5}$$
$$d_i \leq D_{\max} \qquad \forall\, i \in N \tag{6}$$
$$x_{ijk} \in \{0, 1\} \qquad \forall\, i, j \in N \cup 0, k \in K \tag{7}$$
$$y_{ik} \in \{0, 1\} \qquad \forall\, i \in N \cup 0, k \in K \tag{8}$$
$$a_i, d_i \geq 0 \qquad \forall\, i \in N \cup 0 \tag{9}$$

The objective function minimizes the total costs: the fixed costs per vehicle used, the variable costs for the distance traveled, and the penalties for delays. The constraints (1) make sure that the number of e-scooters loaded onto the vehicle does not exceed the capacity of the vehicle. The constraints (2) are flow conservation constraints, which also make sure that the collecting vehicles start and end their routes at the depot. The constraints (3) ensure that each scooter is collected by one vehicle. The connectivity of the routes is guaranteed by constraints (4), where M represents a large number. A late arrival results in a delay, as determined by constraints (5). The maximum delay cannot be violated, as guaranteed by (6). Finally, constraints (7)–(9) define the domains of the decision variables.

4. Solution Method

The mathematical model explained in Section 3.1 was implemented in CPLEX and tested for small problem instances. However, for realistic real-world instances, a fast algorithm is needed that can provide a high-quality solution within a short computational time. This is especially important as we included dynamic re-optimization, which needed to be executed in real time.

We started by solving the static version of the problem. We proposed a solution method based on the large neighborhood search procedure introduced by [49] and later adapted by [50]). The heuristic method was used to obtain the number of vehicles needed for the collection of e-scooters and the routing plan for the vehicles. In the static version, we assumed fixed values for service times. The solution was then evaluated with the simulated service time. As we did not have information on the actual service times from the company, we created different scenarios for simulation purposes. More information on service time simulation is provided in Section 5.3. After solving the static version of the problem, we solved the dynamic version, wherein service times were updated during planning. More details on dynamic re-optimization are provided in Section 4.2.

4.1. Large Neighborhood Search Framework

The pseudocode of the large neighborhood search used in this paper is presented in Algorithm 1. The goal of the algorithm was to find the overall best solution S^*. We started by obtaining an initial solution through a construction heuristic S (Step 1) and updated the best solution, S^*, by setting $S^* = S$ (Step 2). Next, we defined a set of destroy and repair operators (Steps 3 and 4), which were used to perturb and improve the solution until a stopping criterion was met. We also defined a set of local search operators to improve the solution at the end of each iteration (Steps 5 and 6). In each iteration, we randomly selected one destroy operator to remove a certain number of allocations from the solution (Steps 7 and 8) and one repair operator, which assigned the non-allocated locations to vehicles (Steps 9 and 10). The solution was then further improved by applying a local search procedure (Steps 11 and 12). At the end of each iteration, we evaluated the solution (Step 13) and checked whether the new solution was accepted or not (Steps 14–19).

Algorithm 1 LNS framework.

1: $S \leftarrow$ initial solution obtained from construction heuristic
2: $S^* \leftarrow S$
3: $D \leftarrow$ set of destroy operators
4: $R \leftarrow$ set of repair operators
5: $L \leftarrow$ set of local search operators
6: **while** stopping condition is not met **do**
7:    select destroy operator $d \in D$
8:    $S' \leftarrow$ destroy (S, d)
9:    select repair operator $r \in R$
10:    $S' \leftarrow$ repair (S', r)
11:    select local search operator $l \in L$
12:    $S' \leftarrow$ localSearch (S', l)
13:    evaluate (S')
14:    **if** S' is accepted **then**
15:       $S \leftarrow S'$
16:       **if** S' is better than S^* **then**
17:          $S^* \leftarrow S'$
18:       **end if**
19:    **end if**
20: **end while**
21: return S^*

4.1.1. Initial Solution

An initial solution for the e-scooter collection problem was generated as follows: We started by calculating the minimum number of vehicles needed to execute delivery. For this purpose, we used the information on the available capacity of each van, i.e., how many e-scooters could be loaded onto the van. Furthermore, to improve the lower bound, we calculated the minimum route duration as the minimum travel time plus the service times and compared this value to the time window plus the maximal delay. After obtaining the number of vehicles, we assigned the locations using a regret insertion heuristic, which is explained in more detail in Section 4.1.3.

4.1.2. Destroy Operators

We used three different destroy operators: random removal, worst removal, and related removal. In each iteration, one destroy operator was selected and applied to the solution. All operators had the same chance of being selected.

- Random removal is the simplest destroy operator: q locations were selected at random and removed from the solution.
- In the case of the worst removal operator, we chose several locations that were very expensive. For each location, we calculated the savings in cost that could be obtained if this location was not visited. We selected q locations with the highest savings values and removed them from the solution. We also included a randomized version of the worst removal operator—we selected q locations such that the locations with a higher savings value had a higher chance of being selected.
- The related removal operator identified locations that were similar in some way and removed them from the solution. The authors of [51] argued that shuffling similar requests can yield better solutions. We started by removing p locations from the solution either by applying random or worst removal. We then identified locations that were geographically similar to already deleted ones and deleted up to $q - p$ additional locations, such that locations closer to the already deleted ones had a higher chance of being selected.

p was randomly chosen from the range $\{p_{\min}, p_{\max}\}$, and q from the range $\{q_{\min}, q_{\max}\}$. We made sure that $p_{\max} \le q_{\min}$. In each iteration, at least 1 location was removed.

4.1.3. Repair Operators

After removing locations from the solution, we applied repair operators to re-insert the removed locations into a new solution. We used two regret operators: greedy insertion and regret insertion.

- Within the greedy insertion operator, all non-inserted locations were stored in a non-sorted array. A location was randomly chosen from the array and inserted at the best position in the best route. The procedure terminated when all non-inserted locations had been inserted.
- Within the regret insertion operator, for all locations which were not inserted, a regret value was calculated. The regret value was defined as the difference between insertion costs at the best position and the second best position. After calculating all regret values, we selected the location with the highest regret value and inserted it at the best position. The regret values for the remaining locations were recalculated, and the procedure was repeated until all locations had been inserted. We also used a randomized version of this operator wherein the locations were not inserted based on the descending order of their regret values, but the locations with a higher regret value had a higher chance of being selected for insertion.

Note that the best route for insertion could also be an empty route; hence, within our insertion operators, we allowed the number of vehicles to increase. We did not allow solutions that were infeasible due to capacity or maximum delay restrictions.

4.1.4. Local Search Operators

We used two local search operators: a two-opt operator and a relocate operator. In each iteration, one local search operator was selected randomly and applied.

- The two-opt operator was applied between routes: for each pair of edges, we computed the savings in costs when these edges were removed from the solution and the rest of the route was reconnected. Following the best improvement acceptance strategy proposed in [52], after all savings values were calculated, we selected the highest one. The procedure stopped when no more savings could be achieved.
- The second local search algorithm also worked as an intra-route operator: each location in a route was removed from its current position and re-inserted at the best position within the same route. The procedure was repeated for all locations on the route as long as further savings could be found.

4.1.5. Acceptance Criteria

For the presented problem, we used acceptance criteria based on simulated annealing. This procedure was first introduced in [53] as a local search metaheuristic capable of avoiding local optima. At the end of each iteration, we evaluated the solution and compared it to the incumbent solution and the best solution. A better solution was always accepted. However, a fraction of non-improving solutions were accepted instead of incumbent solutions to avoid a local optimum. The probability that a solution was accepted was based on the costs of the solution, and it decreased with each iteration.

4.2. Dynamic Re-Optimization

We extend our LNS procedure so that it could also take dynamic re-optimization into account. In the dynamic setting, we made use of revealed information to improve our routing decisions. We assumed that information on the service times needed to locate and load the e-scooters would be revealed with time. This information could be used to recalibrate the current position of the van and to check whether delays on the routes could be expected. Delays on identified routes could then be better managed by relocating some of the delayed assignments to other drivers.

The adjusted LNS procedure is shown in Algorithm 2. We started with an initial solution obtained using a construction heuristic and defined the destroy, repair, and local search operators. We additionally kept track of time point t, which denoted the current time and was necessary for re-optimization. Re-optimization was executed in the block 6–26. At the beginning, we set $t = 0$ (Step 2). Within the re-optimization block, time t was increased by fixed time intervals t_{fix} (Step 25). The re-optimization procedure stopped when time t reached the end of the time window at the depot, E_0 (Step 7).

At the beginning of each re-optimization iteration, solution S needed to be fixed at a time interval up to time t, i.e., time interval $\{0, t\}$. To fix part of the solution, we used the information from the simulated service times to recalculate the arrival times at locations and the current position of the driver. No location that had been visited up until time t could be changed. Destroy, repair, and local search operators could only be applied to locations that were visited after time t. In order to create a solution method that could also be used in the real world, we assumed that the drivers who were already on their way to collect the next scooter should not be disturbed; therefore, all changes on the route were applied to locations that a driver should visit after the next one. The destroy, repair, and local search operators applied were the same as described and used in Section 4.1.

Algorithm 2 Dynamic re-optimization framework.

1: $S \leftarrow$ initial solution obtained from construction heuristic
2: $t \leftarrow 0$ re-optimization time point
3: $D \leftarrow$ set of destroy operators
4: $R \leftarrow$ set of repair operators
5: $L \leftarrow$ set of local search operators
6: **while** $t \leq E_0$ **do**
7:   freeze S in interval $\{0, t\}$
8:   $S^* \leftarrow S$
9:   **while** stopping condition is not met **do**
10:     select destroy operator dependent on time t, $d(t) \in D$
11:     $S' \leftarrow$ destroy $(S, d(t))$
12:     select repair operator dependent on time t, $r(t) \in R$
13:     $S' \leftarrow$ repair $(S', r(t))$
14:     select local search operator dependent on time t, $l(t) \in L$
15:     $S' \leftarrow$ localSearch $(S', l(t))$
16:     evaluate (S')
17:     **if** S' is accepted **then**
18:       $S \leftarrow S'$
19:       **if** S' is better than S^* **then**
20:         $S^* \leftarrow S'$
21:       **end if**
22:     **end if**
23:   **end while**
24:   $S \leftarrow S^*$
25:   $t \leftarrow t + t_{fix}$
26: **end while**
27: return S

5. Data and Parameters

For the analysis, we used the data provided by an e-scooter rental company pertaining to the locations of e-scooters, their recharging times, and the time windows for picking up the scooters in the night and distributing them in the morning. Further information regarding the costs and distances were taken from the literature.

5.1. E-Scooter Locations

The e-scooter rental company provided data on the locations of their e-scooters at 10 p.m. for March 2021. The data included information on the scooter ID, date, latitude, and longitude for 1000 e-scooters each day. The depot of the operations team in charge of collecting the e-scooters was located in the center of Vienna. Due to privacy issues, no detailed information on the locations of the e-scooters can be provided.

5.2. Time Windows and Delays

The operating hours of the respective e-scooter sharing company ended at 10 p.m., i.e., the e-scooter collection process started at 10 p.m. In order to ensure the timely charging of the e-scooters and their distribution in the morning, the latest time for picking up the scooters was set to 12 a.m. The time windows were defined as soft time windows, which meant that delays were allowed but penalized according to the objective of the model. If the pickup of a scooter was delayed, the distribution of the scooter in the morning would also be delayed. Every minute delay, therefore, "cost" EUR 0.19, which was derived from the rental pricing scheme per minute of usage. Furthermore, for every late e-scooter, additional fixed costs of EUR 1 were incurred, as the scooter was not available for usage. The maximum delay was set to 30 min.

5.3. Service Time Modeling

The service time was an important parameter as it captured the uncertainty within the e-scooter collection problem. The service time at a location includes the search for a parking space, finding the e-scooter, and then loading and securing it onto the van.

The operations team assumed that the average service time s_i at each location i was equal to 3 min. However, in the real world, these times often vary. For the analysis, we created different scenarios to analyze the impact of the service time on the planning and overall costs. We first calculated the routing plan using a default value for service times of 3 min. In the dynamic case, information on real-world service times was disclosed and used to adjust the routing plan. We assumed that the time interval t_{fix} was equal to 20 min, i.e., the routing plan was adjusted every 20 min until the end of the time window at the depot at 12 am. In the static case, the plan was evaluated only at the end.

To simulate the real-world service times, we assumed that the service times were normally distributed with a mean value of 3 min. We developed three scenarios with different values for standard deviation: 1, 3, and 5, respectively, where the minimum service time was 1 min and the maximum 15 min.

5.4. Vehicle Capacity and Costs

The vehicle type assumed for this analysis was a small delivery van. The operations team reported that the typical van used was a PEUGEOT Boxer with a maximum capacity of 30 e-scooters.

The drivers' costs were based on the collective agreement for employees in the delivery van industry effective as of 16 November 2021 [54]. For the analysis, we assumed a fixed hourly compensation of 12 EUR based on a freelance contract.

For the kilometer charge, we used the average fuel consumption and the diesel price as of January 2023. We assumed an urban consumption of 6.10–7.10 L per 100 km. In January 2023, the average gasoline price amounted to EUR 1.78 per liter (see [55]). The kilometer charge was calculated as $(6.1 + 7.1)/200 \times 1.78 = 0.12$ EUR/km.

5.5. Travel Distance and Time

To calculate the distance between locations, we used the improved formulas for air distance, which take into account the longitude and latitude and the curvature of the earth and calculate the distance based on the Pythagorean theorem (see [56]). The air distance was used instead of the real-world distance, as the real-world distance matrix between 1000 locations would have to be saved in a large file, and retrieving the data from a large file would affect the computation time.

The distance between two circles of latitude is constant and is equal to 111.3 km. However, the distance between two longitudes is dependent on the latitude. The following formula can be used to calculate the distance between two longitudes: diff = 111.3 cos(lat), where lat is the mean value of the two latitude values in radians. The conversion of degrees to radians follows the formula: $1^\circ = \pi 180 rad \approx$ 0.01745. If lon_1, lon_2, lat_1, and lat_2 are the longitude and latitude of two locations, the formula used to calculate the distance is:

$$\text{distance} = \sqrt{d_x d_x + d_y d_y} \tag{10}$$

$$\text{where} \tag{11}$$

$$d_x = 113 \cos(lat)(lon_1 - lon_2) \tag{12}$$

$$lat = 0.01745 \frac{(lat_1 + lat_2)}{2} \tag{13}$$

$$d_y = 113(lat_1 - lat_2) \tag{14}$$

The travel time between locations was calculated using the distance and the information regarding the average driving speed in 21 districts of Vienna provided by the operations team.

5.6. LNS Parameters

After the pretesting was carried out, we selected several parameters that yielded good solutions. The termination criteria of the LNS procedure were set to 2000 iterations or 200 itartions without improvement. The cooling rate for the simulated annealing was set to 0.9. The $p_{\min}$ and $p_{\max}$ were set to 5% and 10% of all locations, respectively, and the $q_{\min}$ and $q_{\max}$ to 10% and 30% of all locations.

6. Results

Table 3 shows the results for instances 1 to 15 of the dataset, and Table 4 shows the results for instances 16 to 31. The column target shows the type of results: (i) P stands for planned costs, which were calculated with a default value for a service time of 3 min; (ii) D stands for dynamic policy and shows the actual costs if dynamic re-optimization was allowed; and (iii) S stands for static policy, showing the actual costs if no re-optimization was allowed. The actual costs were obtained by simulating the service times using different values for standard deviation (SD). Columns 3–5 show the results for a standard deviation of 1, columns 6-8 the results for a standard deviation of 3, and columns 9–11 for a standard deviation of 5. For all three scenarios, we show the value of the objective function, i.e., the total costs for the planned scenario and the actual costs with simulated service times for the static and dynamic policies. Furthermore, we show the gap between the static and dynamic policies and the planned costs.

It was evident that there were not many variations in costs and planning between the days. The planned objective value was around 2699–2773 for all thirty-one days, with no delays and 37–38 vehicles used for the collection of 1000 e-scooters. As the value of the standard deviation had no impact on the planned costs, only on the evaluation, the planned costs for each day between scenarios were the same. The evaluations of the dynamic and static policies were, however, noticeably different for each scenarios. With the increase in the standard deviation, the delays and the value of the objective function for both the static and dynamic policies increased. The dynamic policy outperformed the static policy for each day and in each scenario. For SD = 1, the static policy resulted in an increase in the planned costs of 7% to 10%, whereas the dynamic policy managed to keep the increase to 3–6%. In the case of SD = 3, the static policy was responsible for an additional 17–22% increase in costs, whereas the dynamic policy resulted in a 7–11% increase. The impact of the uncertainty of the service times was even more evident in the case of SD = 5, where the static policy resulted in a 40–50% increase in costs. The dynamic policy managed to keep the increase between 18 and 28%. The impact of the uncertainty of the service times on the costs was mainly due to the very tight time windows available for the collection of e-scooters.

Table 3. Results for instances 1 to 15 (SD—standard deviation, P—planned, D—dynamic policy, S—static policy, obj.—value of objective function, GAP—gap to the planned costs).

		SD = 1		**SD = 3**		**SD = 5**	
Instance	**Target**	**Obj.**	**GAP**	**Obj.**	**GAP**	**Obj.**	**GAP**
1	P	2771		2771		2771	
	D	2900	4.66%	3002	8.34%	3367	21.52%
	S	2997	8.16%	3291	18.78%	3974	43.41%
2	P	2772		2772		2772	
	D	2882	3.97%	3046	9.88%	3304	19.19%
	S	2979	7.47%	3254	17.38%	3917	41.30%
3	P	2773		2773		2773	
	D	2896	4.42%	3055	10.16%	3285	18.45%
	S	2997	8.10%	3302	19.06%	3952	42.51%
4	P	2772		2772		2772	
	D	2871	3.57%	3035	9.49%	3386	22.15%
	S	2979	7.46%	3257	17.49%	3886	40.18%
5	P	2771		2771		2771	
	D	2867	3.44%	3030	9.34%	3313	19.57%
	S	2985	7.73%	3280	18.37%	3956	42.75%
6	P	2771		2771		2771	
	D	2871	3.62%	3018	8.90%	3297	18.99%
	S	2978	7.46%	3275	18.20%	3939	42.15%
7	P	2702		2702		2702	
	D	2860	5.84%	2945	8.98%	3372	24.77%
	S	2972	10%	3312	22.58%	4073	50.74%
8	P	2771		2771		2771	
	D	2888	4.21%	3028	9.25%	3343	20.60%
	S	3001	8.27%	3310	19.42%	4043	45.86%
9	P	2701		2701		2701	
	D	2840	5.14%	3017	11.70%	3408	26.17%
	S	2941	8.87%	3251	20.37%	3951	46.28%
10	P	2702		2702		2702	
	D	2843	5.20%	2972	9.99%	3248	20.21%
	S	2935	8.61%	3251	20.30%	3982	47.35%
11	P	2771		2771		2771	
	D	2874	3.69%	3041	9.75%	3322	19.87%
	S	2989	7.85%	3281	18.39%	3955	42.70%
12	P	2699		2699		2699	
	D	2834	5.00%	2963	9.79%	3305	22.43%
	S	2929	8.52%	3222	19.38%	3891	44.13%
13	P	2700		2700		2700	
	D	2812	4.14%	2966	9.84%	3248	20.28%
	S	2926	8.37%	3236	19.83%	3961	46.69%
14	P	2702		2702		2702	
	D	2833	4.87%	2946	9.02%	3240	19.92%
	S	2931	8.48%	3212	18.87%	3906	44.58%
15	P	2702		2702		2702	
	D	2821	4.41%	2976	10.15%	3298	22.05%
	S	2919	8.02%	3209	18.73%	3925	45.26%

Table 4. Results for instances 16 to 31 (SD—standard deviation, P—planned, D—dynamic policy, S—static policy, obj.—value of objective function, GAP—gap to the planned costs.

		SD = 1		SD = 3		SD = 5	
Instance	**Target**	**Obj.**	**GAP**	**Obj.**	**GAP**	**Obj.**	**GAP**
16	P	2702		2702		2702	
	D	2814	4.14%	2957	9.43%	3454	27.82%
	S	2923	8.16%	3253	20.40%	4017	48.67%
17	P	2702		2702		2702	
	D	2830	4.73%	2997	10.93%	3302	22.20%
	S	2931	8.47%	3229	19.48%	3928	45.38%
18	P	2773		2773		2773	
	D	2874	3.65%	2991	7.89%	3303	19.11%
	S	2997	8.08%	3286	18.51%	3987	43.78%
19	P	2703		2703		2703	
	D	2811	4.01%	2914	7.79%	3201	18.43%
	S	2918	7.95%	3254	20.37%	3953	46.23%
20	P	2701		2701		2701	
	D	2840	5.12%	2955	9.38%	3304	22.30%
	S	2924	8.25%	3213	18.95%	3941	45.91%
21	P	2702		2702		2702	
	D	2824	4.50%	2939	8.76%	3219	19.12%
	S	2918	7.99%	3218	19.11%	3910	44.70%
22	P	2703		2703		2703	
	D	2831	4.74%	2957	9.39%	3358	24.25%
	S	2927	8.27%	3262	20.67%	4015	48.55%
23	P	2772		2772		2772	
	D	2885	4.06%	3066	10.57%	3277	18.20%
	S	2995	8.02%	3301	19.06%	4006	44.49%
24	P	2703		2703		2703	
	D	2830	4.69%	2998	10.90%	3249	20.20%
	S	2946	8.99%	3271	21.01%	4024	48.88%
25	P	2704		2704		2704	
	D	2841	5.08%	2940	8.74%	3288	21.61%
	S	2932	8.43%	3278	21.23%	4048	49.70%
26	P	2772		2772		2772	
	D	2875	3.71%	3009	8.56%	3278	18.25%
	S	3009	8.54%	3334	20.28%	4079	47.14%
27	P	2773		2773		2773	
	D	2873	3.59%	3000	8.19%	3305	19.19%
	S	2982	7.53%	3252	17.28%	3892	40.32%
28	P	2773		2773		2773	
	D	2889	4.20%	2971	7.14%	3338	20.39%
	S	3001	8.22%	3344	20.59%	4086	47.36%
29	P	2773		2773		2773	
	D	2889	4.18%	3006	8.42%	3340	20.48%
	S	3007	8.46%	3350	20.81%	4038	45.65%
30	P	2704		2704		2704	
	D	2837	4.93%	3009	11.29%	3363	24.38%
	S	2951	9.15%	3286	21.54%	4044	49.56%
31	P	2772		2772		2772	
	D	2885	4.05%	3017	8.81%	3301	19.06%
	S	2978	7.41%	3267	17.85%	3961	42.88%

Table 5 shows the aggregated results for 31 instances and the most important key performance indicators—such as the average value of the objective function, the average delay in minutes and EUR, and the average distance in kilometers for the static and dynamic policies. With the dynamic re-optimization of the routes, the costs could be reduced significantly. The average daily difference in objective value was 4% or EUR 106 in the case of a standard deviation of 1, 8% or EUR 277 for a standard deviation of 3, and 17% or EUR 665 for a standard deviation of 5. Delays could be reduced as well: delays in minutes could be reduced by 57–60%, depending on the standard deviation, and the number of delayed e-scooters and the costs for delays could be reduced by 49–54%, or EUR 109 to 671, on average per day. The re-optimization, however, led to an increase in distance traveled: the vehicles had to travel between 3% and 5% more, or between 37 km and 55 km further.

Table 5. Aggregated results over 31 instances (SD—standard deviation, D—dynamic policy, S—static policy).

	SD1	SD3	SD5
Avg. Objective Value			
S	2961	3269	3975
D	2855	2992	3310
diff	106	277	665
diff in %	4%	8%	17%
Avg. Delay in Minutes			
S	730	2084	5364
D	317	828	2127
diff	413	1255	3237
diff in %	57%	60%	60%
Avg. Delay in EUR			
S	225	533	1239
D	116	252	569
diff	109	281	671
diff in %	49%	53%	54%
Avg. Distance in KM			
S	1121	1121	1121
D	1158	1169	1176
diff	−37	−48	−55
diff in %	−3%	−4%	−5%

7. Managerial Implications and Discussion

Rental e-scooters are a novel mode of transportation that can be used for short trips, e.g., for leisure trips, to commute to work or school, or as an addition to public transport. There are multiple benefits of rental e-scooters: they can use bike lines and therefore help avoid congestion, and they propagate active mobility. Additionally, they can complement public transportation and help to reduce crowding, especially during rush hours.

However, there are many concerns related to e-scooters, which include irresponsible rider behavior, safety issues, vandalism, cluttered streets, and space problems. Police reports and case studies on patients with injuries associated with e-scooters have shown that many underage riders use e-scooters illegally, and some riders do not observe traffic rules and speed limits or use e-scooters under the influence. In order to successfully integrate rental e-scooters in urban traffic, regulations are needed. The first regulations in the city of Vienna were issued in the summer of 2018, appearing in the form of Municipal Laws (decrees) published by the Vienna City Administration. As of 1 June 2019, e-scooters fall under the same regulations as bicycles in traffic. Furthermore, the Vienna City Administration issued amended guidelines in the summer of 2020 to balance the scooter distribution within the city. The upcoming planning phase contains further restrictions and integration elements such as the Mobility Sharing Dashboard. From 2023, in addition to parking sheriffs, scooters will also begin to monitor user behavior via geo-fencing technology.

An additional problem related to e-scooters is their collection from the streets at night by operation teams. The results of our case study indicated that there is significant potential for improvement when it comes to organizing the collection of e-scooters from the streets by vans. Switching from manual to software-based planning for the vans' routes and using optimization techniques could help to reduce delays in e-scooter distribution early in the morning. Furthermore, using dynamic planning to re-optimize the vans' routes could help to better deal with uncertainty in service times. Based on the assumed compensation scheme for drivers in our case study, dynamic re-optimization could reduce daily costs for delays by EUR 106 in cases of lower uncertainty and up to EUR 665 in cases of higher uncertainty. Note that these savings do not include the costs of purchasing or developing such planning software. The results of our study showed that dynamic re-optimization led to a decrease in delays but an increase in distance traveled, i.e., the benefits of re-optimization were positively correlated with the purchase prices of diesel vans and the prices of using a scooter and negatively correlated with diesel prices.

A reduction in delays might have a further positive impact on the customers. If an e-scooter is available at the time a potential rider starts their commute, they might choose it instead of a less environmentally friendly mode of transportation. Furthermore, a reliable service might attract new users, which would also be beneficial for the companies.

8. Conclusions, Limitations and Future Research

The goal of this paper was to investigate the problem of e-scooters and their collection from the streets of Vienna. We first provided some insights into the state of the market for rental e-scooters and then addressed the problem of the efficient collection of e-scooters by a fleet of vehicles.

E-scooter rental companies use the concept of shared mobility and a free-floating sharing system. The first providers entered the Viennese ridesharing market in September 2018. As of 2023, 10 companies have launched their services in Vienna, but only 5 of them are still active: Lime, Bird, Tier, Kiwi, and Link. The main reasons for leaving the Viennese market were: (i) high competition, (ii) harsh weather conditions and decreased demand during winter months, and (iii) strict regulations and laws imposed by the Vienna City Administration.

The interview conducted with an operations team responsible for managing the inbound and outbound flows of e-scooters for an e-scooter rental company in Vienna showed that there was high potential for improvement when it came to the collection of e-scooters from the streets in the night. The planning and routing of vans responsible for collection was carried out manually, which led to sub-optimal solutions. Furthermore, the planning was always static and did not consider the uncertainty or availability of data.

We formulated the e-scooter collection problem as a version of the vehicle routing problem and developed a solution method based on a large neighborhood search. Furthermore, we evaluated the impact of the uncertainty of service times on the quality of the solution. We developed different scenarios to simulate the service times by assuming that they followed a normal distribution. We showed that, if the uncertainty of service times was high, the impact on costs was high. This was mainly due to the very tight time windows available for the pickup of e-scooters. The increase in costs could reach 50% if the standard deviation was high.

We additionally proposed a dynamic policy that used real-time information on service times to update the solution and re-optimize the routing plan. We showed that, with the help of re-optimization, the costs of delays could be decreased by 50–60% compared to under static planning. To assure that delays are minimized, the vehicles would have to travel around 3–5% further; however, the savings in costs for delays could still reach EUR 665, depending on the uncertainty of the service times.

A limitation of this study was that no comparison to the company's current collection policy could be carried out in order to verify the validity of the results. Furthermore, the company could not provide historical data regarding service times, which might have helped to identify patterns in service time distribution.

Some ideas for future work might include measuring the impact of e-scooter collection processes on the environment, e.g., by considering costs for the CO_2 emitted by vans. Furthermore, a cost analysis of using electric vans for collection instead of diesel vans could be considered. An additional idea is to extend the optimization model by also solving the problem of the distribution of e-scooters early in the morning.

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