Dynamic location for charging operations of shared free-floating e-scooters

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Short summary

Shared electric scooters (e-scooters) have recently become a popular mode of micromobility solution and this rapid growth causes significant operational challenges. One of the challenges micromobility companies face is collecting idle low-charge fleets from different corners of the city. The collector is usually a truck that needs to make a tour in town to collect these e-scooters. One solution can be for the operator to dynamically define special zones where e-scooters with low-charge are collected. In this paper, we propose a two-layered approach to tackle the problem. We propose a dynamic programming approach to investigate the required number and locations of designated low-charge drop-off points for the first layer of the problem. A simulated origin-destination data set of 30 e-scooters on TU Delft campus area is used for a time horizon of 8 working days and a time discretization level of 15 minutes. The results suggested consolidating low-charge e-scooters in three low-charge drop-off locations considering the state of charge (SOC) and distance of e-scooters from the low-charge drop-off zones. Then, we discuss the potential implications of our findings on recharging operations and spatial efficiency that are defined dynamically.

Keywords: Shared electric micro-mobility, dynamic programming, data-driven zoning, real-time operational decision, fleet rebalancing.

1 Introduction

A free-floating shared mobility system gives the user the flexibility to pick up and drop off the vehicle anywhere in the operating area. Operational issues are brought on by this flexibility, particularly in vehicle charging operations. A dynamic route design for the charging truck or overnight charging can be used to empower shared micromobility systems, but both of these methods are either very expensive for the system's performance or cause computational complexity Osorio et al. (2021).

In free-floating shared micromobility, the majority of the studies focus on dynamic routing problems and consider locations of gathering points as given for collecting vehicles or rebalancing Luo et al. (2022). In Mahmoodian et al. (2022) a dynamic hubbing strategy was addressed to satisfy the first demand of the following day and improve the efficiency of the shared bike rebalancing scheme. However, their main focus is on the rebalancing plan for simulated hubs. A unified overnight charging and vehicle rebalancing approach is suggested by Osorio et al. (2021) to carry out these tasks for a shared e-scooter system more effectively. They provide a charging-and-routing plan that concurrently determines an effective pickup and drop-off strategy while taking into account the SOC of all onboard e-scooters. Although they recommend breaking up a large zone into smaller zones in order to lessen the computational complexity for future studies, it has neither been implemented nor dynamic data-driven zoning discussed.

One potential approach to defining and addressing such problems is through the utilization of time-space network modeling techniques, as demonstrated in the context of logistic networks by Akyüz et al. (2023). However, it should be noted that this approach can be computationally intensive and time-consuming. As an alternative, dynamic programming modeling may offer significant advantages in terms of optimization performance, as demonstrated in the work of Al-Kanj et al. (2020). Unlike the current literature, we consider a dynamic and data-driven approach to decide on consolidating the low-charge e-scooters and in the second layer of the network charging them with a moving charger on spot. Specifically, in our proposed method as soon as the first zone is selected for the first low-charge e-scooter to drop off, this zone becomes the point of interest for all future e-scooters whose charge drops in this zone and its neighboring zones. While considering the service level indicator for the rider which is the distance deviation that the selected low-charge drop-off zone causes from the rider's destination.

2 Methodology

To investigate the designated low-charge drop-off areas, a dynamic programming model based on the destination and SOC of the low-charge e-scooter is designed. We considered real-world practices for e-scooters that become unavailable after their battery level dips below 18% (Felyx.com). Therefore, we set a robust battery level threshold of 25% to define the low-charge e-scooter. The decision epochs or time steps are modeled in discrete time $t = \{0, 1, 2, ..., 32\}$ with 15 minutes duration over 8 working hours. If the decision epoch is at time t, then all information arriving between $t-1$ and t is collected and assigned at time t. $t = 0$ indicates the beginning of the operation. An e-scooter is shown with i index where $i \in \{1, ..., \mathrm{N}\}$ and N refers to the total number of low-charge e-scooters. To improve the computational complexity of the model, the operating area is discretized into several same-size hexagons. Each hexagon is considered as a potential low-charge drop-off location. The zones are shown j where $j \in \{1, ..., \mathrm{Z}\}$ and Z represents the total number of hexagons.

Using the language of dynamic resource management, e-scooters, and potential low-charge drop-off locations are resources (R). The physical system state vector is then given by $S_t^R = (R_{ti}, R_{tj})$, in which R_{ti} and R_{tj} indicate the states of e-scooters and potential low-charge drop-off areas at time t, respectively. The state vector of e-scooters over time is defined below.

$$R_{ti} = \begin{pmatrix} i_1 \\ i_2 \end{pmatrix} = \begin{pmatrix} \text{current location of e-scooter} \\ \\ \text{SOC} \end{pmatrix}$$

Where the current location of the e-scooter equals to user's destination and corresponds to the latitude and longitude coordinates of where the low-charge e-scooter is located at time t and searching for a low-charge drop-off location. Also, the state vector of potential low-charge drop-off locations changes over time in terms of the number of low-charge e-scooters parked at the low-charge drop-off location and is defined as following

$$R_{tj} = \begin{pmatrix} j_1 \\ j_2 \end{pmatrix} = \begin{pmatrix} \text{zone index} \\ \\ \text{sum of low-charge e-scooters} \\ \text{parked in the zone till time } t \end{pmatrix}$$

The action of the dynamic model is a binary variable indicating whether the potential low-charge drop-off location with attribute R_{tj} should be offered to a low-charge e-scooter with attribute vector R_{ti} at time t.

$$x_{ij}^t = \begin{cases} 1 & \text{if e-scooter } i \text{ is sent to low-charge drop-off location } j \text{ at time } t \\ \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The decision variable x_{ij}^t must satisfy the following constraints:

$$\sum_{j}^{Z} x_{ij}^t = 1 \qquad \forall\ t,\ i \tag{2}$$

$$\sum_{i}^{N} \sum_{t}^{T} x_{ij'}^t \leq \sum_{i}^{N} \sum_{t}^{T} M(1 - x_{ij}^t) \qquad \forall\ (j, j') \in \text{adjacent zones} \tag{3}$$

$$x_{ij}^t = \{0, 1\} \qquad \forall\ t,\ i, j \tag{4}$$

Equation (2) indicates that each low-charge e-scooter should only be assigned to one zone at each time step. In equation 3, we define the neighboring zone context. In zoning the operating area, we obtained adjacent sets for each zone. If the grid distance between zones is less than one grid, those zones are instant neighbors (they have common boundaries) and are in the same adjacent set.

Equation 3 states that if zone j becomes a drop-off location, then all of the zones in its adjacent set cannot be an option (M refers to a big number). Equation (4) shows the variable domain. In addition, we consider the feasibility of trips from the final destination of e-scooters and selected low-charge drop-off locations based on the distance between these two locations at time t (d_{ij}^t). If this distance equals traveling more than three zones the trip becomes infeasible. Similarly, the insufficiency of the SOC to perform the trip makes the trip infeasible.

Transition function

The transition function represents how the system evolves over time. We model the transition function deterministically. E-scooters' current location or user's destination can be obtained through GPS information. However, in this study, we simulate the OD trips based. The SOC of e-scooters is calculated using the OD matrix by eq. (5), under the assumption that each e-scooter at most can perform one trip during each time step.

$$\mathrm{SOC}_i^t = \mathrm{SOC}_i^{t-1} - (\delta * \text{travelled distance of e-scooter } i \text{ between time } (t-1) \text{ and } t) \tag{5}$$

where δ indicates the rate of discharge per kilometer. The value of this parameter is calculated by considering the e-scooter battery Volt, the maximum distance, and the maximum speed it can perform. Regarding changes in zone states, the attribute of the drop-off zones will change as the number of low-charge e-scooters parked in the zone till time t (i.e. j_2) changes. $\sum_{t=1}^{t-1} q_t(j)$ captures the number of parked low-charge e-scooters at zone j up to time t. Equation (6) specifies that at the beginning of the planning horizon, there is no low-charge e-scooter parked in the system, and equation 7 calculates the number of parked low-charge e-scooters at time t in zone j based on the state of the system in the previous time step $(t-1)$, it shows the summation of all parked low-charge e-scooters till $t-1$ and the number of e-scooters that are sent to the low-charge drop-off location at time t. This parameter is a post-decision parameter and will be updated after the decision is made at time t. The model uses the value of the parameter for the previous time step to make a decision at time t.

$$q_j^t = 0 \qquad t = 0, \forall j \tag{6}$$

$$q_j^t = q_j^{t-1} + \sum_i^N x_{ij}^t \quad \forall\, t > 0, j \tag{7}$$

When the e-scooter is not low-charge, its SOC will be updated through equation 5 based on its trip between time $t-1$ and t. Therefore, We denote the transition function by

$$S_t = S^M(S_{t-1}, X_t) \tag{8}$$

where $S^M()$ governs the transition from pre-decision state S_{t-1} to pre-decision state S_t, and X_t is a decision vector containing x_{ij}^t decisions. $S^M()$ is a general statement for all of the transition functions we mention in this section.

Objective function

Each decision in the system produces a contribution c_{ij}^t to the system, especially to the routing costs of the charging truck. Collecting low-charge e-scooters in designated areas within the operating zone intends to save the system's routing costs for recharging operations. Hence, the objective function of the model aims at assigning low-charge e-scooter i to the nearest feasible low-charge drop-off zone j, if there is any. We aim at maximizing the reward that might obtain by the consolidation of low-charge e-scooters by equation 9.

$$c_{ij}^t = \begin{cases} \sum_{t=0} q_j^{t-1} - d_{ij}^t & \text{if } x_{ij}^t = 1 \\ \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Where the contribution is defined based on the number of parked low-charge e-scooters till time $t-1$ at location j (q_j^{t-1}) and the service level indicator which assures that the distance between the low-charge drop-off location j and the final destination of the e-scooter i trip should be small (d_{ij}^t). We assume linear contribution, as shown in equation 10.

$$C_t(S_t, x_t) = \sum_i^N \sum_j^M c_{ij}^t x_{ij}^t \tag{10}$$

Policy maps a state to an action/ decision. The optimal policy ($\pi \in \Pi$) maximizes the sum of contributions over all time periods as shown in equation 11.

$$F_t^*(S_t) = \max_{\pi \in \Pi} \left(\sum_{t=0}^T C(S_t, X_t^\pi(S_t)) | S_{t-1} \right) \tag{11}$$

where $X_t^\pi(S_t)$ is a function that determines x_{ij}^t given S_t when we are taking policy π, and Π is a set of decision functions or policies. To find the best policy, we intend to maximize the reward function subject to the above-mentioned constraints.

3 Results and discussion

We used simulated data of 30 e-scooters operating on the campus of TU Delft in one working day (8 hours), which was divided into 32 time slots as we considered every 15 minutes as a time step, to solve a toy problem as a proof of concept for our model. The rate of discharge is set at 8% per km. At the start of the planning period, it is expected that e-scooters are fully charged. Each of the 37 regular hexagons, each with a side length of 60 m, that make up the operating area can serve as a low-charge drop-off location.

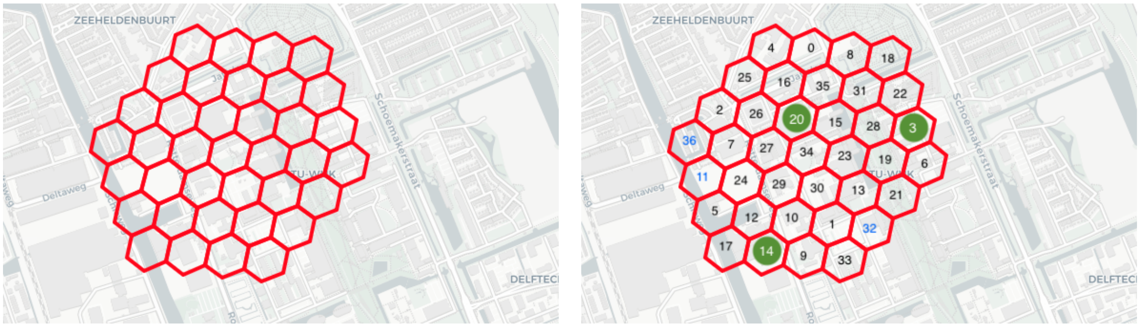
The outcomes of using the model on this set of data are shown in Table 1, where 12 low-charge e-scooters emerged in 12 separate zones. The first column indicates the time steps in which low-charge e-scooters show up. The second column contains e-scooters' specific ids. The third column shows the final destination of e-scooters trips. The term 'outside' in this column specified that the destination of the e-scooter trip is outside of the operating zone. Therefore, it should be left within the operating area. Column 5 indicates the final selected consolidated low-charge drop-off zones. Also, the SOC of low-charge e-scooter before and after their assignment to the drop-off zone are shown in columns 4 and 6, respectively.

The optimality gap of the obtained results is 0%, which tells at each time step, the model finds the optimal solution. At the end of the planning horizon, selected zones are zone numbers 14, 20, and 3 with 4, 5, and 3 low-charge e-scooter parked in these zones, respectively. The mean occurred deviation from the destination is 114 m, and 41 m and 194 m are the minimum and maximum values of the deviations from the riders' final destinations, respectively.

The model will determine the initial e-scooter(s) that showed up as low-charge, calculate the distance between the location of the e-scooter and its surrounding zones, and then provide the rider with a drop-off zone that is close to her destination while also following the neighboring zone constraint equation 3. For instance, in Table 1, the first low-charge e-scooters appeared at time step 19, in zones 9 and 27. If allowed to be left at the destinations, these zones have 4 neighboring zones in common (i.e., {10, 12, 29, 30}). Also, the required travel distances for e-scooters to reach the centers of the destination zones are 40 m, and 50 m for vehicles 3 and 25, respectively. Whereas, selected drop-off locations i.e. zones 14 and 20 have fewer common neighboring zones (i.e., {24, 29, 30}) and the distances between the locations of e-scooters and the centers of the selected zones are not much larger (70 m for both e-scooters). Therefore, zones 14 and 20 are selected as the first low-charge drop-off zones, and the number of parked low-charge e-scooters in these zones will increase, which means they become more relevant to be a drop-off zone for the e-scooters appear in the next time steps. Using the same logic, the model sends the e-scooter to zone 14 at time step 20.

At time 21, one low-charge e-scooter appears in zone 3, which is farther than the permitted distance (service level assurance) from the selected drop-off zones 14 and 27, and {31, 15, 28, 23, 19} zones are in a neighboring distance of the selected drop-off locations so they can not be a potential drop-off location, then it is allowed to be left at its destination (as its distance from potential zone 6, 19, 21, 13, and 18 are greater than the distance to the centroid of zone 3). For the rest of the time steps, the low-charge e-scooters are consolidated in these three drop-off locations following the same reasoning. It is worth noting that, we also assure that e-scooters are able to perform the trip to low-charge drop-off zone with sufficient SOC. Figure 1a shows the zoning structure of the operating area. In Figure 1b the selected low-charge drop-off zones are shown in green circles, and the zones which are in adjacent sets of the selected drop-off zones are shown in black color. Zones in blue color are neither a low-charge e-scooter destination nor under the coverage area of the selected zones.

Regarding recharging operations, in the upper level of the recharging operation problem, a routing problem arises, where the charging truck's traveling distance needs to be minimized. The routing problem involves determining the optimal path that the charging truck should take to recharge the e-scooters, taking into account the locations of the consolidated low-charge e-scooters and the charging truck's constraints. The objective of this routing problem is to minimize the total traveling distance of the charging truck while satisfying the demand for e-scooter charging. By applying this method, we are shrinking the size of the network for the charging truck by decreasing the visiting nodes. In the proposed example, the charging truck has 3 nodes to visit to recharge the low-charge e-scooters instead of visiting them scattered in 12 nodes. Then, the upper level of the problem, which is the routing problem of the recharging truck and will be studied in a further step of this research.



(a) Discritizing the operating zone (TUD)   (b) Optimal low-charge drop-off locations

Figure 1: An overview of zoning and optimal low-charge drop-off location

4 Conclusions

This study addressed one of the operational challenges faced by shared electric scooters (e-scooter). In this study, we propose a data-driven approach to dynamically define designated drop-off areas for low-charge e-scooters by capturing the spatial and temporal characteristics of the e-scooters and potential drop-off zones. A simulated data set of 30 e-scooters in TU Delft campus area is used. The results suggest that the low-charge e-scooters can be consolidated in three drop-off locations among 37 potential zones over 8 working hours. By adopting this approach, the average deviation in distance of e-scooters from their intended endpoint is found to be 114 meters, a distance that is generally considered to be within the range of what is typically considered suitable for walking distance.

One of the significant advantages of our approach is the optimization of spatial usage by e-scooters, which is particularly crucial for low-charge e-scooters. Furthermore, our model ensures that the travel of the e-scooter to the suggested drop-off zone is feasible in terms of the deviation from the destination and its state of charge after performing the trip. Moreover, defining consolidated low-charge drop-off zones out of a discrete space of operating area can have a considerable impact on minimizing the traveling distance of the charging truck and decreasing the computational complexity of solving the model in continuous space. Overall, the approach of limiting visiting nodes to recharge low-charge e-scooters through consolidating can lead to a reduction in operational costs and improved system performance in shared micromobility systems. The subsequent routing problem of the charging truck can further optimize the recharging operations and enhance the overall efficiency of the system.

Table 1: Overview of the studied sample and selected drop-off zones

Time step	**e-scooter id**	**low-charge e-scooter location**	**The SOC before trip to drop-off zone (%)**	**Selected drop-off zone**	**The SOC after trip to drop-off zone (%)**
19	3	9	24.4	14	23.2
	25	27	24.0	20	22.9
20	16	12	24.5	14	22.8
21	6	3	24.4	3	23.9
22	23	outside	24.4	14	21.4
23	0	9	24.4	14	21.3
24	10	outside	24.6	3	22.3
	19	20	24.8	20	24.4
	22	7	24.3	20	21.3
25	20	23	24.8	20	22.9
27	29	0	24.8	20	22.9
30	17	19	24.4	3	23.4

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