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Integrated operator and user-based rebalancing in dockless shared e-micromobility systems

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Abstract

Shared electric mobility systems as a disruptive means of transport faces with different operational challenges, particularly in the case of dockless e-micromobility setting where users can pick up and drop off e-bikes/e-scooters anywhere they want. This flexibility leads to a potential imbalance between supply and demand, which is known as bike rebalancing problem (BRP). To address this issue, strategies are being implemented by operators and users. In this study, an integrated operator and user-based rebalancing strategy is proposed for dockless e-bike/e-scooter sharing systems to optimize the system's costs and benefits. An on-demand e-micromobility sharing system is simulated using the network of Manhattan to evaluate the proposed method. The proposed rebalancing method has resulted in a 76% and 19% increase in the number of successful trips compared to system without rebalancing and system with dynamic recharging, respectively. It also leads to improvement in walking distance of users.

1. Introduction

In recent years, bike/scooter-sharing systems have been expanded in cities around the world to serve first and last-mile needs in multimodal transport networks (Zhang et al., 2022). Station-based bike-sharing systems require users to rent bikes from stations where bikes are stored and returned. Dockless free-floating bike-sharing systems, on the other hand, enable users to rent and return bikes at any locations within the operating area.

However these systems may suffer from the bike imbalance problem, where bikes become unevenly distributed, leading to an imbalance between supply and demand. This problem needs to be addressed to enhance service quality and satisfy demand effectively (Ghosh et al., 2017).

Bike rebalancing problem (BRP) has been classified into two categories: static BRP (SBRP), which considers the system's status in the last time interval, and dynamic BRP (DBRP), which considers the variation of demand over time (Ghosh et al., 2017). The strategies used in rebalancing can be classified as operator-based or user-based. In operator-based rebalancing, operators and a fleet of rebalancing trucks reposition bikes between regions (Li et al., 2021), while user-based rebalancing incentivizes users to perform rebalancing tasks (Li and Liu, 2021), (Zhang et al., 2019). An integration of operator-based and user-based rebalancing is less studied with potential of inclusion of benefits of the two strategies and moderating their shortcomings.

Electric bike and scooter sharing systems have become more popular due to their convenience and speed compared to regular bikes (Kazemzadeh and Ronchi, 2022). However, the e-bike/e-scooter rebalancing problem has been less considered in previous studies. This paper designs an integrated rebalancing strategy for dockless e-mobility systems. This type of rebalancing is more complex due to the need to simultaneously consider battery charging and repositioning tasks, as well as checking the level of charge before incentivizing user-based rebalancing.

This study proposes an integrated operator-based and user-based rebalancing method for dockless e-bike/e-scooter sharing systems using a mixed-integer-nonlinear-rebalancing program (MBNRP). The proposed model determines which e-bikes/e-scooters should be repositioned by a fleet of repositioning trucks or users to minimize the total cost and maximize the total profit of operator. The proposed method aims to reduce the number of unfulfilled requests for e-bikes/e-scooters by predicting demand in each node using historical data for future time periods. The study assumes battery swapping as the method used for charging e-bikes/e-scooters, and the level of charge of each individual bike is considered in the model.

The proposed model is implemented in a simulation environment, and the performance of the method is compared with some benchmark rebalancing methods. Users' decision-making is modeled with a utility choice model, and the branch and bound method is used to solve the MBNRP efficiently.

The remainder of the article is structured as follows. Section 2 presents the problem. In Section 3, the proposed optimization model is developed. Section 4 introduces simulation, some benchmarks for evaluating the proposed model and the results.

2. Problem description

This study introduces an electric bike/scooter-sharing rebalancing strategy for dockless systems using integrated operator-based and user-based strategies.

The operating day is divided into some time intervals. Rebalancing tasks are performed at the end of each time interval to prepare the system for the demand in the next time step. Location of available bikes are known since e-bikes and e-scooters are equipped with GPS. Demand in each node for each time interval is predicted based on historical data. The proposed algorithm relocates idle bikes from their location to other nodes to rebalance the supply to reduce unmet demands in the next time step, increasing the profit and minimize operating costs of truck-based rebalancing and user-based rebalancing.

The proposed method determines a plan for truck-based and user-based rebalancing for the next time step based on data at the end of current time step. The plan includes e-bikes/e-scooters which should be recharged and relocated by each truck to intended destinations, e-bikes/e-scooters that must be incentivized for user-based rebalancing, bikes which should be visited by trucks to be recharged and trucks' routing plan. The proposed on-demand e-micromobility model considers the interaction between three parts: bikes, the platform and passengers.

2.1. E-Bikes

E-bikes and e-scooters form the supply side of the system. The characteristics of Bike i at time τ are as follows:

$$< \mathrm{Id}_i{}^{\mathrm{b}}, x_i{}^{\mathrm{b},\tau}, y_i{}^{\mathrm{b},\tau}, l_i{}^{\mathrm{b},\tau}, s_i{}^{\mathrm{b},\tau} >$$

where $\mathrm{Id}_{\mathrm{i}}{}^{\mathrm{b}}$ denotes the ID of bike i, $x_i{}^{\mathrm{b},\tau}$ and $y_i{}^{\mathrm{b},\tau}$ are bi-dimensional location of bike at time τ. $l_i{}^{\mathrm{b},\tau}$ is level of charge and $s_i{}^{\mathrm{b},\tau}$ denotes the status of bike i at time τ (1 if bike unrented, 0 if rented, and 2 when relocating by trucks).

2.2. The platform

The platform has the information of bikes and passengers requesting at each time τ. The information of all components of the system becomes updated whenever a passenger sends a request to the platform and selects and reserves a bike or drops off a bike. Once a request is made by Passenger k at time τ, the platform calculates the distance of the passenger from all available bikes. Among available bikes ($s_i{}^{\mathrm{b},\tau} = 1$), bikes whose distance to Passenger k (Δ_{ik})

is less than a predefined acceptable walking distance (ω) are introduced to the passenger. Among introduced options Passenger k considers bikes/scooters that their level of charge (${l_i}^{\mathrm{b},\tau}$) is more than required level for completing his/her intended journey ($l_k^{\mathrm{p},\tau}$) as possible options. Following this, among possible options, passengers choose a bike based on utility model, which is defined in Subsection 2.3.
Pricing mechanism of the e-micromobility system is based on e-bike/scooter rental period in minutes. User should pay an initial fee to unlock the bikes (f_0) and pay f_1 dollars per minutes. Let C_{ki}^{r} and δt_{ki} be the rental cost and rental time of e-bike i for Passenger k.

$$C_{ki}^{r} = f_0 + f_1 . \delta t_{ki} \tag{3}$$

The pricing structure for user-based rebalancing of e-bikes entails passengers paying an initial fee (f_0) and being exempt from incurring variable costs based on rental time f_1 , so the amount of reward related to user-based rebalancing for Passenger k selecting e-bike i is equal to $f_1 . \delta t_{ki}$.

2.3. Passengers

Let P^{τ} denotes set of passengers requesting to the system at time τ. The characteristics of Passenger k requesting at time τ are:

$$< {x_k}^{\mathrm{p},\tau}, {y_k}^{\mathrm{p},\tau}, {xd_k}^{\mathrm{p},\tau}, {yd_k}^{\mathrm{p},\tau}, {l_k}^{\mathrm{p},\tau} >$$

${x_k}^{\mathrm{p},\tau}, {y_k}^{\mathrm{p},\tau}, {xd_k}^{\mathrm{p},\tau}, {yd_k}^{\mathrm{p},\tau}$ indicate current location/destination of Passenger k. ${l_k}^{\mathrm{p},\tau}$ is required level of charge for Passenger k to complete his/her journey.

The platform provides passengers with a set of e-bikes/e-scooters (n_{o_k} possible options for Passenger k) to choose from. If a passenger does not choose a bike, they will travel using other transportation modes. The choice behavior of users is modeled as a utility maximization process. The utility of potential options of Passenger k can be expressed as follows:

$$\text{Selecting bike } i\text{: } u_{ki} = \beta_k + \beta_k^{\mathrm{t}} . \Delta_{ki} + \beta_k^{\mathrm{c}} . C_k^{r} \tag{4}$$

$$\text{Selecting other modes: } u_k^{o} = \beta_k^{\mathrm{o}} \tag{5}$$

where β_k and β_k^{o} are utility constants. β_k^{t} and are β_k^{c} are utility coefficient per unit distance and cost for Passenger k. Δ_{ki} and C_k^{r} are observed variables related to the walking distance of Passenger k to reach Bike i and cost of the journey, respectively. Therefore, the probability that Passenger k selects Bike i is:

$$Pr_{ki} = e^{u_{ki}} \Big/ \left(\sum_{j=1}^{j=n_{o_k}} e^{u_{kj}} + e^{u_k^{o}} \right) \tag{6}$$

3. Problem formulation

The proposed model aims to minimize the cost of mixed truck-based and user-based rebalancing in an e-micromobility system, while maximizing the system's profit. The cost of truck-based rebalancing includes the travel cost of repositioning trucks, and cost of battery swapping per bike. The cost of user-based rebalancing is related to the amount of reward given to users who relocate bikes.

In the e-micromobility sharing system, the main objective of rebalancing is to satisfy the demand and minimize the imbalanced penalty (p_j) caused by the difference between predicted demand and actual inventory in Node j. Another benefit of rebalancing is the potential increase in rental fees (because of longer trips to be served) by using rebalancing trucks to exchange depleted batteries with fully charged ones.

The network includes set of nodes N = B ∪ O , where B represents set of nodes in which bikes are located and O represents center of regions that have more demand for e-bikes/e-scooters. The proposed method accounts four actions for each e-bike/e-scooter: truck-based rebalancing, truck-based recharging, user-based rebalancing, and do nothing. The Mixed Binary Rebalancing Problem (MBRP) determines the relocation strategy of each e-bike/e-scooter separately. The proposed mixed binary non-linear problem is first linearized, then it is considered as a mixed binary linear problem which is solved by the branch and bound method. We conducted the optimization on Matlab 2020 using Intlingprog algorithm. Required notations are shown in Table 1.

Table 1: Notations

Notations	Descriptions
N	Set of nodes
B	Set of bikes' locations
O	Set of center of regions with high e-bikes/e-scooters demand
$\boldsymbol{Q}$	Set of trucks
$\boldsymbol{i, j}$	Indices for nodes
$\boldsymbol{q}$	Indices for trucks
$\boldsymbol{I_j}$	Initial bike inventory at Node j
$\boldsymbol{F_j}$	Final bike inventory at Node j
$\boldsymbol{\widetilde{D}_j}$	Predicted demand for the next time step at Node j
s	Unit battery swapping cost
$\boldsymbol{\alpha}$	Level of charge to rental fee conversion factor
c	Unit travel cost
$\boldsymbol{M}$	A positive value that is large enough
$\mathbf{l_{full}}$	Level of charge of a full charged battery
$\boldsymbol{l_i}$	Level of charge of the bike located in Node i
$\boldsymbol{d_{ij}}$	Distance of Node i to Node j
$\boldsymbol{r_{ij}}$	Reward of user-based rebalancing from Node i to j
$\boldsymbol{p_j}$	Unit imbalanced penalty related to shortage or surplus in Node j
$\boldsymbol{k^q}$	Capacity of rebalancing Truck q
$\boldsymbol{x_{ij}^q}$	Decision variable for truck-based rebalancing. 1 if the bike located in Node i is recharged and relocated to j by Truck q; 0 otherwise
$\boldsymbol{y_{ij}^q}$	Decision variable for routing of trucks. 1 if the Truck q passes from Node i to j; 0 otherwise
$\boldsymbol{z_{ij}}$	Decision variable for user-based relocation. 1 if the bike located in Node i is taken by a user from i to j
$\boldsymbol{G_j^q}$	An auxiliary continuous variable to eliminate subtours of Truck q
$\boldsymbol{Q_{ij}^q}$	Number of bikes carried by Truck q when travelling from Node i to j

The mixed binary rebalancing problem is as follows.

$$\min \sum_{q\in Q}\sum_{i\in N}\sum_{j\in N} \mathrm{s}\, x_{ij}^q - \sum_{q\in Q}\sum_{i\in N}\sum_{j\in N} \alpha\,(\mathrm{l}_{\mathrm{full}} - l_i)\, x_{ij}^q + \sum_{q\in Q}\sum_{i\in N}\sum_{j\in N} \mathrm{c}\, d_{ij}\; y_{ij}^q + \sum_{i\in N}\sum_{j\in N} r_{ij}\; z_{ij} + \sum_{j\in N} p_j |\widetilde{D}_j - F_j| \tag{7}$$

s.t

$$\sum_{j\in N} y_{ij}^q \le 1 \qquad \forall i \in N, q \in Q \tag{8}$$

$$\sum_{j\in N} y_{ij}^q = \sum_{j\in N} y_{ji}^q \qquad \forall i \ne j, q \in Q \tag{9}$$

$$\sum_{q\in Q}\sum_{j\in N} x_{ij}^q + \sum_{j\in N} z_{ij} \le 1 \qquad \forall i \in N \tag{10}$$

$$\sum_{i\in N} x_{ij}^q \le k^q . \sum_{i\in N} y_{ij}^q \qquad \forall q \in Q, j \in N \tag{11}$$

$$\sum_{j\in N} x_{ij}^q \le \sum_{j\in N} y_{ij}^q \qquad \forall q \in Q, i \in N \tag{12}$$

$$G_j^q \ge G_i^q + 1 - \mathrm{M}(1 - y_{ij}^q) \tag{13}$$

$$\sum_{i\in N} x_{im}^q = \sum_{j\in N} Q_{jm}^q - \sum_{j\in N} Q_{mj}^q \qquad \forall q \in Q, m \in N \tag{14}$$

$$\sum_{i\in N} x_{ij}^q \le \sum_{i\in N} Q_{ij}^q \qquad \forall j \in N \tag{15}$$

$$Q_{ij}^q \le k^q . y_{ij}^q \tag{16}$$

$$\sum_{q\in Q}\sum_{i\in N} x_{ij}^q + \sum_{i\in N} z_{ij} \le \max\big(0, \widetilde{D}_j - I_j\big) \qquad \forall j \in N \tag{17}$$

$$\sum_{q\in Q}\sum_{j\in N} x_{ij}^q + \sum_{j\in N} z_{ij} \le I_i \qquad \forall i \in N \tag{18}$$

$$F_j = I_j + \sum_{q\in Q}\sum_{i\in N} x_{ij}^q + \sum_{i\in N} z_{ij} - \sum_{q\in Q}\sum_{i\in N} x_{ji}^q - \sum_{i\in N} z_{ji} \qquad \forall j \in N \tag{19}$$

$$x_{ij}^q\, , y_{ij}^q\, , z_{ij} \in \{0,1\} \tag{20}$$

$$Q_{ij}^q\, , G_j^q \;\in\; I \tag{21}$$

The objective function (7) minimizes total cost of rebalancing and maximizes system's profit. Constraint (8) ensures that each truck should visit each station at most one time, and flow conservation of trucks is guaranteed in constraint (9). Constraint (10) guarantees that just one rebalancing method should be used for each bike. Constraint (11) restricts the number of bikes carried by the truck to each node to trucks' capacity. Constraints (12) ensures that truck should visit the bike that should be carried to other nodes. Constraint (13) is utilized to eliminate subtours. Constraint (14) and (15) are used to ensure inventory conservation of bikes carried by trucks. Constraints (16) implies that the number of bikes carried between nodes by each truck should be limited to the truck capacity. Constraints (17) ensures that the final bike inventory should not exceed predicted/estimated demand at each node in the next time step. Constraint (18) restricts the number of e-bikes/e-scooters taken from each node to the initial bike inventory in that node.Constraint (19) defines final number of bikes in each node. Constraints (20) and (21) are domain constraints.

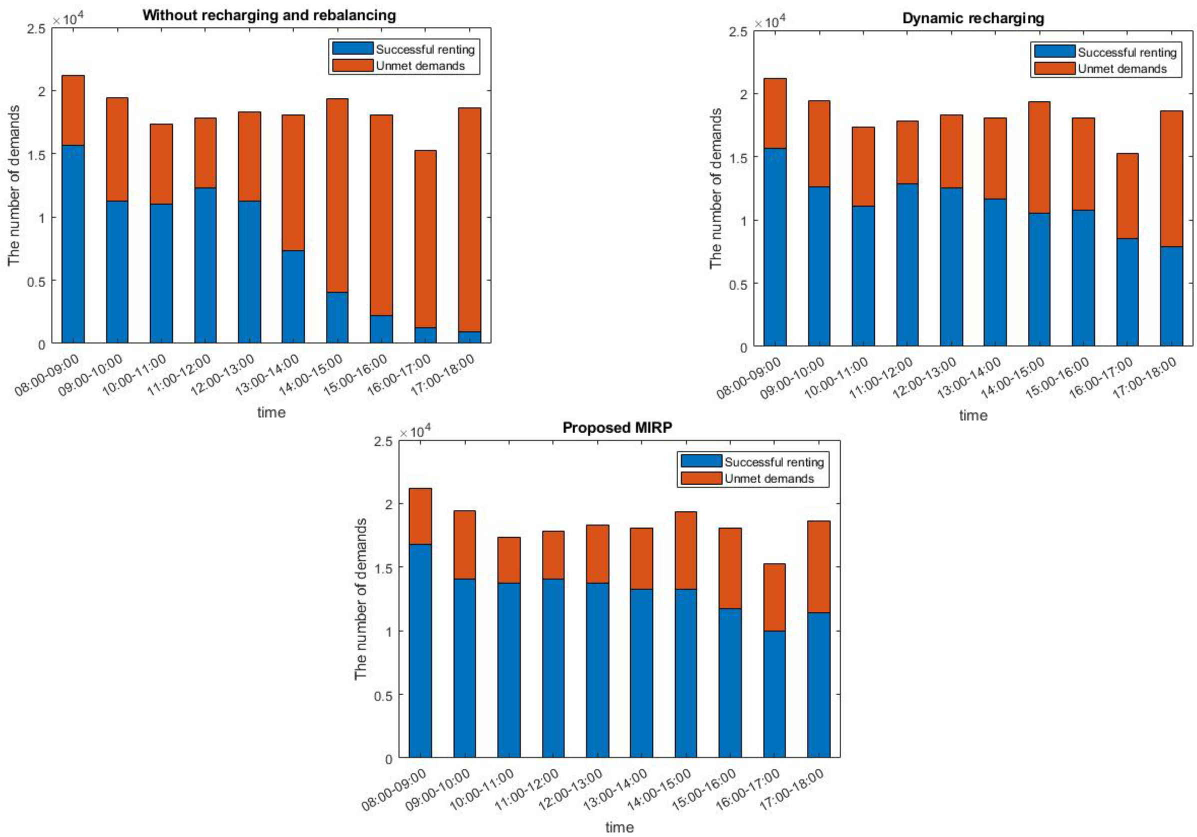
4. Simulation and results

To evaluate the proposed method, a simulation of an on-demand e-micromobility shared system is conducted in MATLAB, using Manhattan as the network. Taxi demand of Manhattan in a weekday is used as demand to compare how an e-micromobility system could perform against the taxi system. Note that the demand is time-varying throughout the day. We compare the effectiveness of the proposed MBRP model with two other approaches, including (i) system without rebalancing: bikes are utilized by users without any charging or repositioning activity during an operating day, and (ii) system with dynamic recharging: used bikes with less than 20 percent level of charge are recharged by recharging trucks in some time intervals during an operating day. At the beginning of each time interval, the platform advises recharging trucks to visit and recharge bikes with less than 20 percent level of charge based on bikes current situation. The optimum route of recharging vehicles is determined based on vehicle routing problem (VRP) model.

Number of successful renting/unmet demands is considered as a performance metric for evaluating the developed method. As it is demonstrated by simulation results in Figure 1, the proposed integrated rebalancing method could improve the operation of the system. The number of successful trips has increased by 76% and 19% in the proposed rebalancing method compared to system without recharging/rebalancing and system with dynamic recharging. In the proposed method, walking distance per person, which is an important performance metric for shared e-micromobility systems, is about 0.6 km less than that of two other benchmarks.

This study sheds light on an integrated operator-based and user-based rebalancing strategy in the e-bike sharing systems, future research could explore the implementation of a dynamic incentive system for user-based rebalancing. Such a system could enhance the likelihood of users accepting user-based rebalancing while also increasing the overall profitability of the system.

Figure 1: Comparison of successful/ unmet demands among three scenarios



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