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Full Length Article

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

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A R T I C L E I N F O

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A B S T R A C T

This study proposes a rebalancing method for a dockless e-micromobility sharing system, employing both trucks and users. Platform-owned trucks relocate and recharge e-micromobility vehicles using battery swapping technology. In addition, some users intending to rent an e-micromobility vehicle are offered incentives to end their trips in defined locations to assist with rebalancing. The integrated formulation of rebalancing and recharging accounts for each e-micromobility vehicle's characteristics, such as location and charge level. The problem is formulated as a mixed binary problem, which minimizes operational costs and total unmet demand while maximizing the system's profit. To solve the optimization problem, a Branch and Bound method is employed. Rebalancing decisions and routing plans of each truck are obtained by solving the optimization problem. We simulate an on-demand shared e-micromobility system with the proposed integrated rebalancing method and conduct numerical studies. The results indicate that the proposed method enhances system performance and user travel times.

1. Introduction

The shared e-micromoibility, as a disruptive transportation mode in cities, is known to be low-carbon, environment-friendly, and sustainable. In recent years, e-bike sharing systems (BSS) and e-scooter sharing systems have been expanded in many cities to serve first and last-mile needs in multimodal transportation networks, e.g., see Chen et al. (2018) and Dell'Amico et al. (2014). In the literature, these systems have been demonstrated to offer significant societal benefits (Zhang and Liu, 2021). Therefore, exploring various operating strategies to manage these systems efficiently could be highly advantageous.

There are two types of e-micromobility sharing systems based on their operation: station-based systems and dockless systems. In station-based e-micromobility sharing systems, users must rent e-micromobility vehicles from stations where these e-vehicles are stored and returned (Raviv and Kolka, 2013). Dockless free-floating e-micromobility sharing systems, on the other hand, enable users to rent and return e-vehicles at any location within the operating area. In terms of operations, e-micromobility systems including e-bikes and e-scooters, exhibit comparable attributes. Therefore, within this context, we employ the term 'e-bikes' as a representative for both e-bikes and e-scooters for the sake of brevity.

In dockless systems, users can locate available e-bikes through online maps and select and reserve them. However, these systems may suffer from the e-bike imbalance problem, where e-bikes become unevenly distributed due to asymmetric travel patterns within the day (Li et al., 2016). This leads to an imbalance between supply and demand (Ghosh et al., 2017). This problem is known as the bike rebalancing problem (BRP), which needs to be addressed to enhance service reliability (Du et al., 2020). The BRP entails transferring bicycles from locations with an abundance of bikes to areas experiencing a deficiency, with the goal of decreasing the number of unmet customer demands (Stokkink and Geroliminis, 2021).

In the literature, BRP has been categorized into static BRP (SBRP) and dynamic BRP (DBRP). The SBRP considers the last status of the system (available bikes in the operating area) while assuming variation in demand in different parts of the operating area is negligible during the rebalancing period (Liu et al., 2018; Papazek et al., 2014). In contrast, DBRP considers demand variation over time (Ghosh et al., 2017; Wang and Szeto, 2021). From the perspective of strategies used in rebalancing, BRP can be classified into operator-based BRP and user-based BRP. Operator-based rebalancing involves the use of a fleet of rebalancing trucks by operators to relocate bikes across different regions (Dell'Amico et al., 2018; Li et al., 2021). On the other hand, user-based rebalancing relies on user incentivization, where users voluntarily participate in

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rebalancing tasks in return for a reward, which could be considered as a discount on the rental fee or a paid incentive fee (Cheng et al., 2021; Li and Liu, 2021; Zhang et al., 2019). An integrated approach combining operator-based and user-based rebalancing strategies has been introduced for non-electric bikes in Xu et al. (2022) to address the issue of inadequate deployment of rebalancing trucks by operators.

The rebalancing problem becomes particularly crucial in the context of electric bikes (e-bikes) and electric scooters (e-scooters), which have gained popularity in large cities due to their enhanced convenience and higher speeds compared to traditional bicycles (Kazemzadeh and Ronchi, 2022). This challenge arises from the need to ensure that these e-vehicles remain operational throughout the day by addressing their charging requirements, thereby preventing instances of e-bikes and e-scooters being rendered idle due to low battery levels (Xu et al., 2022).

Accordingly, the e-bike/e-scooter rebalancing problem considering the level of charge of e-bikes/e-scooters has a notable effect on the supply usage and profitability of the system. Chu et al. (2022) proposed an operator-based mixed-integer programming model for dockless e-scooters considering a battery swapping threshold for e-scooters. An overnight operator-based rebalancing and on-board charging is proposed in Osorio et al. (2021), in which the state of charge of e-bikes and the required duration of on-board charging for e-bikes while being transported on rebalancing vehicles is taken into account in the formulation. Fast en-route charging opportunities for various electric vehicles significantly help to address the travel range limitations of these vehicles (Hu et al., 2022). In the context of battery recharging and rebalancing operations, Zhou et al. (2023) introduced a strategy for rebalancing planning and battery swapping. This approach uses charging cabinets and involves deploying two separate teams of staff. The deployment is guided by predictions of e-bike inventory levels and battery status. Three distinct states of battery charge levels are considered in the planning process.

The above studies shed light on the significance of factoring in the level of charge when addressing the e-bike/e-scooter rebalancing problem. However, prior research has not delved into addressing an integrated operator-based and user-based rebalancing approach for e-scooters/e-bikes while considering their level of charge. Such a rebalancing problem for e-micromobility sharing systems is more challenging to address because of the need to manage e-bikes that require charging and repositioning simultaneously. Additionally, it is essential to determine the optimal charge level for e-bikes allocated to user-based rebalancing, while also considering the cost and benefits of battery charging, all in an integrated and effective manner.

This study develops a method for integrated operator-based and user-based rebalancing for dockless e-bike/e-scooter sharing systems. We propose a mixed-binary-nonlinear rebalancing program (MBNRP). The proposed model determines e-bikes/e-scooters that should be repositioned by a fleet of repositioning trucks or users to minimize the total cost and maximize the total profit of the system. The proposed system is a dockless, reservation-based e-bike sharing platform where users reserve an available e-bike, walk to its location, and park it anywhere after use.

We assume battery swapping as the method used for charging e-bikes/e-scooters. In such a system, operators of the trucks change the battery of e-bikes/e-scooters with a full one. Trucks equipped with on-board charging technology transport depleted batteries, enabling them to recharge while in transit. The objective function considers the charge level of each individual e-bike, along with the costs and benefits associated with the rebalancing and recharging of these e-bikes. Users are encouraged to participate in rebalancing activities by receiving incentives in exchange for concluding their trips with rented e-bikes and dropping them off at specified locations designated by the platform. The incentive considered in this study exempts the trip variable fare for those who participate (while the initial unlock fee of e-bikes applies).

The proposed model is tested in a simulation environment, and the performance of the proposed method is compared with a number of rebalancing benchmark methods. Users' decision making has been modeled with a utility choice model, and the branch and bound method is used to solve the MBNRP efficiently. Furthermore, the dockless e-bike sharing system, incorporating the proposed operational rebalancing and recharging strategies, is compared to a simulated e-hailing system. This comparison aims to evaluate the performance of sustainable and environmentally friendly shared e-bikes, when managed optimally, against e-hailing systems.

The contributions of this paper are as follows. First, this study presents an optimization formulation for rebalancing and recharging in e-bike systems, integrating both operator-based and user-based rebalancing dynamically throughout the day. Second, the proposed method incorporates the specific characteristics of each e-bike, including the precise battery charge levels, into an integrated rebalancing approach. While existing research typically partition the e-bike fleet into a number of groups, considering each e-bike's charge level allows for more efficient decisions regarding which e-bikes should be charged or allocated for user-based rebalancing. This approach adds a layer of complexity to the objective function by requiring that routing decisions for both e-bikes and trucks be jointly optimized. Third, our paper introduces an incentivization system for e-bike sharing with predefined user destinations for incentivized e-bikes.

The remainder of the article is structured as follows. Section 2 presents the problem description. In Section 3, the proposed optimization model is developed. Section 4 introduces simulation and the benchmarks for evaluating the proposed model, and the results of comparison among the proposed method and benchmarks, including a e-hailing system, are shown in Section 5. In Section 6, we conclude the analysis and discuss future research directions.

2. Problem description

This study develops a rebalancing strategy for electric bike/scooter dockless shared systems using integrated operator-based and user-based strategies. The studied e-bike sharing system operates based on a reservation-based system. When a passenger requests the platform, they are presented with information of e-bikes within a predefined acceptable walking distance, along with their charge levels. If the passenger decides to use an e-bike, they must first reserve it through the application. After making the reservation, the passenger will walk to the e-bike's location, unlock it using the application, and then ride it to their destination. Given that the e-bike system is dockless, there are no designated docks or specific parking and charging locations. Passengers are free to pick up and drop off e-bikes anywhere within the operating area. Required notations are shown in Table 1.

The proposed integrated rebalancing method for e-bikes is operational throughout an operating day dynamically. The network is denoted as a directed graph $G = (\widehat{N}, \widehat{A})$. The set of nodes $\widehat{N}$ comprises intersections of the network. $\widehat{A}$ is the set of arcs representing the streets and roadways for vehicular traffic across the operating area. These nodes and arcs are used to pre-calculate the shortest paths in the network. The location of e-bikes is known as they are equipped with GPS devices. Throughout the remainder of this paper, we will refer to the locations of all idle e-bikes considered for rebalancing and locations where e-bikes should be rebalanced as set N.

The operating day is divided into a number of time intervals (Δt min). The rebalancing process is performed at the end of each time interval to prepare the system to meet the predicted demand at the next time interval. We assume the approximate location and number of incoming requests (demands) throughout the operating area for each time interval are predicted based on historical data of user rental patterns. The system has information on the locations of all idle e-bikes. Node j (with coordinates x_j and y_j) represents the anticipated location of demand D_j that can be multiple over Δt min. The platform identifies idle e-bikes within an acceptable walking distance ω of each node j. Consequently, there are three possible states for each anticipated demand location (node j): (1) If the current inventory of idle e-bikes within the distance ω of node j

Table 1
Nomenclature.

Problem description	
$\beta_k, \beta_k^{\mathrm{o}}$	Utility constants
$\beta_k^{\mathrm{t}}, \beta_k^{\mathrm{i}}, \beta_k^{\mathrm{c}}$	E-bike utility coefficient per unit walking time, travel time, and cost for passenger k
$\beta_k^{\mathrm{o,t}}, \beta_k^{\mathrm{o,i}}, \beta_k^{\mathrm{o,c}}$	Other modes utility coefficient per unit waiting time, travel time, and cost for passenger k
C_k^{r}	Rental cost for passenger k
C_k^{o}	Trip cost for passenger k
δt_{ki}	Rental time of Passenger k to complete his/her journey using e-bike i
δt_k	In-vehicle travel time of passenger k using other modes
Δ_{ki}	Walking distance of passenger k from e-bike i
Δt_{ki}	Walking time of passenger k from e-bike i
f_0	Initial unlock fee
f_1	Trip variable fare
$\mathrm{ID}_i^{\mathrm{b}}$	ID of e-bike i
$l_i^{\mathrm{b},\tau}$	Level of charge of e-bike i at time τ
$l_k^{\mathrm{p},\tau}$	Required level of charge for passenger k at time τ
o_{ki}^{τ}	Binary variable determining whether e-bike i is a possible option for passenger k or not
Pr_{ki}	Probability that passenger k selects e-bike i
$s_i^{\mathrm{b},\tau}$	Status of e-bike i at time τ
u_{ki}	Utility of passenger k if select e-bike i
u_{ki}	Utility of passenger k using e-bike i
u_k^{o}	Utility of passenger k if select traveling with other transport modes
ω	Acceptable walking distance
w	Waiting time in other modes
$x_i^{\mathrm{b},\tau}, y_i^{\mathrm{b},\tau}$	Bi-dimensional location vector of e-bike i at time τ
$x_k^{\mathrm{p},\tau}, y_k^{\mathrm{p},\tau}$	Bi-dimensional location vector of passenger k at time τ
$\overline{x}_k^{\mathrm{p},\tau}, \overline{y}_k^{\mathrm{p},\tau}$	Bi-dimensional location vector of destination of passenger k at time τ
Proposed mixed binary rebalancing problem (MBRP)	
Set	
A_i	Set of nodes that are accessible for e-bike located in node i with current level of charge l_i
N	Set of nodes
T	Set of rebalancing trucks
Index	
i, j	Indices for nodes
q	Indices for trucks
Parameter	
D_j	Predicted demand for the next time step at node j
F_j	Final e-bike inventory at node j
I_j	Initial e-bike inventory at node j at the end of current interval
k^q	Capacity of rebalancing truck q
l_i	Level of charge of e-bike located in node i
l_{full}	Level of charge of a fully-charged battery
M	A large positive value
p_j	Net imbalanced penalty related to shortage or surplus in node j
Q_{ij}^q	Number of e-bikes carried by truck q when traveling from node i to j
r_{ij}	Reward of user-based rebalancing from node i to j
s	Unit battery swapping cost
c	Unit travel cost of rebalancing trucks
α	Level of charge to rental fee conversion factor
θ	Recharging threshold
$\widehat{b}$	Limit fees paid for user-based rebalancing in each time interval
$\widehat{d}$	Limit distance traveled by trucks in each time interval
d_{ij}	Distance of node i to node j
Decision variable	
x_{ij}^q	Decision variable for truck-based rebalancing: 1 if e-bike located in Node i is recharged and relocated to j by Truck q; 0 otherwise
y_{ij}^q	Decision variable for routing of truck q: 1 if Truck q passes from Node i to j; 0 otherwise
z_{ij}	Decision variable for user-based relocation: 1 if e-bike located in Node i is taken by a user from i to j; 0 otherwise

matches the anticipated demand D_j, neither the node nor the idle e-bikes within ω radius will be considered for rebalancing. (2) If the anticipated demand D_j exceeds the available idle e-bikes within the acceptable walking radius, the idle e-bikes within distance ω of node j will not be considered for rebalancing activities; however, node j will be considered for rebalancing due to e-bike deficit. (3) If the number of available idle e-bikes within the distance ω of node j exceeds D_j, the surplus idle e-bikes will be considered for rebalancing. Also, if there is no anticipated demand within an acceptable walking distance from each idle e-bike, that idle e-bike will be considered for rebalancing. Additionally, idle e-bikes with battery levels below a certain threshold (θ) will be considered for recharging. These locations are treated as nodes that potentially need to be visited by trucks for rebalancing and recharging activities. Note that, the anticipated demand locations, idle e-bike locations, and corresponding node locations vary dynamically throughout the day and are defined at the start of each time interval.

We assume there are n repositioning trucks in the operating area. Once the rebalancing and recharging plan is determined by the platform, the necessary information—such as the routing plan for each truck, which e-bikes require charging, and which e-bikes should be picked up and dropped off at specific locations—is transmitted to the respective trucks. By the start of the next time interval, the trucks commence their assigned tasks. Each truck starts empty at the beginning of each time interval, since the total travel time for a truck is limited to the duration of the time interval to conduct all repositioning and recharging tasks. The repositioning trucks visit determined nodes by the method in which idle e-bikes are located, pick up certain e-bikes (depending on their charge level), and then take them to the specific rebalancing destination nodes. The routing plan of each truck is determined in the final solution.

The technology used for charging is battery swapping. Portable fully-charged batteries are replaced by truck operators when visiting the nodes in which idle e-bikes are located. Depleted batteries are transported by trucks equipped with on-vehicle charging technology, allowing them to be recharged during transit and subsequently used in the following time intervals. Given that the number of batteries exceeds the number of e-bikes, there will be a sufficient quantity of charged batteries available in the trucks during each time interval of the day. Consequently, this research does not necessitate modeling the charging locations or the number of batteries transported by the trucks.

In the context of user-based rebalancing, the model identifies which e-bikes should be relocated by users, specifies their targeted destinations, and then presents these designated e-bikes to passengers on the platform as incentivized options with pre-determined destinations. If a passenger selects one of these incentivized e-bikes and agrees to the designated destination, they reserve the e-bike. Next, they proceed to its location and ride it to the specified destination. Upon arrival, they drop off the e-bike.

The proposed method determines a plan for operator-based and user-based rebalancing for the next time interval based on data at the end of the current time step. The approach entails identifying idle e-bikes that require to be charged and relocated to their assigned destinations using trucks, idle e-bikes that must be incentivized for user-based rebalancing, e-bikes that should be visited by trucks to be charged (and not be relocated), and trucks routing plan.

The proposed on-demand e-micromobility system considers the interaction between four parts: the operating area, e-bikes, the platform, and the passengers. The detailed descriptions of each component are presented below.

2.1. Operating area

We use the network of the operating area, including all streets and intersections ($G = (\widehat{N}, \widehat{A})$). Users can travel with e-bikes throughout the city and park the rented e-bikes without any spatial restrictions.

2.2. E-bikes

E-bikes form the supply side of the system. We assume the number of e-bikes in the system is constant throughout the day. The characteristics of e-bike i at time τ are $< \mathrm{ID}_i^{\mathrm{b}}, x_i^{\mathrm{b},\tau}, y_i^{\mathrm{b},\tau}, l_i^{\mathrm{b},\tau}, s_i^{\mathrm{b},\tau} >$, where $\mathrm{ID}_i^{\mathrm{b}}$ denotes the ID of e-bike i. $x_i^{\mathrm{b},\tau}$ and $y_i^{\mathrm{b},\tau}$ are bi-dimensional location of e-bike i at time τ. $l_i^{\mathrm{b},\tau}$

is level of charge and $s_i^{b,\tau}$ denotes the status of e-bike i at time τ (1 if e-bike not rented, 0 if rented, and 2 when the e-bike is waiting to be picked up by a truck or is relocating by a truck).

2.3. Platform

The platform has the information of passengers requesting at each time τ including their current location vectors $(x_k^{p,\tau}, y_k^{p,\tau})$. The information of all components of the system becomes updated whenever a passenger sends a request to the platform and selects and reserves an e-bike or drops off the rented e-bike. Once a request is made by passenger k at time τ, the platform calculates the distance of the passenger from all available e-bikes $(s_i^{b,\tau} = 1)$. Among the available e-bikes, the e-bikes with distance to passenger $k(\Delta_{ki})$, less than a predefined acceptable walking distance threshold (ω) are introduced to the passenger. Among introduced options, passenger k considers e-bikes that their level of charge $(l_i^{b,\tau})$ is more than the required level for completing his/her intended journey $(l_k^{p,\tau})$ as qualified options. Therefore, the binary variable o_{ki}^{τ} determines whether e-bike i is a qualified option for passenger k or not.

$$o_{ki}^{\tau} = 1(\omega > \Delta_{ki})1(l_i^{b,\tau} > l_k^{p,\tau}) \tag{1}$$

where the function $1(x)$ defines the indicator function of event x, i.e., $1(x) = 1$ if x is true, and $1(x) = 0$ otherwise. Following this, among qualified options, passengers choose an e-bike based on a utility model defined in Section 2.4.

The pricing mechanism of the e-micromobility system is based on the rental period (after picking up the reserved e-bike). Users pay an initial fee to unlock the selected e-bikes (f_0) and pay f_1 per minute. The rental cost of each e-bike varies for users, depending on the locations where the e-bikes are stationed and the distance to the user destination. Accordingly, the rental cost for each e-bike is calculated as the below formula. Let C_{ki}^{τ} and δt_{ki} be the rental cost and rental time for passenger k traveling to his/her destination using e-bike i.

$$C_{ki}^{\tau} = f_0 + f_1 \delta t_{ki} \tag{2}$$

2.4. Passengers

Passengers are the demand side of the system. Passengers are impatient, which leads to a situation where, upon making a request to the system, if the system is unable to present suitable e-bikes to passengers or if passengers cannot find qualified options, they will leave the platform. Passengers choose an e-bike considering the walking distance from their current location to the e-bike's location, their value of time, the required level of charge for completing their journey, and the cost of renting the e-bike. The characteristics of passenger k requesting at time τ are $< x_k^{p,\tau}, y_k^{p,\tau}, \overline{x}_k^{p,\tau}, \overline{y}_k^{p,\tau}, l_k^{p,\tau} >$, where $x_k^{p,\tau}, y_k^{p,\tau}, \overline{x}_k^{p,\tau}$, and $\overline{y}_k^{p,\tau}$ indicate current location and destination of passenger k, respectively. τ is the time the passenger requests to the platform. Let $l_k^{p,\tau}$ be the required level of charge for passenger k to complete his/her journey.

At first, a passenger whose location is known requests to the platform. The platform provides the passenger with a set of e-bikes within accepted walking distance (ω). Among introduced e-bikes, the passenger considers e-bikes whose levels of charge are more than their required level of charge as qualified options to choose from (n_{0_k} qualified options are shown to passenger k through converting the level of charge to distance). If the passenger does not choose an e-bike, he/she will travel using other modes of transport. In this paper, ride-hailing system is considered as the alternative mode of transport. The choice behavior of users is modeled as a utility maximization process. The utility of potential options of passenger k can be expressed as Eqs. (3) and (4):

$$\text{Selecting bike } i: \; u_{ki} = \beta_k + \beta_k^{t} \Delta t_{ki} + \beta_k^{i} \delta t_{ki} + \beta_k^{c} C_{ki}^{\tau} \tag{3}$$

$$\text{Selecting other modes: } \; u_k^{o} = \beta_k^{o} + \beta_k^{o,t} w + \beta_k^{o,i} \delta t_k + \beta_k^{o,c} C_k^{o} \tag{4}$$

where β_k and β_k^{o} are utility constants. β_k^{t}, β_k^{i}, and β_k^{c} are utility coefficients per unit walking time, in-vehicle travel time, and cost for passenger k. Δt_{ki}, δt_{ki}, and C_{ki}^{τ} are the walking time of passenger k to reach e-bike i, travel time of passenger k using e-bike i, and cost of riding an e-bike for the passenger, respectively. $\beta_k^{o,t}$, $\beta_k^{o,i}$, and $\beta_k^{o,c}$ represent utility coefficients for waiting time of the passenger, in-vehicle travel time of the passenger, and cost of the trip for the passenger in a ride-hailing system, respectively. We denote waiting time as w, which is considered a constant. Travel time and cost of the trip for passenger k are also denoted as δt_k and C_k^{o}. In an e-bike sharing system, the walking time, travel distance, and travel cost for a passenger depend on the chosen e-bike. In contrast, in a ride-hailing system, these variables are determined by the passenger's trip attributes. Therefore, the variables for selecting other modes are simply a function of matched passenger k with a ride-hailing vehicle. Therefore, the probability that passenger k selects e-bike i can be modeled as

$$Pr_{ki} = \frac{e^{u_{ki}}}{\sum_{j=1}^{j=n_{0_k}} e^{u_{kj}} + e^{u_k^{o}}} \tag{5}$$

Once an e-bike is chosen, the passenger reserves it. Subsequently, the passenger proceeds to the e-bike's location and rides it to his/her intended destination. The e-bike becomes available again once the passenger drops it off.

In the case of user-based rebalancing, where users are incentivized to participate by leaving the rented e-bike at a different destination, the rental cost outlined in Eq. (2) would be adjusted. These destinations are determined based on the predicted demand for the upcoming time interval. If the predicted demand at a given location is less than the number of e-bikes within ω, that location is designated as a rebalancing destination. Consequently, if a user selects a bike assigned to user-based rebalancing, they will drop off the incentivized rented e-bike at that location. Users are offered the option to rent incentivized e-bikes by only paying the unlock cost (f_0), without incurring the variable part $(f_1 \delta t_{ki})$. Consequently, the rental cost for these incentivized e-bikes is lower. Based on Eq. (5), users are more likely to choose these e-bikes and participate in rebalancing.

3. Problem formulation

The proposed model minimizes the cost of an integrated operator-based and user-based rebalancing in a shared e-micromobility system while maximizing the system's profit. The cost of operator-based rebalancing includes the travel cost of repositioning trucks (C_{routing}) and the cost of battery swapping per e-bike $(C_{\text{recharging}}^{o})$. The cost of user-based rebalancing is related to the amount of incentive given to users who relocate e-bikes $(C_{\text{rebalancing}}^{u})$.

On the other hand, the benefit of recharging is the potential increase in rental fees (because of longer trips to be served). Additionally, 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 for e-bike and final e-bike inventory in node j.

The proposed method accounts for four actions for each e-bike: (1) operator-based rebalancing and recharging, (2) operator-based recharging, (3) user-based rebalancing, and (4) doing nothing. The mixed binary rebalancing problem (MBRP) determines the relocation strategy of each individual e-bike. This decision takes into account factors such as the e-bike's current position, the positions of trucks, the battery charge level, and the cost associated with each relocation strategy. Required notations are shown in Table 1. The assumptions underlying our model are outlined as follows.

- Rebalancing and recharging plans are based on current idle e-bikes.
- The routing and rebalancing plans are communicated to rebalancing trucks, which are then dispatched.
- Each truck starts empty at the beginning of each time interval, equipped with the required charged batteries.
- Trucks visit each node only once per interval and are tasked with picking up and dropping off designated e-bikes at predetermined nodes.
- For e-bikes allocated solely for charging, truck operators replace the depleted battery with a fully charged one without transporting the e-bike.
- Batteries in e-bikes rebalanced by trucks are replaced with fully-charged ones.
- E-bikes designated for user-based rebalancing are presented to users via the platform, and batteries of e-bikes relocated by users are not replaced.

The routing and travel cost of trucks is considered in Eq. (6). The cost of operator-based rebalancing is related to the distance between the current position of truck q and the node to which the truck should drive to pick up or drop off an e-bike (d_{ij}) and the unit cost (c) of relocating e-bikes by the truck (including the cost of hiring an operator and fuel consumption of the truck). y_{ij}^q is a binary decision variable that is equal to 1 if truck q traverses from node i to j, 0 otherwise. T and N represent the set of rebalancing trucks and the set of nodes, respectively. C_{routing} indicates cost of routing as Eq. (6):

$$C_{\text{routing}} = \sum_{q\in T}\sum_{i\in N}\sum_{j\in N} c d_{ij} y_{ij}^q \tag{6}$$

To model the cost of operator-based rebalancing, decision variable x_{ij}^q are introduced, indicating whether the e-bike located in node i is repositioned to node j by truck q (equals to 1) or not (equals to 0). If j equals the index of the current position of the e-bike (node i), it means that the e-bike in node i should only be recharged; otherwise, the e-bike located in node i should be relocated to node j and recharged simultaneously. The recharging cost per e-bike is related to the battery swapping process, recharging batteries, and the time needed for this task. s refers to the unit battery swapping cost per e-bike. Cost of operator-based recharging ($C^{\text{o}}_{\text{recharging}}$) is defined as Eq. (7):

$$C^{\text{o}}_{\text{recharging}} = \sum_{q\in T}\sum_{i\in N}\sum_{j\in N} s x_{ij}^q \tag{7}$$

The cost of user-based repositioning is related to the incentive of relocating an e-bike from node i to destination j for users (r_{ij}). z_{ij} is the user-based repositioning binary decision variable equal to 1 if the e-bike located in node i should be relocated by a user to node j; 0 otherwise. Cost of user-based rebalancing ($C^{\text{u}}_{\text{rebalancing}}$) is calculated as Eq. (8):

$$C^{\text{u}}_{\text{rebalancing}} = \sum_{i\in N}\sum_{j\in A_i} r_{ij} z_{ij} \tag{8}$$

It should be noted that for user-based rebalancing, the e-bike's battery charge level must be sufficient to enable relocation to node j. Therefore, A_i represents the set of nodes that can be reached by the e-bike located in node i with a specific level of charge ($A_i \in N$).

Another cost associated with user-based rebalancing pertains to the battery consumption compared to operator-based rebalancing. The cost of battery usage in user-based rebalancing ($C^{\text{u}}_{\text{battery}}$) is calculated as Eq. (9):

$$C^{\text{u}}_{\text{battery}} = \sum_{i\in N}\sum_{j\in A_i} \gamma d_{ij} z_{ij} \tag{9}$$

where γ represents the conversion factor that translates the distance traveled by the user during e-bike relocation into the corresponding battery charge consumption.

However, user-based rebalancing provides a benefit by directly serving a user. Specifically, while truck-based rebalancing involves transporting the e-bike via truck, user-based rebalancing involves a user directly handling the e-bike, thereby receiving service. μ represents the benefit associated with fulfilling user demand. Therefore, $B^{\text{u}}_{\text{rental}}$ can be defined as Eq. (10):

$$B^{\text{u}}_{\text{rental}} = \sum_{i\in N}\sum_{j\in A_i} \mu z_{ij} \tag{10}$$

The benefit of operator-based rebalancing of e-bikes is relevant to the rental cost, which is related to the distance traveled by the rented e-bikes and their level of charge. When the truck relocates an e-bike, its depleted battery is replaced with a fully charged one. Hence, the benefit of recharging can be approximated with the distance that the e-bike can travel with a fully-charged battery, l_{full}. $B^{\text{o}}_{\text{rental}}$ refers to potential rental benefit from e-bikes relocated and charged by operators. α is the conversion factor to convert the distance that e-bikes could travel to the rental fee.

$$B^{\text{o}}_{\text{rental}} = \sum_{q\in T}\sum_{i\in N}\sum_{j\in N} \alpha (l_{\text{full}} - l_i) x_{ij}^q \tag{11}$$

However, note that since the charging strategy is considered as battery swapping on the trucks, the batteries of e-bikes relocated by users will not be replaced with fully charged ones.

The other objective of the BRP is minimizing the number of unmet demands in each time step. This term strives to minimize the differences between predicted demand in each node (D_j) and final bike inventory after rebalancing is carried out (F_j). The $\sum_{j\in N} p_j |D_j - F_j|$ indicates the cost of penalty related to the difference between D_j and F_j, which should be minimized.

Ultimately, the overall mixed binary rebalancing and recharging problem is formulated as Eqs. (12)–(30):

$$\begin{aligned}\min_{x_{ij}^q, y_{ij}^q, z_{ij}} \quad & \sum_{q\in T}\sum_{i\in N}\sum_{j\in N} c d_{ij} y_{ij}^q + \sum_{q\in T}\sum_{i\in N}\sum_{j\in N} s x_{ij}^q + \sum_{i\in N}\sum_{j\in A_i} (r_{ij} + \gamma d_{ij} - \mu) z_{ij} \\ & - \sum_{q\in T}\sum_{i\in N}\sum_{j\in N} \alpha (l_{\text{full}} - l_i) x_{ij}^q + \sum_{j\in N} p_j |D_j - F_j|\end{aligned} \tag{12}$$

s.t.

$$\sum_{j\in N} y_{ij}^q \le 1 \qquad \forall i\in N, q\in T \tag{13}$$

$$\sum_{j\in N} y_{ij}^q = \sum_{j\in N} y_{ji}^q \qquad \forall i\ne j, q\in T \tag{14}$$

$$\sum_{q\in T}\sum_{j\in N} x_{ij}^q + \sum_{j\in A_i} z_{ij} \le 1 \qquad \forall i\in N \tag{15}$$

$$\sum_{i\in N} x_{ij}^q \le k^q \sum_{i\in N} y_{ij}^q \qquad \forall j\in N, q\in T \tag{16}$$

$$\sum_{j\in N} x_{ij}^q \le \sum_{j\in N} y_{ij}^q \qquad \forall i\in N, q\in T \tag{17}$$

$$\sum_{i\in N} x_{im}^q = \sum_{j\in N} Q_{jm}^q - \sum_{j\in N} Q_{mj}^q \qquad \forall m\in N, q\in T \tag{18}$$

$$\sum_{i\in N} x_{mi}^q = \sum_{j\in N} Q_{mj}^q - \sum_{j\in N} Q_{jm}^q \qquad \forall m\in N, q\in T \tag{19}$$

$$\sum_{i\in N} x_{ij}^q \le \sum_{i\in N} Q_{ij}^q \qquad \forall j\in N, q\in T \tag{20}$$

$$Q_{ij}^q \le k^q y_{ij}^q \qquad \forall i,j\in N, q\in T \tag{21}$$

$$\sum_{q\in T}\sum_{i\in N}x_{ij}^{q}+\sum_{i\in A_i}z_{ij}\leq \max(0,D_j-I_j) \qquad \forall j\in N \tag{22}$$

$$\sum_{q\in T}\sum_{j\in N}x_{ij}^{q}+\sum_{j\in A_i}z_{ij}\leq I_i \qquad \forall i\in N \tag{23}$$

$$F_j=I_j+\sum_{q\in T}\sum_{i\in N}x_{ij}^{q}+\sum_{i\in A_i}z_{ij}-\sum_{q\in T}\sum_{i\in N}x_{ji}^{q}-\sum_{i\in A_j}z_{ji} \qquad \forall j\in N \tag{24}$$

$$\sum_{q\in T}\sum_{i\in N}\sum_{j\in N}cd_{ij}y_{ij}^{q}\leq \widehat{d} \tag{25}$$

$$\sum_{i\in N}\sum_{j\in A_i}z_{ij}r_{ij}\leq \widehat{b} \tag{26}$$

$$x_{ij}^{q}\in\{0,1\} \qquad \forall i,j\in N,q\in T \tag{27}$$

$$z_{ij}\in\{0,1\} \qquad \forall i,j\in N \tag{28}$$

$$y_{ij}^{q}\in\{0,1\} \qquad \forall i,j\in N,q\in T \tag{29}$$

$$Q_{ij}^{q}\geq 0 \qquad \forall i,j\in N,q\in T \tag{30}$$

In the objective Eq. (12), the component related to the imbalance between predicted demand and final bike inventory, $\sum_j p_j|D_j-F_j|$ is nonlinear. In order to linearize $|D_j-F_j|$, using auxiliary integer variable H_j, Eqs. (31) and (32) are introduced:

$$H_j\geq D_j-F_j \qquad \forall j\in N \tag{31}$$

$$H_j\geq -(D_j-F_j) \qquad \forall j\in N \tag{32}$$

The objective Eq. (12) minimizes the total cost of rebalancing and maximizes the system's potential profit. Equation (13) ensures that each truck should visit each node at most one time, and flow conservation of trucks is guaranteed in Eq. (14). Equation (15) guarantees that only one rebalancing method should be used for each bike. Equation (16) restricts the number of e-bikes carried by the truck to each node to trucks' capacity. Equation (17) ensures that trucks should visit the e-bike that should be carried to other nodes. Equations (18)–(20) are used to ensure inventory conservation of e-bikes carried by trucks. Equation (21) implies that the number of e-bikes carried between nodes by each truck should be limited to the truck capacity. Equation (22) ensures that the final bike inventory should not exceed predicted/estimated demand at each node in the next time step. Equation (23) restricts the number of e-bikes taken from each node to the initial bike inventory in that node. Equation (24) defines the final number of bikes in each node. Equations (25) and (26) limit the distance traveled by trucks in operator-based rebalancing and the total amount of reward given to users in user-based rebalancing to distance limit and budget limit thresholds. Equations (27)–(30) are domain constraints.

The proposed mixed binary non-linear problem (Eq. (12)) is linearized using Eqs. (31) and (32), and is considered as a binary linear problem (MBLP) by setting variables' domain between 0 and 1. The branch and bound method is used to solve the MBLP on Matlab 2020. This method systematically explores branches of feasible solutions, where each branch represents a subset of the relaxed problem, which ignores the integer constraints. If the relaxed solution is not integer-feasible, the algorithm creates branches by selecting a variable with a fractional value and forcing it to take integer values, thus generating new subproblems. For each branch, the algorithm solves the linear relaxation to find a bound on the objective function. These bounds help determine whether the subproblems should be further explored (branched) or pruned. The process iterates, branching and bounding on the remaining subproblems, and updating the best-known solution (incumbent) whenever a superior integer solution is found. This approach ensures an efficient and systematic search for the optimal solution. The BB method can be further enhanced by leveraging the unique structure of the problem to increase algorithm efficiency in future research.

4. Simulation model

In this section, the simulation model of the on-demand e-micromobility sharing system is introduced. The diagram of simulating an on-demand shared e-micromobility system is shown in Fig. 1. The simulation and related experiments are conducted in Matlab 2020. For the operating network, we use the Manhattan network, including all streets and intersections.

The process starts with the entry of a new passenger into the system. If there is no e-bike within an acceptable walking distance, the passenger will leave the platform. However, if there are e-bikes available within the acceptable walking distance, they are presented to the passenger as qualified options. The passenger can then select an e-bike based on the required level of charge and their utility. After reserving the e-bike, the passenger walks to its location, picks it up, and begins their trip. The process concludes when the passenger arrives at their destination and drops off the rented e-bike.

For the rebalancing activity, at the end of each time interval, based on the locations of idle e-bikes and the predicted demand for the next time interval, the platform uses the proposed MBRP model to determine which truck should visit specific nodes. The model decides where to relocate e-bikes from and to, and which e-bikes need charging. E-bikes that should be incentivized for user-based rebalancing are also identified, and the rebalancing activities then commence. To more accurately reflect real-world conditions, the simulation accounts for errors in the predicted demand in terms of both location and quantity compared to the actual demand in the upcoming time interval. For location errors, the coordinates of the predicted demand are randomly altered within a 250-m radius. Regarding the number of demands, the simulation introduces variability: 15% of the predicted demand does not occur, 15% of the demand arises in unpredicted locations, and the quantity of predicted demand at each location fluctuates randomly between −10% and +10%.

Once rebalancing/recharging activities start (concurrent to the general operation of the e-bike sharing platform), based on the routing plan, trucks begin visiting e-bikes and rebalancing destinations to either swap batteries or pick up/drop off e-bikes for rebalancing. A time of 10 s is allocated for battery swapping, as well as for picking up or dropping off e-bikes.

E-bikes assigned for user-based rebalancing are displayed to passengers as incentivized e-bikes with designated destinations. When a passenger opts for one of these e-bikes, they pay an unlock fee without incurring the variable fee and must drop off the e-bike at the specified destination. In user-based rebalancing, it is assumed that passengers who choose and rent incentivized e-bikes will comply with the requirement to return them to predefined locations. If an incentivized e-bike is not used within the allocated time interval, it will be reassigned for the Mixed Rebalancing Problem in the subsequent time interval.

4.1. Network and demand data

In the simulation model, the network of Manhattan is considered as the test network. The network includes nodes and links such as streets, bridges, highways, and tunnels. Routing of rebalancing trucks and rented e-bikes follows the shortest path such that the shortest path and travel time for users, rented e-bikes, and rebalancing trucks are pre-calculated using Dijkstra algorithm and stored in a look-up table. In this study, we assume a constant speed throughout the network, without accounting for varying traffic conditions, as the bike network is considered separated from other modes of transportation.

The demand dataset used in this study is the taxi demand data of Manhattan in one working day in June 2016. Each trip record has the

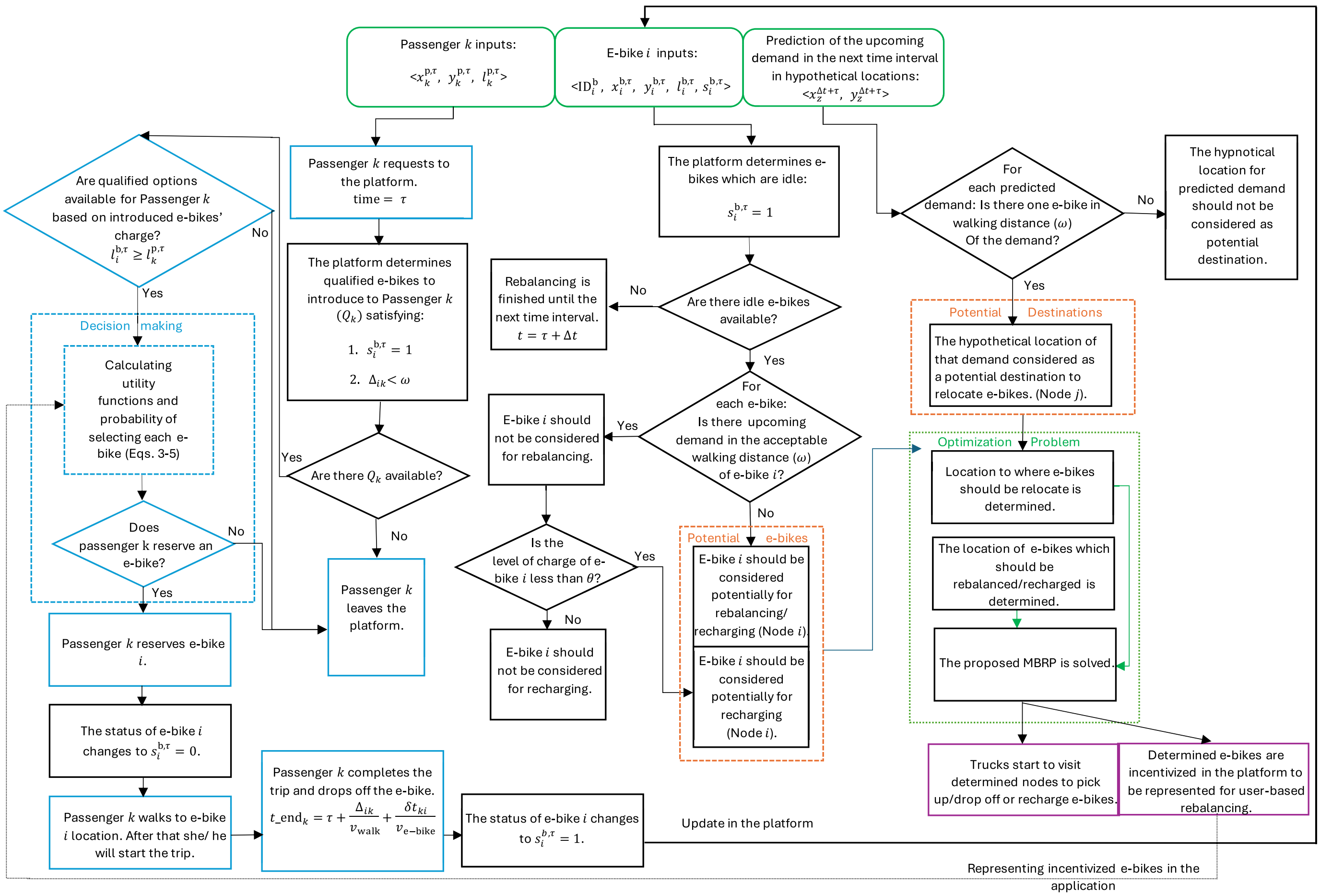

Fig. 1. Simulation flowchart of the on-demand shared e-micromobility system with the proposed integrated rebalancing method.

start/end time and latitude and longitude of the start/end location of each journey. The system receives requests from 45,000 individuals, with morning and evening demand peaks. The number of e-bikes in the system is assumed to be 3,000. Initial bike inventory in each node is randomly generated at 08:00 a.m. The simulation is conducted for 10 h between 08:00 a.m. to 06:00 p.m. Users access the platform over time, sending requests that include their coordinates captured via the GPS on their mobile phones. The platform displays e-bikes that are within a convenient walking distance of the user, along with their battery charge levels and the rental costs including a variable cost rate ($/km) and a fixed cost (an unlock fee). Users will cancel their requests if they cannot find a qualified e-bike. Whereas users who find and reserve a qualified e-bike would walk to the e-vehicle locations, start their journey, and drop the vehicle off when reaching their destination.

4.2. Benchmarks

The performance of the proposed MBRP model is compared with three repositioning strategies.

Benchmark 1: No charging – no rebalancing (NC-NR). E-bikes are utilized by users without any charging or repositioning activity during an operating day. At the start of each day, e-bikes are fully charged and randomly distributed.

Benchmark 2: Operator-based charging – no rebalancing (OC-NR). In this scenario, e-bikes with less than θ percent level of charge are recharged by recharging trucks during an operating day. An operating day is divided into some time intervals (Δt). At the beginning of each time interval, the platform advises recharging trucks to visit and recharge e-bikes with less than θ percent level of charge based on these e-bikes' current location. The optimum route of recharging trucks is determined based on the vehicle routing problem (VRP) model. The VRP optimization allocating e-bikes to trucks and minimizing the total travel cost of trucks is defined below:

$$\min \sum_{q\in T}\sum_{i,j\in N_\theta} c_{ij} u_{ij}^q \tag{33}$$

$$\text{s.t.} \sum_{q\in T}\sum_{j\in N_\theta} u_{ij}^q = 1 \qquad \forall i \in N_\theta \tag{34}$$

$$\sum_{j\in N_\theta} u_{ij}^q = \sum_{j\in N_\theta} u_{ji}^q \qquad \forall i \in N_\theta, q \in T \tag{35}$$

$$G_j^q \geq G_i^q - \mathrm{M}\left(1 - u_{ij}\right) \qquad \forall i,j \in N_\theta \tag{36}$$

$$u_{ij}^q \in \{0,1\} \qquad \forall i,j \in N_\theta, q \in T \tag{37}$$

The objective Eq. (33) minimizes the total travel costs of recharging trucks. Let c_{ij} be the travel cost from node i to j. u_{ij}^q is a binary variable equals to 1, if truck q traverses node i to j, and 0 otherwise. N_θ is the set of all nodes that have e-bikes with less than θ percent level of charge. Equation (34) forces trucks to observe each node only once. Equations (35) and (36) are used for flow conservation and subtour elimination, where G_i^q and G_j^q represent the load of the truck q after visiting node i and node j (number of visited nodes). M is a sufficiently large constant, used to enforce the constraint when u_{ij} equals to 1. If u_{ij} is 0, the constraint is relaxed by the large constant M. These constraints effectively prevent the formation of subtours by ensuring a consistent sequence of node visits.

Benchmark 3: Operator-based charging and rebalancing (OC-OR). In practice, shared e-micromobility system platforms deploy rebalancing trucks to relocate idle e-bikes to nodes with high demand for shared e-bikes. In such a rebalancing method, the optimization model is based on decreasing the cost of truck routing and the penalty caused by the imbalance between the predicted demand of each node and the final bike inventory of that node. In this benchmark, we assume that the batteries of e-bikes are swapped with a full one while rebalancing with rebalancing trucks. Truck-based e-bike rebalancing problem formulation is obtained when we assign 0 to z_{ij} in the objective Eqs. (12), (13) and (32).

5. Numerical experiments

Numerical experiments using the proposed mixed rebalancing method and three benchmarks are conducted in the simulation environment considering the Manhattan road network. Real data of taxi passenger demand of Manhattan from 08:00 a.m. to 06:00 p.m. on Jun 2, 2016 is considered as demand for the simulation. 20-min interval is assumed as the time span for conducting rebalancing and/or recharging activities throughout the operating day. It is assumed that there are 3,000 e-bikes and 10 rebalancing trucks in the operating area working continuously from 08:00 to 18:00. For each benchmark, 4 simulation experiments are conducted. In order to make a comparison among the proposed method and benchmarks, various performance metrics are reported in Section 5.2.

5.1. Experiment setup

Parameters related to the passenger choice model introduced in Section 2.4 are shown in Table 2. The bounded normal distributions are used to set the parameters for each passenger individually. The pricing parameters are presented in Table 3. The incentivization works such that the variable cost of trip fare for e-bikes, which should be relocated by users, will be zero (i.e., $f_1 = 0$). However, they still pay the initial unlock fee (f_0). The speeds of users, e-bikes, and trucks are assumed as 1.5 m/s, 20 km/h, and 45 km/h, respectively. In the dynamic simulation model, a time allocation of 10 s is designated for truck operators to pick up or drop off e-bikes, as well as to swap their batteries.

Table 2
Passenger choice parameters.

Parameter	Description	Unit	Mean	Standard deviation	Lower bound	Upper bound
β_k	Utility constant for selecting e-bikes	—	−1.745	0.2	−2	−1.5
β_k^t	Utility coefficient for trip walking time	1/min	−0.021	0.005	−0.025	−0.02
β_k^i	Utility coefficient for trip travel time	1/min	−0.016	0.005	−0.02	−0.01
β_k^c	Utility coefficient for trip cost	1/$	−0.048	0.02	−0.05	−0.018
β_k^o	Utility constant for selecting other modes	—	−2.467	0.2	−2.6	−2.2
$\beta_k^{o,t}$	Utility coefficient for trip waiting time	1/min	−0.026	0.005	−0.03	−0.022
$\beta_k^{o,i}$	Utility coefficient for trip travel time	1/min	−0.014	0.004	−0.18	−0.01
$\beta_k^{o,c}$	Utility coefficient for trip cost	1/$	−0.056	0.02	−0.08	−0.055

Note: Values are sourced from Luo et al. (2023).

Table 3
Platform's pricing, matching, rebalancing, and recharging parameters.

Parameter	Description	Unit	Value
ω	Acceptable walking distance	m	500
f_0	Initial unlock fee	$	1
f_1	Trip variable fare	$/min	0.38
c	Unit travel cost of rebalancing trucks	$/km	1.01
s	Unit battery swapping cost	$	0.1
γ	Battery consumption cost conversion factor	$/km	0.0028
μ	Benefit of demand fulfillment	$	1
α	Level of charge to rental fee conversion factor	$/%	0.57
p_j	Net imbalanced penalty	$	1
θ	Recharging threshold	%	20
w	Waiting time (other modes)	min	3.40

Note: All values are sourced from Jiao and Ramezani (2024), Li and Liu (2021), Xu et al. (2022), and Zhou et al. (2023).

5.2. Experiments results

One crucial objective of a shared e-micromobility system is to increase met (serviced) demands. Fig. 2 illustrates the number of met/unmet demands over time with different rebalancing methods. It can be observed that the proposed real-time integrated rebalancing method demonstrates superior performance compared to other repositioning methods, as it achieves the highest number of successful demands.

The average walking distance of passengers and the total distance traveled by the fleet of e-bikes are considered as two main metrics of the shared e-micromobility system. The first metric is related to the spatial distribution of e-bikes throughout the operating area over time. The second one reflects the supply utilization factor. The total traveled distance is influenced by the battery charge level of e-bikes, which diminishes over an operating day if effective charging is not implemented. Figs. 3 and 4 display these two metrics for the proposed method and the three benchmarks.

Fig. 3 illustrates that the average walking distance increases over time, which is due to the uneven distribution of e-bikes throughout the operating day. The analysis reveals that the highest walked distance is associated with the benchmark scenario where no charging or rebalancing is implemented. This indicates the distribution of e-bikes, leading to longer walking distances for users to find available e-bikes. In contrast, although walking distances increase throughout the day, the rise is less pronounced compared to other benchmarks, and the MBRP average walking distance values are lower than those of the other methods. This finding highlights the effectiveness of the mixed rebalancing strategy in achieving its primary goal: increasing the accessibility of e-bikes for users. The reduced walking distance suggests that the proposed method results in e-bikes being more readily available to users and thereby improving the overall efficiency and convenience of the e-bike sharing system. This improvement is crucial for user satisfaction, operational success, and higher income of the micromobility sharing system, as it directly addresses the challenge of e-bike availability and accessibility.

The total traveled distance of passengers (equivalent to the fleet total traveled distance) is shown in Fig. 4, revealing an important trend in the NC-NR benchmark. It is evident that the traveled distance decreases over time in this benchmark due to the absence of e-bike charging within the system. Consequently, only passengers with shorter travel distances are able to rent available e-bikes. The profit of the system, which is related to traveled distance by the fleet of e-bikes, is also decreased due to the reduction in travel distance.

The numbers of rebalanced and recharged e-bikes throughout an operating day are shown in Fig. 5. As can be seen from Fig. 5, a

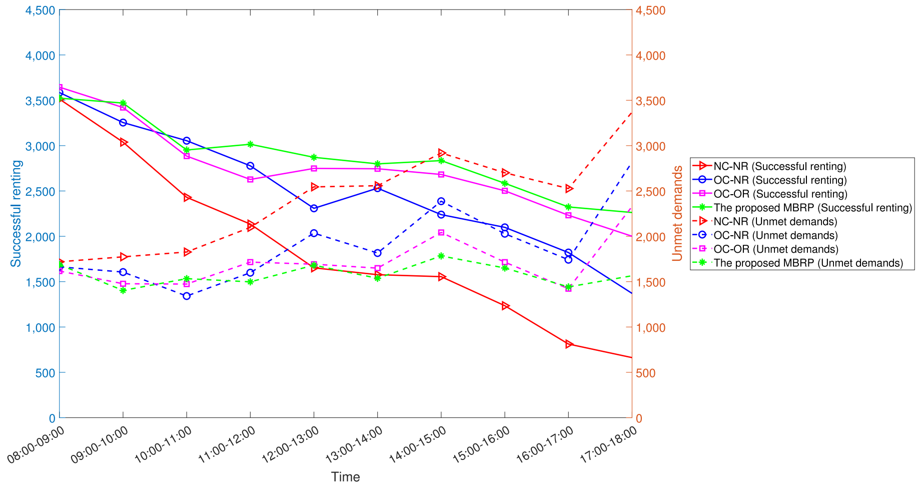

Fig. 2. Number of successful renting and number of unmet demand for various benchmarks and the proposed MBRP method.

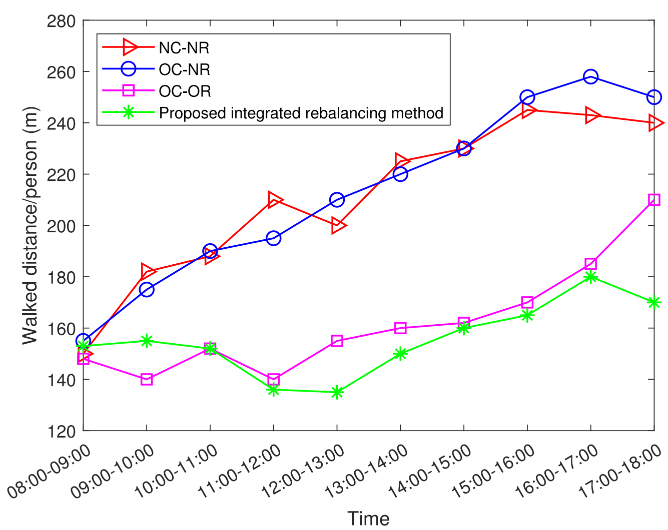

Fig. 3. Average walked distance/person (m) for successful trips based on time of the day with various rebalancing and recharging methods.

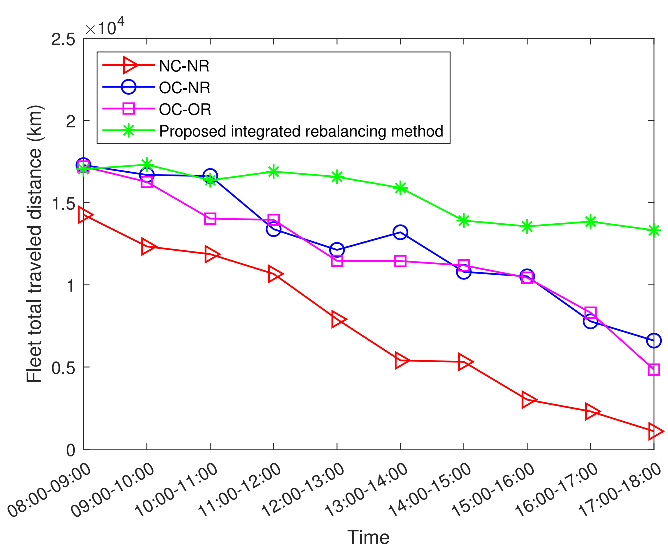

Fig. 4. Fleet total traveled distance (km) based on time of the day with various rebalancing and recharging methods.

considerable portion of rebalanced e-bikes is allocated to user-based rebalancing, especially during peak hours.

Table 4 compares the performance of the simulated e-bike sharing system operated under four different rebalancing strategies: NC-NR, OC-NR, OC-OR, and MBRP. Each strategy is evaluated based on several key metrics, including the number of successful trips, unserviced demand, distance metrics, income, operating cost, and total profit. A notable observation in Table 4 is the higher profit of the proposed method in comparison with the other benchmarks.

Among the strategies, MBRP demonstrates the highest performance across most metrics, with 28,636.5 successful trips, the lowest unserviced demand, and the highest total income and profit, which is 15% higher than those of a system using either the OC-NR or OC-OR rebalancing system. This strategy, however, incurs the highest operating cost (associated with user incentivization in addition to operator-based rebalancing costs). Nonetheless, due to its superior rebalancing system, which includes both operator-based and user-based methods, it generates the highest income, ultimately resulting in the highest overall profit.

On the other hand, NC-NR, which involves neither rebalancing nor charging, shows the lowest performance, with only 58% successful trips compared to MBRP, the highest unserviced demand, and the lowest total income and profit. The OC-NR and OC-OR strategies offer moderate performance improvements over NC-NR. These comparisons highlight the substantial benefits of incorporating rebalancing and charging strategies, particularly the proposed mixed approach, despite the higher operational costs.

Table 5 compares the number of e-bikes recharged and rebalanced by trucks and users throughout an operating day. Notably, in the OC-NR and OC-OR strategies, a greater number of e-bikes are charged or rebalanced by operators compared to the MBRP method. In the MBRP strategy, a notable finding is that operators recharge and rebalance fewer e-bikes, while users play a significant role in rebalancing. User-based rebalancing trips account for 44% of the total rebalancing activities. Additionally, the number of e-bikes rebalanced through the proposed methods is 32% higher compared to the number rebalanced using the OC-OR method. This shift towards user-based rebalancing can substantially reduce the reliance on trucks for rebalancing operations. As a result, there are considerable environmental and social benefits, such as reduced emissions, decreased traffic congestion, and lower operational costs. By lessening the need for truck-based rebalancing, the strategy promotes a greener and more sustainable approach to e-bike sharing systems. This highlights the success of the integrated rebalancing method, where user participation in rebalancing complements operator efforts, leading to an efficient and effective system.

Moreover, with the NC-NR method, the average charge level of the

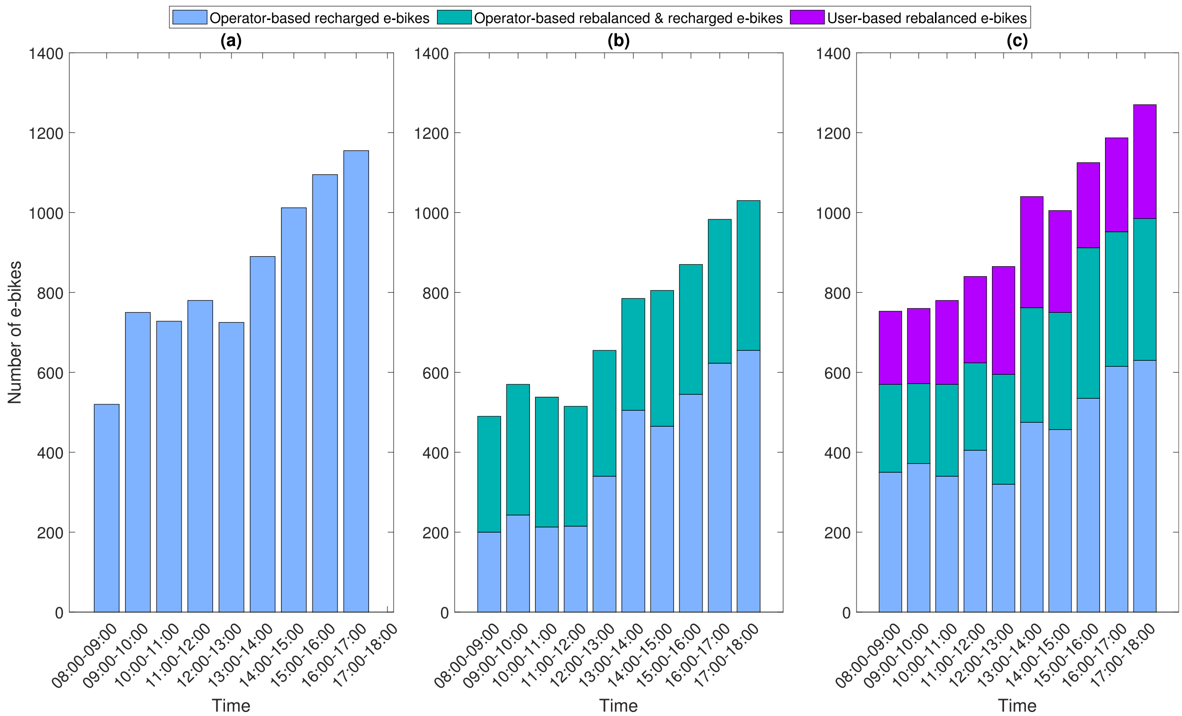

Fig. 5. Number of e-bikes with various methods: (a) benchmark with operator-based recharging - no rebalancing; (b) benchmark with operator-based rebalancing and charging; and (c) the proposed integrated method.

Table 4
Comparison of the performance of the system operated with different rebalancing strategies throughout an operating day (average of four simulations).

	NC-NR	OC-NR	OC-OR	MBRP
Number of successful trips	18,610.6	25,041.1	27,486.9	28,636.5
Number of unserviced demand	26,037.9	19,636.4	17,134.0	16,011.6
Distance traveled per trip (km)	4.06	4.82	4.17	5.10
Distance traveled per e-bike (km)	25.18	40.23	38.30	48.68
Distance walked per user (km)	0.206	0.308	0.157	0.152
Total income ($)	104,747.67	162,636.67	158,154.12	195,129.11
Total operating cost ($)	0.00	4,142.80	4,058.24	3,823.76
Total incentivization cost ($)	0.00	0.00	0.00	12,965.91
Total profit ($)	104,747.67	158,493.87	154,095.88	178,339.44

Table 5
Number of rebalanced/recharged e-bikes and total traveled distance by rebalancing trucks in different rebalancing strategies throughout an operating day (average of four simulations).

	NC-NR	OC-NR	OC-OR	MBRP
Number of e-bikes recharged by trucks	0.0	9,123.1	4,553.2	4,771.8
Number of e-bikes rebalanced and recharged by trucks	0.0	0.0	3467.3	2810.1
Number of rebalancing trips by users	0.0	0.0	0.0	2219.8
Total traveled distance by rebalancing trucks (km)	0.00	3,198.52	3,224.03	3,035.22
Average level of charge of the fleet (%)	21.8	47.1	42.0	36.3

fleet throughout the operating day is, on average, 20% lower compared to strategies that involve continuous charging of the fleet. This significantly contributes to the decrease in the number of successful rentals under the NC-NR method. In contrast, the OC-NR and OC-OR methods yield comparable results; however, since the OC-NR method involves trucks solely responsible for visiting the bikes, it maintains the highest number of charged bikes and the highest average charge level.

The objective of e-bike repositioning is to ensure proportional spatial distribution of e-bikes with respect to the travel demand throughout the operating area. To observe the effects of the proposed integrated rebalancing method, Fig. 6 presents the spatial distribution of e-bikes throughout the Manhattan area. In this figure, each point represents the location of an e-bike, with the color indicating the bike's charge level. Fig. 6) compares the spatial distribution of e-bikes from the early hours to the end of the day with various e-bike sharing systems that employ different rebalancing methods. As depicted in Figs. 6a–6c, during the final hours of the operating day, there are clusters of e-bikes in some regions of the network. The proposed integrated rebalancing method effectively addresses this issue by preventing excessive accumulation of e-bikes in particular regions within the operating area and ensuring their efficient redistribution throughout the entire area.

An inconspicuous observation, discernible in Fig. 6 when comparing the OC-NR method to the NC-NR method, is that even the charging of e-bikes can yield positive effects on the redistribution of bikes throughout the city.

5.3. *Comparison with the e-hailing system*

In this section, we compare the performance of the e-micromobility sharing system with the proposed rebalancing and recharging system against an e-hailing system considered as the other modes. To this end, an e-hailing system is modeled in the simulation, and the results of the shared e-micromobility system are compared with the performance of this system with 3,000 vehicles. The speed of e-hailing vehicles is

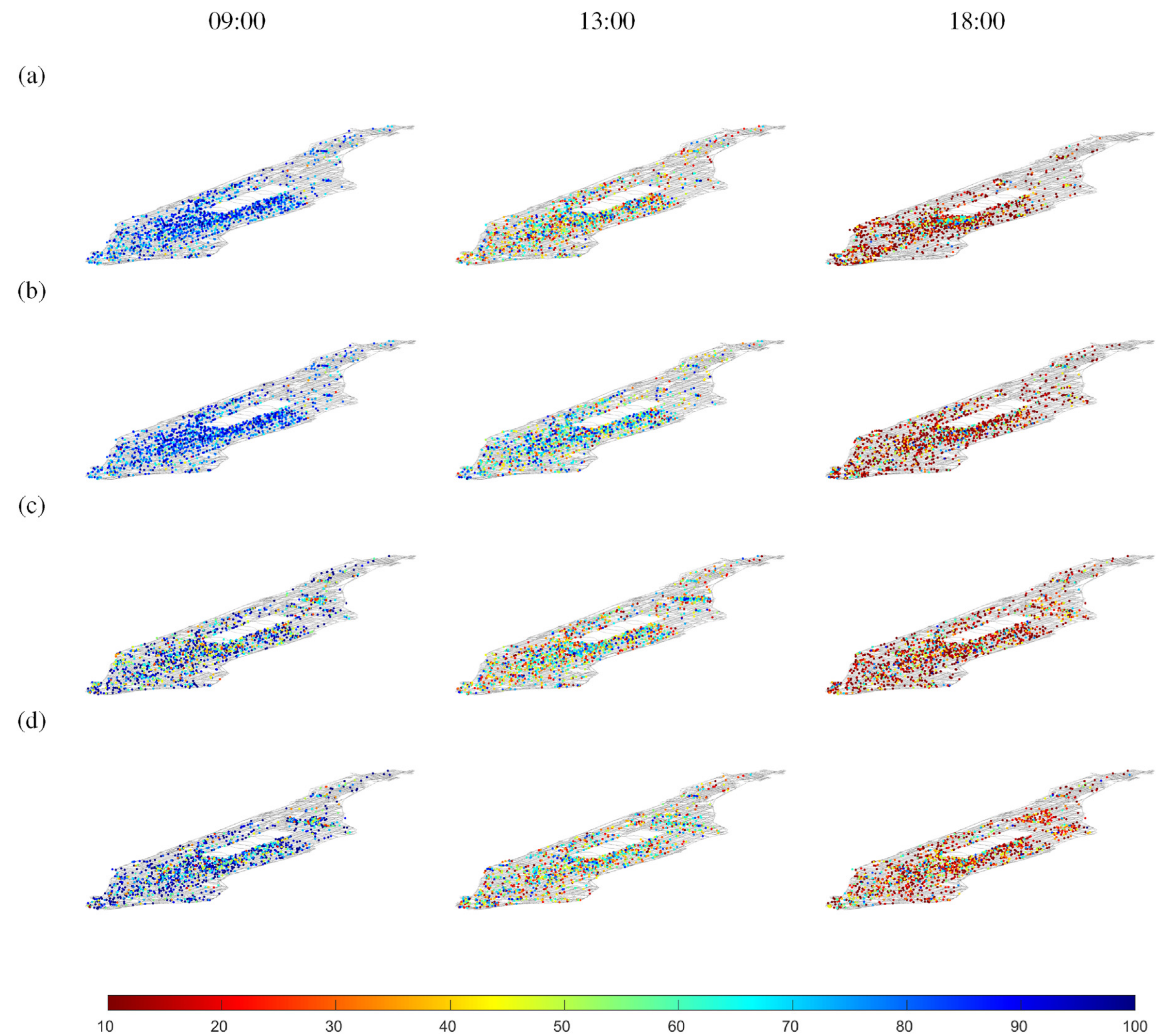

Fig. 6. Spatio-temporal distribution of location of e-bikes in various methods: (a) NC-NR, (b) OC-NR, (c) OC-OR, and (d) the proposed MBRP method. The color shows the level of charge.

assumed to be 45 km/h. The experiment setup and the pricing mechanism of this system are presented in Table 6. The attributes of e-hailing vehicle n at time τ are as $< x_n^{t,\tau}, y_n^{t,\tau}, s_n^{t,\tau} >$, where $x_n^{t,\tau}, y_n^{t,\tau}$ indicate two bi-dimensional location of e-hailing vehicle n at time τ, and $s_n^{t,\tau}$ denotes the status of e-hailing vehicle n at time τ (0 if e-hailing vehicle is occupied or dispatched to pick up a passenger, and 1 otherwise).

The e-hailing system operates through the interaction between passengers, the platform, and e-hailing vehicles. Initially, e-hailing vehicles are distributed randomly throughout the city. When passenger K requests a ride via the platform, the system matches them with the closest idle e-hailing vehicle within an acceptable distance (ϕ). According to their choice model (introduced in Eq. (4)), the passenger may either accept the matched e-hailing vehicle or choose an alternative mode of transportation. In the modeled e-hailing system, an e-hailing vehicle not allocated or dispatched to pick up a passenger will remain at its current location (the destination of the previous trip) until it is matched with another passenger. The total income of the system includes an initial payment for each successful trip and a variable fare based on the total distance that the passenger travels. The costs associated with this system include the drivers' commissions for each ride, which is the percentage of income from e-hailing online systems that are offered to drivers.

Table 7 presents the comparison of the results between the simulated e-hailing system and the shared e-micromobility system utilizing the proposed integrated rebalancing and recharging method. Results in Table 7 highlight a substantial disparity in profitability between the e-bike sharing system employing the proposed integrated rebalancing method and the e-hailing system. Despite the e-hailing system earning a higher income due to its higher fares, the operating costs, including drivers' commission of each ride (which is related to driver's income, fuel cost, depreciation cost of the e-hailing vehicle for driver) result in a lower overall profit compared to the e-bike sharing system with MBRP.

Table 6
Pricing setup of the e-hailing system.

Parameter	Description	Unit	Value
c^t	Driver's commission of each ride	%/ride	75
f_0^t	Initial pay	$	3
f_1^t	Trip variable fare	$/km	2.17
ϕ	Acceptable distance	km	1

Note: All values are sourced from Gu et al. (2024), Sun et al. (2020), and Zhou et al. (2023).

Table 7
Results comparison of the performance of the shared e-micromobility system with the proposed rebalancing method and the e-hailing system throughout an operating day (average of four simulations).

	Proposed e-micromobility sharing system	E-hailing system
Number of successful trips	28,636.5	28,220.6
Distance traveled per trip (km)	5.10	7.35
Average distance walked by passengers (km)	0.152	0.00
Average distance derived to pick up passengers (km)	0.00	0.55
Total income ($)	195,129.11	547,014.00
Total operating and incentivization cost ($)	16,789.67	410,260.50
Total profit ($)	178,339.44	136,753.50

6. Conclusions and future research

This study has formulated an integrated operator-based and user-based rebalancing problem in a shared e-micromobility system, considering the attributes of each e-bike. The integrated rebalancing system employs platform-owned trucks to relocate and recharge e-bikes, while users are also encouraged to participate in rebalancing through incentives. This incentivization reduces the cost of renting an e-bike, with users only required to pay an initial unlock fee. The objective is to minimize the total cost of rebalancing and the number of unmet demands while maximizing system's profit, accounting the distance traveled by rented e-bikes.

The numerical results demonstrate that the proposed method can increase the number of successful rentings and their travel distances. Despite incurring certain operational costs, the system will experience an overall increase in profits due to the fulfillment of more demands and users traveling longer distances. We compared the operation and profitability of the proposed e-bike sharing system to an e-hailing system. The results show that with an efficient operating system, including recharging and rebalancing, the e-bike sharing system can fulfill a comparable number of demands with lower operating costs.

Future research should take into account time- and location-varying incentivization strategies (Jiao and Ramezani, 2022) to potentially increase platform profit and the likelihood of users accepting rebalancing tasks. Moreover, an extension of this paper will involve investigating the optimal incentive strategy needed to eliminate truck-based rebalancing, aiming for a more sustainable e-bike sharing system. Future research can study incentivization through loyalty programs. Another avenue for future research could involve the management of battery charging at designated docks or charging stations. This addition would introduce a new layer of complexity, making the overall formulation mimic more comprehensively the operations of the e-micromobility fleet. Another potential direction for future research could involve determining the required charge levels to meet anticipated demand. This would ensure that e-bikes rebalanced through user-based strategies are adequately equipped to serve future demand. Future research on e-bike sharing systems could explore the use of learning methods to optimize rebalancing activities (Yang and Ramezani, 2022).

Replication and data sharing

The related codes used in this study can be found at https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page.

CRediT authorship contribution statement

Elnaz Emami: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohsen Ramezani:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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