Joint Rebalancing and Charging for Shared Electric Micromobility Vehicles with Energy-informed Demand

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ABSTRACT

Shared electric micromobility (e.g., shared electric bikes and electric scooters), as an emerging way of urban transportation, has been increasingly popular in recent years. However, managing thousands of micromobility vehicles in a city, such as rebalancing and charging vehicles to meet spatial-temporally varied demand, is challenging. Existing management frameworks generally consider demand as the number of requests without the energy consumption of these requests, which can lead to less effective management. To address this limitation, we design RECOMMEND, a rebalancing and charging framework for shared electric micromobility vehicles with energy-informed demand to improve the system revenue. Specifically, we first re-define the demand from the perspective of energy consumption and predict the future energy-informed demand based on the state-of-the-art spatial-temporal prediction method. Then we fuse the predicted energy-informed demand into different components of a rebalancing and charging framework based on reinforcement learning. We evaluate the RECOMMEND system with 2-month real-world electric micromobility system operation data. Experimental results show that our method can be easily integrated into a general RL framework and outperform state-of-the-art baselines by at least 26.89% in terms of net revenue.

CCS CONCEPTS

• **Applied computing** → **Transportation**; • **Computing methodologies** → *Planning and scheduling*.

KEYWORDS

E-scooter; Rebalancing; Charging; Reinforcement Learning

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1 INTRODUCTION

Background and Goal: Shared micromobility (e.g., shared bikes and scooters), as an emerging way of urban transportation, has been increasingly popular in recent years. For example, Lime, a major shared micromobility service provider, serves more than 155 million users in 2022 [19]. As an alternative way to conventional automobiles, users use shared micromobility vehicles for short-distance trips such as from bus stops to home, enabling convenient mobility through multi-modal transportation [42] and less environmental impact by reducing emission from traffic congestion in rush hours [40]. The success of shared micromobility largely depends on the effective and efficient management of micromobility vehicles (e.g., bikes or scooters). With thousands of micromobility vehicles spreading in cities, it is challenging to effectively manage these vehicles, e.g., rebalancing vehicles to different regions to meet the spatial-temporally varied demand [11]. Further, recent blooming of electric micromobility vehicles (e.g., e-bikes or e-scooters) introduces additional management challenges as charging has to be considered simultaneously, e.g., minimizing charging cost while rebalancing [38]. Thus, the goal of this work is to design an efficient shared electric micromobility management framework considering both rebalancing and charging.

State-of-The-Art (SoTA) and Limitations: Existing vehicle management works have been designed for two main scenarios, including (i) conventional non-electric vehicles such as taxis [1, 5, 20, 35, 37] and bikes [1, 6, 14, 16, 17, 24, 26, 32] and (ii) electric vehicles such as e-taxis [38, 39], e-buses [25, 34], shared e-cars [2, 8, 22, 30, 41], and e-scooters [11, 12, 29]. For works of non-electric vehicles, they focus on rebalancing vehicles to different regions to match future demand and lack charging scheduling capacity, so they cannot be applied in our scenario. For works of electric vehicles, they consider both rebalancing and charging. They generally follow a paradigm that first predicts the number of future requests as demand and rebalances vehicles to meet the future demand. When vehicles' energy level is lower than a certain threshold (e.g., 15% [4]), a charging schedule is planned to recharge those low-energy vehicles. We argue that a key limitation of such a paradigm is that it does not consider future energy consumption while predicting future demand. That is, the demand is defined only as the number of requests without the energy consumption of these requests, which can lead to less effective scheduling. For example, the number of rebalanced vehicles meets the number of future requests, but the vehicles' remaining energy is not sufficient for future trips. This limitation can be even more significant for shared micromobility considering the limited battery capacity of micromobility vehicles (e.g., e-bikes or e-scooters), compared to electric cars.

Opportunities and Challenges: In this work, we re-define the demand from the perspective of energy consumption and aim to design a framework of using energy-informed demand (i.e., considering both trip demand and trip energy consumption) to guide micromobility vehicles scheduling (i.e., rebalancing and charging). Specifically, we take advantage of the recent advancement of reinforcement learning (RL) in vehicle scheduling [30][22] and aim to incorporate energy-informed demand prediction into RL-based vehicle scheduling. There are two challenges. First, RL-based scheduling methods generally consist of multiple components such as state, policy, and reward. It is challenging to seamlessly integrate predicted energy-informed demand with these components in a general RL framework. Second, managing thousands of micromobility vehicles in a city is computationally expensive [13] considering the large searching space (i.e., the large number of possible rebalancing and charging strategies). It is non-trivial to design a computationally efficient method to find the optimal strategy.

Our work: We design RECOMMEND, a rebalancing and charging framework for shared electric micromobility vehicles with energy-informed demand. We first formally define the micromobility vehicle rebalancing and charging problem and introduce a general RL-based rebalancing and charging framework. Then we adopt a state-of-the-art spatial-temporal prediction method to predict energy-informed demand. Based on the prediction, we incorporate the prediction as add-on modules into the RL framework. Specifically, we integrate the demand modules into components, including the state, action, and reward. We further design a demand-guided method to guide the charging and rebalancing policy learning process for faster convergence. Results show that our methods can be easily integrated into a general RL framework and achieve superior performance compared with state-of-the-art baselines. The key contributions of this work are as follows:

(1) We are the first to solve the problem of rebalancing and charging shared electric micromobility vehicles considering energy-informed demand.

(2) Technically, we design a RL-based framework where energy-informed demand is seamlessly fused in different components and supervises policy search to improve the efficiency of policy learning.

(3) We collaborate with a micromobility service provider and evaluate our approach based on real-world data in a city with more than 900 deployed vehicles. Our experimental results show that our method outperforms the state-of-the-art baselines by at least 26.89% in terms of net revenue. An ablation study is performed to show the effectiveness of different technical components.

2 BACKGROUND & MOTIVATION

In this section, we first introduce how a gerneral shared electric micromobility vehicle system works and its operational data. Then we motivate our work by analyzing the importance of energy-informed demand from two perspectives: rebalancing and charging.

2.1 Electric Micromobility Vehicle System

Fig. 1 shows the operation of a general shared electric micromobility vehicle system, including four key elements: the system operation center, users, the electric micromobility vehicles, and the trucks. The system generally works with two phases: the **usage phase** (e.g., users request and use vehicles) and the **scheduling phase** (e.g., trucks rebalance and charge vehicles). In the usage phase, a user first unlocks an available vehicle from the user's smartphone and then rides this vehicle to the destination. The vehicle automatically records and uploads its status (e.g., location and energy level) to the system operation center. After a certain usage period (e.g., 1 day), in the scheduling phase, the system operation center generates a rebalancing and charging plan (e.g., which vehicles to relocate, which vehicles to charge, and a suggested truck route) based on the status of all the vehicles and sends the plan to trucks. The trucks follow the plan to perform rebalancing and charging. In our work, we specifically consider charging through battery swapping [27], which our partner currently uses. Our work can also be easily generalized to other charging methods, such as centralized charging by relocating vehicles to a charging station for overnight charging [30] (detailed discussion in Section 6).

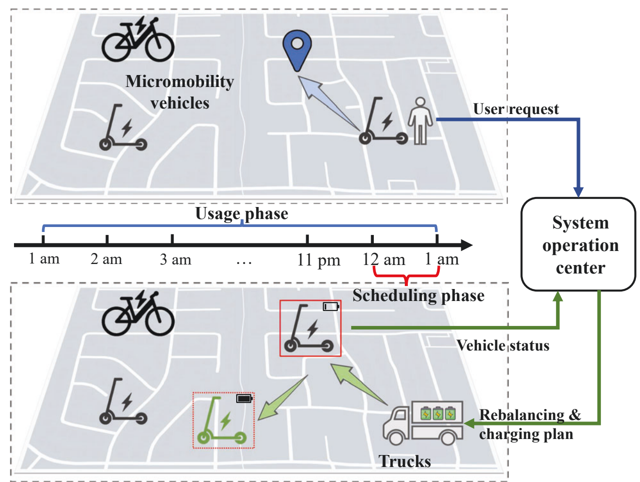


Figure 1: Electric micromobility system operation

2.2 Data Description

We use a real-world dataset provided by a shared electric micromobility service provider with whom we cooperate. This dataset spans two months, from August 2021 to September 2021, and consists of 54,021 trips and 912 shared electric micromobility vehicles. Whenever there is a change in the vehicle status, such as location and availability, real-time status updates are uploaded to the platform. These updates include the vehicle ID, vehicle status, event types (e.g., trip start or trip end), vehicle GPS location, battery energy level (measured as a percentage), timestamp, and other relevant information (details in Table 1).

2.3 Why Energy-informed Demand Matters

Our work is built upon the assumption that energy-informed demand is important for shared electric micromobility management. In this part, we perform data-driven investigation to verify this assumption from two perspective: rebalancing and charging.

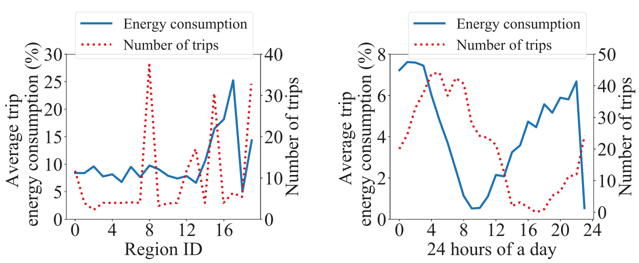
2.3.1 Significance of Energy-informed Demand on Rebalancing. For rebalancing, the key goal is to move vehicles to meet users' future

Table 1: Attributes in each record

Vehicle Id	Vehicle Latitude	Vehicle Longitude	Event Types
e.g., 30100292	e.g., 40.5214	e.g., -74.4567	trip-start / trip-end / battery-low / battery-charged / rebalance-pick-up/ rebalance-drop-off
Vehicle State	**Event Time**	**Event Id**	**Vehicle Energy (%)**
available / on-trip unavailable	e.g., 2021-08-31 18:10	e.g., e5b149bc-4400	e.g., 73%

requests in different regions. We analyze the difference of the number of trips and the average trip energy consumption in a region and discuss how they behave differently toward the goal from both the spatial and temporal perspective.

Spatial Perspective: Fig. 2a shows the average trip energy consumption and the number of trips in different regions. Each region is defined as a 800 meters × 800 meters grid, following the existing practice [22, 24]. In the conventional scheduling methods, the goal is to meet the number of trips (i.e., requests) in each region, without differentiating vehicles with different energy levels. However, as shown in Fig. 2a, two regions with a similar number of trips can have significantly different energy consumption (e.g., region 16 and region 18). This is mainly because the demand in different regions can vary a lot (e.g., people in some regions may tend to ride further or shorter than others). That indicates we cannot simply regard user demand as only number of requests without considering energy consumption.



(a) Spatial perspective **(b) Temporal perspective**

Figure 2: The significance of energy-informed demand on rebalancing compared with trip-informed demand from the spatial and temporal perspectives

Temporal Perspective: Fig. 2b shows the average trip energy consumption and the number of trips at different time slots of a day. Compared to the number of trips, it shows energy consumption has a significantly different pattern. For example, the number of trips reaches to the lowest between 4 pm and 10 pm, but the average energy consumption is relatively high. Therefore, besides preparing enough shared electric micromobility vehicles, we need to relocate vehicles with certain remaining energy based on the temporal distributions of energy consumption to avoid the unsatisfied demand due to the lack of energy.

Based on the above analysis, we argue that energy-informed demand is important for rebalancing from both the spatial and temporal perspectives, compared with trip-informed demand. In addition, to meet users' demand, we need to consider both the remaining energy of vehicles and users' energy-informed demand when we rebalance those vehicles in the system.

2.3.2 Significance of Energy-informed Demand on Charging. One important question of charging electric micromobility vehicles is when to charge the vehicles. Traditional methods generally set a static charging threshold and charge vehicles when the remaining energy is lower than the threshold. We argue that without considering the energy-informed demand, traditional methods can result in two issues. First, if the charging threshold is too low (i.e., many vehicles are not charged) and the future energy consumption is high, then the future demand cannot be satisfied. Second, if the charging threshold is too high (i.e., most vehicles are charged) but the future energy consumption is low, then vehicles may still satisfy the demand based on their remaining energy without charging, leading to wasted unnecessary charging. To quantitatively study these two issues, we define two corresponding metrics: (1) the demand satisfaction rate representing the ratio of satisfied demand (i.e., $\frac{\text{total satisfied demand}}{\text{total demand}}$) and (2) the unnecessary charging rate representing the ratio of vehicles that do not need be charged but still can satisfy future demand (i.e., $\frac{|\{v_i : e_i^{c_t} > 1 - e_i^{c_{t+1}}\}|}{|\{v_i : e_i^{c_t} < threshold\}|}$ where v_i is vehicle i, $e_i^{c_t}$ is the energy level of v_i before the t_{th} charging).

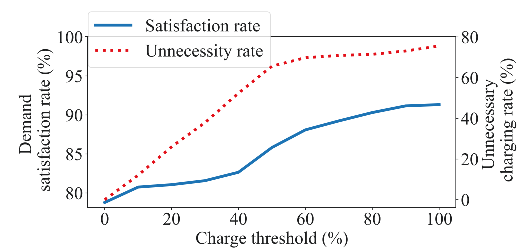


Figure 3: Demand satisfaction rate and unnecessary charging rate under different charging threshold

As shown in Fig. 3, the charging threshold impacts the demand satisfaction rate and unnecessary charging rate significantly. Even if we set the charging threshold as 100% (i.e., fully charge all the vehicles), there are still nearly 10% trips in one day that cannot be satisfied. It also shows that if we set the charging threshold as 100%, there are nearly 80% of them are unnecessary. As a result, we simply waste the operation time and increase the charging cost, potentially damaging the vehicles because of frequent battery swapping [28]. In addition, if we set the charging threshold as 0%, the unnecessary charging rate is nearly 0, while the satisfaction rate decreases to approximately 80%. It means that many vehicles' remaining energy cannot support users' daily trip energy consumption, leading to unsatisfied demand. In summary, knowing the energy-informed demand is important for deciding the charging strategy.

3 PROBLEM FORMULATION

In this section, we formulate the problem of rebalancing and charging shared electric micromobility vehicles.

Definition 1 (Shared Electric Micromobility Vehicle Rebalancing and Charging Problem). *Given the spatial-temporal distribution of users' demand, the location and energy status of electric micromobility vehicles, and the number of available trucks, we* *aim to answer two questions: (1) which region each vehicle should be dispatched to and (2) which vehicle should be charged, so as to maximize the total revenue of a shared electric micromobility system while minimizing the charging cost and traveling cost of trucks.*

Problem Setting: We partition a city into N equal size grids (i.e., $\{z_1, z_2, ..., z_N\}$) and each grid is considered as a region. A day is divided into T equal-length time intervals. We discretize vehicles' amount of energy into L different levels. Q trucks are available for the system to rebalance and charge micromobility vehicles. To describe the spatial-temporal distribution of shared electric micromobility vehicles in a city, we use $S_t^{i,l}$ to denote the number of shared electric micromobility vehicles with energy level l in region i at the beginning of time slot t.

We define the energy-informed demand as $F_t^{i,j,l} \in \mathbb{N}$, representing the number of users' requests from region i to region j at time slot t that need to consume energy by l levels. Therefore, for the whole city, we define the vehicle supply and demand during time slot t as $S_t \in \mathbb{N}^{N \times L}$ ($S_t = \{S_t^{i,l}\}, \forall\, i \in N, \forall\, l \in L$) and $F_t \in \mathbb{N}^{N \times N \times L}$ ($F_t = \{F_t^{i,j,l}\}, \forall\, i, j \in N, \forall\, l \in L$), respectively T_{trip}^t represents the revenue of the system from users' usage at time slot t, related to the users' demand and the supply of vehicles, formulated as:

$$T_{trip}^t = f_{trip}(S_t, F_t) \tag{1}$$

Scheduling: When making the rebalancing and charging decisions, the operator considers the current vehicle supply S_t and the energy-informed demand of the future h time slots, i.e., $F_{t:t+h}$. We define $a_{reb}^t \in \mathbb{N}^{N \times N \times L}$ ($a_{reb}^t = \{a_{reb}^{i,j,l,t}\}, \forall\, i, j \in N, \forall\, l \in L$) as the rebalancing strategy and $a_{cha}^t \in \mathbb{N}^{N \times N \times L}$ ($a_{cha}^t = \{a_{cha}^{i,j,l,t}\}, \forall\, i, j \in N, \forall\, l \in L$) as the charging strategy at time slot t, considering the scheduling of the vehicles of different remaining energy levels in different regions. $a_{reb}^{i,j,l,t}$ and $a_{cha}^{i,j,l,t}$ are rebalancing and charging strategies for vehicles with remaining energy level l between region i and region j. So, the scheduling $\{a_{reb}^t, a_{cha}^t\}$ is formulated as:

$$\{a_{reb}^t, a_{cha}^t\} = f_s(S_t, F_{t:t+h}), \tag{2}$$

where f_s is the function taking the vehicle supply and future demand as input and outputting the rebalancing and charging strategy.

Cost: After determining $\{a_{reb}^t, a_{cha}^t\}$, we compute the optimal truck routes for the actual rebalaning and charging, which introduces monetary cost to the system operator, i.e., electricity payment for charging batteries C_t^c and traveling cost of trucks C_t^r. In summary, we use the following equation to describe the monetary cost of scheduling:

$$C_t^s(a_{reb}^t, a_{cha}^t) = C_t^c + C_t^r \tag{3}$$

Note that other potential costs can be easily integrated in the equation.

Objective: Our goal is to develop an optimal algorithm to provide effective rebalancing and charging schedules for shared electric micromobility vehicles, in order to maximize the total net revenue R (i.e., total income from serving users minus the cost of rebalancing and charging):

$$argmax_{a_{reb}^t, a_{cha}^t}\ R = \sum_{t=1}^{T} f_{trip}(S_t, F_t) - \sum_{t=1}^{T} C_t^s(a_{reb}^t, a_{cha}^t) \tag{4}$$

4 DESIGN

In this section, we first introduce our rebalancing and charging framework based on multi-agent reinforcement learning (MARL). Then we introduce how energy-informed demand is fused into different parts of our framework.

4.1 Multi-agent Reinforcement Learning

Motivated by existing work [30], we model the problem of rebalancing and charging shared electric micromobility vehicles as a cooperative Markov game G for N agents, which is defined by a tuple $G = \{\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma\}$. $\mathcal{S}$ represents the set of states. $\mathcal{A}$ denotes the action space of agents. $\mathcal{R}$ is the reward function. $\mathcal{P}$ denotes the transition probability function. γ is the discounted factor. We give the definitions of these notations as follows.

Agent: We define an agent for each region, which decides rebalancing and charging for all the vehicles in the region. The reason that we define an agent for each region rather than a centralized agent for the whole city is that a centralized agent can introduce large action and state space [21, 33], which is computationally intractable.

State: At the beginning of the time slot t, the state of region i is defined as $\mathbf{s}_t^i = \{S_t^i, F_{t:t+h}\}$. S_t^i denotes the set of available vehicles in region i at time slot t. Specifically, $S_t^{i,l}$ is the number of available vehicles with remaining energy level l in region i at time slot t. $F_{t:t+h}$ denotes the energy-informed demand from slot t to $t+h$, which is predicted by a pre-trained prediction model[33].

Action: Agent i for region i takes a set of actions $a_t^i = \{a_{reb}^{i,j,l,t}, a_{cha}^{i,j,l,t}\}$, given the current state s_t^i. $a_{reb}^{i,j,l,t}$ denotes the shared electric micromobility vehicles with remaining energy level l that are relocated from region i to region j at time slot t, and $a_{cha}^{i,j,l,t}$ is the proportion of the vehicles with energy level l that are rebalanced from region i to region j and charged at time slot t.

Reward: The reward of an agent is defined by the trip revenue from serving users, the average traveling cost of truck-based scheduling, and the cost of charging vehicles (i.e., the number of vehicles' batteries swapping).

$$r_t^i = T_{trip}^t - \alpha \cdot \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{l=1}^{L} a_{cha}^{i,j,l,t} - \beta \cdot M, \tag{5}$$

where T_{trip}^t is the total trip revenue at time slot t, α is the coefficient of the transformation to monetary reward, which is determined by the vehicle electricity volume and current electricity price. β is another coefficient of the transformation to monetary reward, determined by truck fuel consumption and current fuel price. M is the total truck mileage for the whole city.

Transition probability function: Transition probability function denotes the probability of state s_t transferred to the next state s_{t+1} given the action a_t.

Discounted factor: Discounted factor γ represents the extent that the agents pay attention to the future reward compared with the immediate reward, $\gamma \in [0, 1)$. If $\gamma = 0$, it indicates that the agent only cares about the immediate reward and learns the actions that cause the immediate reward.

Based on the above setting, the objective of all region agents is to collaboratively maximize expected average cumulative reward, i.e., $G_t = [\sum_{t=1}^{\infty} \gamma^{t-1} \sum_{i=1}^{N} R(s_t^i, a_t^i)|s_1 = s]$. The Q-value of joint state s_t and action a_t under policy π_θ is denoted by: $Q^{\pi_\theta}(s_t, a_t) = E[\sum_{k=0}^{\infty} \gamma^k \sum_{i=1}^{N} R(s_{t+k+1}^i, a_{t+k+1}^i)|\pi_\theta, s_t, a_t]$.

4.2 Design Overview

We design a framework based on multi-agent reinforcement learning for rebalancing and charging shared electric micromobility vehicles, as shown in Fig. 4. We regard the problem as interactions between region agents and the shared electric micromobility system environment. Consequently we formulate it as a Markov Decision Process (MDP). In the MDP, we define an agent for each region and region agents make decisions about how to rebalance and charge the shared electric micromobility vehicles in their regions. Based on the historical records, demand prediction module aims to predict the future energy-informed demand as a part of the inputs of agents' policies and action supervision module. Based on the current states, region agents' policies output the rebalancing and charging strategies to meet the future energy-informed demand. To prevent region agents from selecting inefficient actions, the predicted energy-informed demand is fused to supervise the actions that region agents provide. Given the rebalancing and charging strategies provided by region agents, the truck route optimization module is used to provide optimal truck routes for schedules, reducing truck traveling cost. The immediate reward is the net revenue, covering the trip revenue, truck traveling cost for rebalancing, and charging cost. Then the region agents try to improve their own policies based on the reward. Our objective is to maximize the long-term net revenue of the whole system.

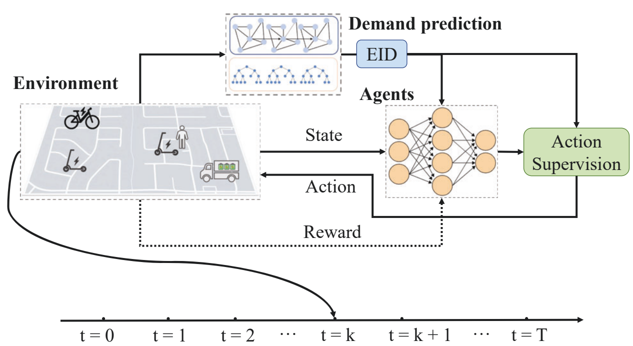


Figure 4: An overview of DRL framework for rebalancing and charging e-scooter sharing system with energy-informed demand (EID)

4.3 Prediction of Energy-informed Demand

In our model, the energy-informed demand plays an important role in replacing and charging where we consider both trip-informed demand prediction and energy consumption estimation.

For the trip-informed demand prediction, we predict the number of trips between each region pair at each time slot before the next scheduling, i.e., $f_k^{i,j}$ $(k \in \{t, t+1, ..., t+h\})$. Here, $f_k^{i,j}$ denotes the number of trips from region i to region j at time slot k. To achieve the trip-informed demand prediction, we regard the whole city as a graph where each grid is a node and use a spatial temporal graph convolutional network [36], which inputs the historical shared electric micromobility vehicle usage, so as to predict the future vehicle flows.

In energy consumption estimation, our goal is to predict the energy consumption distributions of trips between each pair of regions, denoted as $e_k^{i,j,l}$ $(k \in t, t+1, ..., t+h)$. Here, $e_k^{i,j,l}$ represents the ratio of trips starting from region i to region j during time slot k with energy consumption l. To achieve this estimation, we employ an XGBoost-based model[3]. This model takes into consideration various factors such as spatial features (e.g., region index, points of interest), temporal features (e.g., day of the week, hour of the day), external factors (temperature, weather), and historical records as inputs to predict the distributions of different energy consumption levels.

After getting the predicted number of trips and energy consumption distributions, we combine them together to get the predicted energy-informed demand of each region pair:

$$F_k^{i,j,l} = f_k^{i,j} e_k^{i,j,l}, \tag{6}$$

where $F_k^{i,j,l}$ denotes the number of trips with energy consumption level l starting from region i to region j at time slot k, $k \in \{t, t+1, ..., t+h\}$, and the predicted energy-informed demand beginning at timeslot k is defined as: $F_k = \{F_k^{i,j,l}\}, \forall\, i, j \in N, \forall\, l \in L$.

4.4 Incorporate Energy-informed Demand into Different Steps

In this section, we introduce how energy-informed demand is fused in different steps of the general RL-based framework.

4.4.1 RL agent with energy-informed demand: In order to fulfill users' energy consumption requests, region agents in MARL aim to develop effective strategies for rebalancing and charging shared electric micromobility vehicles within their respective regions. Considering the energy-informed demand, we classify the vehicles in each region into several groups based on their remaining energy levels, i.e., $S_t^{i,l}$, which denotes the number of vehicles with energy level l in region i at time slot t. We then include the predicted energy-informed demand $F_{t:t+h}$ as part of an agent's state. Consequently, the policy of each region agent considers the distributions of the vehicles with different remaining energy levels in its own region and the future energy-informed demand.

A vehicle not only needs to be vacant but also must have sufficient energy to transport a user from the origin to the destination. To accommodate as much of the energy-informed demand as possible, we differentiate the vehicles based on their remaining energy and rebalance vehicles with varying energy levels among the regions. This approach allows us to integrate energy-informed demand into the agent's action. The rebalancing action of a region agent is defied as $a_{reb}^{i,j,l,t}$, which denotes the proportion of shared electric micromobility vehicles with remaining energy level l to be rebalanced from region i to region j at time slot t. Considering the dynamic spatio-temporal energy consumption, some vehicles have to be charged before rebalancing, even though their remaining energy is still high, while some vehicles don't have to be charged, even though their remaining energy is still low. So, we define $a_{cha}^{i,j,l,t}$, which denotes the proportion of shared electric micromobility vehicles of energy level l to be rebalanced from region i to region j and need to be charged at time slot t. The supply of vehicles is changed by the above actions:

$$S_{t+1}^{i,l} = S_t^{i,l}(1 - \sum_{j=1}^{N} a_{reb}^{i,j,l,t} + \sum_{j=1}^{N} a_{reb}^{j,i,l,t}) \tag{7}$$

$$S_{t+1}^{i,L} = S_t^{i,L}(1 - \sum_{j=1}^{N} a_{reb}^{i,j,L,t} + \sum_{j=1}^{N} a_{reb}^{j,i,L,t} + \sum_{j=1}^{N}\sum_{l=1}^{L-1} a_{cha}^{i,j,l,t}) \tag{8}$$

From the above definitions, we build the relationship between state and action, with energy-informed demand.

4.4.2 Demand-Guided Policy Learning: Even though we consider each region as an agent, the process of rebalancing and charging shared electric micromobility vehicles with different remaining energy levels among regions is still complicated, considering the division of regions and energy levels. As a result, the search space of agent policies needs to be narrowed down. Specifically, we aim to prevent the agent from selecting inefficient actions. Therefore, we design action supervision module to achieve this goal.

In this module, we utilize the future h-hour energy-informed demand $F_{t:t+h}$ to supervise the actions taken by region agents. Specifically, we use these demands to simulate the operation of an electric micromobility system, allowing us to determine the number of user requests that can be satisfied. Each predicted demand can only be fulfilled by vehicles with remaining energy levels equal to or higher than its energy consumption level. The remaining energy levels of the vehicles decrease after completing trips based on the energy consumption levels associated with their matched demand. Following the simulation of the system using predicted energy-informed demand, we calculate the trip revenue by considering the number of users' predicted demand satisfaction and the average trip duration based on historical data of shared electric micromobility vehicle usage. Hence, we obtain the predicted net revenue, considering future trip revenue, truck traveling cost, and charging cost:

$$R_{pre}^t(F_{t:t+h}, a_t) = T_{pre} - \alpha \cdot \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{L} a_{cha}^{i,j,l,t} - \beta \cdot M_{pre}, \tag{9}$$

where T_{pre} and M_{pre} are the total time duration and truck mileage cost in the simulation of the electric micromobility system operation with predicted energy-informed demand. The definitions of α and β are the same as those in Eq. (5). We then determine whether the actions provided by region agents should be executed, considering whether the future net revenue is non-negative. Since our aim is to ensure that the joint actions of rebalancing and charging have a long-term impact on future vehicle usage, it indicates that region agents are choosing ineffective actions if they do not result in positive future trip revenue. In such cases, these actions may be abandoned, and no schedules will be generated for shared electric micromobility vehicles in the current time slot:

$$a_t' = \begin{cases} 0 \ or \ a_t & R_{pre}^t(F_{t:t+h}, a_t) < 0 \\ a_t & R_{pre}^t(F_{t:t+h}, a_t) \geq 0 \end{cases}$$

4.5 Truck Route Optimization

In this section, we formulate the truck route optimization problem as a spatial-temporal mixed integer programming (STMIP) problem and introduce its objectives and constraints to generate optimal truck routes for scheduling shared electric micromobility vehicles.

Since the electric micromobility system after rebalancing try to satisfy all the demand in the next m hours, we assume that the truck-based rebalancing needs to be done in the next one hour to minimize the impact of demand loss. Accordingly, we divide one hour into T' time slots. Through scheduling policies, we can easily know the energy distribution of shared electric micromobility vehicles before and after the scheduling, denoted as $d_{i,l}^o$, $d_{i,l}^r$. They are sent as inputs to STMIP to generate the feasible truck routes for rebalancing and charging shared electric micromobility vehicles.

The variables used in the model are defined as follows: $x_{i,j,v,t}$ denotes if truck v visits region i at the beginning of time slot t and departs from region i to region j at the end of time slot t. Based on $x_{i,j,v,t}$, we define $\theta_{i,v,t}$ that if truck v is present in region i at time slot t. $P_{i,l,v,t}$ and $D_{i,l,v,t}$ denote the number of shared electric micromobility vehicles of energy level l to be picked up and dropped off by truck v in region i at time slot t respectively.

Since we know $d_{i,l}^o$, $d_{i,l}^r$, the distribution of shared electric micromobility vehicles of different energy levels before and after the rebalancing, we want to finally transform the origin distribution to the rebalanced distribution, as shown in the following equation:

$$d_{i,l}^o + \sum_{t=1}^{T'}\sum_{v=1}^{V} D_{i,l,v,t}\theta_{i,v,t} - \sum_{t=1}^{T'}\sum_{v=1}^{V} P_{i,l,v,t}\theta_{i,v,t} = d_{i,l}^r \tag{10}$$

We define $Q_{v,t}$ that represents the truck load of truck v at time slot t to build the temporal relationship between $P_{i,l,v,t}$ and $D_{i,l,v,t}$:

$$Q_{v,t} = Q_{v,t-1} + (\sum_{i=1}^{N}\sum_{l=1}^{L} P_{i,l,v,t} - \sum_{i=1}^{N}\sum_{l=1}^{L} D_{i,l,v,t})\theta_{i,v,t} \tag{11}$$

To make sure that each truck visits and departs from only one region, we define $\theta_{i,v,t}$ that represents if truck v is present in region i at time slot t. We also set the constraints on it:

$$\theta_{i,v,t} = \sum_{j=1}^{N} x_{i,j,v,t}, \quad \sum_{i=1}^{N} \theta_{i,v,t} = 1 \tag{12}$$

Besides $x_{i,j,v,t}$, we also define $c_{i,j}$ and D_{max} as the distance between region i and region j and the longest distance that truck can reach in one time slot, so as to set a constraint on truck reachability:

$$c_{i,j}x_{i,j,v,t} < D_{max} \tag{13}$$

The objective of our STMIP model is to minimize the final total truck mileage cost, formulated as follows:

$$\min \sum_{v=1}^{V}\sum_{t=1}^{T'}\sum_{i=1}^{N}\sum_{j=1}^{N} c_{i,j}x_{i,j,v,t} \tag{14}$$

5 EVALUATION

In this section, we conduct experiments to evaluate our models, answering the following research questions:

- RQ1: How does our model perform, compared with other baselines?
- RQ2: How effective are the energy-informed demand (EID) in the scheduling of rebalancing and charging shared e-scooters in our model?
- RQ3: How much impact does the action supervision module (AS) have on the convergence of our model?
- RQ4: How do factors impact the performance?

5.1 Evaluation Methodology

Dataset: We conduct our experiments based on a real-world shared e-scooter usage data. More details can be seen in Section 2.
Experiment settings: We divide the dataset into two parts: one month's usage data is used for the training set, and another month's data is used for the test set. We divide the remaining energy and energy consumption into 10 levels, ranging from 0 to 100. In terms of region division, each region has a size of 800 $meters \times 800$ $meters$ in the experiments. We divide a day into 24 equally-length time intervals, and the interval of rebalancing and charging schedules is 12 hours. For truck route optimization, we set the max truck load to be 30 e-scooters, the max truck number to be 20. The maximum reachable distance per unit time interval is 5km. We divide one hour into 20 equally-length time intervals for truck routes. The trip revenue is \$0.5 per minute. The truck traveling cost per kilometer is set at \$2.422. The charging cost is valued at \$0.69 per e-scooter.
Implementation: We implement our method and baselines with PyTorch 1.9.1, Python-mip 1.14.2, gym 0.21.0 in Python 3.7 environment and train it with 32 GB memory and GeForce RTX 3080 Ti GPU. Stochastic gradient descent optimizer is applied to minimize the loss, and the learning rate is 1e-4. The max training episode number is 1900, and discounted rate $\gamma = 0.99$. Abandonment rate in the action supervision module is 0.5.
Baselines: We evaluate the performance of our model with the following four baselines:

- **No Rebalance & Charging (NRC)**: It simulates the e-scooter sharing system operation without rebalancing and charging actions.
- **State-of-The-Practice (SoTP)**: It represents the practice scheduling used by our platform collaboration, which is based on a static charging threshold.
- **MADDPG** [21]: It is a multi-agent reinforcement learning framework to achieve the cooperative or competitive relationship of agents in the environment.
- **Record** [30]: It is a state-of-the-art electric carsharing rebalancing and charging algorithm based on the definition of the dynamic deadline for scheduling.

Variants of our model: We also consider the significance of different variants of our models:

- **Our model without energy-informed demand (w/o EID)**: In order to verify the importance of energy-informed demand, we remove it and use trip-informed demand instead. However, we still use demand with energy consumption during real-world simulation in the environment to get the trip revenue. Besides this, we replace the dynamic charging threshold with the static charging threshold.
- **Our model without action supervision module (w/o AS)**: To demonstrate the effect of action supervision, we remove this module. Therefore, any rebalancing or charging action is directly sent to truck route optimization module.

5.2 Overall Performance (RQ1)

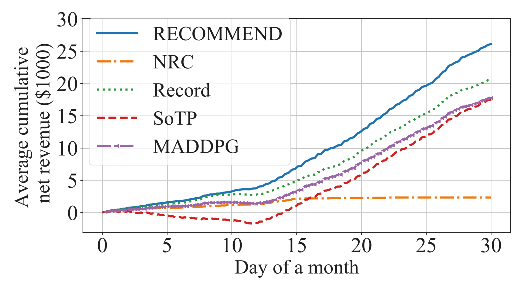


Figure 5: Total net revenue of different approaches

To evaluate the model performance, we focus on the cumulative net revenue in one month. Fig 5 shows that the final cumulative net revenue of RECOMMEND is higher than that of other baselines obviously. The daily revenue is also higher than others in most of the time. Compared with state-of-the-art works, RECOMMEND achieves a significant improvement in net revenue, with an increase of 26.89%. One possible reason is that other baselines assume that other baselines assume homogeneity among trips within the same region pair and simply attempt to match the number of available e-scooters with the incoming demand. As a result, the scheduled vehicles may not be qualified to be picked up by users due to the limit of remaining energy. Even though these vehicles may temporarily satisfy immediate energy consumption requests, their low-battery status prevents them from being used multiple times before the next scheduling. In addition, other baselines may cause too much unnecessary charging because of their static charging threshold. For example, if certain vehicles can fulfill user demands with low-energy consumption for several days in regions where demand is scarce, they may not need to be charged even if their remaining energy falls below the charging threshold. Conversely, some vehicles may require premature charging when there are future requests with high energy consumption, even if their remaining energy is higher than the static charging threshold. Table 2 demonstrates that not only does RECOMMEND outperform other baselines in terms of trip revenue and average satisfaction rate, but it also exhibits lower total costs, particularly in regard to charging costs. This provides further support for our assertion.

Though the demand prediction and energy consumption estimation are challenging problems, they are not the focus of our work. The key contribution is to consider energy-informed demand in the rebalancing and charging of shared electric micromobility systems, leading to our key technical design of incorporating energy-informed demand in a MARL-based framework. We use metrics of mean absolute error (MAE) and mean square error (MSE) to evaluate the performance of trip-informed demand prediction and energy consumption estimation. The evaluation results are shown in Table 3. How to improve the prediction performance will be our future work.

Table 2: Performance comparison of different approaches on the real-world data

Method	Trip Revenue ($)	Total Cost ($)	Net Revenue ($)	Charging Cost ($)	Daily Average Revenue ($)	Average Satisfaction Rate (%)
Record [30]	24236.90 (±196.19)	3655.52 (±86.21)	20581.38 (±140.38)	992.22 (±23.39)	807.90 (±6.54)	81.6
MADDPG [21]	23766.0 (±189.14)	5505.89 (±79.50)	18260.11 (±121.97)	1696.71 (±24.49)	792.20 (±6.30)	79
SoTP	23842.28	6104.80	17737.47	2066.55	794.74	81.25
NRC	2340	-	2340	-	78	7.9
RECOMMEND	**28062.5 (±185.78)**	**1946.38 (±67.62)**	**26116.12 (±114.46)**	**511.29 (±17.76)**	**935.41 (±6.19)**	**94.5**

Table 3: Performance of energy-informed demand prediction

Category	MAE (%)	MSE (%)
Trip-informed demand prediction	3.24	2.96
Energy consumption estimation	3.09	1.23

Table 4: Performance comparison of different variants in EID

Method	Trip Revenue ($)	Total Cost ($)	Net Revenue ($)
w/o EID in state	22607.50 (±183.84)	3286.49 (±62.14)	20321.01 (±114.64)
w/o EID in action	24779.99 (±180.23)	5422.15 (±74.64)	19357.84 (±120.09)
RECOMMEND	**28062.5 (±185.78)**	**1946.38 (±67.62)**	**26116.12 (±114.46)**

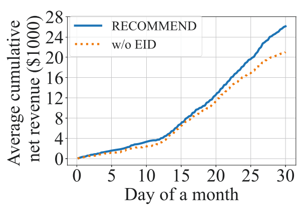


Figure 6: The effect of energy-informed demand

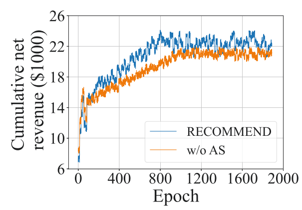


Figure 7: The significance of action supervision

5.3 Ablation Study (RQ2 & RQ3)

The effect of energy-informed demand: Fig. 6 shows the cumulative net revenue of our model and its variant EID. When we do not consider the energy-informed demand, and charge e-scooters according to the static charging threshold instead, even if the system sometimes is able to satisfy all the real-world demands, it first cannot make vehicles charged ahead of time to meet the users' energy consumption requests which are higher than the charging threshold, and unnecessarily charge the vehicles in the regions with few low-energy consumption demands. As a result its total cumulative net revenue must be lower than our model (less trip revenue and more charging cost). We also develop two variants by removing the EID module from the state part and the action supervision part, respectively. The evaluation results in Table 4 can demonstrate the importance of EID structure.

The significance of action supervision: After each episode, we save the total net revenue to see the changes of total net revenue of our model in the training process. Fig. 7 shows the progression of the net revenue as we train models. And we can see that compared with the variant AS, our model is faster to converge by 16.8%. The possible reason is that the action supervision possibly filters the inefficient scheduling strategies and narrows the search space for policy optimization. Without it, the model may usually choose the "bad" behaviors and need more time to improve its policy.

Table 5: Performance comparison under different scheduling intervals

Method	Trip Revenue ($)	Total Cost ($)	Net Revenue ($)
3-hour interval	27830.93 (±186.79)	7523.86 (±69.17)	20307.07 (±124.04)
24-hour interval	26017.07 (±182.71)	1428.12 (±65.83)	24588.95 (±109.85)
12-hour interval	**28062.5 (±185.78)**	**1946.38 (±67.62)**	**26116.12 (±114.46)**

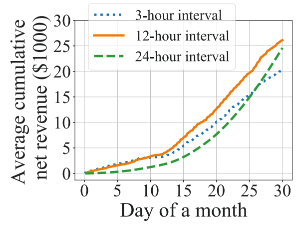


Figure 8: The effect of schedule interval

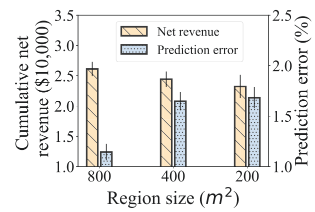


Figure 9: The effect of region size

Table 6: Net revenue under different prediction errors

Prediction error (%)	2.32	2.62	3.38	3.39
Net revenue ($/trip)	2.37	2.28	2.09	2.08

5.4 Impact of Factors (RQ4)

Rebalancing & charging interval: Fig. 8 shows the performance comparison $w.r.t.$ interval of scheduling of rebalancing and charging for shared electric micromobility system. The best interval of scheduling is 12 hours. It indicates that even though short-interval scheduling may satisfy more user's energy-informed demand, it increases much more scheduling costs, which decreases the final net revenue. In addition, although long-interval scheduling reduces the scheduling cost, it makes more energy-informed demand unsatisfied, under the quantity limit of shared electric micromobility vehicles in a region, which also decreases the final net revenue. The results in Table 5 support our opinion.

Region size: Fig. 9 displays the average cumulative net revenue and prediction error of energy-informed demand under different region sizes. The optimal region size is 800m × 800m. It indicates that the smaller region size leads to more individual regions in a city, which complicates the truck routes and causes more truck traveling costs. In addition, the smaller region size leads to the bigger size of the flow matrix of the system vehicle usage, which complicates the prediction task, causing higher prediction error. However, too big size of region will lose the mobility of vehicles of the city, and the inter-region scheduling problem may transform into an intra-region scheduling problem.

Prediction error: We conduct experiments to reveal how the prediction error affects the model performance, as shown in Table 6. It shows that the prediction error has a significant impact on the

Table 7: Performance comparison under differernt prediction errors

Method	Trip Revenue ($)	Total Cost ($)	Net Revenue ($)	Charging Cost ($)	Average Satisfaction Rate (%)
Oracle	29083.93 (±184.61)	1953.77 (±63.57)	27130.16 (±110.43)	687.44 (±15.84)	97.9
w/o prediction	24039.9 (±201.11)	3834.29 (±89.72)	20205.61 (±154.17)	1014.36 (±24.19)	79.2
RECOMMEND	**28062.5 (±185.78)**	**1946.38 (±67.62)**	**26116.12 (±114.46)**	**511.29 (±17.76)**	**94.5**

model performance, and the worse prediction generally leads to worse performance. In addition, we introduce an oracle method (i.e., the prediction is 100% correct) as an upper bound of the performance and a variant without future prediction. The results in Table 7 show that our performance is very close to the oracle method with an overall low prediction error.

6 DISCUSSION

Lessons: Based on the results from our work, we summarize the following learned lessons:

- *Rebalancing and charging shared electric micromobility vehicles should take the energy-informed demand into consideration*, which makes it significantly different from the traditional rebalancing and charging approaches based on trip-informed demands.As shown in Table. 2, both the trip revenue and the scheduling cost are directly impacted when ignoring the energy consumption of users' demands.
- *Multi-agent reinforcement learning should consider filtering impossible actions considering the large optimization space*, which improves its efficiency to converge, shown in Fig. 7.

Limitations: (i) We evaluate our model RECOMMEND on a real-world dataset. However, due to its privacy, the period of the evaluation dataset is only one month and only in New Brunswick. We expect to analyze our model in multiple scales of cities as well as long terms. (ii) we only consider directly utilizing predicted energy-informed demand to help generate and supervise the rebalancing and charging actions. The further use of energy-informed demand will be considered as our future work.

Ethics and privacy: The vehicle and trip information utilized in our work is offered by a shared electric micromobility provider. For trip information, all the user ID, trip ID, and vehicle ID have been anonymized by the provider. We utilize the vehicle information (locations, time, remaining energy) when the vehicle state changes and generate the vehicle mobility in the system.

Different charging methods: Our work uses battery-swapping as the charging method, given the practice from our platform collaboration. However, we envision our methods can be easily extended to other charging methods, such as centralized charging by moving vehicles to a charging station. Note that the output from our reinforcement learning is which vehicle to relocate and which to charge. This is independent of the concrete charging methods. The only adaption needed is to change the truck routing, which can be achieved by modifying Equation 14 with additional travel distances between regions and the charging station.

7 RELATED WORK

Non-electric vehicle rebalancing: Some researchers have focused on the rebalancing non-electrically-driven shared vehicles, such as shared bicycles [7, 10, 15, 17, 18, 23, 24, 33]. A budgeting system was constructed to motivate users to help the bike-sharing system relocate bicycles after travel, and a deep reinforcement learning framework was designed, which has widely used in real-world resource allocation system [7, 15, 24, 33], to simulate this user-motivated bicycle rebalancing problem. [18, 23] considered rebalancing bikes on use of bike-trailers. [10, 17] considered the shared bike rebalancing problem as a truck-based rebalancing problem, and clustered the regions based on station community discovery and generate the rebalancing problem as a spatial-temporal mixed integer programming problem.

Electric vehicle rebalancing & charging: Another part of research focuses on the electricity-driven vehicles, such as shared electric cars [9, 22, 30, 31, 38, 41]. [41] cared about the investment cost of purchasing electric cars and hiring staff for rebalancing. They formulate this problem as a mixed integer linear programming optimization problem to find the best scheduling strategy. [38] designed a novel charging strategy of proactive partial charging, which allows e-taxis to get partially charged before they are in battery-low status. They considered the idle time to travel to charging stations and waiting time at charging stations as costs and proposed a charging and SPMIP-based relocating framework to optimize the scheduling strategy. [22] cared about the increase of stations that store shared electric cars and achieved rebalancing and charging by giving users monetary reward to encourage them to rebalance electric cars after use. They try to maximize the revenue of the electric car sharing system with minimum cost on user incentives. [30, 38] tried to find the dynamic deadline for rebalancing and charging shared electric cars. Besides caring about the overall profit efficiency, [9, 31] focused on the profit fairness of electric taxi fleets by considering both the passenger travel demand and taxi charging demand, designing a centralized multi-agent actor-critic approach to tackle this problem. Different from their works, we focus on energy-informed demand and design a rebalancing and charging framework with energy-informed demand.

8 CONCLUSION

In this work, we focus on the problem of rebalancing and charging shared electric micromobility vehicles. We design a multi-agent reinforcement learning framework called RECOMMEND, which incorporates energy-informed demand and an action supervision module, to make vehicles meet as many users' energy consumption requests as possible while reducing the unnecessary charging cost. The evaluation results show that RECOMMEND achieves an improvement of at least 26.89% in net revenue compared with other state-of-the-art works.

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