Joint Rebalancing and Charging for Shared Electric Micromobility Vehicles with Human-system Interaction

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ABSTRACT

The use of shared electric micromobility vehicles, such as bikes and scooters, has become increasingly popular. It leads to the problem of management (i.e., rebalancing and charging). Existing approaches typically assume that all vehicles have an equal chance of being selected for a ride, which is not practical. To overcome this limitation, we propose a reinforcement-learning-based framework incorporating human-system interaction. We first predict the likelihood of each vehicle being selected, then integrate this prediction into the reinforcement learning framework. The aim is to create a more realistic simulation process to guide policy learning more effectively. Our experimental results demonstrate the effectiveness of incorporating human-system interaction.

CCS CONCEPTS

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

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1 INTRODUCTION

The use of shared micromobility vehicles, such as bikes and scooters, has become increasingly popular in urban transportation [1]. These vehicles provide a convenient and eco-friendly alternative to conventional automobiles, particularly for short-distance trips. They also support multi-modal transportation by complementing public transit systems. However, as the number of shared micromobility vehicles continues to increase in cities, effective management of these vehicles has become a significant challenge. One such challenge is to balance the distribution of vehicles to different regions to meet the spatial and temporal demand [2], especially considering the recent blooming of electric micromobility vehicles that require charging while rebalancing [3]. Thus, this work aims to design an efficient shared electric micomobility management framework considering both rebalancing and charging.

A general shared electric micromobility vehicle system consists of four key components: a system operation center, users, vehicles, and trucks. To start a ride, a user unlocks an available vehicle from their smartphone and rides it to their destination. The vehicle automatically reports its status (e.g., location and energy level) to the system operation center. After a certain period of usage (e.g., one day), the system operation center generates a plan for rebalancing and charging vehicles based on the status of all vehicles in the system. The plan specifies which vehicles need to be relocated and which vehicles need to be charged. The center then sends the plan to the trucks. The trucks follow the plan to perform rebalancing and charging activities as needed.

Existing works on electric vehicle management [3, 4] focus on relocating vehicles to different regions to match future demand based on a learned rebalancing and charging policy. To learn the optimal policy, they set up a simulation environment using historical user request data. In this environment, the demand is simulated using historical data on user requests, such as pickup locations, drop-off locations, and energy consumption. For each request, the simulation environment randomly assigns a vehicle with sufficient energy levels (higher than the energy consumption) near the pickup location to the user. After multiple rounds of simulation, the rebalancing and charging policy is learned, with a maximized reward based on factors such as request satisfaction ratio and total revenue. However, this learning paradigm has a key limitation in that it does not consider user preferences in selecting vehicles, i.e., human-system interaction. It assumes that each vehicle has an equal chance of being selected [5]. Our research has found that this assumption does not hold, as different vehicles have significantly different chances of being selected due to factors such as remaining energy levels and vehicle conditions (new or old) (see Section 2 for details). This issue means that existing simulation processes cannot reflect real-world vehicle usage patterns.

We propose a rebalancing and charging framework for shared electric micromobility vehicles that considers human-system interaction. We first model human-system interaction as vehicle selection and predict the vehicle selection based on their characteristics. Then, using this prediction, we incorporate human-system interaction into a general Reinforcement Learning (RL) framework to guide policy learning. Our preliminary data-driven analysis and experimental results show that human-system interaction is an important factor to be considered in micromobility vehicle management and can be used to learn a better scheduling policy.

2 MOTIVATION

We define a matrix called the *selection probability* matrix to represent the probability that a vehicle is selected in past trips, showing how likely a vehicle is to be selected by a user. Figure 1 presents the distribution of vehicle selection probabilities based on the data from our collaborated micromobility service platform, revealing that different vehicles have different probabilities of being selected.

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Thus, the assumption that each vehicle has an equal chance of being selected is not practical.

We compare the distribution of vehicles in different regions (divided into equal-sized grids) when considering human-system interaction (i.e., user preference-based vehicle assignment) versus random vehicle assignment. We divide vehicle energy into 10 levels and count the number of vehicles in each level. We then calculate the difference between the two assignment methods for each level and aggregate the results in a box plot, shown in Fig. 2. The plot clearly illustrates a significant difference in the number of vehicles with different energy levels when considering human-system interaction, which indicates that ignoring human-system interaction results in a simulation process that cannot accurately reflect real-world vehicle usage patterns.

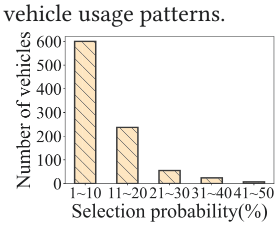

Figure 1: The distribution of vehicle selection probabilities

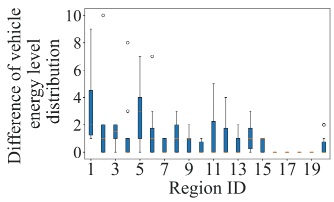

Figure 2: The impact of interaction on vehicle energy level distributions in all regions

3 PROPOSED FRAMEWORK

We formulate the vehicle scheduling problem as a cooperative Markov game G for N agents (i.e., each region as an agent) following [6], which is defined by a tuple $G = \{\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma\}$. $\mathcal{S}$ represents the set of states of region agents (e.g., the number of vehicles and their energy levels). $\mathcal{A}$ denotes the action space of agents (i.e., where a vehicle should be relocated to and which vehicles should be charged). $\mathcal{R}$ is the reward function, calculating the net revenue based on the trip revenue and cost. $\mathcal{P}$ denotes the transition probability function. γ is the discounted factor. To achieve efficient scheduling, a multi-agent reinforcement learning (MARL) method is used to learn the policy, as shown in Figure 3. At each time slot, each agent gives an action based on its own state and policy. Then the users request vehicles at different locations and time slots. After a certain time period (e.g., a day), the agent receives the reward, updates its policy, and gives the next action.

For vehicle selection prediction, we design an XGBoost-based model [7], considering five significant characteristics of the vehicle itself (selection probability, remaining energy levels, nearby vehicles, historical trips, and rank of energy in the nearby vehicles). The output is which vehicle is selected for each request. Table 1 shows the prediction results. The prediction model is used in the simulation process to assign vehicles for each user request.

Table 1: Performance of vehicle selection prediction

AUC (%)	ACC (%)	Recall (%)	F1 (%)	Precision (%)
79.49%	82.05%	72.46%	71.96%	71.47%

4 EXPERIMENTS & FUTURE WORK

We conducted comparison experiments using different approaches to demonstrate the effectiveness of considering human-system interaction, including MARL with interaction, MARL without interaction, NB (no rebalancing), and SoTP (the practical scheduling

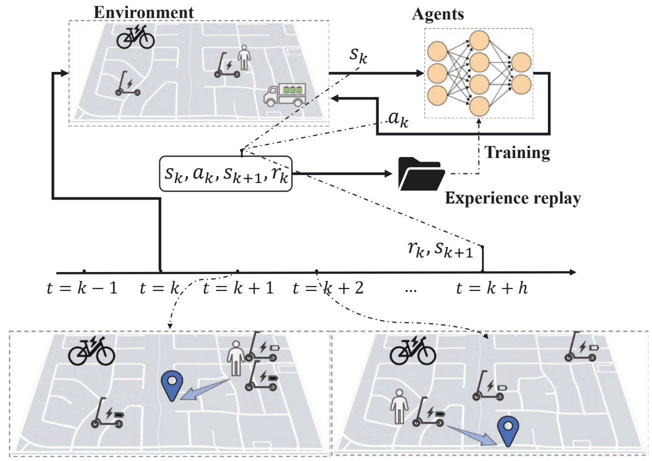

Figure 3: RL-based scheduling framework

used by our collaborative platform). Figure 4 shows their performance in terms of net revenue. Compared to MARL without interaction, MARL with interaction can achieve a better net revenue.

In the future, we will conduct a more comprehensive data analysis on the factors that influence human vehicle selection and improve its prediction. We will further enhance the MARL framework for rebalancing and charging by adding more agent information and constraints to achieve better net revenue. Additionally, we will explore how to incorporate human-system interaction into the MARL framework to guide policy learning.

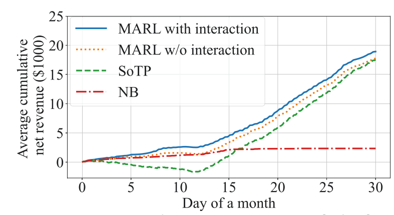

Figure 4: Total net revenue of different approaches

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