

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

Heng Tan¹, Yukun Yuan², Shuxin Zhong³, Yu Yang¹

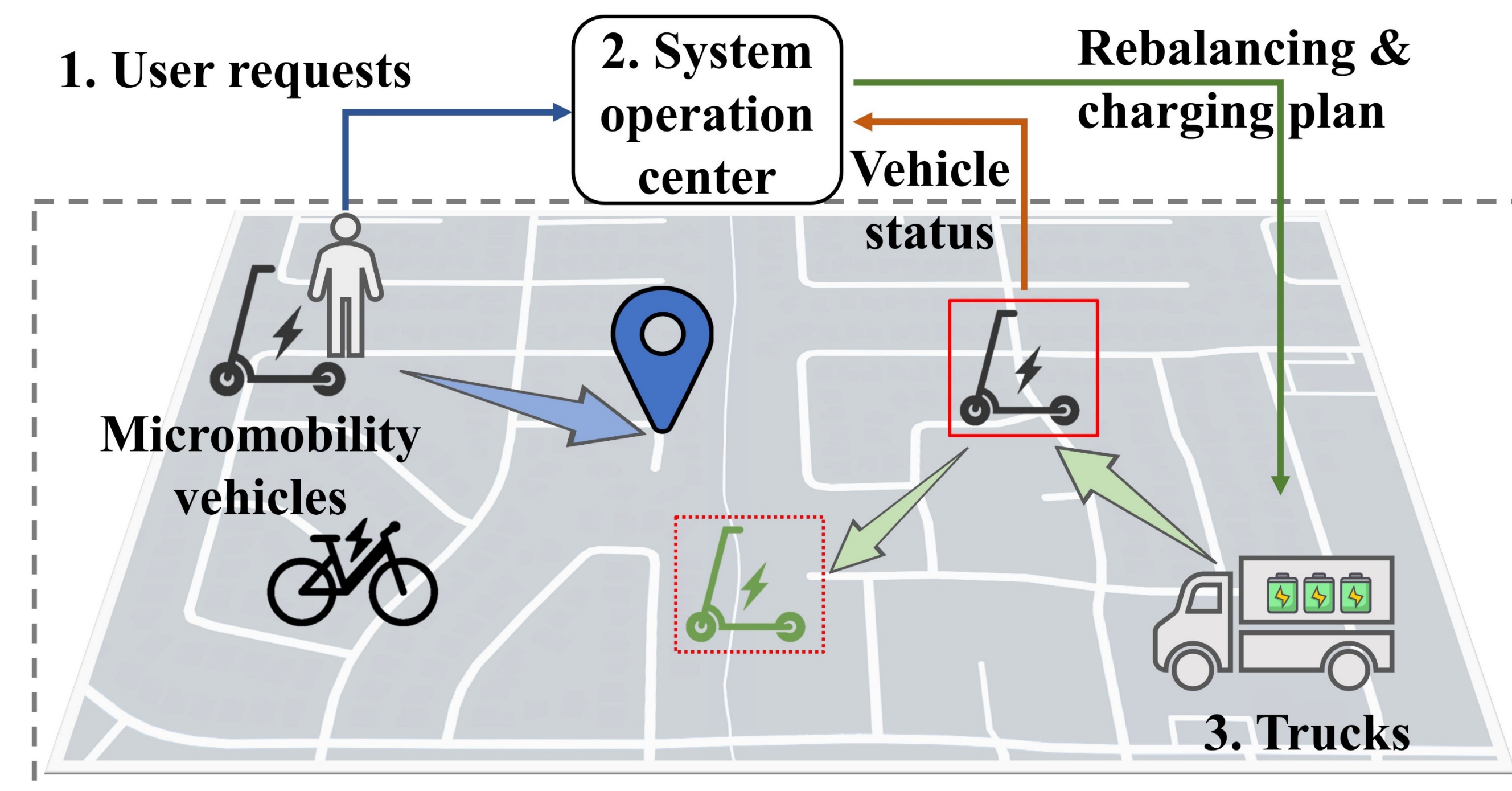
¹Lehigh University, ²University of Tennessee at Chattanooga, ³Rutgers University



Introduction

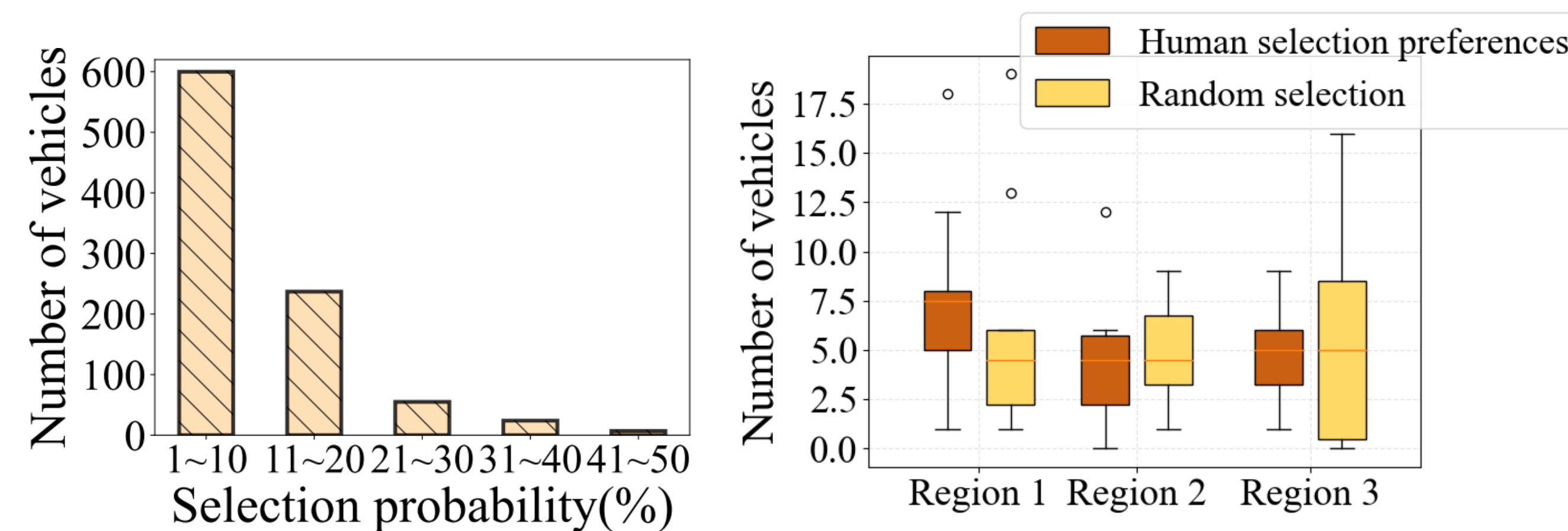
Electric micromobility system operation:

1. User requests: pick up, ride and drop off vehicles.
2. System operation center: makes decisions about rebalancing and charging plan.
3. Trucks: perform actual work following the plan.



Motivation

- Existing works [1][2]: they assume that each vehicle has the equal chance to be selected and vehicles are randomly picked up by nearby users.
- Our work: we consider human preferences on selecting vehicles motivated by the following two observations:



Observation 1:

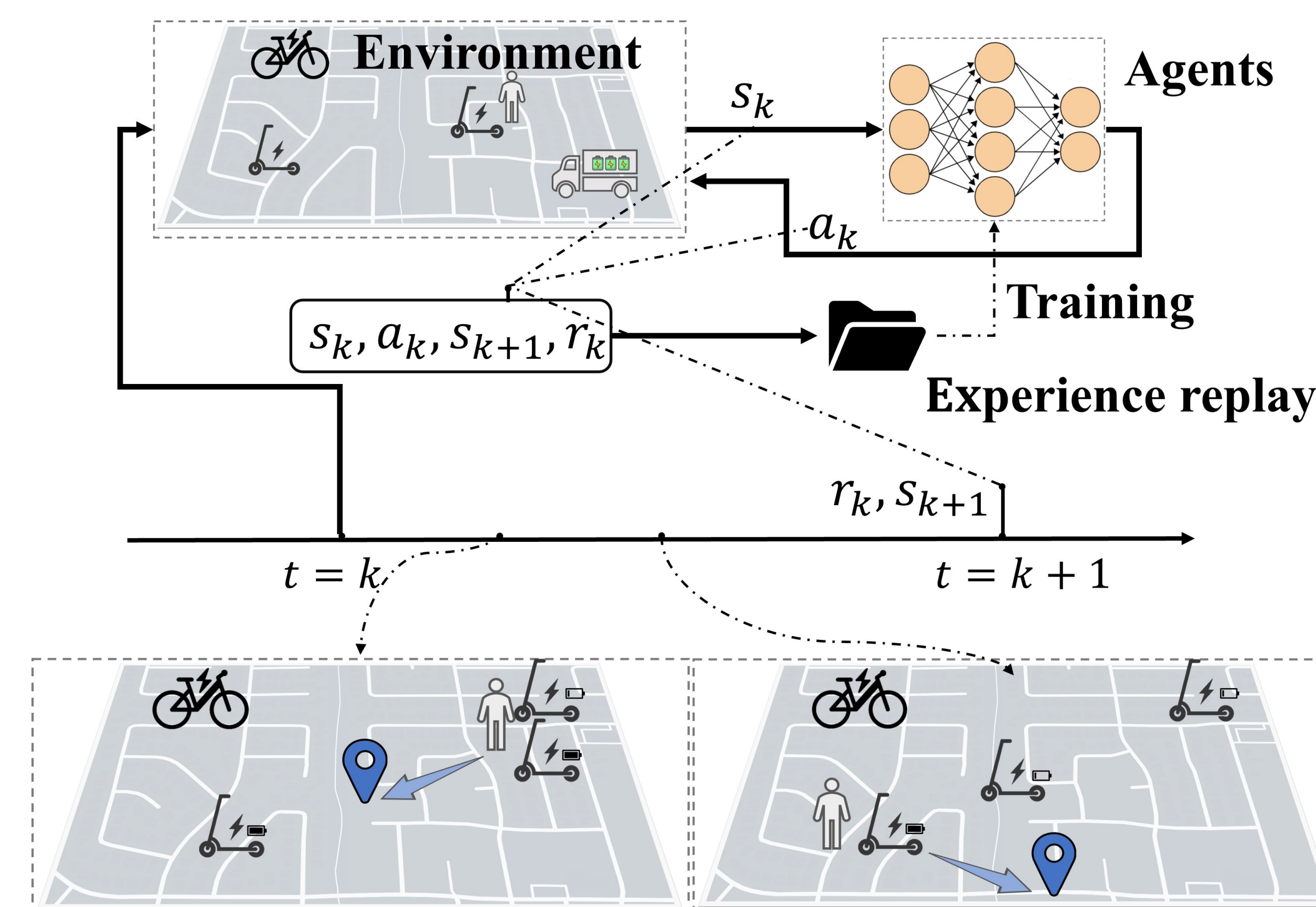
Different vehicles have different probabilities to be selected.

Observation 2:

Human selection preferences greatly affect the energy distribution of vehicles

Methodology

We propose a reinforcement learning-based framework incorporating human-system interaction as followed:

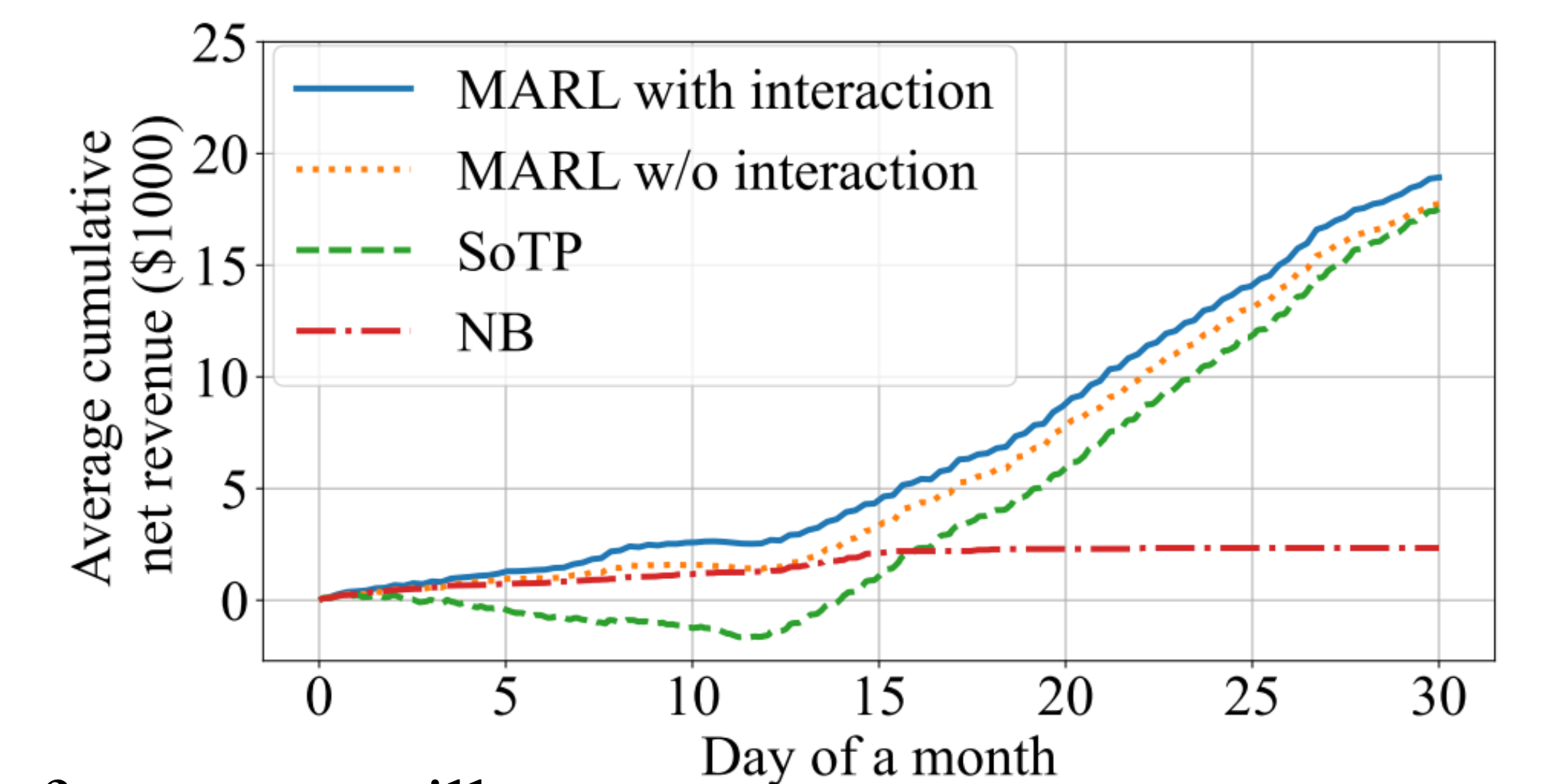


- Each region is regarded as an agent. At time slot k , all the region agents' policies output scheduling actions based on local supply and demand. Given the scheduling actions, the truck routing optimization module provide optimal truck routes to implement the actions. All the unscheduled vehicles will be continuously used by customers.
- We consider the net revenue as the agents' reward. The objective is to maximize the expected total reward of the whole system.
- To incorporate human-system interaction, we first predict the probability of each vehicle being selected. Then we assign the vehicle to users based on their selection probabilities.
- For the prediction model, we design a Xgboost-based model, considering five characteristics of the vehicle itself, such as remaining energy, and historical trips, etc. Its performance is shown as below:

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

Evaluation & Future Work

- We conduct experiments based on a real-world e-scooter usage data, which is collected from Aug 2021 to Sept 2021 in New Brunswick, covering 932 e-scooters.
- We compare our model with baselines, including multi-agent reinforcement learning (MARL) with interaction, MARL without interaction, NB (no rebalancing), and SoTP (the practical schedules of our collaborative platform).



In the future, we will:

1. Explore how to incorporate human-system interaction into other components of MARL framework.
2. Explore how to quantify the uncertainty of vehicle selection prediction.

References

- [1] Wang, Guang, et al. Record: Joint real-time repositioning and charging for electric carsharing with dynamic deadlines. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pages 3660–3669, 2021.
- [2] Yaping Ren, et al. Rebalancing bike sharing systems for minimizing depot inventory and traveling costs. IEEE Transactions on Intelligent Transportation Systems, 21(9):3871–3882, 2019.

Acknowledgements

This work is partially supported by NSF 2246080.