Poster Abstract: Human-Centric Data-Driven Optimization and Recommendation in EV-Interfaced Grid at City Scale

Jingping Nie[1], Lanxiang Hu[1], Yian Liu[1], Yuang Fan[2], Matthias Preindl[1], and Xiaofan Jiang[1]
[1]Columbia University, New York, New York, USA [2]New York University, New York, New York, USA
{jn2551, lh3116, yl4875, matthias.preindl}@columbia.edu, yf1317@nyu.edu, jiang@ee.columbia.edu

ABSTRACT

The fast development of electric vehicles (EV) and EV chargers introduces many factors that affect the grid. EV charging and charge scheduling also bring challenges to EV drivers and grid operators. In this work, we propose a human-centric, data-driven, city-scale, multivariate optimization approach for the EV-interfaced grid. This approach takes into account user historical driving and charging habits, user preferences, EV characteristics, city-scale mobility, EV charger availability and price, and grid capacity. The user preferences include the trade-off between cost and time to charge, as well as incentives to participate in different energy-saving programs. We leverage deep reinforcement learning (DRL) to make recommendations to EV drivers and optimize their welfare while enhancing grid performance.

CCS CONCEPTS

• **Hardware → Smart grid**; *Renewable energy*; • **Theory of computation → Reinforcement learning**.

KEYWORDS

Grid Optimization, Electrical vehicles, Human-centric Optimization, Recommender System, Deep Reinforcement Learning

ACM Reference Format:
Jingping Nie, Lanxiang Hu, Yian Liu, Yuang Fan, Matthias Preindl, and Xiaofan Jiang. 2022. Poster Abstract: Human-Centric Data-Driven Optimization and Recommendation in EV-Interfaced Grid at City Scale. In *The 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '22), November 9–10, 2022, Boston, MA, USA.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3563357.3567752

1 INTRODUCTION

Electrical vehicles (EVs) along with new generations of smart EV chargers and grids have quickly extended the benefits of fast-growing cyber-physical technologies to smart city development with a connected, intelligent, sustainable and human-centric infrastructure [4]. Various works focus on the research in and applications of cutting-edge techniques to co-optimize the grid performance and EV drivers' driving experience by reducing monetary and time cost to charge their cars in daily commuting.

BuildSys '22, November 9–10, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9890-9/22/11…$15.00
https://doi.org/10.1145/3563357.3567752

Deep reinforcement learning (DRL) has recently gained attention for solving grid optimization and human-centric recommendation problems in an unsupervised manner [3]. However, many of these methods require a substantial amount of real-world data to learn optimal policies and handle unpredictable human behaviors. Collecting enough data remains a large challenge from existing smart grid infrastructure [1]. In addition, EV charging stations are managed by different companies, and can have different charging levels and plug types. To the best of our knowledge, there is no widely available method for researchers to acquire holistic city-scale charging station information (e.g., charger type, availability, and price). Recently, various works have actively constructed EV driving and charging datasets [5], as well as charging scheduling datasets [2] for researchers to tackle different optimization problems. However, many datasets are still limited in size, lacking generalizability and scalability, and most importantly biased based on the data collection methodology.

Studies typically leverage existing EV driving and charging datasets or simulated results. Few works use real-time data, have real EV drivers in the loop, or track preferential metadata for each EV driver. To address these issues, we propose a data-driven city-scale EV driving and charging optimization approach and a recommender system with human-in-the-loop based on DRL to optimize for grid performance and utility of EV drivers. The proposed approach profiles individual EV-EV driver pairs, and incorporates real-time and historical timestamped driving and charging data collected by on-board diagnostic II (OBD II) scanners from real drivers. We chose New York City (NYC) as the example city due to the availability of various data sources. We *organize and augment* the data from existing datasets, online resources, and 4-month data collected from three real EV drivers who live in the NYC area. For each *new* EV-EV driver pair, data augmentation techniques, considering the driver's preferences, are applied. The recommendations to the EV drivers are generated from a DRL model (shown in Figure 1a).

2 DATA SOURCE AND DATA AUGMENTATION

We collected and cleaned representative datasets from a variety of authoritative sources and previous research projects. The sources are then grouped into one of the three major categories: driving and charging data for EV drivers, city-scale mobility data, and grid infrastructure data.

Driving and Charging Data: We collected three EV drivers' daily driving patterns using OBD II scanners. To ensure data generalizability with data augmentation, we adopt datasets with emphasis on vehicle energy consumption and EV charging [2, 5]. The driving and charging records are converted into a standardized format with only a compact yet useful set of data fields for each trip including user ID, trip ID, timestamp, speed, distance traveled, state of charge

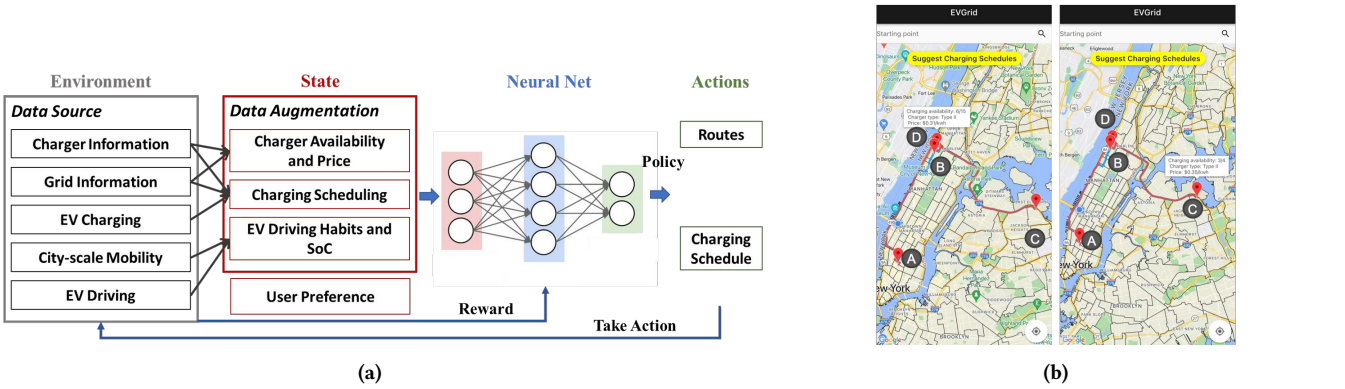

Figure 1: (a) System architecture of the proposed optimization based on DRL. (b) The smartphone App for the EV driver.

(SoC), longitude, latitude, etc.

City-Scale Mobility Data: City-mobility data, including traffic data from the Department of Transportation and National Household Travel Survey, are studied to extract distributions for human mobility habits like origins, destinations, trip types, and travel distances. Along with driving records, charging records, and preferences for each profiled EV-EV driver pair, we also augment individual trips from the city-scale mobility pattern to generate *States* for EV drivers.

Grid and Charging Systems Data: To address the *Reward* in the proposed DRL approach, we also incorporate city-scale grid information and charging systems in the *Environment*. They include hosting capacity, charging station locations, real-time charger availability, charging rate and electric price from sources like NYISO, Plugshare, Nyserda, ConEdison, and PSEG to support data augmentation and model-based policy optimization. To account for missing charging prices and real-time availability for many chargers in our data sources, we use k-means clustering within the same county region for charging prices and a probabilistic algorithm to map charger availability based on existing chargers and real-time traffic.

3 SYSTEM ARCHITECTURE

As shown in Figure 1a and illustrated in Section 2, the proposed DRL-based approach contains four parts to provide recommendations (*Actions*) for NYC EV drivers in real time. Drivers can visualize recommendations through a custom smartphone app (Figure 1b).

Specifically, *Environment* includes the historical and real-time data sources. *State* consists of the augmented data based on the data sources as well as the *User Preference* (what aspect(s) the driver wants to optimize). After the user adjusts the tailored weights for cost, time of trip & charging, and incentives to participate in various energy-saving and peak-reduction programs, this information will be input into the deep neural network (DNN), where the *Reward* is generated based on the real-time *Environment*. In particular, the *Reward* is based on the grid capacity, the traffic conditions, as well as the city-scale EV routing and charging scenarios considering other EVs and EV drivers in the city. This DRL architecture learns policies to generate *Actions* for the EV driver. *Actions* contain the suggested *Routes*, as well as *Charging Schedule* that tells user where and when to charge and how long to charge, based on the driver's preferences and driving habits.

Figure 1b shows an example recommendation for an EV driver who wants to minimize the total monetary cost, leave location A in the morning, stop at the location B for five hours, and arrives at location C before dinner. Considering the SoC, traffic, and travel habits of this user, our approach recommends two different charging strategies. The most recommended action is to charge at location D, which is close to location B (with the route annotated in red). The alternative recommendation is to charge at the destination, location C (with the route annotated in blue).

4 CONCLUSION

We propose a data-driven optimization approach in the EV-interfaced grid with human-in-the-loop based on DRL to provide recommendations, including routing strategies and charging scheduling, to improve EV drivers' utility in a city scale. This approach can provide insights for EV drivers, EV charger owners, and grid operators.

ACKNOWLEDGMENTS

This research was partially supported by the National Science Foundation under Grant Numbers CNS-1704899, CNS-1815274, CNS-1943396, CNS-1837022, and CMMI-2218809. The views and conclusions contained here are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of Columbia University, NSF, or the U.S. Government or any of its agencies.

REFERENCES

[1] Xuan Nhat Lam, Thuc Vu, Trong Duc Le, and Anh Duc Duong. 2008. Addressing cold-start problem in recommendation systems. In *Proceedings of the 2nd international conference on Ubiquitous information management and communication*. 208–211.

[2] Zachary J Lee, Tongxin Li, and Steven H Low. 2019. ACN-data: Analysis and applications of an open EV charging dataset. In *Proceedings of the Tenth ACM International Conference on Future Energy Systems*. 139–149.

[3] Jingping Nie, Yanchen Liu, Liwei Zhou, Xiaofan Jiang, and Matthias Preindl. 2022. Deep Reinforcement Learning Based Approach for Optimal Power Flow of Microgrid with Grid Services Implementation. In *2022 IEEE Transportation Electrification Conference & Expo (ITEC)*. IEEE, 1148–1153.

[4] Jingping Nie, Liwei Zhou, Margaret Frances Kaye, Christine Cecilia Silveira, Afam Nwokolo, Xiaofan Jiang, and Matthias Preindl. 2022. High-Performance Optimal Power Flow Estimation for EV-Interfaced Microgrids With Standardized Grid Services. *IEEE Transactions on Industry Applications* (2022).

[5] Geunseob Oh, David J Leblanc, and Huei Peng. 2020. Vehicle energy dataset (VED), a large-scale dataset for vehicle energy consumption research. *IEEE Transactions on Intelligent Transportation Systems* (2020).