Scalable, Multi-Agent Reinforcement Learning for Dynamic Workplace EV Charging: Cost Efficiency and Grid Curtailment Response

Skalierbares Multi-Agenten-Verstärkungslernen für dynamisches Laden von Elektrofahrzeugen am Arbeitsplatz: Kosteneffizienz und Reaktion auf Netzabregelung

Electric vehicles (EVs) are becoming more popular throughout the world as governments and consumers work to minimize greenhouse gas emissions and fossil fuel reliance [1]. Workplace charging is a particularly attractive use case since EVs are frequently parked for extended periods of time (6-8 hours), allowing for more flexible scheduling. Current workplace charging techniques often use rule-based ways to evenly distribute power across all EVs [2]. This even allocation strategy ignores changing energy costs and does not respond when grid operators seek power restriction [3].

Recent research has shown that model-free, multi-agent reinforcement learning (MARL) frameworks with centralised training and decentralised execution (CTDE) can achieve significant cost savings (around 9% lower cost) and load variation improvements (up to 36% reduction) when compared to static methods [3, 5]. Furthermore, federated and pre-trained systems have emerged as potential ways for scalable control that do not require retraining when the number of charging stations varies [3,4,5].

Despite substantial breakthroughs in MARL for EV charging management, the majority of research is focused on residential or general charging settings. There is also a vacuum in specifically addressing the office charging setting, which combines extended parking periods, dynamic energy pricing, and urgent grid curtailment requirements.

Research Objectives and Questions

This thesis seeks to create, build, and test a scalable MARL-based energy management system for workplace EV charging. To outperform typical rule-based schedulers, the system will use dynamic energy price and respond quickly to grid curtailment signals.

Important Research Questions:

- How may transfer learning be used to adapt a previously trained model to varying system sizes without requiring whole retraining?
- How efficiently does the MARL-based system implement dynamic power curtailment requests from the grid operator in real time compared to rule-based methods?
- How much does a MARL-based scheduler cut charging expenses at a workplace compared to a rule-based scheduler that distributes power uniformly without considering dynamic energy prices?

Proposed Methodology and Major Steps

The proposed work consists of the following parts:

- Review MARL-based EV charging management, dynamic pricing, and workplace charging strategies.
- Model workplace EV charging as an MDP with EV state-of-charge, arrival/departure schedules, dynamic energy prices, and grid curtailment signals.

- Create a scalable MARL framework strategy for decentralised control of charging stations.
- Use a rule-based scheduler to fairly distribute available power across EVs as a baseline, while ignoring dynamic price implications.
- Conduct simulation studies with genuine workplace charge data to assess cost efficiency and response to grid curtailment requests.

Proposed Timeline:

- Month 1: Review of Literature, Gathering of Data, and Configuration of the Environment.
- Month 2: Establish a baseline rule-based scheduler
- Month 3: Design and create the distributed MARL framework.
- Month 4: Using actual workplace charging data, implement and simulate both MARL and rule-based controllers while recording important performance indicators.
- Month 5: Analyze simulation results, compare system performance (cost efficiency and curtailment response).
- Month 6: Final revisions and thesis writing.

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