

Joint Control of Bidirectional Electric Vehicle Charging and Home Energy Scheduling Using Reinforcement Learning

MSc. Thesis Proposal Autumn 2019

Author:

Christian Baumann, MSc. Student CSE

Supervisors:

Bratislav Svetozarevic, Post-doc, ehub group

Philipp Heer, Group Leader, ehub group

July 15, 2019

1 Introduction

Electric vehicles (EVs) that allow bidirectional charging can be used as batteries in smart homes to store energy e.g. from photovoltaic (PV) systems and used later on. When consuming mentioned energy it has to be in such a way that the user's requirements on the use of the EV are still satisfied. Therefore this project tries to find a control strategy using reinforcement learning that jointly controls the charging / discharging of the EV and the home energy systems.

2 Objectives and Goals

The goal of this thesis is to jointly coordinate charging and discharging of an plugged-in EV and manage the home energy system of a smart home. This shall be achieved by learning a control strategy using model-free reinforcement learning using past data only and implement it in a real-world application at Empa to evaluate it empirically. We evaluate two nested problems, first a simpler base problem is analyzed and later on more advanced problem that extends the first one. They are structured as follows.

2.1 Base Problem

Control of EV charging and heat pump boiler of DFAB including energy from PV. The driving patterns of the EV are assumed to be known at least a few hours ahead. The objective of the optimization will be to minimize the electricity costs while maintaining home user's comfort requirements. We either assume constant or varying, but ahead known, electricity prices.

2.2 Extended Problem

Same setup as in the base problem, but adding heating / cooling and ventilation (AC) as control objectives. Further, energy storage in a home battery (or hydrogen generation) will be incorporated and weather forecasts shall be taken into account to improve control policy.

2.3 Further Possible Extensions

- Analyze impact of larger number of EVs on objective.
- Analyze influence of battery capacity of EVs.
- Use real-time electricity prices with forecast model.

3 Methods of Investigation / Implementation

As a reinforcement learning algorithm, fitted Q-iteration (FQI) will be used since it is model-free and can be trained using past data only. Further in [Rue+17] an extension of FQI is proposed that can take into account forecasted data to help improving the control policy. The implementation will be done in python. The EV (e.g. Nissan Leaf, Renault Zoe) will be simulated by using a static battery at NEST and limiting the capacity to one of the EVs considered in the study.

4 Background / Prior Work

Most papers only consider either controlling the home energy system, e.g. [WYZ17; Che+18; Rue+17], or EV charging, e.g. [WW11; CLK15; CLK13; SDD19; KPL18; Van+15]. In the case of EVs, often the charging of a fleet of EVs is considered. There are a few works that combine them, e.g. [KL18;>NNL15; YJZ16; Kim+13; NL14], whereas most of them use some kind of receding horizon control strategy. The goal of this work is to use reinforcement learning to do control, since [Ern+09] showed that RL can have similar performance to receding horizon control, MPC in this case, even if it does not know the dynamics model which is required for MPC. The authors of [KL18] actually use RL to home energy management even considering EVs, but only as load, they do not directly control the charging of the EV. As mentioned before, we aim to use FQI as RL algorithm. It has been applied in various control applications related to EV charging and home energy management, e.g in [Rue+17; CLK15; SDD19; Van+15]. Certainly this listing is not complete, but it should give an overview of related current research.

5 Timetable and Milestones

- **Task 1:** Finalize the scope of control problem, i.e. build the final list of inputs (measurements, information signals, past data) and outputs (P/Q charging/discharging profiles at Empa side) and come up with a ML-based control strategy.
- **Task 2:** Building prediction models for the measurements of interest and doing dimension reduction. Get results from past measurement and / or simulated data.

- **Task 3:** Implementing the control strategy at Empa.
- **Task 4:** Test implementation and analyze results.
- **Task 5:** Finalize report and presentation.

References

- [Che+18] Yujiao Chen et al. “Optimal control of HVAC and window systems for natural ventilation through reinforcement learning”. In: *Energy and Buildings* 169 (2018), pp. 195–205. ISSN: 0378-7788. DOI: <https://doi.org/10.1016/j.enbuild.2018.03.051>. URL: <http://www.sciencedirect.com/science/article/pii/S0378778818302184>.
- [CLK13] A. Chiş, J. Lundén, and V. Koivunen. “Scheduling of plug-in electric vehicle battery charging with price prediction”. In: *IEEE PES ISGT Europe 2013*. 2013, pp. 1–5. DOI: 10.1109/ISGTEurope.2013.6695263.
- [CLK15] A. Chiş, J. Lundén, and V. Koivunen. “Optimization of plug-in electric vehicle charging with forecasted price”. In: *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. 2015, pp. 2086–2089. DOI: 10.1109/ICASSP.2015.7178338.
- [Ern+09] D. Ernst et al. “Reinforcement Learning Versus Model Predictive Control: A Comparison on a Power System Problem”. In: *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 39.2 (2009), pp. 517–529. ISSN: 1083-4419. DOI: 10.1109/TSMCB.2008.2007630.
- [Kim+13] B. Kim et al. “Bidirectional Energy Trading and Residential Load Scheduling with Electric Vehicles in the Smart Grid”. In: *IEEE Journal on Selected Areas in Communications* 31.7 (2013), pp. 1219–1234. ISSN: 0733-8716. DOI: 10.1109/JSAC.2013.130706.
- [KL18] Sunyong Kim and Hyuk Lim. “Reinforcement Learning Based Energy Management Algorithm for Smart Energy Buildings”. In: *Energies* 11.8 (2018). ISSN: 1996-1073. DOI: 10.3390/en11082010. URL: <https://www.mdpi.com/1996-1073/11/8/2010>.
- [KPL18] H. Ko, S. Pack, and V. C. M. Leung. “Mobility-Aware Vehicle-to-Grid Control Algorithm in Microgrids”. In: *IEEE Transactions on Intelligent Transportation Systems* 19.7 (2018), pp. 2165–2174. ISSN: 1524-9050. DOI: 10.1109/TITS.2018.2816935.
- [NL14] D. T. Nguyen and L. B. Le. “Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference”. In: *IEEE Transactions on Smart Grid* 5.1 (2014), pp. 188–199. ISSN: 1949-3053. DOI: 10.1109/TSG.2013.2274521.
- [NNL15] H. T. Nguyen, D. T. Nguyen, and L. B. Le. “Energy Management for Households With Solar Assisted Thermal Load Considering Renewable Energy and Price Uncertainty”. In: *IEEE Transactions on Smart Grid* 6.1 (2015), pp. 301–314. ISSN: 1949-3053. DOI: 10.1109/TSG.2014.2350831.
- [Rue+17] F. Ruelens et al. “Residential Demand Response of Thermostatically Controlled Loads Using Batch Reinforcement Learning”. In: *IEEE Transactions on Smart Grid* 8.5 (2017), pp. 2149–2159. ISSN: 1949-3053. DOI: 10.1109/TSG.2016.2517211.

- [SDD19] N. Sadeghianpourhamami, J. Deleu, and C. Develder. “Definition and evaluation of model-free coordination of electrical vehicle charging with reinforcement learning”. In: *IEEE Transactions on Smart Grid* (2019), pp. 1–1. ISSN: 1949-3053. DOI: 10.1109/TSG.2019.2920320.
- [Van+15] S. Vandael et al. “Reinforcement Learning of Heuristic EV Fleet Charging in a Day-Ahead Electricity Market”. In: *IEEE Transactions on Smart Grid* 6.4 (2015), pp. 1795–1805. ISSN: 1949-3053. DOI: 10.1109/TSG.2015.2393059.
- [WW11] Wenbo Shi and V. W. S. Wong. “Real-time vehicle-to-grid control algorithm under price uncertainty”. In: *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*. 2011, pp. 261–266. DOI: 10.1109/SmartGridComm.2011.6102330.
- [WYZ17] T. Wei, Yanzhi Wang, and Q. Zhu. “Deep reinforcement learning for building HVAC control”. In: *2017 54th ACM/EDAC/IEEE Design Automation Conference (DAC)*. 2017, pp. 1–6. DOI: 10.1145/3061639.3062224.
- [YJZ16] L. Yu, T. Jiang, and Y. Zou. “Distributed Online Energy Management for Data Centers and Electric Vehicles in Smart Grid”. In: *IEEE Internet of Things Journal* 3.6 (2016), pp. 1373–1384. ISSN: 2327-4662. DOI: 10.1109/JIOT.2016.2602846.