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Optimization Techniques for Home Energy Management Systems in Novel Power Markets: A Comparative Analysis

Motivation

Meeting global energy needs in a cost-efficient and sustainable way is one of the most important levers for tackling climate change. In this context, buildings consume around 40% of the world's energy supply. Since the residential sector accounts for three quarters of this share, households' play an important role in the green energy transition [12]. In line with this, there is an increasing demand for renewable energy generation. It is expected that by 2050, half of all homes in the European Union will be involved in renewable energy generation, either individually or through local energy communities, turning formerly passive electricity consumers into prosumers with bidirectional energy flows [6]. This push for a renewable, decentralized energy system offers several advantages. Equipped with smart technologies, the introduction of dynamic pricing makes households more responsive to energy shortages [4]. In addition, peer-to-peer (P2P) trading schemes promise significant benefits for both consumers (monetary) and the power grid (sustainability, stability, security) [5]. Despite these benefits, microgrid design must consider inclusivity to ensure that those who cannot participate are not left behind [18].

Problem description and research gap

Realizing the advantages of a decentralized energy system while providing individual and community benefits requires new technologies to reduce complexity for both residential prosumers and microgrid managers. In this regard, a home energy management system (HEMS) can play an important role by optimizing a household's energy profile according to certain metrics, mainly electricity prices [3]. For this purpose, it receives external information about weather and prices and communicates with household appliances, the energy supplier, and the HEMS of other prosumers. The algorithm then determines an optimal load schedule, battery storage management, and power trading behavior.

The relevant literature spans natural and social sciences, from electrical- and information systems engineering to computer science and economics. Since the electrical engineering literature is less concerned with designing energy management and -trading algorithms and the research on game theory does not discuss how to accurately model microgrids and their households, the following discussion of the research gap centers around the most relevant fields, information systems engineering and computer science. Here, existing research mainly focuses on the architecture of microgrid information flows and the design of the HEMS algorithm. One branch of research studies these phenomena as multi-agent systems (MAS), using agent-based modeling and simulation (ABMS) ([19], [1]). These studies typically employ optimization techniques, in particular integer linear programming ([20], [13]) and meta-heuristics such as genetic algorithms ([15], [16], [17]). Another branch of research leverages the recent advancements in reinforcement learning to better address many of the challenges optimization-based HEMS face, namely (I) uncertainty in system parameters such as renewable energy generation, electricity prices, etc., (II) temporally and spatially coupled subsystems, (III) time-consuming computation due to extremely large solution spaces in real-time applications, and (IV) limited generalizability across different building environments [22]. The existing studies in this domain mainly differ in four aspects: The number of RL agents (where one agent represents one HEMS), the energy subsystems considered, P2P trading scheme design, and the benchmarking of their results against other methods (see table 1 below).

Authors, Year	**RL agents**	**Energy subsystems**	**P2P**	**Algorithm**	**Benchmarks**
Mocanu et al., 2019 [10]	Single-agent	EV, HVAC, PV, SL	No	DPG	DQN
Li et al., 2020 [8]	Single-agent	EV, HVAC, SL	No	TRPO	MPC, DQN
Alfaverh et al., 2020 [2]	Single-agent	ESS, EV, PV, SL	No	DQN	No
JM Master thesis	**Single-agent**	**ESS, EV, HVAC, PV, SL**	**Yes**	**PPO**	**ILP**
Zhang et al., 2019 [23]	Multi-agent	ESS, EV, PV	Yes	PPO	ILP
Prasad et al., 2019 [14]	Multi-agent	ESS, PV	Yes	DQN	No
Lee et al., 2020 [7]	Multi-agent	SL	No	PPO	No
Ye et al., 2021 [21]	Multi-agent	ESS, EV, HVAC, PV, SL	Yes	DDPG	No

Table 1: RL Agents in Energy Systems Research

Many studies limit the scope and potential of a HEMS by not considering all relevant energy subsystems. Few studies assess the potential of P2P trading among members of an energy community, which is a key lever for creating benefits at the individual and community level. Finally, the performance trade-off between black box ML models and traditional optimization techniques is only considered in one study (see [23]). Therefore, a research gap exists for a single-agent RL study that considers all relevant residential energy subsystems, evaluates the benefits of local P2P trading, and connects the two branches of research by comparing reinforcement learning and linear programming. Another research gap exists when extending this setting to a multi-agent context.

Idea and research contribution

The master thesis aims to fill the first research gap. It can build on an agent-based model developed for the city of Ingolstadt in Bavaria, Germany. The model uses Ingolstadt's own data on houses and their PV potentials, representative Bavarian load profiles of households, EVs and heat pumps, and wholesale electricity tariffs and feed-in tariffs provided by the German Fraunhofer Institute for Information Technology. Augmented with other data sources, the model already considers all energy subsystems relevant for the master thesis (see table above). The study uses linear programming to optimize households' load scheduling and P2P trading behavior [9]. These results serve as the benchmark against which the RL approach of the master thesis can be compared.

Furthermore, the thesis builds on the Automatic Power Exchange for Distributed Energy Resource Networks (APEX), an open-gate forward market design that bears the ability to incorporate flexible orders as well as distribution network constraints [11]. In this auction-based marketplace, the performance of different optimization techniques (e.g., MILP and RL) for controlling decentralized energy assets' power will be compared. Moreover, the thesis will replace the physical grid constraints considered in [11] with a more realistic and controllable open-source distribution system simulation environment (GridLAB-D or OpenDSS).

Replacing the HEMS optimization (MILP) with a reinforcement learning (RL) algorithm should lead to performance improvements, especially with more degrees of freedom. In the baseline scenario, HEMS are provided with a perfect forecast and bids submitted to the APEX market consist only of the quantity to be sold/bought. In this setting, the MILP optimizer is expected to deliver optimal performance. This performance is used as a benchmark for the RL optimizer. The first step is to introduce noise into the forecast (proportional to its horizon). In this setting, the RL optimiser, being able to learn more general patterns, is expected to outperform the MILP at a given level of noise. In a second step, bids submitted to the APEX market include both price and quantity bought/sold, introducing a strategic bidding element. As MILP optimizers can only optimize for either quantity or price, they will continue to focus on the former and act as price takers based on their price forecast. The RL optimizer, however, has the ability to output both price and quantity bought/sold. In this way, it can learn and potentially exploit strategic bidding behaviour, i.e. submitting orders with higher purchase prices in times of energy shortages. In this setting, the RL agent is expected to continue to outperform the MILP.

Apart from the main question of HEMS performance with different optimization techniques, the implementation of a novel marketplace that allows end-user participation and the consideration of physical network constraints that are as close as possible to the real constraints of distribution systems provide interesting degrees of freedom for future analysis. For example, the model can be used to simulate different variations of the APEX market design, such as market matching that optimizes total welfare (price * quantity) or total sales (quantity). Furthermore, by introducing flexible orders, the model could be used to quantify their effect on both household financial performance and system stability.

In summary, the thesis by Jochen Madler focuses on the evaluation of home energy management design in novel power markets, comprising the following working steps:

1. Literature review on existing home energy management optimization studies and novel distribution-level electricity market designs
2. Implementation of Automatic Power Exchange (APEX) in Python using the Gurobi interface
3. Implementation of the HEMS MILP optimizer in Python using the Gurobi interface
4. Implementation of the HEMS RL optimizer in Python using the Tensorflow interface
5. Implementation of the distribution system simulation environment in Python using the GridLAB-D or OpenDSS interface
6. Design of several simulation settings to quantify the HEMS performance difference with (a) noisy forecast data and (b) strategic bidding behavior
7. Application of model to derive managerial insights for HEMS design

Jochen Madler will work on this topic from 01.04. - 31.06.2023 as an individual research phase and from 01.07. - 31.12.2023 as a master's thesis. From 01.07. - 30.11.2023, Mr. Madler will be with Prof. Ram Rajagopal at the Stanford Sustainable Systems Lab as a visiting student researcher.

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