A Review – Home Renewable Energy Management Systems in Smart Grids

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Abstract. This paper presents a review on the Home Energy Management Systems (HEMS) for renewable energy production and used optimization methods. The HEMS is an important Smart Grid application. It is used to monitor and optimally manage the energy flows in buildings including renewable energy production, energy storage and smart home appliances. In this paper, two different methods for the optimal HEMS are selected and compared: Model Predictive Control (MPC) and Reinforcement Learning (RL). As a conclusion, the RL method can overcome the disadvantages of the MCP in the highly dynamic environment of buildings and renewable energies, and is a promising method for HEMS in Smart Grids. Finally, an experimental set-up of the hybrid renewable energy system is presented and its operation is discussed under the Time-of-Use energy management strategy.

1. Introduction
The building sector has a high impact on greenhouse gas (GHG) emissions and final energy consumption in the European Union (EU) and worldwide by being the largest energy end-use sector with a share of about 40% [1]. Due to the increasing amount of electrical appliances and electric vehicles in buildings, the electricity demand is increasing along with the increased energy prices. This and fossil fuel shortage has led to a raised share of renewable energy generation within the power grid and on the demand side as well. The consumers in the power grid are becoming prosumers who produce, utilize, and store their own electricity and still interact with the main power grid [2]. The growing electricity demand and amount of prosumers in the grid result in the lower reliability of the main power grid. Due to this, a concept of Smart Grid (SG) is required. The SG aims to be a self-sufficient and interactive system that allows integrating distributed renewable energy sources and energy storage into the power grid. This ensures a more reliable and sustainable bi-directional energy flow between the prosumer and the power grid [3,4]. The SG is enabled by smart appliances and two-way communication between the power grid utility and prosumer [5].

In terms of energy efficiency and optimized energy flows, the SG can operate effectively with smart demand-side prosumers if those enable continuous consumption and production metering, electrical appliances control and communication with the grid [5]. This kind of operation is called Demand Side Management (DSM) or Demand Response (DR) which is seen as a key application of the SG to maintain the systems reliability and to balance electricity use at the prosumers side [3]. The other SG applications are electric vehicle charging/discharging, distributed generation with storage and electricity market integration.

To facilitate the DSM in buildings, a significant SG application called Home Energy Management System (HEMS) is utilized. The HEMS allows the prosumer to monitor production and consumption,
and it optimizes the energy flows according to the desired objective function. Due to this, different optimization-based techniques are used to implement HEMS in buildings.

In this paper, two different HEMS optimization approaches are presented and reviewed: Model Predictive Control (MPC) and Reinforcement Learning. First, the architecture of the HEMS is presented, and two optimization approaches are discussed and compared. Finally, the real-time results from the PV/battery storage system are presented to demonstrate HEMS in terms of the Time-of-Use optimization.

2. Home renewable energy management system

The energy management system (EMS) is required in any energy system in which more than one energy source is used to satisfy a certain energy demand [6]. The EMS is used to facilitate the optimal use of multiple energy sources in an intelligent and reliable way in the environment with various uncertainties, such as renewable energy production and load demand [7].

The home energy management system (HEMS) is one of the most important applications of the SG. It is defined as the optimal management system which monitors and manages electric storage, electric vehicle (EV), renewable energy generation and consumption of smart appliances in buildings [4]. The HEMS is enabled by Advanced Metering Infrastructure (AMI), or Smart Meters, which has a two-way communication between the prosumer and utility of the power grid. The HEMS provides an opportunity to reduce the electricity bill of the building by shifting the load to off-peak time, to reduce energy demand and environmental impact by improving utilization of appliances and integrating efficiently renewable energy production with storage to the building [4,8]. The general architecture of the HEMS is presented in figure 1.

![Figure 1. Architecture of HEMS [5].](image)

Figure 2. DR classification [9].
2.1. Demand side management
The DSM is applied in each level of electricity users from residential to industrial. The DSM enables optimal scheduling of electrical appliances by shifting part of the prosumers’ on-peak loads to the cheaper off-peak time. The DSM aims to enhance the energy flexibility of buildings, improve energy efficiency and generate savings in energy costs at the prosumer’s side [5]. The DSM performs dynamic energy management by handling the prosumers’ early initiated information of consumption and production. This facilitates the utility and power grid to shift the load from on-peak load hours.

The demand response of the DSM can follow a price-based or incentive-based scheme, as presented in figure 2 [1,9]. The price-based scheme is usually used in the building sector when the prosumers adjust their energy use depending on the dynamic rates of the grid electricity [9]. In the case of TOU, RTP and CPP, energy cost savings are generated by shifting the controllable load to the low electricity price period.

3. Optimization approach for home renewable energy management system

3.1. Model predictive control
The aim of the HEMS is to solve a load scheduling problem in buildings in terms of defined objectives. MPC is used to solve this optimization problem by taking into account future predictions of the most important variables, such as load demands, renewable energy production and real-time energy prices. In this case, the scheduling problem is seen as a receding-horizon optimal control problem [5]. MCP requires an accurate dynamic model of the system, a cost function with constraints to be minimized and an optimization algorithm. The algorithm is often based on mathematical optimization methods, such as linear or non-linear programming. However, heuristics and metaheuristics approaches can also be used as an optimizer if the problem has multiple objectives. MPC is based on the iterative optimization of the dynamic model. The model state is recorded at the current discrete time t and used with the future predictions to optimize the next control action for time t+T.

Shivam et al. [10] presented a multi-objective predictive energy management method for the HEMS, including PV production, battery storage and load demand. They used machine learning methods to predict PV energy production and load for the multi-objective MPC to control the battery charge/discharge. The method decreased energy costs and CO₂ emissions.

3.2. Reinforcement learning
Machine learning is a group of methods that learn to identify patterns from historical data. These methods use the patterns to predict or perform decision making. Machine learning has the following three types: supervised learning, unsupervised learning and reinforcement learning (RL) [11].

RL is a physical model-free algorithm that can adapt to its uncertain environment by learning optimal policy of control actions through the historical data and interaction with the system. Due to the increasing amount of data and complexity of the systems, the RL has increased its popularity for HEMS and is seen as a data-driven option for model-based approaches, such as MPC.

Usually, the decision making problem of the single-agent RL algorithm is formalized using a Markov Decision Process (MDP), which can handle multi-stage decision making in a discrete-time framework. The MDP includes four main elements presented in figure 3: a space of states S, a space of actions A, a reward function r to be maximized and transition probabilities between the states P [9]. In MDP, at a discrete-time step t, the agent detects the state S_t of the environment, selects an action A_t which leads to a new state S_{t+1} where a reward is given to the agent [11]. The agent aims to maximize the reward by its actions, and in this way, it learns the optimal control policy. The most used RL technique is Q-learning [11,12].
Svetozarevic et al. [13] presented a study where they implemented the RL method to smart home to control EV charging/discharging and room temperature while minimizing energy costs and maintaining thermal comfort simultaneously. They used historical data from a building and weather to obtain the optimal control policy without complex physical modelling of the building. Finally, the controller was deployed on a real building, and 30% energy savings was reached compared to the conventional controller.

3.3. Comparison between MPC and RL

Both MPC and RL techniques are suitable for energy management in smart homes with a high share of intermittent renewable energy sources. However, there are some advantages and disadvantages between these two techniques, which are shortly discussed here.

A well-performing MPC requires a sufficient physical model of the controlled system to generate future trajectories of the system. These trajectories with future forecasts are used in the optimization process to find an optimal control for each time step. However, if such a detailed physical model is not available or the system is too complex to get an accurate model, the optimal control might be difficult to achieve [14]. The MPC relies also on the future forecasts, of which accuracy depends on the used forecasting methods and historical data. Modelling and forecasting are two disadvantages of the MPC in the case of the HEMS problem, which have high amount uncertainties and is a complex problem. Additionally, the model-based control does not adapt to the unexpected changes in the real system in the short- or long-term but continue the optimization process based on the applied model [14].

The advantage of the RL technique is that it can overcome the disadvantages of the MPC. The RL is a model-free approach in which the agent learns continuously the dynamics of the system. This makes the approach adaptive. Additionally, the RL does not require future forecasts because it learns the optimal policy from the direct interaction with the environment [14]. On the other hand, there may exist underlying system dynamics that are not learnt by the RL algorithm despite a large amount of data [14]. This can lead to a lack of optimal control. The RL technique requires a training period to achieve optimal control. This can be seen as a disadvantage in the cases where historical data is not available for training the controller. When compared to the MPC, as an exploration strategy, the RL
rely on a certain amount of randomness, which leads to immature feasibility, robustness and stability theory and constraint handling [14]. These are full-fledged in terms of MPC.

4. Case study of renewable energy management

4.1. Methodology
The hybrid renewable energy systems (HRES) were reviewed in [15]. In this section, a case study of a HRES consisting of four DualSun PV panels with 1.2 kWp, presented in figure 5, and the Enphase AC battery with a capacity of 1.2 kWh is presented. The battery has a maximum charge and discharge power of 270 W. The electrical load is a sum of certain home appliances. The installation was realised at ICube, CNRS laboratory in Strasbourg, France. The battery storage is located inside the building. Each PV panel is connected to own Enphase micro-inverter to convert DC output to AC power and to maximize production using Maximum Power Point Tracking algorithm. In terms of communication, the installation includes an Enphase Envoy-S gateway which operates between micro-inverters and web-based Enphase Enlighten monitoring software. Envoy-S is used to monitor PV production from micro-inverters, manage battery charge/discharge and collect consumption data every 15 min interval.

4.2. Results
The collected data was analysed in the Enlighten software and two weekdays in October 2021 were selected to present in this paper as an example of the EMS in the HRES. Figure 4 presents the electricity price profile for the TOU scheme which was given for the Envoy-S to optimally manage the battery charge/discharge depending on the PV production, load and grid electricity price.

Figure 5. The PV installation at ICube.

Figure 6. Operation of the HRES over two days.
During a day, the electricity price varied from 0.11 to 0.18 €/kWh. The peak hours were from 07:00 to 12:00 and 18:00 to 24:00. Figure 6 presents the experimental results of the HRES operation during two selected days. The HRES operated under the presented TOU scheme, which is recognized in the battery charge and discharge in figure 6.

The battery was enabled to charge during the night to be ready for the morning consumption peak. During the first day, the consumption started after 7:00, and the battery was discharged to avoid using the grid electricity at a high price. At the same time, the available PV production was used to fulfil the demand. When the consumption was reduced, the battery was charged fully by the PV production. The evening consumption peak started before 18:00, and first, the grid electricity was used to save money and battery energy for the period of the high electricity price. The next day, the morning consumption started already before the high price period and first the grid electricity was used to be ready for the high price period. These experimental results show the energy management method which optimizes the energy costs of the system depending on the given TOU scheme.

5. Conclusion
In this paper, the HEMS for renewable energy production were reviewed. Additionally, the experimental results of the HRES operation under TOU scheme were presented.

Smart homes are complex systems. Due to this, more advanced and intelligent HEMS are required. The MPC is an advanced and well developed optimal control method. However, it requires an accurate physical model of the system dynamics to perform the optimal control process. Additionally, the MPC relies on future forecasts that might be difficult to obtain in the highly dynamic environment of smart homes. On the other hand, the RL is a model-free method that learns the optimal control policy by interacting with its environment. An increasing amount of data makes it feasible to train a well-performing RL controller for the HEMS. The RL method can overcome the disadvantages of the MPC. However, it relies on some amount of randomness, which can lead to unstable control. The RL method is promising, especially, in terms of smart homes, and requires more investigation.

For future work, the RL based energy management strategies will be investigated by using data from the hybrid renewable energy system.

6. References
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