AN ONLINE MULTI-SCALE OPTIMIZATION FRAMEWORK FOR SMART PV SYSTEMS

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ABSTRACT: Effective utilization of renewable energy is a big motivation to renovate the conventional power systems toward smart energy systems. However, renewable energy is often small scale and intermittent. Hence, the online energy management is necessary to balance between demand and energy production. This paper proposes an online multi-scale optimization framework for smart PV systems in order to reduce the inherent complexity when trying solve the complete problem at a fine-grain time resolution. The proposed framework realizes the effective energy management by solving several optimization problems covering multi time scale. Experimental results shows that the proposed framework can reduce the purchased energy from the utility grid by 19.1% compared with other baseline methods.
Keywords: PV system, online energy management, multi-scale optimization

1 INTRODUCTION

Effective utilization of renewable energy is a big motivation to renovate the conventional power systems toward smart energy systems. The smart energy systems are often equipped with photovoltaic (PV) panel, battery, and various home appliances as electric load. Since the renewable energy such as solar power generation is usually small scale and intermittent, the effective energy management is necessary to take a balance between demand and energy production [1].

Many studies have been reported on modeling the system components required to predict system behavior accurately. For example, PV forecasting model provides a forecast of energy production for short term and localized areas [2] [3] and for long term and global areas [4]. Regarding the lithium-ion battery, three types of battery models have been developed according to accuracy and complexity: the black-box model, the equivalent circuit model [5], and the electrochemical model [6]. In addition, the load flexibility model of home appliances have been developed to predict the power demand [7]. These models have been developed individually, and few studies have focused on integrating these models into the energy management as a whole approach [8] [9].

In this paper, we focus on developing an online optimization framework for smart PV systems combining various system models. In order to realize the effective energy management, we should consider simultaneously the long and short-term system dynamics including appliance scheduling, PV output variation, and battery condition. Therefore, we formulate the multi-scale optimization problem to achieve a solution considering two different time scale. In this way, we improve the modeling capability and save computational time.

The rest of this paper is organized as follows. Section 2 describes the architecture of the online optimization framework and system model. Section 3 proposes multi-scale optimization in our framework. Section 4 demonstrates the simulation results, and finally Section 5 concludes this paper.

2 THE ONLINE OPTIMIZATION FRAMEWORK

2.1 Overview

Fig.1 shows the overview of our framework. Input of this framework are forecasting data of PV power generation and measured data of electric demand. Output of the framework is operation plan for the system. The key idea of this framework is the iteration of forecasting and optimization. First, the framework obtains the PV power forecasting data in the near future such as upcoming half an hour. Then the framework optimizes the energy utilization in order to minimize the purchased energy from the utility grid. The energy utilization includes battery charge/discharge, power purchase, and appliance schedule. This optimization problem is mathematically formulated, and the optimal results can be obtained by mathematical solver. Finally, the obtained plan is applied to the system operation. The feature of our framework is multi-scale optimization to consider simultaneously the fast and slow system dynamics. The energy storage in a battery requires fine time scales because the internal time constants are sub second. Hence, the battery is modeled as equivalent circuit, and accurate behavior can be obtained [5]. The framework optimizes the battery utilization based on the equivalent circuit model, and the optimization is performed under the realistic battery behavior. On the other hand, this framework also supports appliance schedule within one day planning period. Because the impact of scheduling decisions is quite coarse for the appliances and because here the time constants are very long, it is not necessary to schedule this at fine grain. The time scales of these problems are completely different. Thus, these two problems are separately discussed. However, our framework treats these problems in one global optimization loop so not independently.

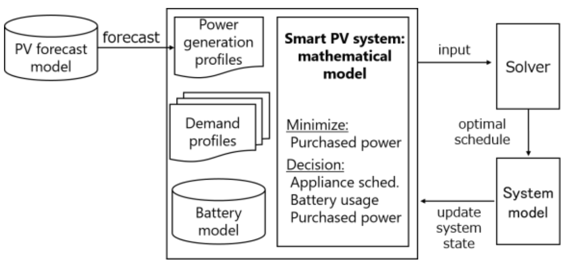

Figure 1: Online multi-scale optimization framework for smart PV systems

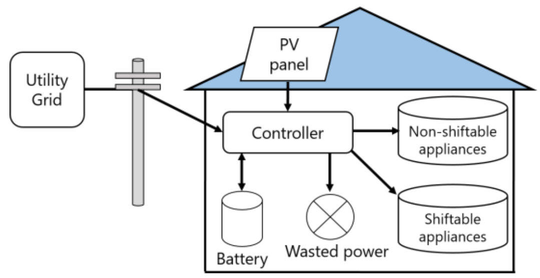

Figure 2: Smart PV system structure

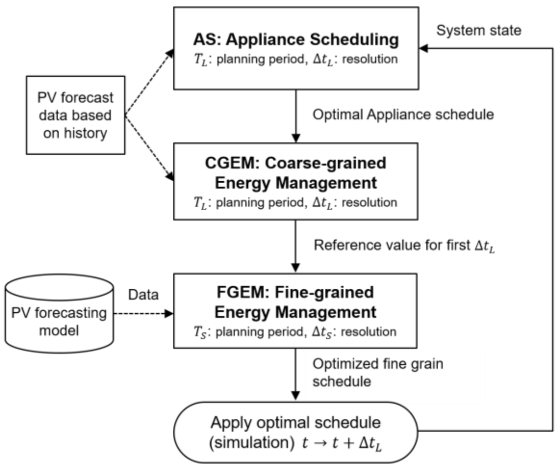

Figure 3: Multi-scale optimization flow of the proposed framework

2.2 System model

1) Smart PV system structure: Fig.2 shows our smart PV system model. We assume a smart building as a smart PV system, which comprises a PV panel, a battery to store the generated energy, appliances to consume the energy, and a controller to control power flow. The smart PV system only buy the electricity from the power company via the utility grid in case power shortage. On the other hand, the surplus energy is charged to the battery, or wasted inside the system.

2) Battery: We use an equivalent circuit model introduced in [5] as a lithium-ion battery model. This model can accurately predict a battery runtime and a nonlinear I-V characteristics based on state of charge (SOC) of the battery. In this paper, the equivalent circuit model is implemented in the optimization problem in order to obtain effective battery utilization and estimate the internal state of the battery accurately.

3) PV forecasting: PV generation is considered to have a great fluctuation due to meteorological stochastic phenomena. Therefore, the forecast data of PV generation is necessary to balance between demand and energy production. We use the forecast data provided by the PV energy yield forecasting technique as the input of the optimization. That provides a sufficient planning for the battery storage scheduling loop.

4) Appliance model: We assume that every smart PV systems have two sets of appliances: non-shiftable (the starting time cannot be deferred) and shiftable (the starting time can be shifted to the other time slot and would not be interrupted) appliances. We consider a shiftable appliance scheduling to balance between demand and PV production under a constraint of user preferences. Each shiftable appliance is characterized by four parameters [7]: (1) operating time, (2) configuration time, which is the time to be able to start the appliance, (3) deadline, which is the time by which the appliance must be completed, and (4) rated power. The shiftable appliance must be scheduled from the configuration time until deadline.

3 PROPOSED MULTI-SCALE OPTIMIZATION

Fig.3 shows the multi-scale optimization flow of the proposed framework. The framework is composed of multiple optimization stages for each purpose, considering different two time scales, which are coarse- and fine-grain time scale. In this way, we deal with long- and short-term system dynamics simultaneously. Let t be a set of global time steps for the whole process. T_L and T_S are the planning period of coarse and fine-grain time scale, respectively. Then, Δt_L and Δt_S denote the time resolution of coarse- and fine-grain time scale, respectively. First, appliance scheduling (AS) is performed to decide the appliance utilization schedule. This schedule is obtained for long period Tc such as one day with coarse-grain resolution Δt_S. Then, the coarse-grained energy management optimization (CGEM) is performed under the obtained appliance schedule. At these stages, the planning period is still long, and PV power forecasting is roughly performed: history-based prediction. After that, for each time step, fine-grained energy management optimization (FGEM) is performed to decide precise control. At this fine-grained stage, the operation plan is obtained for short period T_S with fine-grain resolution Δt_S such as a second. Based on these plans, actual behavior is simulated by an accurate model including the equivalent circuit battery model, and update the SOC value of the battery to execute these optimizations again. The framework iterates this process every internal period, e.g. 15 min, in order to realize the online optimization, aiming to minimize the purchased energy from the utility grid.

The details of the framework are described as follows:

3.1 Appliance scheduling

The scheduling problem of smart buildings over coarse-grain time scale is solved. Typically, Tc and Δt_L take 24 h and 15 min, respectively. In the AS, we use the simplified battery model, which is formulated as the nonlinear parameters of the equivalent circuit model are treated as constant. This reduces a computational time significantly since the optimization problem is maintained in a linear shape. Thus, this problem is the mixed-integer linear programming (MIP). The objective is to minimize the purchased energy, and the solution of the AS contains the optimal scheduling for shiftable appliances, the battery and the power purchase from the utility grid. Only the optimal scheduling of shiftable appliances is employed, the rest are discarded and recalculated in the following problem.

3.2 Coarse-grained energy management optimization

The CGEM realizes the optimal energy management for the same time scale as AS. The appliance schedule obtained by AS is used, and the schedule of battery and the power purchase are recalculated to minimize the purchased energy. In order to determine the battery power schedule considering the battery accurate characteristics, the full equivalent circuit battery model described in Section 2 is introduced to the formulation. Because this model includes nonlinear equations, this problem is the non-linear programming (NLP). Then, the obtained SOC trajectory of the battery is utilized as a references value in the FGEM.

3.3 Fine-grained energy management optimization

The FGEM calculates short-term precise control of the smart PV systems to interpolate coarse-grain time scale, that is, fine-grain time scale is considered. The short-term PV forecast model provides the forecast profiles of PV power generation. The equivalent circuit battery model is also introduced to the optimization problem. The FGEM normally employs 15 min period as T_S, because a 15 min period is a well balanced between PV forecast accuracy and dimension of the optimization problem. On the other hand, this problem requires a high temporal resolution such as a second-order since the time constant of the battery dynamics is sub second. Therefore, the time resolution Δt_S is basically set to be 1 sec. In addition, we introduce the constraint to ensure that the terminal SOC converges to the references SOC provided by CGEM. This problem is also the NLP. The precise battery power schedule optimized by the FGEM is applied to a system.

4 EXPERIMENTAL RESULTS

In this section, to demonstrate the effectiveness of the proposed framework, we perform optimization and simulation with practical assumptions, and the proposed framework is compared with other baseline methods. The simulation period is one day (00:00 24:00). The parameters of the proposed framework are: T_L = 24h, Δt_L = 15min, T_S = 15min, and Δt_S = 1s. Thus the optimization flow is executed every 15min. CBC [10] and IPOPT [11] are used as the MIP solver and the NLP solver, respectively.

The system configuration of the smart PV system is shown in Table.I. The coarse-grain PV forecast data is manually generated by adding noise to the measured value, and the fine-grain PV forecast data is obtained by commercially available solution. The number of the shiftable appliances is 50, and we generate them based on three appliances shown in Table.II.

Table I: System configuration of the smart PV system

System	PV panel	Demand (non-shiftable)	Battery	
Parameter	Peak power	Peak power	Capacity	Initial SOC
value	20kWh	10kWh	16kWh	50%

Table II: Base setting of the shiftable appliances

Shiftable appliance	Rated power (kW)	opetating time (min)
Dish washer	0.7	90
Clothes washer	0.5	45
Tumble dryer	1.24	120

In the experiment, we perform on three scenarios with different weather and PV forecast accuracy: the “bad”, “typical”, and “good” day. In addition, the following four methods are compared:

- Proposed framework (Proposed): Appliance scheduling and the equivalent circuit model is implemented in the framework, and PV forecast data is used as input.
- Ideal input case (Ideal input): We assume that the forecasting error is 0. Then, the measured PV production is used as input in the proposed framework.
- Using shiftable appliances as soon as possible (ASAP): The AS stage is eliminated from the framework. The shiftable appliances are switched on immediately whenever the configuration time comes. The other assumptions are the same as for the proposed framework.
- Crude black-box battery modeling (BBM): The black-box battery model, which is the simplest linear battery model, is used in optimization problems instead of the equivalent circuit model. The other assumptions are the same as for the proposed framework.

Table.III shows the performance of proposed and other baseline methods with different scenarios. Since the weather and total PV production vary with the scenario, simple comparison of total purchased energy between scenarios is not possible. The proposed framework achieves consistently the lower purchased energy over ASAP and BBM, and total purchased energy is reduced by up to 19.1%. On the other hand, the proposed framework obtains the worse purchased energy compared to the case of ideal input, with the purchased energy increase up to 15.4%. This is due to the forecasting error of PV forecast production.

Fig.4 shows the scheduled power of the shiftable appliances. The proposed framework shifts much shiftable demand to around the noon. At the time 10 a.m. 13 p.m., the PV production exceeds the non-shiftable demand, and the surplus energy is generated. Therefore, the shiftable appliances is shifted to this period in order to balance PV production and demand.

Fig.5 shows the battery’s SOC trajectories obtained by simulation with different battery models and input for the “bad” day. Firstly, the black-box battery model cannot access a full capacity of the battery. This is because the optimal solutions are validated with the equivalent circuit battery model, and the inaccurate black-box battery model has a great error about the capacity in comparison to the equivalent circuit one. Therefore, in the BBM, the surplus PV energy is wasted without being charged to the battery, and the purchased energy increases as shown in Table.III. Secondly, it is indicated in Fig.5 that the battery operation changes due to the forecasting accuracy. Compared to the case of ideal input, the SOC results obtained by forecast input is fluctuating during the peak time of PV production. The forecasting error of input causes the error of the battery utilization.

These results shows that the introduction of appliance scheduling and accurate battery model are effective to reduce the purchased energy. The forecasting error have an equally great impact on the solutions of optimization

Table. III: The results of the purchased energy from the utility grid under different scenarios

Forecast scenario	Total purchased energy, kWh				The purchased energy ratio to Proposed		
	Ideal input	Proposed	ASAP	BBM	Ideal input	ASAP	BBM
"bad"	76.8	90.9	99.6	108.2	84.6%	109.6%	119.1%
"typical"	65.5	66.7	78.4	71.3	98.1%	117.5%	106.9%
"good"	67.2	67.3	78.8	68.3	99.8%	117.2%	101.6%

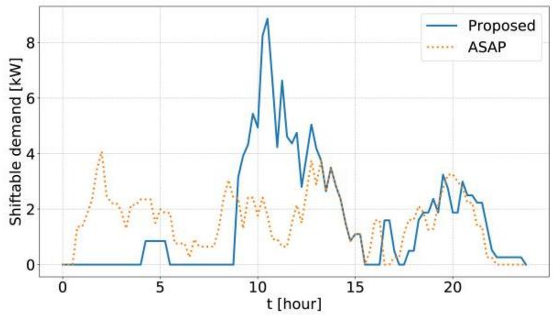

Figure 4: The results of the appliance scheduling for the "bad" day

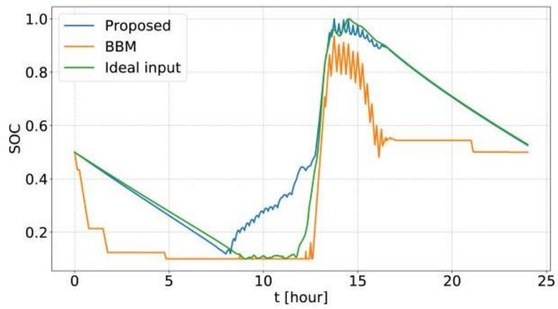

Figure 5: The results of the battery's SOC trajectory for the "bad" day

problems. However, the "bad" day in this experiment is an exception and the worst case in terms of forecast accuracy. In practice the forecasting error will be smaller such as "typical" and "good", and as future extension, the introduction of our own methodology [2] can further improve on this. Therefore, its impact for the performance will clearly be the smallest of all.

5 CONCLUSION AND OUTLOOK

This paper proposes an online multi-scale optimization framework for smart PV system in order to minimize the purchased energy from power company. The proposed framework solves three interconnected optimization problems considering long- and short-term system dynamics simultaneously. Moreover, various system models are integrated into the framework to realize an effective energy management. The results are compared with baseline methods and demonstrate that the proposed framework reduced the purchased energy under different scenarios.

Future work includes extending the proposed framework to multi-objective optimization towards minimizing system operating cost and greenhouse gas emissions, etc. In particular, improving the battery lifetime is one of the most important objectives for smart PV systems. In addition, dynamic electricity pricing will be introduced as an additional input in order to curtail or shift the power usage.

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