Thermal Comfort Aware Online Energy Management Framework for a Smart Residential Building

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***Abstract*—Energy management in buildings equipped with renewable energy is vital for reducing electricity costs and maximizing occupant comfort. Despite several studies on the scheduling of appliances, a battery, and heating, ventilating, and air-conditioning (HVAC), there is a lack of a comprehensive and time-scalable approach that integrates predictive information such as renewable generation and thermal comfort. In this paper, we propose an online energy management framework to incorporate the optimal energy scheduling and prediction model of PV generation and thermal comfort in the manner of the model predictive control (MPC) approach. The energy management problem is formulated as coordinated three optimization problems covering a fast and slow time-scale.This heavily reduces the time complexity without significant negative impact on the global nature and quality of the result. Experimental results show that the proposed framework achieves optimal energy management that takes into account the trade-off between the electricity bill and thermal comfort.**

***Index Terms*—online energy management, model predictive control, thermal comfort, smart PV system**

I. Introduction

Realizing a sustainable future, an energy management system has the most critical role in smart energy systems such as smart homes and smart buildings. The smart energy systems are often equipped with photovoltaic (PV) panel, battery, and various appliances as electric load. In particular, the heating, ventilation, and air conditioning (HVAC) is generally responsible for a significant proportion of the building consumed energy. The main concern of occupants in a building is to reduce electric bills and maximize occupant comfort; thus, co-scheduling all energy subsystems, including the HVAC with comfort consideration, is becoming more attractive.

Many studies have been reported on scheduling the energy subsystems in a building [1]–[3]. Time deferrable appliances such as dishwashers can be scheduled by solving the mixed-integer linear programming (MIP) [1]. The model predictive control (MPC) and receding horizon approach are often employed to schedule the battery and the HVAC with future information [2], [3]. However, these works often assume the impossible situation that the amount of renewable generation is perfectly known in advance. Moreover, they focus on HVAC scheduling as just an energy reduction problem, with no consideration for thermal comfort. Hence, there is a lack of a comprehensive and time-scalable approach for a building incorporating the predictive information for renewable generation and thermal comfort.

In this paper, we focus on developing an online optimization framework for a smart residential building. The proposed framework aims to minimize the electric bill and maximize the thermal comfort, balancing the trade-off between them.

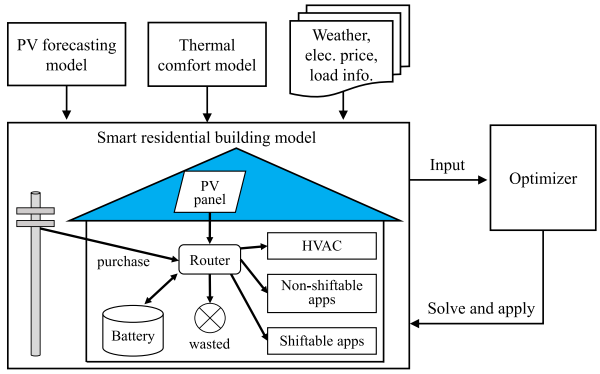

Fig. 1. Schematic view of online energy management framework for a smart residential building.

The MPC structure, covering a fast and slow time-scale, is capable of getting the optimal schedules for appliances, a battery, and HVAC in real-time. Besides, we introduce a PV generation forecast and thermal comfort estimation model to provide useful information. Notably, a linear regression model of thermal comfort predicts optimal temperature set-points adaptively based on a small historical data subset.

II. Online Energy Management Framework

Fig.1 shows an overview of our framework. The key idea of this framework is the iteration of prediction and optimization at different time scales. First, the framework obtains the PV power forecasting and thermal comfort estimation in the near future, e.g., the upcoming one day. The framework then optimizes the schedules of energy subsystems, including appliances, HVAC, and a battery at a medium resolution to reduce the complexity. After that, a short-term scheduling loop is performed to incorporate the solution at a fine-grain resolution. The optimization problem is mathematically formulated and solved by mathematical solvers. Finally, the obtained schedules are applied to the targeted system. While prior work formulated an online energy manenement framework [4], this paper additionally extends to minimize electric bills as well as maximize thermal comfort.

A. System model

Smart residential building structure: In Fig. 1, our target building model is shown. We assume a smart residential building comprises PV panels, a battery to store the generated energy, appliances that include non-shiftable / shiftable appliances and HVAC, and a router to control energy flow. This model only buys the electricity from the power company via the utility grid in case of a power shortage. On the other hand, the surplus energy is charged to the battery, or wasted inside the system without selling to the grid.

PV forecasting: The PV generation has a high fluctuation due to meteorological stochastic phenomena. Thus, the PV generation forecast is necessary to balance demand and energy production. We use the forecast data provided by the PV nowcasting model [5], which can predict short-term generation based on sky-image, NN model, and highly accurate physics-based modeling framework [6]. That provides sufficient planning for online energy management.

Battery: We use an equivalent circuit model introduced in [7] as a liquid-state lithium-ion battery model. This model can accurately predict a battery runtime and non-linear I-V characteristics based on a state of charge (SOC) of the battery. In this paper, this model is implemented to reduce the charge/discharge energy loss and estimate the battery's internal state accurately.

Appliance model: We consider two sets of appliances: non-shiftable (the starting time can not be deferred) and shiftable (the starting time can be shifted to the other time slot) appliances. The framework also optimizes the shiftable appliance schedule with constraints of user preferences minimizing the electric bill. Each shiftable appliance is characterized by four parameters [8]: (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) power profiles. The shiftable appliance must be scheduled from the configuration time until the deadline.

Building thermal and HVAC model: To provide the indoor temperature control and ensure thermal comfort, we capture the building dynamics using the following equation [9]:

$$T_t^{in} = (1 - \frac{\Delta t}{\tau})T_{t-1}^{in} + \frac{\Delta t}{\tau} \cdot (T_{t-1}^{out} - \frac{P_{AC} \cdot COP \cdot u_t + Q_t^{gain}}{C}) \tag{1}$$

where t is a time index, and Δt is length of time resolution. T^{in} and T^{out} are the indoor and outdoor temperatures, respectively. τ and C show the time constant and the thermal capacitance that represent the building dynamics, and Q^{gain} is the thermal gain for the building such as solar radiation and internal gain. P_{AC} and COP are rated power and coefficient of performance of the HVAC, respectively. We assume the air conditioner with an inverter as HVAC, i.e., HVAC output can be continuously controlled from 0% to 100%. Thus, the manipulated variable u for each time step is introduced and scheduled with the range from 0% to 100%.

B. Thermal comfort estimation

To improve thermal comfort for building zones, we introduce the Fanger's predicted mean vote (PMV) / predicted percentage of dissatisfied (PPD) model [10] widely adopted to a real application. Fanger's model can predict the occupants' level of dissatisfaction in a zone based on environment and occupant parameters, e.g., indoor temperature, humidity, metabolic rate, and clothing insulation.

Since our framework controls the indoor temperature, we need to express Fanger's model as a function of the thermal zone's temperature only. Therefore, we employ a linear regression model same as appeared in [11] to construct a thermal model for the indoor temperature in the following form:

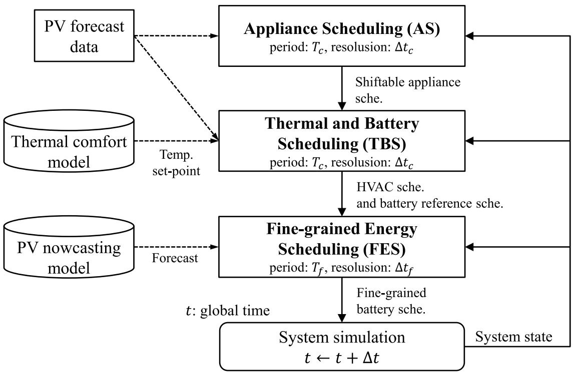

Fig. 2. Dual time-scale optimization flow of online energy management framework.

$$PMV_t = \theta_t^0 + \theta_t^1 \cdot T_t^{in} \tag{2}$$

where θ^0 and θ^1 are the weights. The weights for each t are iteratively updated and refined every time steps using only the historical data of last x days and near time window (-y steps $\sim$ +y steps of same time). This model's concept is based on the fact that Fanger's factors (e.g., metabolic rate, clothing, and so on.) are almost constant for the last few days, while the weather such as humidity can be considered similar for a given time slot between consecutive days [11]. In this paper, x and y are set to 15 and 3 same as in [11].

When the PMV is 0, the dissatisfied rate (PPD) is minimum (5%), i.e., the best case. From the model (2), for all time steps, we extract the temperature set-point $T_{est,t}^{set}$ to minimize the PPD, and the upper / lower bound, denoted by $T_{est,t}^{upper}$ and $T_{est,t}^{lower}$, which ensures the acceptable PPD limit of less than 10% in the ASHRAE 55 standards. These values are used in the objective function and the constraints.

III. Dual time-scale optimization

Fig. 2 shows the dual time-scale optimization flow of the proposed framework. The framework comprises 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, which allows to heavily reduces the time complexity while maintaining high solution quality.

Let T_c and T_f be the planning period of coarse- and fine-grain time scale, respectively. Δt_c and Δt_f be the time resolution of coarse- and fine-grain time scale, respectively. In accordance with the MPC, the framework iterates the following process every internal period, e.g., 15 min. First, the PV forecasting and the comfort estimation model provides predictive information. Then, appliance scheduling (AS) decides shiftable appliance schedule. Next, the thermal and battery scheduling (TBS) calculates the battery and HVAC schedules. These scheduling are obtained for a long period of T_c (e.g., 24 hours), with coarse-grain resolution Δt_c (e.g., 15 min). For the long planning period, PV forecasting is roughly performed: history-based prediction. After that, the fine-grained energy scheduling (FES) is executed to provide precise control for a short period Δt_f (e.g., 15 min) with a resolution Δt_f (e.g., 1 sec). Based on the above procedures, the comprehensive energy management dealing with appliances, HVAC, and a battery is realized in real-time. The details of the framework are described as follows:

A. Appliance scheduling

In the AS, the ON-OFF schedules of shiftable appliances are optimized by solving the MIP problem. To capture long-term system dynamics such as PV generation and electricity prices, T_c and Δt_c take typically 24 hours and 15 min, respectively. The main financial concern of a smart residential building's occupant is the electric bill. Therefore, the objective function is to minimize the electric bill, and the solution of the AS contains the optimal schedules for shiftable appliances and energy purchases from the utility grid. Note that HVAC and battery scheduling are omitted and solved in the next problem, and this decomposition reduces the time complexity significantly. Only the appliance schedules are employed, and the rest are discarded and recalculated in the following problem.

B. Thermal and Battery Scheduling

The TBS realizes the optimal HVAC and battery scheduling for the same time scale as AS. The input is shiftable appliance schedules obtained by AS, electricity price, weather information, and optimal temperature set-points T_{est}^{set} with limits $T_{est}^{upper}/T_{est}^{lower}$ discussed in Sec. II-B. In order to balance trade-off between electric bill and thermal comfort, we employ the weighted sum approach, and the objective function is defined and minimized as follows:

$$J_{opt} = \omega \cdot J_{cost} + (1-\omega) \cdot J_{comfort} + P_e \cdot \sum_{t_c} s_{t_c} \tag{3}$$

where:

$$J_{cost} = \sum_{t_c=0}^{T_c} \xi_{t_c} \cdot E_{t_c} / Bill_{max} \tag{4}$$

$$J_{comfort} = \sum_{t_c=0}^{T_c} (T_{t_c}^{in} - T_{est,t_c}^{set})^2 / |T_{max}^{error}| \tag{5}$$

where ω is the weight to control the trade-off. P_e is a big penalty coefficient, and s_{t_c} is a non-negative slack variable that takes the value by which $T_{t_c}^{in}$ exceeds the limits T_{est,t_c}^{upper} and T_{est,t_c}^{lower}. ξ_{t_c} means electricity price per kWh, and E_{t_c} is the purchased energy from the grid. J_{cost} and $J_{comfort}$ are cost functions indicating electric bill and indoor temperature error from optimal set-point. To treat these functions equally in the weighted sum, they are normalized [12] by possible maximum values $Bill_{max}$ and T_{max}^{error}.

The formulation also includes the battery model. Hence, the TBS realizes the co-scheduling of the HVAC and the battery. Since the battery generally has a great impact on energy usage, this co-scheduling will provides more flexibility to the trade-off between the electric bill and thermal comfort. The accurate battery model includes non-linear equations; thus, this problem has to be dealt with by a non-linear programming (NLP) solver. Then, the obtained battery power trajectory is utilized as reference values in the FES.

TABLE I
RESULTS OF TOTAL ELECTRIC BILL AND AVERAGE PPD FOR PROPOSED AND FIXED SET-POINT METHODS.

Method	Proposed method			
	Comfort	Balanced		Eco
Electric bill [cents]	210	201		189
Average PPD [%]	5.17	5.75		9.22
Method	Fixed set-point method			
	24°C	25°C	26°C	27°C
Electric bill [cents]	235	220	206	192
Average PPD [%]	12.7	6.46	6.15	9.70

C. Fine-grained Energy Scheduling

The FES realizes short-term energy management to interpolate the coarse-grain schedules of the other two problems. We formulate the NLP problem to minimize the mismatch between demand and PV generation. The PV nowcasting model provides the forecast profiles of PV power generation. Besides, the equivalent circuit battery model is integrated to capture the transient energy loss. The FES usually employs 15 min period as T_f, because a 15 min period is well-balanced between PV forecast accuracy and the optimization problem's dimension. Meanwhile, the time resolution Δt_f is set to be 1 sec to consider battery dynamics whose time constant is usually a few seconds. We also introduce the constraint to ensure that the battery power does not deviate greatly from the reference battery power provided by TBS. The precise battery power schedule optimized by the FES is also applied to the targeted system.

IV. Simulation Results

In the simulation study, we consider the simulation period of five days in August. The parameters of the proposed framework are: $T_c = 24$ h, $\Delta t_c = 15$ min, $T_f = 15$ min, and $\Delta t_f = 1$ s. Thus the optimization flow is executed every 15min. The CPLEX v12.9 and IPOPT v3.12 [13] are used as the MIP solver and the NLP solver, respectively. Note that the total solution time of the three optimization problems is average under 10 sec for modern laptop PC (Intel Core-i7 6600U CPU with 2.60 GHz clock frequency and a 16 GB of DDR3 RAM). Therefore, the solution can be obtained in real-time, even using the solvers that are not fully optimized for runtime.

We consider real-time pricing policy as the electricity pricing scheme and use the actual profiles from company ComEd, US. The peak power of the PV panel is set to 4 kWp, and the average error of the PV forecast is 25% for the long-term and 12% for the short-term [5], respectively. The battery size is 4kWh, and the parameters of the circuit model are chosen from [7]. The average daily total demand is 18 kWh without HVAC. We use the DRED dataset as demand profiles of non-shiftable and shiftable appliances [14]. Three shiftable appliances, including dishwasher, clothes washer-dryer, and EV charger, are scheduled once a day. The rated power and the COP of the HVAC are 2 kW and 2.5, respectively. We use the building, occupants, weather data in the public dataset of the

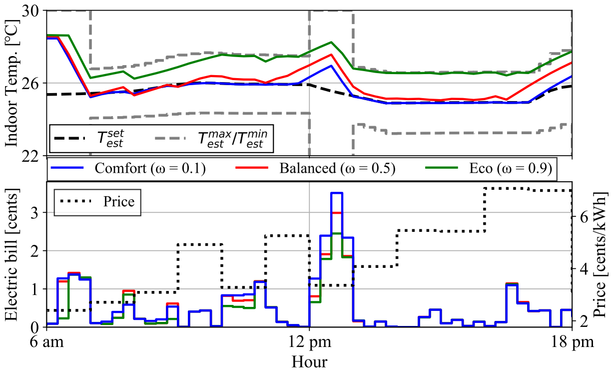

Fig. 3. Comparison of indoor temperature and electric bill for occupied period with different weights.

US office [15]. We assume that the target residential building is occupied all day from 8 am-12 pm and 1 pm-6 pm.

Firstly, we compare the proposed method, which decides the temperature set-points adaptively based on comfort estimation, with a method that employs a fixed set-point for indoor temperature [16]. Depending on the value of the weights ω, three modes are derived from the proposed method. Hence, "Eco", "Balanced", and "Comfort" correspond to $\omega = 0.1, 0.5, 0.9$, respectively. Table I shows the results of the total electric bill and actual average PPD for five days. From the results, the proposed method outperforms the fixed set-point method in both electric bills and PPD. In particular, both "Comfort" and "Balanced" achieved a PPD of less than 6%. This result implies that the comfort estimation model provides a suitable temperature set-point.

In Fig. 3, the resulting indoor temperature and electric bill during the occupied period for each mode are shown. Fig. 3 reveals that the pattern of indoor temperature and electricity purchase changes according to the value of the weights ω. In the upper figure, it is shown that the temperature set-point given by the comfort estimation model T_{est}^{set} adaptively changes, and the upper and lower temperature bound, denoted by T_{est}^{upper} and T_{est}^{lower}, also changes. From the lower figure, when the electricity price is low such as 10 am and 12 pm, the electricity is mainly purchased to reduce the electric bill. The proposed method considers the adaptive temperature set-point as well as the electricity price.

Fig. 4 shows the trade-off between the electric bill and average PPD with different battery capacities. Each point of curves corresponds to different weights, which are $\omega = 0.1, 0.3, 0.5, 0.7, 0.8, 0.9$ from the left. As shown in Fig. 4, the battery introduction has a high impact on the trade-off. Meanwhile, the large battery of 10kWh saturates the trade-off; thus, the battery capacity should be carefully chosen considering the trade-off and initial cost of the battery.

V. Conclusion and Outlook

This paper proposes a thermal comfort aware online energy management framework for comprehensive energy scheduling (e.g., shiftable appliances, HVAC, a battery) in a smart residential building. We formulate the optimization problem as an MPC approach that incorporates PV prediction and thermal comfort estimation models. The result shows that the proposed

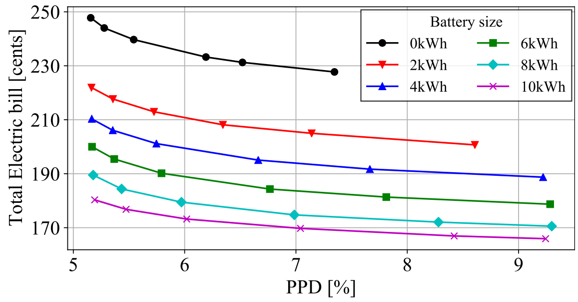

Fig. 4. Battery size impact on trade-off between electric bill and PPD.

method can balance the trade-off between the electric bill and thermal comfort.

In this research, we employ an adaptive temperature set-point approach based on Fanger's model. However, there would be a gap between Fanger's model and actual comfort in the practical case. Therefore, one future work is to reflect the occupant's preference based on occupant's vote and sensing information, targeting a cyber-physical system (CPS). On the other hand, we assume that the HVAC system is ideal, e.g., COP is set to constant. Accordingly, the introduction of an accurate HVAC model is also the future direction to realize an energy-efficient framework.

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