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PAPER

Thermal-comfort Aware Online Co-scheduling Framework for HVAC, Battery Systems, and Appliances in Smart Buildings**

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SUMMARY Energy management in buildings is vital for reducing electricity costs and maximizing the comfort of occupants. Excess solar generation can be used by combining a battery storage system and a heating, ventilation, and air-conditioning (HVAC) system so that occupants feel comfortable. Despite several studies on the scheduling of appliances, batteries, and HVAC, comprehensive and time scalable approaches are required that integrate such predictive information as renewable generation and thermal comfort. In this paper, we propose an thermal-comfort aware online co-scheduling framework that incorporates optimal energy scheduling and a prediction model of PV generation and thermal comfort with the model predictive control (MPC) approach. We introduce a photovoltaic (PV) energy nowcasting and thermal-comfort-estimation model that provides useful information for optimization. The energy management problem is formulated as three coordinated optimization problems that cover fast and slow time-scales by considering predicted information. This approach reduces the time complexity without a significant negative impact on the result's global nature and its quality. Experimental results show that our proposed framework achieves optimal energy management that takes into account the trade-off between electricity expenses and thermal comfort. Our sensitivity analysis indicates that introducing a battery significantly improves the trade-off relationship.
key words: *energy management system, model predictive control, real-time co-scheduling, thermal comfort, PMV, PV forecasting, HVAC, battery system, smart appliances*

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1. Introduction

To achieve a sustainable future, an energy management system (EMS) plays the most critical role in such smart energy systems as smart homes and smart buildings [1]. The electrical load of smart energy systems often includes a photovoltaic (PV) panel, a battery system, and appliances. An EMS coordinately manages such equipment and provides key functions to effectively use renewable generation for such purposes as cost-minimization and thermal-comfort maximization. In addition, ease of access to valuable weather forecasts, demand load, and PV generation through internet connections and the internet of things (IoT) enables an EMS to act as the core of an energy infrastructure that satisfies occupants' preferences in real-time.

Heating, ventilation, and air-conditioning (HVAC) systems account for a significant proportion ($> 40\%$) of a building's energy consumption [2]. HVAC systems also affect the thermal comfort of the occupants, which influences their productivity and health. Therefore, the main concerns of the building's occupants are to simultaneously reduce their electricity expenses and maximize their thermal comfort by controlling the HVAC systems. The combination of PV generation and a battery system maintains thermal comfort without compromising electricity costs. For example, when electricity prices are high, PV generation can meet HVAC demand. When a battery system is fully charged, the flexibility of HVAC control is greatly enhanced. Therefore, co-scheduling all energy subsystems, including PV panels, battery storage system, and HVAC, is becoming more attractive.

Many studies have been reported on the scheduling of equipment in buildings. Qayyum et al. proposed optimal scheduling of such time-deferrable appliances as dishwashers and tumble dryers by basing PV generation on mixed-integer linear programming (MIP) [3]. Telouw et al. developed a multi-objective MIP problem to optimize operation costs and CO_2 emissions by scheduling electrical energy storage and heat storage in a smart community [4]. Duman et al. also formulated an MIP-based home EMS to perform a day-ahead load scheduling, focusing on HVAC, batteries, PV generation, and electric vehicles, to minimize system costs and maximize thermal comfort [5]. However, applying these day-ahead approaches in the real world can lead to unexpected cost increases due to such uncertainties as load demand and renewable energy.

To address the uncertainties, online optimization techniques are gaining attention. Model predictive control (MPC) is one of the promising schemes to optimize EMS operations with future information. This approach iteratively computes optimal control based on system prediction models and forecasting information at every time step. Abreu et al. developed a hierarchical MPC for a building EMS (BEMS) to coordinately schedule many controllable loads and demonstrated the robustness of the MPC strategy [6]. Cui et al. focused on a MIP-based receding horizon approach to optimize battery and HVAC operations for cost reduction [7]. Perez et al. proposed a centralized MPC scheme to minimize the peak demand of HVAC and time-defferable appliances [8]. Killan et al. presented a comprehensive approach for a home EMS based on a mixed-integer quadratic programming (MIQP) -based MPC for the maximization of renewable utilization, cost minimization, and thermal-comfort improvement [9]. However, these works still do not consider any specific forecasting method for renewable generation or assume impossible situations where the amount of renewable generation is completely known in advance. In addition, they focus on HVAC scheduling as an energy-reduction problem without addressing thermal comfort. Therefore, a comprehensive and time-scalable approach must incorporate predictive information for renewable generation and thermal comfort.

In this paper, we develop a thermal comfort aware online co-scheduling framework for a smart building by extending the energy management framework proposed in [10]. The work [10] proposed the dual time-scale approach that divides the time-scale into coarse- and fine-grained scales to consider both slow and fast dynamics. They also employed the MPC structure which can obtain the optimal schedules for appliances and a battery system in real-time using PV forecasting model. However, the work [10] only focuses on minimizing the electricity expense and does not consider thermal comfort, which is an important factor in the building. To address this issue, we extend the approach [10] to consider thermal comfort by introducing HVAC scheduling with a thermal-comfort model. The objective of our proposed method is to minimize electricity expenses and maximize thermal comfort, balancing the trade-off between them. We model the building thermal dynamics and HVAC system and introduce the thermal-comfort estimation model that predicts an optimal temperature set-point. The HVAC scheduling is mathematically formulated and integrated into the optimization flow of the framework. Thus, the main contribution of this work is to achieve better trade-off relationships between electricity expenses and thermal comfort by integrating the HVAC scheduling into the multi time-scale energy management framework. Finally, the proposed framework effectively combines two prediction models, the PV forecasting model and the thermal-comfort model, and three coordinated optimization problems covering slow and fast system dynamics.

The remainder of this paper is organized as follows. Section 2 explains our proposed co-scheduling framework.

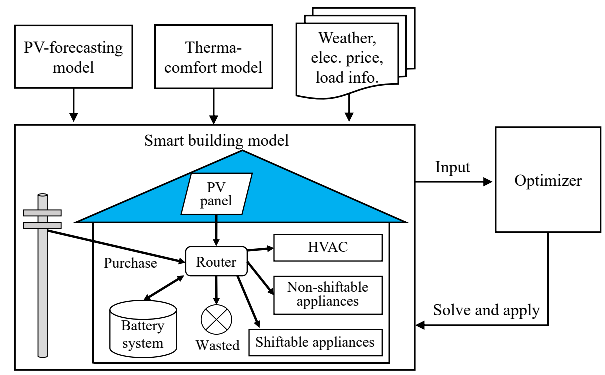

Fig. 1 Schematic view of online energy management framework

Section 3 describes a mathematical formulation of the dual time-scale optimization problem. Section 4 shows simulation results that demonstrate the effectiveness of our proposed method, and finally Section 5 concludes this paper.

2. Proposed Co-scheduling Framework

Fig. 1 overviews our framework whose key idea is the iteration of prediction and optimization at different time scales. First, the framework obtains PV-power forecasting and thermal-comfort estimation in the very near future, e.g., the next day. It then optimizes the schedules of energy subsystems, including appliances, a HVAC, and a battery system, whose time resolution is coarse-grained, such as 15 min, to reduce computational complexity. After that, a short-term scheduling loop incorporates the solution at a fine-grained resolution. The optimization problem is mathematically formulated and solved by an optimization solver. Finally, the obtained schedules are applied to the target system. Although our previous work developed an online energy management framework [10], this paper extends it to control a HVAC system with thermal-comfort estimation to minimize electricity expenses and maximize thermal comfort.

2.1 System model

Smart building structure Fig. 1 shows our smart building model. We assume a smart building that is comprised of PV panels, a battery storage system to store surplus PV generation, appliances, including non-shiftable/shiftable types, and a HVAC. The power/energy flow inside a household is assumed to be managed by a smart inverter-based control system, denoted by an energy router [11, 12]. This building only buys electricity from the power company through a utility grid during power shortages. Surplus energy is charged to the battery system, and when batteries are completely charged, the excess energy is wasted instead of being sold to the grid. Since a reverse power flow often destabilizes power grids, our model maximizes PV utilization.

PV forecasting PV generation has high fluctuation due to meteorological stochastic phenomena. Thus, a PV-generation forecast is necessary to balance demand and en-

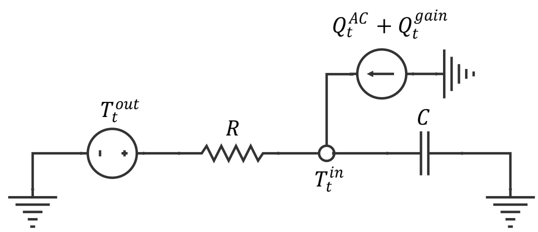

Fig. 2 Thermal equivalent circuit model of buildings

ergy production. We used the forecast data provided by the PV-nowcasting model [13], which can predict short-term generation based on sky images, neural network (NN) models, and a highly accurate physics-based modeling framework [14]. The model can predict power output at one-second granularity every minute for 15 minutes horizons, which enables the maximum utilization of PV generation. Day-ahead PV forecasting over 24 hours is also required to efficiently schedule battery and demand loads. In this study, we manually generated forecasting profiles by adding Gaussian noise to the ground-truth. Note that in the future such day-ahead forecasts will be readily available from meteorological information providers. These two PV forecasts provide sufficient planning for online energy management.

Battery We used an equivalent circuit model [15] as a liquid-state lithium-ion battery model, which can accurately predict battery runtimes and nonlinear I-V characteristics based on the battery's state of charge (SOC). We integrated an equivalent circuit model into the optimization problem to address accurate battery dynamics. This step reduces the charge/discharge energy loss and enables accurate estimation of the battery's internal state.

Appliance model We consider two sets of appliances: non-shiftable (the starting time cannot be deferred) and shiftable (it can be shifted to other time slots). The framework also optimizes the shiftable-appliance schedule with the constraints of user preferences to minimize electricity expenses. Each shiftable appliance is characterized by four parameters [16]: (1) operating time, (2) configuration time, which denotes when to start the appliance, (3) deadline, which denotes the time by which its operation must be completed, and (4) power profiles. Shiftable appliances must be scheduled from their configuration times until their deadlines. We optimize the schedule of shiftable appliances to minimize electricity expense.

Building thermal dynamics and HVAC model We describe a building's thermal dynamics with a thermal equivalent circuit model [17] (Fig. 2). In the model, the building's thermal behavior is analogous to its electrical behavior. Let t be a time index. The building characteristics are represented by thermal resistance R and thermal capacity C, and these values are identified based on building data sheets. Here time constant τ shows the thermal response speed:

$$\tau = R \cdot C \tag{1}$$

In the model, the indoor temperature for next time T_{t+1}^{in} can be calculated:

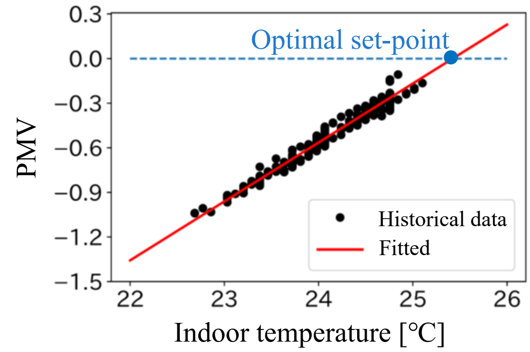

Fig. 3 Example of linear regression model for PMV

$$\begin{aligned} T_{t+1}^{in} &= (1 - \frac{\Delta t}{\tau}) \cdot T_t^{in} \\ &+ \frac{\Delta t}{\tau} \cdot \{T_t^{out} - 1000 \cdot R \cdot (Q_t^{AC} + Q_t^{gain})\} \end{aligned} \tag{2}$$

where Δt is the length of the time resolution. T_t^{out} is the outdoor temperature, Q_t^{AC} is the thermal gain due to a HVAC system, and Q_t^{gain} refers to such thermal gain as solar irradiation and internal heat. The relationship between HVAC's thermal gain and electrical power is given:

$$Q_t^{AC} = -P_{AC} \cdot COP \cdot u_t \tag{3}$$

where P_{AC} and COP are the rated power and HVAC's coefficient of performance. We assume that HVAC includes an inverter system whose output can be continuously controlled from 0% to 100%. Then, the manipulated variable u_t is introduced and scheduled in a range from 0 (0%) to 1 (100%). Finally, the power consumption of the HVAC D_t^{hvac} at time t is calculated by:

$$D_t^{hvac} = P_{AC} \cdot u_t \tag{4}$$

2.2 Thermal-comfort estimation

To improve the thermal comfort for building zones, we introduce Fanger's predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) index [18], both of which are widely adopted for real applications. The PMV is an index that shows a scale of occupants thermal sensation, and it ranges from -3 (too cold) to +3 (too warm). The PMV can be calculated by a nonlinear complex function based on environment and occupant parameters, e.g., indoor temperature, humidity, metabolic rate, and clothing insulation. Once the PMV is calculated, the PPD, which is a percentage of people that feels thermal discomfort in the indoor space, is derived from the following empirical equation [18]:

$$PPD = 100 - 95^{(-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2)} \tag{5}$$

When the PMV is 0.0, the PPD is minimum (5%), i.e., this indoor space is the most comfortable for occupants. Since

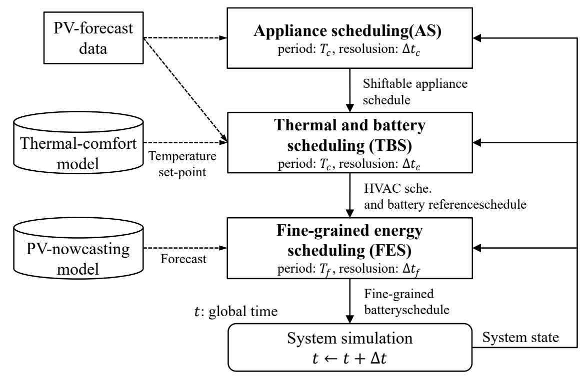

Fig. 4 Dual time-scale optimization flow of online energy management framework

our framework controls the indoor temperature by HVAC scheduling, approximating Fanger's model (PMV) as a function of the thermal zone's temperature is sufficient.

To estimate the comfort of indoor temperature, we employ the following linear regression (LR) model from a previous work [19]:

$$PMV_t = \theta_t^0 + \theta_t^1 \cdot T_t^{in} \tag{6}$$

where θ_t^0 and θ_t^1 are the weight coefficients of the LR model. The main idea of this previous model [19] is to efficiently manipulate historical data in the construction of the LR model. Fanger's factors (e.g., metabolic rate and clothing) are almost constant for the last few days, while such environmental factors as humidity and air velocity are generally similar for a given time slot between consecutive days. Therefore, the LR model is built for each time step, and the weight coefficients θ_t^0, θ_t^1 are refined for each time step using only the latest historical data of the last x days and a near time window (-y $\sim$ +y steps of the same time).

An example of the LR model for PMV is shown in Fig. 3. The PMV is fitted as the LR model based on the historical data points. The optimal temperature set-point is the temperature where the PMV is 0.0. Following ASHRAE's 55 standards [20], PPD's acceptable limit is less than 10%, which corresponds to a PMV of ± 0.5. From the model (6), we can obtain the optimal temperature set-point $T_{est,t}^{set}$, and the upper/lower bounds, denoted by $T_{est,t}^{upper}$ / $T_{est,t}^{lower}$:

$$T_{est,t}^{set} = -\theta_t^0/\theta_t^1 \tag{7}$$
$$T_{est,t}^{upper} = (-\theta_t^0 + 0.5)/\theta_t^1 \tag{8}$$
$$T_{est,t}^{lower} = (-\theta_t^0 - 0.5)/\theta_t^1 \tag{9}$$

These values are used in the objective function and in the constraints of our optimization problem.

3. Dual Time-scale Optimization

Fig 4 shows the dual time-scale optimization flow of the proposed framework. It is comprised of multiple optimization stages for each purpose, considering two different time scales: coarse- and fine-grained. In this way, we simultaneously deal with long- and short-term system dynamics, which allows great reduction of the time complexity while maintaining high solution quality. In this framework, we also employ an MPC approach to tackle forecast errors and considered the latest system states. MPC's key idea is the iteration of forecasting and optimization [21]. First, future control inputs over the planning period are obtained by solving the optimization problem based on system models and forecast information. After that, the only first-sample solution is applied, and the optimization is iterated by shifting the planning period back one step. Its feedback structure can potentially compensate for the uncertainty of the variation of load demand and PV-forecasting errors.

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

Note that this paper employs the dual time-scale approach proposed in the literature [10]. According to the literature, the dual time-scale scheme drastically reduces the total time steps. If only one time-scale scheme is employed, the planning period will be typically 24 hours with 1 sec resolution (86400 steps) to capture both fast and slow system dynamics. Meanwhile, in the dual time-scale, the AS and the TBS typically have 96 steps (24 hours period with 15 min resolution), and the FES have 900 steps (15 min period with 1 sec resolution). The total time step of the proposed framework is reduced up to 96 times compared to the one time-scale scheme. In this way, the proposed framework can reduce the time complexity. On the other hand, this approach divides the coarse-grained optimization into two problems, AS and TBS, based on the literature [10]. This is because the considerable time scale of each device is different; the appliance scheduling and demand load with daily cycle require a long planning period of at least 24 hours to obtain an optimal solution, while the battery and the HVAC have shorter time constants than the appliances, and the fine-grain time scale also should be considered. Thus, the proposed framework firstly performs the AS and secondly performs the TBS and the FES, following the order of a length of the time scale. In terms of the time scale differences, this problem split is a reasonable assumption, and we have also succeeded in further reducing computational time.

Due to space limitations, we primarily discuss the extended part of the framework in the following section; refer to the literature [10] for detailed formulation of the AS and FES.

3.1 Appliance scheduling

In the AS, the ON-OFF schedules of shiftable appliances are optimized by solving the MIP problem. To capture such long-term system dynamics as PV generation and electricity prices, T_c and Δt_c are typically set for 24 hours and 15 min. The main concern of a smart building's occupants is electricity expenses. Therefore, our objective function is to minimize them, and the AS solution contains 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 significantly reduces the time complexity. Only appliance schedules are employed, and the rest are discarded and recalculated in the following problem.

3.2 Thermal and battery scheduling

The TBS achieves optimal HVAC and battery scheduling for the same time scale as AS. Its input obtained from the other part of the framework includes the shiftable-appliance schedules obtained by the AS $D^{shft}_{t_c}$ and optimal temperature set-points T^{set}_{est,t_c} with upper/lower bounds $T^{upper}_{est,t_c}/T^{lower}_{est,t_c}$ discussed in Section 2.2. The mathematical formulation of the TBS is described as follows:

Given

$$\{G_{t_c}, D^{base}_{t_c}, D^{shft}_{t_c}, \xi_{t_c}, T^{set}_{est,t_c}, T^{upper}_{est,t_c}, T^{lower}_{est,t_c}, O_{t_c}, Q^{gain}_{t_c}, T^{out}_{t_c}\},\ \forall t_c$$

Find

$$\{E_{t_c}, Y_{t_c}, u_{t_c}, s_{t_c}, I^{bat}_{t_c}\},\ \forall t_c$$

Minimize

$$\omega \cdot J_{cost} + (1-\omega)\cdot J_{comfort} + P_e \sum_{t_c=0}^{T_c} s_{t_c} \quad (10)$$

Subject to

$$(1)-(4),\ \forall t_c$$

$$J_{cost} = \frac{\sum_{t_c=0}^{T_c} \xi_{t_c}\cdot E_{t_c}}{Bill_{max}} \quad (11)$$

$$J_{comfort} = \frac{\sum_{t_c=0}^{T_c} O_{t_c}\cdot (T^{in}_{t_c} - T^{set}_{est,t_c})^2}{|T^{error}_{max}|} \quad (12)$$

$$T^{lower}_{est,t_c} - s_{t_c} \le T^{in}_{t_c} \le T^{upper}_{est,t_t} + s_{t_c},\ \forall t_c \quad (13)$$

$$0 \le s_{t_c},\ \forall t_c \quad (14)$$

$$E_{t_c} + G_{t_c} + B_{t_c} = D^{base}_{t_c} + D^{shft}_{t_c} + D^{hvac}_{t_c} + Y_{t_c},\ \forall t_c \quad (15)$$

$$0 \le E_{t_c},\ \forall t_c \quad (16)$$

$$0 \le Y_{t_c},\ \forall t_c \quad (17)$$

$$I^{bat}_{min} \le I^{bat}_{t_c} \le I^{bat}_{max},\ \forall t_c \quad (18)$$

$$SOC_{t_c+1} = SOC_{t_c} - \frac{I^{bat}_{t_c}\cdot \Delta t_c}{C_{nom}},\ \forall t_c \quad (19)$$

$$SOC_{min} \le SOC_{t_c} \le SOC_{max},\ \forall t_c \quad (20)$$

$$V^{bat}_{t_c} = f(I^{bat}_{t_c}, SOC_{t_c}),\ \forall t_c \quad (21)$$

$$B_{t_c} = I^{bat}_{t_c}\cdot V^{bat}_{t_c},\ \forall t_c \quad (22)$$

For the inputs of this problem, G_{t_c} is the PV generation, $D^{base}_{t_c}$ is the demand load of the non-shiftable appliances, ξ_{t_c} is the electricity, and O_{t_c} is the occupied information: $O_{t_c} = 1$ if the room is occupied, otherwise 0. The decision variables of this problem are the energy purchased from the utility E_{t_c}, the wasted energy Y_{t_c}, the manipulated variable of the HVAC u_{t_c}, the slack variable s_{t_c} to avoid a violation for the comfort temperature range, and the battery current $I^{bat}_{t_c}$ which takes a positive/negative value when discharging/charging. In the objective function (10), the first term J_{cost}, which is defined by the equation (11), indicates electricity expenses. The second term $J_{comfort}$, which is defined by the equation (12) means the error between the indoor temperature and the optimal set-point. ω is a weight parameter to control the trade-off between J_{cost} and $J_{comfort}$. These functions are normalized by possible maximum values $Bill_{max}$ and T^{error}_{max} to treat them equally in the weighted sum [22]. The third term in the objective indicates the penalty term that prevents the room temperature from violating the comfort temperature range. P_e is a large penalty constant (e.g., set to 1000) for a temperature violation. s_{t_c} is a non-negative slack variable that represents the excess value when $T^{in}_{t_c}$ exceeds limits T^{upper}_{est,t_c} or T^{lower}_{est,t_c}, and these constraints are defined by the equations (13) and (14). ξ_{t_c} denotes the electricity price per energy. Finally, the objective of this problem is to minimize the electricity expenses and maximize the thermal comfort.

We explain the other constraints of this problem (15) - (22). Where B_{t_c} denotes the charging/discharging energy of the battery, which takes a positive value when discharging and a negative value when charging. I^{bat}_{min} and I^{bat}_{max} are the maximum charging and discharging current of the battery. SOC_{t_c} is the SOC level of the battery, i.e., the amount of energy available in the battery expressed by a proportion, ranging from 0 (0%) to 1.0 (100%). SOC_{min} and SOC_{max} is the lower and upper bounds of the SOC level decided by the user. C_{nom} is the nominal Ah capacity of the battery, and $V^{bat}_{t_c}$ denotes the terminal voltage of the battery. The equation (15) means that the energy balance inside the system must be kept at any time. The constraints (16) and (17) show that the purchased energy and the wasted energy only take a positive value. The equation (18) shows that the range of the battery current $I^{bat}_{t_c}$ is constrained by its lower/upper bounds. The equation (19) calculates the battery's SOC level at the next time step based on the battery current $I^{bat}_{t_c}$, and the range of the SOC level is constrained by the lower and upper bounds in the equation (20). In the equation (21), the terminal voltage of the battery $V^{bat}_{t_c}$ is calculated by the function f of the battery current and the SOC level, and this function

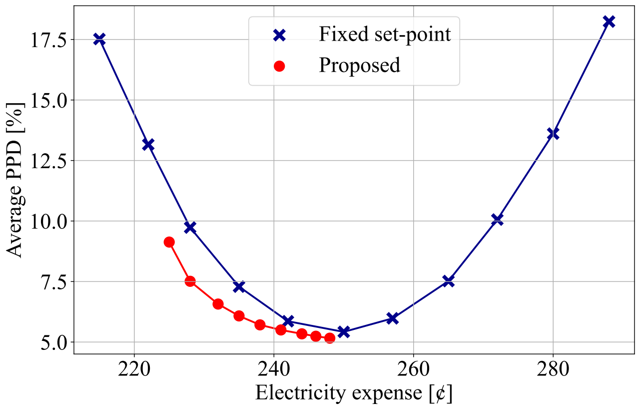

Fig. 5 Trade-off relationship between total electricity expenses and average PPD for proposed and fixed set-point methods

is given by the literature [15]. The equation (22) shows that the battery charging/discharging energy is calculated based on the battery current and the terminal voltage.

The TBS achieves co-scheduling of the HVAC and a battery system. Since batteries greatly impact energy usage, this co-scheduling provides more flexibility to the trade-off between electricity expenses and thermal comfort. Since an accurate battery model includes nonlinear equations (21) and (22), this problem has to be dealt with by a nonlinear programming (NLP) solver. Then the obtained battery power trajectory is utilized as reference values in the FES.

3.3 Fine-grained energy scheduling

The FES realizes short-term energy management to interpolate the coarse-grained 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 the PV-power generation. An equivalent circuit battery model is integrated to capture the transient energy loss. The FES usually employs 15-min periods as T_f, because the PV forecast-accuracy degrades significantly when the prediction period exceeds 15 min [13]. Besides, the time complexity of the FES increases as the planning period increases. In terms of both forecast accuracy and time complexity, the appropriate length of the planning period is 15 min. Time resolution Δt_f is set to 1 sec to consider battery dynamics, whose time constant is usually a few seconds. We also introduce a constraint to ensure that the battery power does not deviate greatly from the reference battery power provided by TBS. We also apply a precise battery power schedule optimized by FES to the targeted system.

4. Simulation Results

To demonstrate the effectiveness of our proposed framework, we conducted a five-day simulation experiment in August. Our target system is a smart building, which has a contract for real-time electricity pricing, and we use actual price profiles from ComEd, US [23]. The PV panel's peak power is set to 4 kWp, and the PV forecast's average error is 25% for long-term and 12% for short-term usages [13]. The battery size is 4 kWh, and the circuit model's parameters were chosen from a previous work [15]. The average daily total demand is 18 kWh without HVAC. We use the DRED dataset as demand profiles for non-shiftable and shiftable appliances [24]. Three shiftable appliances include a dishwasher, a clothing washer/dryer, and an EV charger, all of which are scheduled once a day. The rated power and the HVAC's COP are 2 kW and 2.5. We use the historical thermal-comfort data from a public survey dataset [25], which contains the PMV levels for 24 office occupants for a whole year. The weather conditions are assumed to be the hottest sunny days in a Japanese summer, in which the average temperature is $28°C$. We assume that the target residential building is occupied all day from 8 am to 12 pm and 1 pm to 6 pm.

The following are the parameters of the proposed framework: $T_c = 24\,\mathrm{h}$, $\Delta t_c = 15\,\mathrm{min}$, $T_f = 15\,\mathrm{min}$, and $\Delta t_f = 1$ s. Thus, the optimization flow in Fig. 4 is executed every 15 min. Weight coefficients ω are changed within a range of 0$\sim$1. For the time window of the thermal-comfort estimation, x and y are set to 15 and 3, like in a previous work [19]. CPLEX v20.1 and IPOPT v3.14 are used as the MIP and NLP solvers. Note that the total solution time for the three optimization problems averages less than 10 sec on a 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 with solvers that are not fully optimized for runtimes.

We compared the proposed framework with a method that employed a fixed set-point for indoor temperatures [7,26]. The proposed framework adaptively decides the temperature set-points based on thermal-comfort estimation, and the weight coefficients for the objective function are changed from 0.1 to 0.9. The fixed set-point scheme employs a dual time-scale MPC without HVAC co-scheduling i.e., the difference between the proposed method and the fixed set-point method is only the temperature set-point. The HVAC is controlled with a fixed set-point, so that the indoor temperature adheres to the set-point as much as possible. Table 1 shows the results of the total electricity expenses and average PPD as a comfort criterion over five days. For the proposed method, the weight coefficients control the importance of the electricity expenses and the average PPD. For the fixed set-point method, the higher the temperature set-points the lower the electricity expenses, but the higher the average PPD, i.e., simply reducing the HVAC operation. Fig. 5 plots the result of Table 1 and shows the relationship between the electricity expenses and the average PPD for the different methods. As shown in Fig. 5, the line of the proposed method is below the line of the fixed set-point method. This means that the proposed framework performs a better trade-off relationship between electricity expenses and thermal comfort than the baseline, implying that the comfort-estimation model provides a suitable temperature set-point.

Fig. 6 shows the profiles of the indoor temperature, the

Table 1 Results of total electricity expenses and average PPD for proposed and fixed set-point methods over five days in August

Method	Proposed framework with thermal-comfort estimation									
		$\omega = 0.1$	$\omega = 0.2$	$\omega = 0.3$	$\omega = 0.4$	$\omega = 0.5$	$\omega = 0.6$	$\omega = 0.7$	$\omega = 0.8$	$\omega = 0.9$
Electricity expense [¢]		248	246	244	241	238	235	232	228	225
Average PPD [%]		5.16	5.24	5.34	5.5	5.71	6.08	6.57	7.51	9.13

Method	Fixed set-point method										
	23.0°C	23.5°C	24.0°C	24.5°C	25.0°C	25.5°C	26.0°C	26.5°C	27.0°C	27.5°C	28.0°C
Electricity expense [¢]	288	280	272	265	257	250	242	235	228	222	215
Average PPD [%]	18.24	13.61	10.06	7.52	5.98	5.42	5.86	7.29	9.73	13.16	17.52

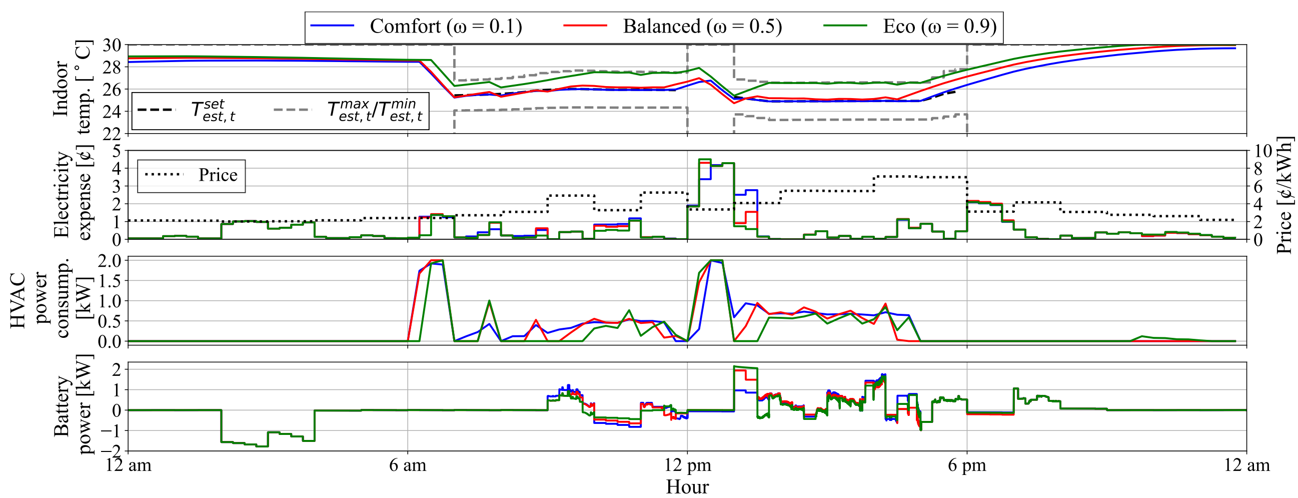

Fig. 6 Profiles of indoor temperature, electricity expenses, HVAC power consumption, and battery power (negative battery power denotes charging, and vice versa) with different weights for second day

electricity expenses, the HVAC power consumption, and the battery power with different weight coefficients. Depending on the value of weights ω, three modes, Eco, Balanced, and Comfort, correspond to $\omega = 0.1, 0.5$, and 0.9. The indoor temperature result shows that temperature set-point $T^{set}_{est,t}$, upper bound T^{upper}_{est}, and lower bound T^{lower}_{est} adaptively changed with time, and the indoor temperature is controlled as intended by the mode. From the bottom three figures, electricity is mainly purchased around 3 am and 12 pm when its price (black dotted line) is low. The HVAC system is also used much more during low price periods at noon and before the occupants arrive. The battery system is charged during low price periods (3 am and 10 am) and discharged during high price periods (1 pm to 7 pm). Remarkably, for different modes, the electricity expense is almost identical from 2 pm to 5 pm, even though the HVAC power consumption is different. This is because the battery discharge was adjusted to align with the HVAC operation during this high price period. Owing to the co-scheduling of the HVAC system and the battery, electricity expenses can be minimized while maintaining thermal comfort. The proposed method considers the adaptive temperature set-point as well as the electricity price and the weight coefficients to minimize the electricity expenses and maximize the thermal comfort.

5. Conclusion and Outlook

This paper proposed a thermal comfort aware online co-scheduling framework for comprehensive energy management that includes shiftable appliances, a HVAC system, and a battery storage system in a smart building. The proposed framework integrates the prediction model of PV generation, thermal comfort, and the optimization problem. We formulate the problem as an MPC approach to consider the uncertainties of PV generation and thermal condition. These three optimization problems, which have different objectives, are reasonably combined by decomposition into dual timescales. The result shows that the proposed method balanced the trade-off between electricity expenses and thermal comfort.

We employed adaptive temperature set-points based on Fanger's model. However, in practical cases, a gap exists between Fanger's model and actual comfort. Therefore, one future work will reflect the preferences of occupants based on their choices as well as sensing information.

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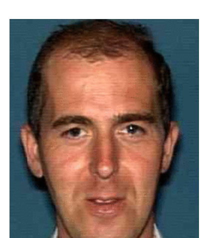

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