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Optimal scheduling of aggregated thermostatically controlled loads with renewable generation in the intraday electricity market ☆

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HIGHLIGHTS

- A novel two-level approach is proposed to schedule aggregated thermal loads.
- Revenues for prosumers in the intraday electricity market are maximized.
- An energy-balanced model is established for aggregated scheduling.
- The imbalanced energy and capacity are considered to be reduced at the same time.
- The effects of imbalance prices, heterogeneity and forecast errors are studied.

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ABSTRACT

A novel two-level scheduling method was proposed in this paper, which helps an aggregator optimally schedule its flexible thermostatically controlled loads with renewable energy to arbitrage in the intraday electricity market. The proposed method maximizes the economic benefits of all the prosumers in the aggregation, and naturally helps balance intra-hour differences between supply and demand of the bulk power systems because the prices of the intraday electricity market reflects the need of the bulk power systems. In the proposed two-level scheduling, the upper level is a model predictive control optimization, of which the objective function is to minimize the sum of energy and capacity cost of imbalances and the constraints are thermal constraints based on a proposed energy-balanced model, while the lower level adopts the typical temperature priority list (TPL) control. Simulation results verified the validity of the proposed method and evaluated the effects of important influencing factors. In the base case, 41.64% imbalance cost was saved compared to the reference TPL-based control. Moreover, three further conclusions were drawn: (a) the proposed method mainly saves the imbalance cost by reducing imbalance peak, thus being suitable for places with high capacity price for imbalances; (b) parameter heterogeneity affects the performance of the proposed method, and average value method performs well only with low heterogeneity; (c) the performance of the proposed method worsens with the increase of forecast uncertainty, but keeps better than that of typical TPL-based control unless the forecast uncertainty gets very strong.

1. Introduction

Renewable energy has been being developed rapidly all around the world during the latest decades, and its penetration in power systems keeps increasing. A large portion of renewable energy is being deployed at the household level in the forms of rooftop photovoltaic arrays and small wind turbines, which makes many residential consumers become "prosumers" that are also able to produce electricity. In spite of various contributions to environmental conservation and sustainable development, renewable energy of high penetration presents great challenges to power systems due to its serious randomness and variability, resulting in significant demand for operating reserves. Traditional large centralized regulating generators are not considered to be an ideal solution because increased ramp and capacity requirement would lower the efficiency, shorten the lifetime and increase the wear-and-tear cost of the generators. In contrast, flexible demand

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Nomenclature

Variables

θ	water temperature (°C)
u	on/off status
r	amount of imbalance electricity (kW h)
l	aggregated thermal load (kW)
α, β, γ, δ	ancillary variables in the linear counterpart

Parameters

Q	heater capacity (kW)
R	thermal resistance (°C/kW)
C	thermal capacitance (kW h/°C)
Δt	length of each time step (h)
M	mass of water in full storage (kg)
d	demand of hot water (kg)
L	heat loss (kW h)
C	specific heat capacity (kW h/kg °C)
P	rated power (kW)
η	coefficient of performance
$\mathbf{N}^{+}$	set of all positive natural numbers
N	number of time steps of a day
p	imbalance price ($/kW or $/kW h)
w	renewable generation (kW)
s	uncontrollable load (kW)
g	day-ahead purchased electricity (kW)
Num	total number of thermal loads
Γ	parameter indicating the tightness of thermal comfort constraints
K	value to calculate Γ
Y	general symbol that represents w or s
ε	forecast error
σ	standard deviation
X	general symbol that represents P, Q, R, C and M

Subscripts

i, t, m, n	time step index
en	environment
cur	before water consumption
low	lower limit
up	upper limit
water	water
standby	standby
0	initial state
e	energy price
c	capacity price
up	lacking electricity
down	having surplus local generation

Superscripts

^	estimation/forecast
–	average value

has become a promising candidate to provide the needed fast-response ancillary services for power systems.

The flexible loads of residential prosumers are usually aggregated to balance the variability of local renewable generation or even to provide ancillary services to bulk power systems. There are generally two categories of methods for power system operators to control aggregations of flexible loads. One is direct load control, in which the blocks of power offered by aggregators are directly dispatched by power system operators. The other one is price response, in which aggregators respond to electricity prices that reflect the relationship between supply and demand of power systems. The research of this paper lies in the latter price response field. To be specific, this paper considers an aggregator that aggregates a population of residential prosumers that owns flexible thermostatically control loads and renewable generation, and studies the optimal scheduling method used by the aggregator to arbitrage in the intraday electricity market. The proposed scheduling method maximizes the economic benefits of the whole population of prosumers in the aggregation on one hand, and naturally helps balance intra-hour differences between supply and demand on the other.

Many relevant papers have been published in this area. First of all, due to great proportion in electricity consumption and thermal energy storage capability [1,2], a series of direct load control methods have been developed to control aggregated thermostatically controlled loads for a set of purposes. For example, Lu investigated the potential of providing intra-hour load balancing services using aggregated heating, ventilating and air-conditioning loads [3]. Lu and Zhang also presented design considerations for a centralized load controller to control thermostatically controlled appliances for continuous regulation reserves [4], and further developed a novel dynamic parameter selection process to optimize the performance of it [5]. Sinitsyn et al. designed safe protocols for generating power pulses with heterogeneous populations of thermostatically controlled loads to provide ancillary services by assisting in balancing generation and load [6], and further introduced timers to endpoint load control enabling better shaping of power pulses [7]. Perfumo et al. developed a model-based feedback control strategy for load management of large groups of thermostatically controlled loads [8]. Callaway developed new methods to model and control the aggregated power demand from a population of thermostatically controlled loads to deliver load following and regulation services with application to wind energy [9]. Mathieu et al. explored state estimation and control methods to coordinate aggregations of thermostatically controlled loads to manage frequency and energy imbalances in power systems [10].

On the other hand, another group of papers have presented price-based scheduling methods for flexible resources. For example, Sossan et al. developed a model predictive control strategy for the space heating of a smart building including cogeneration of a fuel cell-electrolyzer system according to a dynamic electricity price [11]. Vasirani et al. developed an agent-based approach to model and control virtual power plants that are composed of wind power generators and electric vehicles [12]. Subramanian et al. developed and analyzed real-time scheduling algorithms for coordinated aggregation of deferrable loads and storage devices [13]. Ju et al. established a bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind-photovoltaic-energy storage system considering the uncertainty and demand response [14]. Zapata et al. conducted a comparative study of imbalance reduction strategies for virtual power plants that consist of cogeneration devices and photovoltaic installations in the intraday balancing market [15].

Furthermore, some studies developed price-based scheduling or control methods for aggregated thermostatically controlled loads. For example, Lu et al. developed a state-queueing model to analyze the price response of aggregate loads consisting of thermostatically controlled appliances [16], and further studied the modeling uncertainties using that model [17]. Mathieu et al. investigated the potential for aggregations of thermostatically controlled loads to arbitrage intraday wholesale electricity market prices via non-disruptive load control [18]. Bianchini et al. developed a model predictive control approach for demand response in building heating systems [19].

As for the scheduling methodology, the idea of hierarchical scheduling has been widely used in many power system studies. Some researchers used it to deal with the multiple time scales in the scheduling problems, such as the large-time-step day-ahead scheduling and small-time-step intraday adjustment for virtual power plants [14], thermal energy storage systems [20] and building energy systems [21] and the different time scales of combined heat and power plants and demand response in an integrated community energy system [22]. Some researchers used it to tackle the multiple spatial scales involved in the scheduling problems, such as those in a microgrid [23], an electricity distribution network [24] and even a transmission network [25]. Other researchers used the different levels in the hierarchical scheduling to deal with temporal and spatial scheduling respectively [26], or to deal with different energy systems [27].

This paper differs from the above mentioned exiting works in various ways. First of all, compared with the direct load control methods presented in [1–10], the method proposed in this paper assists aggregators to arbitrage in the intraday electricity market to maximize their revenues and thus contribute to the balance of the whole power system in an indirect way. Compared to those price-based methods, this paper deals with the scheduling of thermostatically controlled loads that have unique characteristics which are significantly different from those of other devices such as cogeneration units [11], electric vehicles [12], energy storage systems [13], or general form of flexible loads [14]. Moreover, although some price-based methods were also developed for thermostatically controlled loads such as those in [16–19], this paper further considers the existence of renewable energy and the capacity cost in the intraday electricity market, which makes the problem and its mathematic formulation much different.

Besides, the proposed two-level scheduling method is novel, although there have been a lot of works about hierarchical scheduling in power systems as presented above. Different from the existing works that designed hierarchical scheduling to deal with different time scales, spatial scales or energy systems [14,20–27], the proposed two-level scheduling method is designed to decompose the target scheduling problem into two interactive levels of identical time and spatial scales. Moreover, the proposed two-level scheduling method combines the model predictive control optimization and temperature priority list -based control for the first time, in which the original energy-balanced model is the key to describe the aggregated behavior of the load population at the upper level optimization, thus linking the two levels.

To summarize, this paper studies the optimal scheduling method of aggregated thermostatically controlled loads to arbitrage in the intraday electricity market at the presence of local renewable generation. The main novelty and contribution of the paper is threefold: (i) firstly, a novel two-level scheduling approach is proposed to manage an aggregation of large amounts of thermostatically controlled loads and renewable generation in the intraday electricity market; (ii) secondly, an energy-balanced model for thermostatically controlled loads based on the existing thermal dynamic model is established for the convenience of aggregated scheduling. (iii) thirdly, the imbalanced energy and capacity are considered to be reduced at the same time in the intraday electricity market.

2. Problem description

Residential prosumers owning thermostatically controlled loads and renewable generation are considered in this paper. An aggregator contracts with them and acts as their agent to arbitrage in the electricity markets. That is, the aggregator manages all the resources within it to maximize the economic benefits of the whole population of the prosumers. Specifically, before a day, the aggregator purchases/sells electricity from/to the day-ahead wholesale electricity market based on generation and load forecast, and then within the day, eliminates the real-time electricity imbalance of the aggregation by exchanging electricity with the intraday electricity market. This paper assumes that the trading in the day-ahead electricity market has been settled, and focuses on the optimal scheduling method for the aggregator to arbitrage in the intraday electricity market. The above description is illustrated in Fig. 1.

The term "intraday electricity market" is a general description, which may refer to different entities in different countries. In the U. S., this market is called "real-time energy market", in which load following reserves on time scales of a few minutes are traded [13,18]. In most European countries, it refers to the balancing market, in which the Balance Responsible Parties (in this paper, the aggregator) are charged based on the energy and capacity costs of the power system reserves if their actual generation/consumption deviates from their schedules [15,28].

In this paper, it is assumed that the aggregator does not bid into the intraday electricity market, but rather purchases/sells electricity at whatever price the market clears. It is also assumed that the power input/output of the aggregator is sufficiently small so that the market prices are not affected. If the power input/output of the aggregator is too large to be neglected, the market prices will be affected, thus reducing the potential for arbitrage. In this case, the calculated revenues in this paper can be seen as an estimated upper bound of the revenues of the aggregator in the intraday market. Similar assumptions and analysis can be found in [18].

3. Modeling of thermostatically controlled loads

In this section, an energy-balanced model is established based on the thermodynamics of thermostatically controlled loads for the convenience of formulating them in the scheduling problem. Typical thermostatically controlled loads include air conditioners, heat pumps, electric water heaters and refrigerators. In this paper, electric water heaters are selected as a representative to demonstrate the modeling and scheduling method of thermostatically controlled loads.

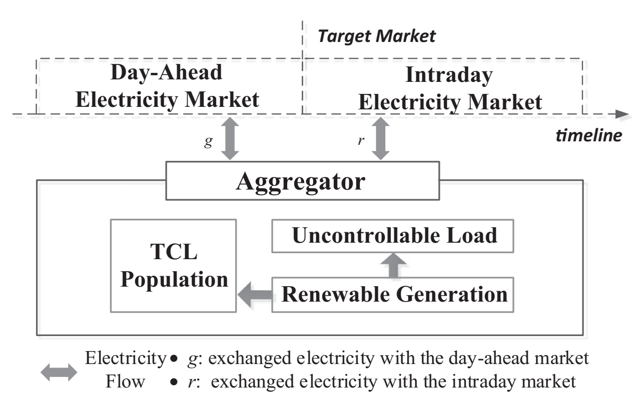


Fig. 1. Problem description.

3.1. Thermodynamic process

The equivalent thermal parameter (ETP) approach [29] is used in this paper to describe the thermodynamics of electric water heaters, i.e. their heat exchange process with the ambient environment and with cold water inflows. Differential equations are used to calculate the water temperature evolution process. Specifically, the water temperature is calculated by

$$\theta_{i+1} = \theta_{\mathrm{en,i}} - (\theta_{\mathrm{en,i}} - \theta_i)\exp(-\Delta t/(RC)) + u_i \cdot QR(1 - \exp(-\Delta t/(RC)) \tag{1}$$

where θ_i is the water temperature in the hot water storage; $\theta_{\mathrm{en},i}$ is the environmental temperature; u_i is the on/off status of the water heater; i represents the ith time step. Q, R and C are heater capacity, thermal resistance and thermal capacitance of the water heater respectively. When hot water is consumed, the water temperature is modified by

$$\theta_i = (\theta_{\mathrm{cur,i}}(M - d_i) + \theta_{\mathrm{en,i}} d_i)/M \tag{2}$$

where $\theta_{\mathrm{cur},i}$ is the water temperature before the consumption at the ith time step; M is the mass of water in full storage; d_i is the demand of hot water drawn during the ith time step.

Throughout the whole scheduling horizon, the hot water temperature is controlled within a range to satisfy the customer demand and device limit, i.e.,

$$\theta_{\mathrm{low}} \leqslant \theta_i \leqslant \theta_{\mathrm{up}} \tag{3}$$

where θ_{low} and θ_{up} are the lower limit and the upper limit of the hot water temperature respectively.

3.2. Energy-balanced model

Formulas (1)–(3) focus more on the temperature evolution process of hot water, but in the scheduling process, we care more about the amount of thermal energy that is gained through heating process, lost due to standby heat loss and hot water use, and needed to guarantee thermal comfort. Besides, the form of formulas (1)–(3) is not convenient for aggregation when formulating the scheduling problem of large amounts of electric water heaters. Therefore, formulas (1)–(3) are used to deduce the following formulas (4)–(7) which will be used to formulate the constraints of the scheduling problem in the next section.

First of all, the heat loss due to hot water use (that is, cold water inflows), $L_{\mathrm{water},i}$, is estimated by

$$L_{\mathrm{water},i} = d_i \cdot c_{\mathrm{water}} \cdot (\theta_i - \theta_{\mathrm{en},i}) \tag{4}$$

where c_{water} is the specific heat capacity of water, while the standby heat loss, $L_{\mathrm{standby},i}$, is estimated by

$$L_{\mathrm{standby},i} = Mc_{\mathrm{water}}(\theta_i - \theta_{\mathrm{en},i})(1 - \exp(-\Delta t/(RC)) \tag{5}$$

Heat loss, including standby heat loss and heat loss due to water use, causes water temperature decrease. Therefore, to maintain the water temperature within the required range $[\theta_{\mathrm{low}}, \theta_{\mathrm{up}}]$, the heating schedule of the electric water heater should satisfy

$$\sum_{n=1}^{i}(u_n \cdot P \cdot \eta \cdot \Delta t) \geqslant \sum_{n=1}^{i}(L_{\mathrm{water},i} + L_{\mathrm{standby},i}) - Mc_{\mathrm{water}}(\theta_0 - \theta_{\mathrm{low}})$$
$$\forall i \in [1, N],\ i \in \mathbf{N}^+ \tag{6}$$

and

$$\sum_{n=1}^{i}(u_n \cdot P \cdot \eta \cdot \Delta t) \leqslant \sum_{n=1}^{i}(L_{\mathrm{water},i} + L_{\mathrm{standby},i}) + Mc_{\mathrm{water}}(\theta_{\mathrm{up}} - \theta_0)$$
$$\forall i \in [1, N],\ i \in \mathbf{N}^+ \tag{7}$$

where P is the rated power of the electric water heater; η is the coefficient of performance (COP) of the electric water heater; θ_0 is the initial temperature of the water in the storage; $\mathbf{N}^+$ represents the set of all positive natural numbers.

Note that the energy-balanced model established above just describes the thermal process of one single thermostatically controlled load only. It is further used in the next section to formulate the thermal comfort constraints in which the thermal behaviors of the whole population of thermostatically controlled loads are described implicitly by accumulating the equations (4)–(7) of each single load.

4. Two-level scheduling of aggregated thermostatically controlled loads with renewable generation in the intraday electricity market

4.1. Two-level scheduling overview

As shown in Fig. 2, the aggregator keeps the real-time energy balance of the aggregation by controlling the flexible thermostatically controlled loads and trading electricity with the intraday electricity market. Through the two-level scheduling, the aggregator maximizes the economic benefits of the whole aggregation in the intraday electricity market by reducing the electricity imbalance. Specifically, (i) the upper level conducts model predictive control (MPC) optimization based on historical data, current measurement data and forecast data, generating the optimized aggregate load signal of the current time step for the lower level; (ii) the lower level conducts temperature priority list-based control (TPL-based control) to follow the aggregate load signal from the upper level, generating the specific load control commands for all the thermostatically controlled loads. The communication infrastructure required by this two-level scheduling framework is the same as that of conducting the typical TPL-based control which has been well described in [4,5].

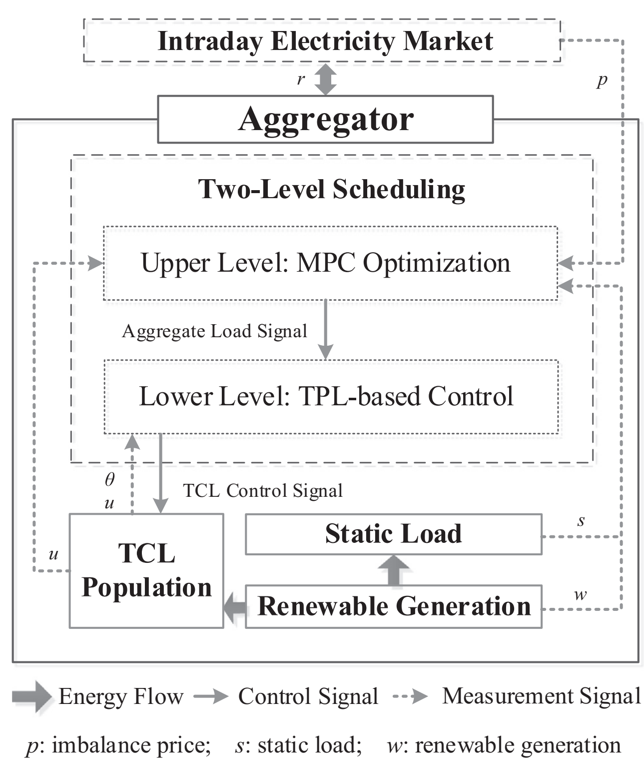


Fig. 2. Two-level scheduling for aggregated thermostatically controlled loads with renewable generation.

4.2. Upper level scheduling: MPC optimization

Model predictive control optimization is conducted at the upper level at each time step, generating the load schedule of aggregated thermostatically controlled loads from the current time step to the end of the scheduling horizon. However, only the load schedule of the current time step will be issued to the lower level to be followed at each time step.

4.2.1. Objective function

The objective of the upper level optimization is to minimize the total imbalance cost of the whole aggregation throughout the scheduling horizon. The aggregator pays the imbalance cost to the intraday electricity market to eliminate the electricity imbalance in the aggregation. The total imbalance cost is calculated by

$$\min\sum_{t=i}^{N}(p_{\text{e-up},t}\cdot r_{\text{up},t}\cdot\Delta t)+\sum_{t=i}^{N}(p_{\text{e-down},t}\cdot r_{\text{down},t}\cdot\Delta t)+p_{\text{c-up}}\cdot\max_{t\in[1,N]}\{r_{\text{up},t}\}+p_{\text{c-down}}\cdot\max_{t\in[1,N]}\{r_{\text{down},t}\} \tag{8}$$

where the first two terms represent the energy cost and the last two terms represent the capacity cost. N represents the number of time steps of a day, and Δt represents the length of each time step; p represents imbalance price; r represents the amount of imbalanced electricity; the subscript i represents the current time step; the subscript "e" and "c" indicate the type of imbalance prices, representing energy price and capacity price respectively; the subscript "up" and "down" indicate the directions of imbalance, "up" representing lacking electricity and "down" representing having surplus local generation (the corresponding imbalance called "up imbalance" and "down imbalance" respectively).

4.2.2. Constraints

In the first place, real-time energy balance in the aggregation should be maintained. Therefore, the following constraints should be satisfied:

$$r_{\text{up},t}=\max\{0,l_t+\hat{s}_t-\hat{w}_t-g_t\} \tag{9}$$

$$r_{\text{down},t}=\max\{0,\hat{w}_t+g_t-l_t-\hat{s}_t\} \tag{10}$$

$$\forall t\in[i,N],\ t\in\mathbf{N}^+$$

where $\hat{w}_t$ and $\hat{s}_t$ are the estimation of total renewable generation and uncontrollable load at the tth time step respectively, which are forecast at the ith time step; g_t is the day-ahead purchased electricity at the tth time step, which is known exactly during the intraday scheduling optimization; l_t is the aggregate load of the thermostatically controlled load population at the tth time step, which is the decision variable to be optimized; i represents the current time step.

In the second place, human comfort on hot water use should be satisfied. Therefore, according to the energy-balanced model established in Section 3.2, the aggregate load of thermostatically controlled load population should satisfy

$$\sum_{m=1}^{i-1}l_m\Delta t+\sum_{n=i}^{t}l_n\Delta t\geqslant\sum_{m=1}^{i-1}\sum_{j=1}^{Num}(L_{\text{water},m,j}+L_{\text{standby},m,j})+\sum_{n=i}^{t}\sum_{j=1}^{Num}(L_{\text{water},n,j}+L_{\text{standby},n,j})-\sum_{j=1}^{Num}M_jc_{\text{water}}(\theta_{0,j}-\theta_{\text{low},j})\quad\forall t\in[i,N],\ t\in\mathbf{N}^+ \tag{11}$$

and

$$\sum_{m=1}^{i-1}l_m\Delta t+\sum_{n=i}^{t}l_n\Delta t\leqslant\sum_{m=1}^{i-1}\sum_{j=1}^{Num}(L_{\text{water},m,j}+L_{\text{standby},m,j})+\sum_{n=i}^{t}\sum_{j=1}^{Num}(L_{\text{water},n,j}+L_{\text{standby},n,j})+\sum_{j=1}^{Num}M_jc_{\text{water}}(\theta_{\text{up},j}-\theta_{0,j})\quad\forall t\in[i,N],\ t\in\mathbf{N}^+ \tag{12}$$

where Num represents the total number of thermostatically controlled loads; i represents the current time step; m and n are the time step index before and after the current time step respectively. Note that the first terms at the left side of (11) and (12) (the sum of $l_m\Delta t$) are known exactly during the optimization because the metering devices can provide the information of historic power consumption of each thermostatically controlled load. The l_n in the second terms at the left side of (11) and (12) are the decision variables to be optimized.

In reality, the terms at the right side of (11) and (12) are difficult to be known exactly during the optimization because: (i) it is difficult for the aggregator to know specific thermal parameters (R, C, etc.) of each thermostatically controlled load; (ii) the hot water use and environmental temperature for each thermostatically controlled load throughout the scheduling horizon are not known; (iii) the temperature of water in the storage for each thermostatically controlled load throughout the scheduling horizon is not known beforehand. Due to the above difficulties, several efforts are made in the following to estimate the unknown or uncertain parameters.

First of all, the parameter distribution characteristics of the thermostatically controlled load population can be estimated by investigating a number of samples of the whole population. Then we can use the average parameter values for each thermostatically controlled load. Similarly, we can investigate the hot water use of typical users, and then use it to estimate the total hot water use of the whole population. Finally, the water temperature in the storage throughout the scheduling horizon is assumed to be a constant value between the lower and the upper bounds. Under the above assumptions, the first term at the right side of (11) and (12) is calculated by

$$\sum_{j=1}^{Num}(L_{\text{water},m,j}+L_{\text{standby},m,j})=l_{m-1}\Delta t-\sum_{j=1}^{Num}\overline{M}c_{\text{water}}(\theta_{m,j}-\theta_{m-1,j}) \tag{13}$$

where $\overline{M}$ is the average value of M; $\theta_{m,j}$ and $\theta_{m\text{-}1,j}$ can be obtained by metering devices as discussed before. The second terms at the right side of (11) and (12) is calculated by (14):

$$\sum_{j=1}^{Num}(L_{\text{water},n,j}+L_{\text{standby},n,j})=Num\cdot\overline{dn}\cdot c_{\text{water}}\left[\bar{\theta}_{\text{low}}+\Gamma(\bar{\theta}_{\text{up}}-\bar{\theta}_{\text{low}})-\hat{\theta}_{\text{en},n}\right]+Num\cdot\overline{M}\cdot c_{\text{water}}\left[\bar{\theta}_{\text{low}}+\Gamma(\bar{\theta}_{\text{up}}-\bar{\theta}_{\text{low}})-\hat{\theta}_{\text{en},n}\right]\times\left[1-\exp(-\overline{T}/\overline{R}/\overline{C})\right] \tag{14}$$

where the parameters with the overbar represent the average value. Γ is the pre-assigned parameter which indicates the tightness of the constraints (11) and (12). Γ = K for (11) and Γ = 1-K for (12), where K ∈ [0,0.5]. The higher the K is, the tighter the constraints would be. Similarly, we calculate the third terms of (11) and (12) using the average values if we do not know the exact parameter values for each load.

4.2.3. Linear counterpart

The objective function (8) and constraints (9) and (10) include the nonlinear terms max{•} which makes the optimization problem difficult to be solved. In this part equivalent linear counterpart is established for them to make it easy to be solved by existing developed linear optimization tools. Specifically, the objective function (8) is transformed to

$$\min\sum_{t=i}^{N}(p_{\text{e-up},t}\cdot\alpha_t\cdot\Delta t)+\sum_{t=i}^{N}(p_{\text{e-down},t}\cdot\beta_t\cdot\Delta t)+p_{\text{c-up}}\cdot\gamma + p_{\text{c-down}}\cdot\delta \tag{15}$$

with additional constraints:

$$\gamma \geqslant \alpha_t \quad \forall t\in[i,N],\ t\in\mathbf{N}^{+} \tag{16}$$

$$\delta \geqslant \beta_t \quad \forall t\in[i,N],\ t\in\mathbf{N}^{+} \tag{17}$$

$$\gamma \geqslant \max\{0, l_m+s_m-w_m-g_m\} \quad \forall m\in[1,i-1],\ m\in\mathbf{N}^{+} \tag{18}$$

$$\delta \geqslant \max\{0, w_m+g_m-l_m-s_m\} \quad \forall m\in[1,i-1],\ m\in\mathbf{N}^{+} \tag{19}$$

where α, β, γ and δ are non-negative ancillary variables, and the right-side terms of (18) and (19) are known constants at the current time step i. Besides, the constraints (9) and (10) are transformed to

$$\alpha_t - l_t \geqslant \hat{s}_t - g_t - \hat{w}_t \quad \forall t\in[i,N],\ t\in\mathbf{N}^{+} \tag{20}$$

$$\beta_t + l_t \geqslant g_t + \hat{w}_t - \hat{s}_t \quad \forall t\in[i,N],\ t\in\mathbf{N}^{+} \tag{21}$$

So far, all the nonlinear terms have been transformed equivalently to linear forms. Therefore, the upper-level MPC optimization is now a continuous linear optimization problem which is composed of the objective function (15), energy-balance constraints (20) and (21), thermal comfort and device constraints (11) and (12) and additional constraints (16)–(19). The total load profile of the thermostatically controlled load population l_t is the decision variables to be optimized as well as the additional variables α, β, γ and δ. Detailed tricks used in the linearization can be found in [30].

4.3. Lower level control: TPL-based control

At each time step, the upper level sends the signal of optimized current total load of thermostatically controlled load population to the lower level. The lower level conducts the typical TPL-based control to follow the total load signal. To support the TPL-based control, communication infrastructure needs to be constructed to collect the real-time temperature and power consumption of each thermostatically controlled load and to send the on/off control signals. TPL-based control has been described in detail in [4,5], and the procedure is summarized briefly as shown in Fig. 3.

5. Case study

Several cases are presented in this section to explore the performance of the proposed two-level scheduling method. In all cases, the proposed two-level scheduling method is compared with the typical TPL-based control to explore its strengths and weaknesses. Base case demonstrates the basic characteristics of the proposed two-level scheduling method, while the other cases explore the effects of various factors.

5.1. Base case

Base case is used to validate the effectiveness of the proposed two-level scheduling method and its basic characteristics. The studied aggregator is assumed to manage 200 controllable electric water heaters, 9 MWp wind generation and 9 MWp uncontrollable loads. The thermal parameters and the hot water use are shown in Table 1 and Fig. 4 respectively. Besides, the wind generation and the total uncontrollable load are shown in Figs. 5 and 6 respectively.

In the base case, the electric water heater population is assumed to be homogeneous, that is, their thermal parameters and water use are assumed to be identical to each other. Moreover, the energy prices for the up imbalance and the down imbalance are assumed to be equal, as shown in Fig. 7, and the capacity prices for the up imbalance and the down imbalance are assumed to be equal as well, to be 100 $/MW h. Besides, during the intraday rolling scheduling process, the forecast of future wind generation and uncontrollable load are considered accurate. It is worth noting that the effects of these assumptions on the performance will be studied respectively through sensitivity analysis in Case I to Case III.

Before the rolling scheduling in the intraday electricity market, the aggregator trades electricity with the day-ahead electricity market based on the day-ahead forecast of all the loads and renewable generation within it, that is,

$$g_i = \hat{s}_i + \hat{l}_i - \hat{w}_i \quad i=1,2\ldots N \tag{22}$$

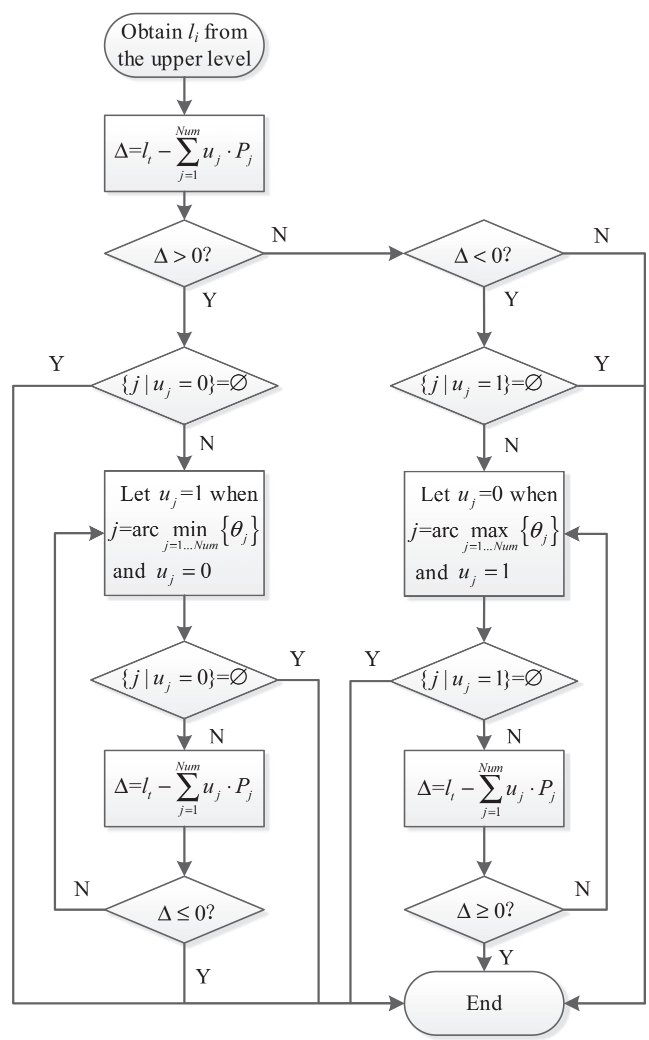


Fig. 3. Flowchart of TPL-based control at the lower level.

Table 1
Thermal parameters of the electric water heaters [29].

P (W)	Q (W)	R (°C/kW)	C (kW h/°C)	M (gallon)	θ_{low} (°C)	θ_{up} (°C)
4500	150	0.7623	431.7	50	60	70

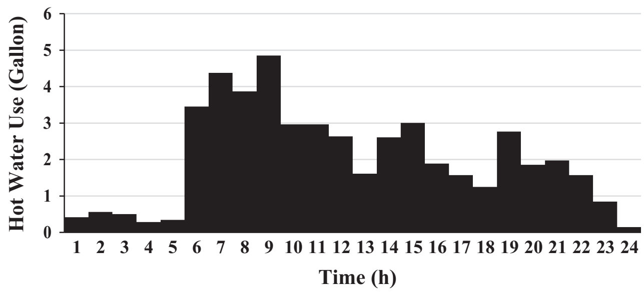


Fig. 4. Hot water use throughout the day [29].

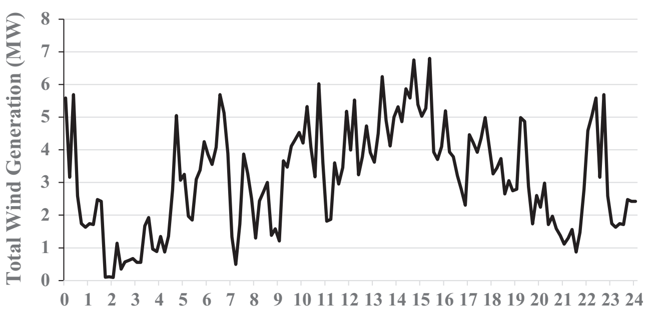


Fig. 5. Total wind generation throughout the day.

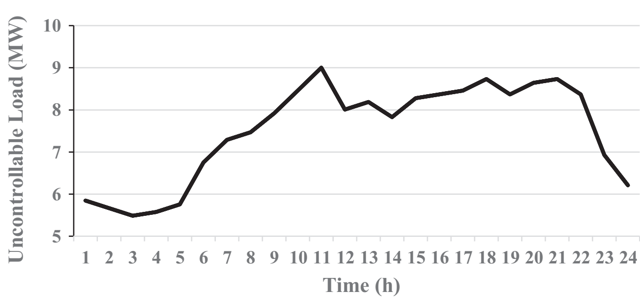


Fig. 6. Total uncontrollable load throughout the day.

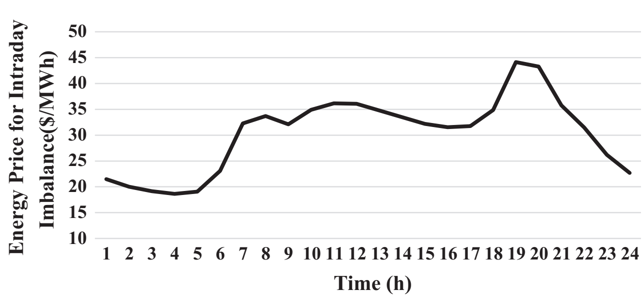


Fig. 7. Energy price for imbalance in the intraday electricity market [31].

Recall that g_i represents the electricity traded in the day-ahead market at the ith time step. $\hat{s}_i$, $\hat{l}_i$ and $\hat{w}_i$ represent the day-ahead estimation of total uncontrollable load, thermal load and renewable generation at the ith time step respectively. In the whole case study section (Section 5), we generally assume that the estimation equals to the actual value plus a random forecast error that follows normal distribution, i.e.

$$\begin{aligned} &\widehat{Y}_t = Y_t + \sum_{n=i}^{t} \varepsilon_n, \quad t = i,\ i+1,\ldots,N \\ &\begin{cases} \varepsilon_n = 0, & n = i \\ \varepsilon_n \sim N(0,\sigma_n^2), & n > i \end{cases} \end{aligned} \tag{23}$$

where $\widehat{Y}_t$ represents the estimation made at the ith time step, for a general variable (load/generation) of the tth time step. Y_t represents the actual value and ε_n represents the forecast error. Note that the deviation of the estimation $\widehat{Y}_t$ from the actual value Y_t increases with the prediction window length (t-i). Specifically for generating the day-ahead estimation of $\hat{s}_i$, $\hat{l}_i$ and $\hat{w}_i$, we could just let i be 1 in (23). The "actual value" of $\hat{l}_i$ is assumed to be the total heat loss (heat loss due to hot water use plus standby heat loss) of the thermostatically controlled load population which is calculated by (4) and (5). In the base case, for day-ahead estimation $\hat{s}_i$, $\hat{l}_i$ and $\hat{w}_i$, the standard deviation σ_n of ε_n is assumed to be 20% of the actual values, so that within the day electricity imbalance will occur and the aggregator needs to reduce the imbalance in the most economical way.

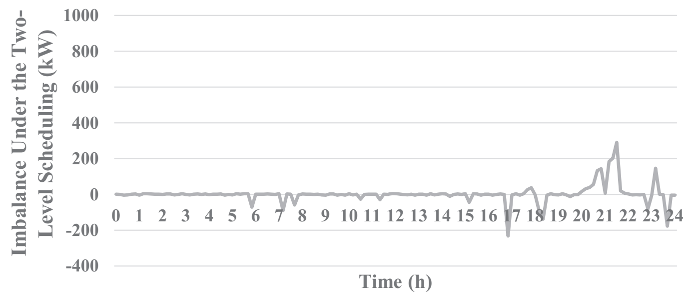
Under the above assumptions, the proposed two-level scheduling and typical TPL-based control are applied to control the thermostatically controlled load to follow the real-time imbalance of the aggregation. The length of time step, Δt, is set as 10 min. The results are presented in Figs. 8, 9 and Table 2. Note that the LINPROG solver in the optimization toolbox of MATLAB is used to solve the upper level MPC optimization considering it is a continuous linear optimization problem.

Fig. 8 shows that the two methods arrange the electric water heaters to work in different ways, which result in different trading patterns in the intraday electricity market, especially during 17:00 to 24:00. From Fig. 8, it can be seen clearly that the maximum imbalance under the two-level scheduling (being 300 kW) is significantly lower than that under TPL-based control (being 800 kW). Because of this, the capacity cost under the two-level scheduling comes to be much lower than that under TPL-based control, as presented in the third column of Table 2. In terms of energy cost, the two methods are quite close, as presented in the second column of Table 2. Therefore, in this case, the proposed two-level scheduling method is able to save 41.64% imbalance cost compared to the TPL-based control method.

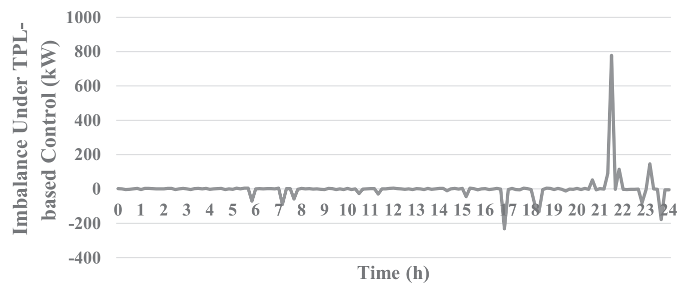
In addition, Fig. 9 shows the water temperature dynamics of the 200 electric water heaters. It can be observed that the water temperatures are always between the lower and the upper limits for both methods, which means that both methods can guarantee the thermal comfort.

5.2. Case I: Effects of imbalance prices

The base case shows that the proposed two-level scheduling is superior to the typical TPL-based control significantly in terms of imbalance cost. However, actually this conclusion might be affected severely by the imbalance prices. Therefore, various imbalance price scenarios are presented to test the proposed

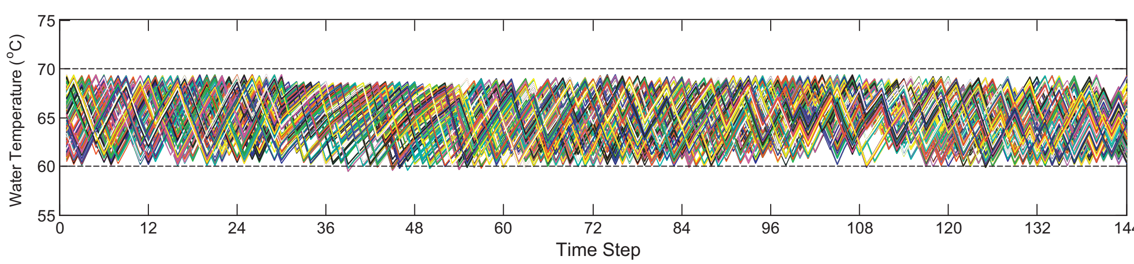


(a) The imbalance under the proposed two-level scheduling throughout the day.

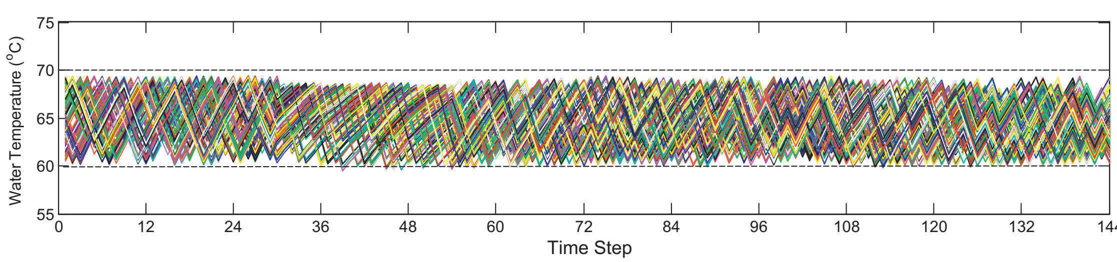


(b) The imbalance under the TPL-based control throughout the day.

Fig. 8. The imbalance under the two methods throughout the day.



(a) Water temperature in the tanks for the 200 electric water heaters under the proposed method.



(b) Water temperature in the tanks for the 200 electric water heaters under the TPL-based control.

Fig. 9. Water temperature dynamics under the two methods.

Table 2
Imbalance cost under the two methods.

Method	Energy cost ($)	Capacity cost ($)	Total imbalance cost ($)
Two-level scheduling	14.32	52.36	66.68
TPL-based control	13.30	100.96	114.26

two-level scheduling method as well as the typical TPL-based control. Note that in all scenarios all the settings and parameters are exactly the same as those of the base case except for the energy prices and the capacity prices. The scenarios and corresponding results are listed in Table 3.

From Table 3, it can be seen that the total cost saving of the proposed two-level scheduling mainly comes from reducing the peak capacity of imbalance. Specifically, the first 3 scenarios demonstrate that the total costs under the two methods are close to each other. The typical TPL-based control behaves even slightly better than the proposed two-level scheduling when there is no capacity charge for imbalance. The latter 5 scenarios show that the proposed two-level scheduling saves more money with the increase of capacity price, steadily saving about 40–50% cost when the capacity price is high.

Table 3
Imbalance cost of the two methods under different imbalance prices.

Scenarios		Total imbalance cost ($)		$\frac{COST_{TLS}-COST_{TPL}}{COST_{TPL}} \times 100\%$
$\frac{p_{e\text{-up}}}{p_{e\text{-down}}}$	p_c ($/kW)	Two-level scheduling	TPL-based control	
0.5	0	17.26	16.75	3.04%
1.0	0	14.22	13.30	6.92%
0.5	0	10.04	9.84	2.03%
1.0	0.01	19.38	23.39	−17.14%
1.0	0.05	39.17	63.78	−38.59%
1.0	0.1	66.68	114.26	−41.64%
1.0	0.5	253.60	518.10	−51.05%
1.0	1.0	551.54	1022.91	−46.08%

5.3. Case II: Effects of heterogeneity and parameter accuracy

In the base case, the electric water heater population is considered homogeneous, which most of the time is not the case in reality. Therefore, the effects of heterogeneity will be examined in this part. Specifically, the thermal parameters of the electric water heater population, P, Q, R, C and M, are assumed to follow uniform distribution. The two methods are tested under different heterogeneity strengths. For the proposed two-level scheduling, two further situations are considered: (i) assume that all the thermal parameters are known exactly before the scheduling; (ii) average values described in Section 4.2.2 are used. The scenarios and corresponding results are presented in Table 4. Note that for all scenarios, all the other settings and parameters are assumed to be same as those of the base case.

The results presented in Table 4 show that the proposed two-level scheduling is easier to be affected by parameter heterogeneity, while the performance of the typical TPL-based control is stable. In spite of this, the proposed two-level scheduling always performs better than the TPL-based control when there are accurate thermal parameters. As for the average value situation, it performs very close to the accurate value situation when the parameter heterogeneity is slight, while its performance gets increasingly worse with significant parameter heterogeneity, being even worse than the typical TPL-based control.

From the results we can also see that parameter accuracy is very important to the proposed method. The parameters of water heaters, such as Q, R, C, P, etc., can be estimated by curve fitting approaches with high accuracy based on the operation measurement data, as described in [3]. Considering the communication infrastructure of TPL-based control measures the real-time temperature and power data for each water heater, it is physically feasible for the aggregator to use these data to identify the parameters for each water heater. If in some cases the aggregator is not allowed to use these data in this way due to some reasons (e.g. privacy concerns), the proposed method using average parameter values or the typical TPL-based control has to be used according to the heterogeneity level.

Table 4
Comparisons of the two methods under different thermal parameters.[a]

Scenarios (X represents P, Q, R, C and M)	Total Imbalance Cost ($)		
	Two-level scheduling		TPL-based control
	Accurate values	Average values	
$X \in [1.0\overline{X}, 1.0\overline{X}]$	66.68	66.68	114.26
$X \in [0.9\overline{X}, 1.1\overline{X}]$	71.25	71.00	105.62
$X \in [0.7\overline{X}, 1.3\overline{X}]$	103.60	164.54	107.71
$X \in [0.5\overline{X}, 1.5\overline{X}]$	103.09	246.17	116.88

[a] $\overline{X}$ equal to the typical thermal parameter values as listed in Table 1.

Table 5
Comparisons of the two methods under different forecast errors.[a]

Scenarios (σ)	Average total imbalance cost ($)	
	Two-level scheduling	TPL-based control
0.0	66.68	114.26
$0.1\overline{Y}$	80.08	
$0.2\overline{Y}$	96.39	
$0.3\overline{Y}$	100.83	
$0.4\overline{Y}$	104.49	
$0.5\overline{Y}$	119.65	

[a] $\overline{Y}$ represent the actual values as presented in Section 5.1.

5.4. Case III: Effects of forecast errors

In the base case, we assume all the intraday forecasts are accurate, including the forecast for wind generation and uncontrollable load. In this part, we explore the effects of forecast errors, which are ineluctable in practice. As presented by (23) in Section 5.1, we assume that all the forecast errors follow the Gaussian distribution. The mean value is assumed to be 0, and the maximum forecast standard deviation σ is assumed to take different values to generate scenarios of different levels of forecast errors. For each level of σ, Monte Carlo simulation method is used to evaluate the two methods by calculating the average cost of 30 scenarios. Note that all the other settings and parameters are the same as the base case. The results are presented in Table 5.

From Table 5, it can be observed that the performance of the two-level scheduling gets worse and worse with the increase of forecast uncertainty. However, its performance keeps better than that of TPL-based control as long as the σ is below 0.5 $\overline{Y}$. Note that the TPL-based control is immune to forecast uncertainty because it relies on no forecast data, but its imbalance cost stays at a comparatively high level.

6. Conclusion

A two-level scheduling method was proposed in this paper to help an aggregator optimally schedule its thermostatically controlled loads with renewable generation to arbitrage in the intraday electricity market. A model predictive control optimization based on the proposed energy-balanced model was used for the upper level, which minimizes the sum of energy cost and capacity cost of imbalances, while the typical TPL-based control was adopted for the lower level.

Simulation results showed the performance of the proposed two-level scheduling method. Compared to the typical TPL-based control, 41.64% imbalance cost was saved by using two-level scheduling in the base case. Several factors affect the performance of the proposed two-level scheduling. Firstly, the two-level scheduling mainly saves the imbalance cost by reducing imbalance peak, thus being suitable for places with high capacity price for imbalances. Secondly, parameter heterogeneity affects the performance of two-level scheduling, and average value method performs well only with low heterogeneity. Thirdly, the performance of the two-level scheduling worsens with the increase of forecast uncertainty, but keeps better than that of typical TPL-based control unless the forecast uncertainty gets very strong.

The above simulation results were obtained based on practical device parameters and market price data, showing that the proposed two-level scheduling method has some advantages over the typical TPL-based control that has been implemented in some places. Therefore, the proposed method can be used by aggregators to optimally schedule their thermostatically controlled loads to arbitrage in the intraday electricity market. In the real world, many aggregators manage flexible thermostatically controlled load resources (e.g. the Open Energi in the UK [32]) and many places have the intraday electricity markets as described in the paper (e.g. the U.S.A. and many European countries). Therefore, the proposed method have good potential in real application.

There is still space for further improving and expanding the research. Future research can develop in the following directions: (i) develop robust scheduling methods to deal with parameter and forecast uncertainty; (ii) propose distributed scheduling and control methods instead of centralized ones for the aggregated distributed energy resources, e.g. the .alternating direction method of multipliers (ADMM) approach [33].

Acknowledgements

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