

Control Strategies of Large-scale Residential Air Conditioning Loads Participating in Demand Response Programs

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Abstract—Residential air conditioning (RAC) loads have great potential to be included in demand response (DR) programs. This paper studies large-scale RAC loads participating in DR programs, such as modeling, parameters identification, DR characteristics and control strategies. First, an aggregate model of large-scale RAC loads are established based on the buildings' performance with heat storage and insulation, avoiding the calculation of a single RAC model. Then, parameters of the aggregate model are identified based on the RACs' power and outdoor temperatures. Based on the aggregate model, DR characteristics of RAC loads are analyzed, including the dynamic relationship between power, outdoor and indoor temperature, and the potential of DR combined with the users' comfort. Next, the DR control strategies adapted for large-scale RAC loads are established by adjusting the temperature set-points. The DR strategies consider users' comfort and calculate the control signals of each RAC load according to the DR power, including adjustment temperature and adjustment time, which are sent to each RAC load for execution. In the DR process, the control center does not need to obtain the users' indoor temperature, which is conducive to protecting the users' privacy. DR strategies of RAC loads when the control degree within/beyond the DR potential are both proposed, and a load recovery control strategy is also introduced. Finally, the effectiveness and accuracy of the proposed model and DR control strategies are verified by simulation results.

Index Terms—Control strategies, demand response, direct load control, parameters identification, residential air conditioning loads.

I. INTRODUCTION

THE rapid development of the energy internet and smart grid that combines energy and information technology has enabled large-scale intermittent energy to be integrated

into the grid. Meanwhile, the rapid development of the economy and improvement of residential living standards leads to increments of peak load demand and peak-to-valley differences. For the problem of power system stability caused by increasing penetration of renewable energy and rapid load growth [1], [2], demand response (DR) is gradually introduced into power system operations, which can effectively accommodate renewable energy, reduce peak-to-valley differences, improve power asset utilization, and enhance power system economic operations by changing the users' electricity consumption mode through using two-way communication systems between supply and demand [3].

The proportion of the residential air conditioning (RAC) load is reaching 30%~40%, even 50% of total load demand in hot summer in the Southeastern cities of China, and has been a major contributor to peak load [4], [5]. Meanwhile, the buildings in which RAC belongs have heat storage characteristics [6], which cause it to become an important DR resource without greatly affecting the users' comfort [3], [7].

Air conditioning (AC) loads participating in DR have been studied by many scholars. Researches on the AC model can be traced back to [8], which modeled AC by simple differential or difference equations to describe the dynamic evolution of indoor temperature. Based on these foundations, N. Lu and D. P. Chassin equalized a single AC load into a circuit model and established a first-order equivalent thermal parameter (ETP) mode, which take the space in a room as a capacitor, and an external envelope as a resistor [9], [10]. Considering the influence of mass in a room for indoor temperature dynamic evolution, a second-order ETP model was proposed [11]–[14]. The parameter calculations of these models involves such factors as room volume, building materials and AC type, which is a huge computational burden, especially in large-scale numbers. In order to calculate the parameters of an individual AC model, simulation software, such as Energy-Plus [15], OpenStudio [16], Grid LAB-D [17], etc., were proposed. However, it is necessary to draw a 3-Dimensional map of the room and input the parameters of the building materials, which in practice, make them unsuitable for a large-scale DR program. In addition, an AC model, from the perspective of heat transfer and storage, was established in [18]. Although the above individual AC models accurately expressed the thermal dynamic process of indoor temperatures,

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the calculation of model parameters involves user privacy, such as house structure, AC type, etc. At the same time, random behaviors, such as indoor activities of users in the room and switching windows also affects the accuracy of parameter identification [19]. When large-scale AC loads participate in DR, a single AC model parameter identification will greatly increase the computational burden.

The power of a single RAC load is small and they need to be aggregated to meet the DR target, while avoiding the difficulty of calculating a single AC load model. Therefore, it is necessary to establish an aggregate RAC (ARAC) model to describe the relationship among the RACs' power, outdoor and indoor temperatures, so as to facilitate the application in DR programs. At present, the establishment of aggregate AC models is primarily classified into three types: 1. Dynamic state distribution model [20]–[22]; 2. Aggregated power distribution model [23], [24]; and 3. Virtual battery model [25]–[27]. In the first type, the variation of probability density of the ACs' operational state is described by a dynamic equation. The main methods include partial differential equations [3], [20] and Markov chains [21], [22]. However, in order to accurately reproduce the population dynamics, these models often require fine gridding of the ACs' state space, which is computationally expensive [21]. In order to solve this problem, the second type of ARAC model was introduced, which described the RACs' power distribution sets without violating any comfort or operational constraints [23], [24]. The sets represent overall flexibility of AC loads. These models were used for predicting DR potential of AC loads and are invalid in specific control strategies. In the third type, modeling aggregate AC loads as a virtual battery model were introduced [25]–[27]. Existing virtual battery models were very conservative for heterogeneous parameters, and several improved methods were proposed in [28], but only for certain specific battery parameters in heterogeneous populations. The above aggregate AC models described range and distribution of aggregated power, but ignored the dynamic evolution of indoor temperature. In [29], the rate of indoor temperature rise/drop was calculated to model aggregate AC loads, but it ignored the heat storage characteristics of buildings.

As a conclusion, in current ARAC models, it is difficult to fully describe the dynamic relationship between indoor temperature, outdoor temperature and the aggregated power of RAC loads. At the same time, most of them are modeled based on individual RAC models, which restrict their practical application due to the computational complexity of every single AC model. Therefore, it is necessary to further study and establish an ARAC model suitable for a DR program to effectively control large-scale RAC loads.

Based on the types of incentives for demand response, existing RAC DR programs, that have been implemented, can be divided into two schemes: indirect load control (ILC) and direct load control (DLC) [11]. In ILC, the power consumption is the controlled response to the dynamic electricity price [30]–[32], and this control mechanism is not reliable and cannot guarantee DR accuracy. The DLC, which has the characteristics of being quick and precise, is widely used in DR control for AC loads [18]. The specific strategies for the DLC of AC

loads are primarily to control the ON/OFF switch [9], [10], [33]–[35] and adjust the temperature set-point [3], [5], [14], [29], [36]. In [9], [33], AC loads were controlled according to indoor temperature priority, which places a heavy burden on the load monitoring and communication system. A model predictive control method (MPC) based on the AC model to avoid real-time monitoring was proposed, but it required the establishment of an accurate physical model [12], [14], [18]. In [29], [34], [37], a centralized control algorithm was designed, and applied to large-scale DR programs limited by the control center's computing power and communication system. Then distributed [35] and decentralized [38] DR methods were proposed, but they also dealt with the calculation of an individual AC model. In [5], [29], [36], DR control strategies of AC loads by adjusting the temperature set-point neglected the release process of the indoor heat storage and had to analyze each of the AC load operation states.

In order to solve the above problems, based on the analysis of thermodynamic characteristics of a single RAC load, an ARAC model is established according to the buildings' performance of heat storage and insulation, and the parameters identification method based on RACs' power and outdoor temperature is proposed. RACs' power can be identified through a non-intrusive system [39]–[41], which presents the foundation of the parameter identification method to be applied in the real world. And then, the RACs' DR characteristics are analyzed, including the dynamic relationship among RACs' power, outdoor and indoor temperature, and the potential of DR combined with the users' comfort. Based on the ARAC model and DR characteristics, DR control strategies for large-scale RAC loads are established by adjusting temperature set-points while considering users' comfort. According to the power level during the DR process, a detailed calculation process for control signals including temperature set-points and adjustment time is also proposed. In these strategies, the control center only needs to calculate and send control signals to each RAC load, avoiding establishing each single RAC model and obtain operation information of each RAC model, which alleviates communication pressure and protects the users' privacy. After the implementation of the DR control, various methods of load recovery are analyzed in order to avoid the severe recovery of load rebound.

The specific contributions of this paper are as follows: 1) This paper establishes an ARAC model based on heat storage and dissipation characteristics, and identifies the model parameters according to total power and outdoor temperature, which avoids calculating individual RAC models. 2) This paper analyzes RACs' DR characteristics, including the dynamic relationship between power, outdoor and indoor temperature, and dynamic DR potential of different power curves combined with the users' comfort. 3) DR control strategies for large-scale RAC loads by adjusting the indoor temperature set-point are established, which avoids determining the operational states of each RAC load. DR control strategies under different response levels are proposed, and the load recovery strategy after DR control is also analyzed.

The remainder of this paper is organized as follows. Section II establishes the ARAC model and presents the

parameters identification method. In Section III, RACs DR characteristics are analyzed. Section IV establishes the RACs DR control strategies for large-scale RACs. The proposed modeling and control strategies are validated through simulations in Section V. Finally, we summarize our research and discuss future studies in Section VI.

II. ARAC MODEL AND PARAMETERS IDENTIFICATION

In this section, we first introduce the configuration of RACs DR program in a smart grid and the assumptions of this paper, then present a single RAC model and analyze its operational characteristics, and establish the ARAC model. Finally, the ARAC model parameters are identified based on the aggregated power of the RAC load and outdoor temperature.

A. Configuration of RACs DR Program in a Smart Grid

In this paper, we propose DR control strategies for large-scale RAC loads to change operational power during the DR period, by adjusting the temperature set-points of the RAC units.

Figure 1 shows a typical DR scenario in a smart grid. A residential community is equipped with N RAC units, and a configured smart meter to identify the RACs' total power. A control center connects the customers to the grid, and sends control signals to each RAC unit through communication networks.

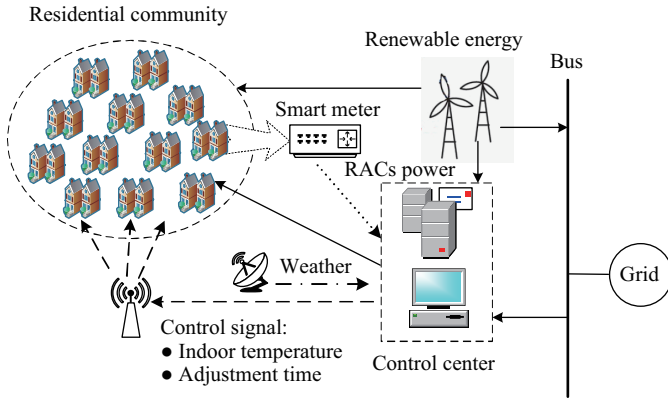


Fig. 1. The demand response of RAC load in a smart grid.

To satisfy the customers' requirements for a pleasant living environment, a comfortable temperature region is set for each residential house. Let $T_{\text{set},i}$ be the indoor temperature set-point of the i th RAC ($i = 1, 2, \dots, N$) and $[T_{\text{min},i}, T_{\text{max},i}]$ denote the comfortable region of the temperature set-point, such that $T_{\text{set},i} \in [T_{\text{min},i}, T_{\text{max},i}]$.

B. Single RAC Model

For modeling the RAC load, the ETP model [18] is extensively utilized. The first-order ETP model, which determines the difficulty and accuracy of the calculation, can accurately describe indoor temperature evolution and operational characteristics [42]. A building, to which the AC belongs, has heat storage and insulation characteristics, which can be equivalent to capacitance and conductance, as shown in Fig. 2 [18]. And

the heat transfer process of a single RAC unit working in cooling mode is shown in Fig. 2. In this paper, without loss of any generality, the RAC load is operating in cooling mode.

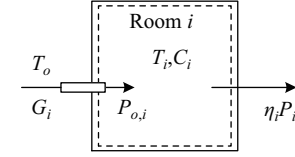


Fig. 2. Heat transfer process of a room.

In Fig. 2, $P_{o,i}$ represents the rate of energy transfer to indoor space in the unit of kW; $\eta_i P_i$ is the rate of energy transfer to outdoor environments by the RAC load in the unit of kW, where η_i and P_i are the cooling energy efficiency coefficient and RAC's power, respectively. If $P_{o,i} \neq \eta_i P_i$, the indoor temperature T_i will change.

From Fig. 2, we can obtain a single RAC load model as follows:

$$C_i \frac{dT_i(t)}{dt} = -m_i(t) \eta_i P_i(t) + (T_o(t) - T_i(t)) G_i + \theta_i$$

$$m_i(t) = \begin{cases} 1, & \text{if } T_i(t) \geq T_{\text{set},i} + \delta/2 \\ 0, & \text{if } T_i(t) \leq T_{\text{set},i} - \delta/2 \\ m_i(t - \varepsilon), & \text{otherwise} \end{cases} \quad (1)$$

where, i is the index of the RAC load; T_o represents the outdoor temperature and T_i represents the unit i indoor temperature, $^{\circ}\text{C}$; C_i represents capacitance, $\text{kW}\cdot\text{h}/^{\circ}\text{C}$; G_i represents the conductance, $\text{kW}/^{\circ}\text{C}$; $m_i(t)$ is the binary variable, which denotes the OFF/ON status of unit i at time t ; $T_{\text{set},i}$ represents the temperature set-point, $^{\circ}\text{C}$; θ is a noise perturbation; δ is the temperature dead-band, $^{\circ}\text{C}$; ε is sampling time.

C. ARAC Model

Since the cooling principle of each RAC load is the same, the indoor temperature is reduced by the operation of the RAC load. Meanwhile, the indoor temperature setting of each RAC load is generally concentrated in a small comfort range and obeys a certain probability distribution. So the RAC load can be aggregated to one ARAC, as shown in Fig. 3. Therefore, a number of RAC loads can be aggregated to one RAC load. The heat transfer process of the aggregate RAC (ARAC) model is presented in Fig. 3.

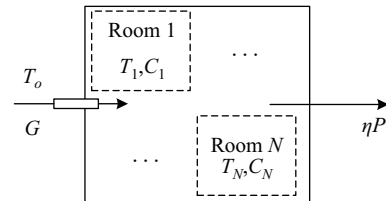


Fig. 3. Heat transfer process of ARAC model.

When the RAC load runs in cooling mode, the indoor temperature is maintained within a comfort range according to the temperature set-point. Therefore, the average indoor

temperature of each RAC load can be used as the indoor temperature of the ARAC model, which can be calculated as:

$$T(t) = \frac{1}{N} \sum_{i=1}^N T_i(t) \approx \frac{1}{N} \sum_{i=1}^N T_{\text{set},i}(t) \quad (2)$$

In a large-scale model, noise perturbation obeys a normal distribution and can be neglected in the ARAC model. Similar to a single RAC load, the ARAC model is:

$$C \frac{dT(t)}{dt} = -\eta P(t) + (T_o(t) - T(t)) G \quad (3)$$

where C and G are the capacitance and conductance of the ARAC model, respectively; η and P are the cooling energy efficiency coefficient and power of the ARAC model, respectively. When the indoor temperature is constant, the heat transfer between indoor and outdoor reaches an equilibrium state, that is:

$$\eta P(t) = (T_o(t) - T(t)) G. \quad (4)$$

D. Identification of ARAC Model Parameters

From the above analysis, the main parameters of the ARAC model are capacitance C and conductance G . Let $X = C/\eta$, $\Gamma = G/\eta$, then (3) and (4) can be rewritten as:

$$C \frac{dT(t)}{dt} = -P(t) + (T_o(t) - T(t)) G \quad (5)$$

$$P(t) = (T_o(t) - T(t)) G \quad (6)$$

As has been proposed in [42], the ARAC model parameters can be calculated as:

$$C = \sum_{i=1}^N C_i/\eta_i \quad (7)$$

$$G = \sum_{i=1}^N G_i/\eta_i \quad (8)$$

However, this calculation method requires an accuracy model of each individual RAC load, which involves the privacy of the residents. Therefore, large-scale RAC loads make this method computationally intractable. As a result, this paper proposes an identification method for the ARAC model parameters based on aggregated power and outdoor temperature.

Since parameters C and G in the ARAC model have different influence mechanisms on the aggregated power according to (5) and (6), we first identify parameter G and then identify parameter C .

It can be seen from (6) that the power of the RAC load is primarily related to G , $T(t)$ and $T_o(t)$ when $T(t)$ is kept constant or changes slightly. In the real world, the indoor temperature is set by the user according to self-preference and held for a period of time, so the average room temperature can be regarded as a constant over a period of time. Therefore, $GT(t)$ can be regarded as a constant. By fitting the historical power of RAC load and outdoor temperature, the linear relationship between total power and outdoor temperature is obtained, in which the slope is the parameter G .

In order to reduce random error caused by data acquisition, indoor temperature fluctuation, etc., selecting multiple sets of data for parameter identification, and the averaging is used as an effective parameter for the ARAC model. This specific calculation is:

$$\mathcal{G} = \frac{1}{L} \sum_{l=1}^L \mathcal{G}_l \quad (9)$$

where l represents the index of the load data set; $\mathcal{G}_l$ is the ARAC parameter identified by load data set l ; L represents the total number of data sets.

The heat capacity parameter C of the ARAC model is then identified. As can be seen from (5), the condition that parameter C can be identified as is $dT(t)/dt \neq 0$. So we need to first screen out eligible data sets. According to (6), the average indoor temperature curve can be evaluated as:

$$T_{\text{ev}}(t) = T_o(t) - \frac{P(t)}{G} \quad (10)$$

It should be noted that (6) is effective when the indoor temperature remains constant or varies little, so $T_{\text{ev}}(t)$ calculated by (10) is believable only when the average indoor temperature is constant or varies little, as shown in Fig. 4. We can see that the transition period of the average indoor temperature change is $[t_{c1}, t_{c2}]$, and we can obtain the values before and after change, T_1 and T_2 . According to (5), we can obtain:

$$C(T_2 - T_1) = - \int_{t_{c1}}^{t_{c2}} P(t) dt + G \int_{t_{c1}}^{t_{c2}} (T_o(t) - T(t)) dt \quad (11)$$

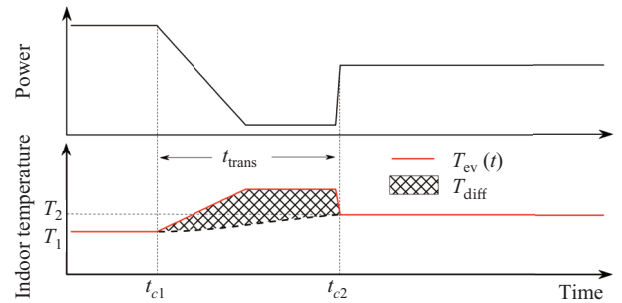


Fig. 4. Identification parameter C of the ARAC model.

The average indoor temperature difference is usually small, so we can assume that the average indoor temperature changes linearly during the transition period, combined with (10), (11) is further simplified as:

$$C(T_2 - T_1) = G \int_{t_{c1}}^{t_{c2}} T_{\text{ev}}(t) dt - \frac{G(T_1 + T_2)}{2} (t_{c2} - t_{c1}) \quad (12)$$

Let $T_{\text{diff}} = \int_{t_{c1}}^{t_{c2}} T_{\text{ev}}(t) dt - (t_{c2} - t_{c1})(T_1 + T_2)/2$, then

$$C = \frac{GT_{\text{diff}}}{T_2 - T_1} \quad (13)$$

Similarly with the identification of parameter $\mathcal{G}$, parameter $\mathcal{C}$ is calculated by averaging the multiple identification:

$$\mathcal{C} = \frac{1}{K} \sum_{k=1}^K \mathcal{C}_k \quad (14)$$

where k is the index of the load data set; $\mathcal{C}_k$ is the ARAC parameter identified by load data set k ; K is the total number of data sets.

III. DR CHARACTERISTICS OF RAC LOADS

No matter what kind of actions are required for RAC loads to participate in the DR programs, such as adjusting temperature set-point or switch status, the indoor temperature will be changed. The rate of indoor temperature change is related to RAC power and outdoor temperature. In this section, the evolution of average indoor temperature influenced by the aggregated power and outdoor temperature will be analyzed in detail.

Figure 5 depicts the DR process of the RACs power. This process reflects the DR characteristics of a RAC load, that is, the relationship between the aggregated power of a RAC load and indoor temperature over a DR period. The dash line with arrows denotes the supplier designed DR power of a RAC load, calculates the indoor temperature, and sends control signals. The solid line with arrows denotes the demander's adjusted indoor temperature set-points according to the control signals, and the occurred new power demand. According to this characteristic, the supplier formulates the DR target of the RAC power during the DR period, calculates the indoor temperature, and then formulates the DR control signals according to the indoor temperature. Users adjust the indoor temperature according to the control signals, which leads to a change in the operational power of the RAC load and achieves the DR target.

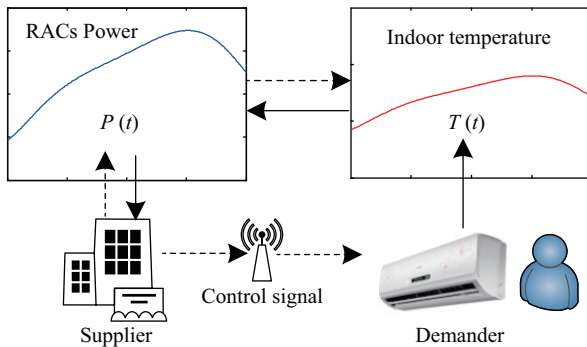


Fig. 5. DR process of RACs power.

As DR is a continuous process over a period of time, and the change of indoor temperature is also time-dependent, so the ARAC model described by the differential Eq. (5) cannot be directly applied to analyze the DR process. In addition, the differential equation cannot be used to determine whether the DR control will lead to the indoor temperature exceeding beyond the comfort range. So we solve the differential equation

(5), and it yields:

$$T(t) = M e^{-\frac{\mathcal{G}}{\mathcal{C}} t} + \frac{1}{\mathcal{C}} e^{-\frac{\mathcal{G}}{\mathcal{C}} t} \int_{t_0}^t (\mathcal{G} T_o(v) - P(v)) e^{\frac{\mathcal{G}}{\mathcal{C}} v} dv \quad (15)$$

where t_0 is the starting time, M is a constant, determined by the initial average indoor temperature, $M = T(t_0)$. Combined with (15) and an acceptable indoor temperature range, the DR potential of the RAC load can be obtained. And it can be used to judge whether the DR power exceeds the potential.

When outdoor temperature and aggregated power are constant during the DR process, the average indoor temperature rises from T_1 to the upper limit of acceptable temperature $T_{\max}$, and the transaction is calculated as:

$$t_{\text{trans}} = \frac{\mathcal{C}}{\mathcal{G}} \ln \frac{\mathcal{G} (T_o - T_1) - P}{\mathcal{G} (T_o - T_{\max}) - P} \quad (16)$$

The above formula also reflects the DR potential, including DR power and DR duration [42]. Under this condition, if the DR duration exceeds t_{trans} , the indoor temperature will exceed the upper temperature limit.

In order to facilitate the calculation of $T(t)$, the DR period is divided into several time slots, Δt . Δt is set to 1 minute. In each time slot, $P(t)$ and $T_o(t)$ can be regarded as a constant, so the average indoor temperature can be calculated as:

$$T(t + \Delta t) = T(t) + \frac{-P(t) + (T_o(t) - T(t)) \mathcal{G}}{\mathcal{C}} \Delta t. \quad (17)$$

Meanwhile, according to the average indoor temperature $T(t)$, the RACs' power can be obtained as:

$$P(t) = (T_o(t) - T(t)) \mathcal{G} - \frac{\mathcal{C} (T(t) - T(t - \Delta t))}{\Delta t}. \quad (18)$$

IV. DR CONTROL STRATEGIES OF A RAC LOAD

According to Section III, the RACs' power can be changed to meet the DR target by controlling the indoor temperature and limiting the residents' comfort.

In order to facilitate the introduction of the control strategy, four assumptions are made. First, the temperature set-point of the RAC load is generally an integer, the indoor temperature set-point acceptable range of residents is set as the integer range, $[T_{\min}, T_{\max}]$. Secondly, the RAC loads run steadily before the DR starts, and the number of RAC loads remains unchanged during the DR process. Thirdly, the RAC rooms are similar in the same community in China. Finally, the DR time horizon is $\mathcal{T}$.

DR strategies of large-scale RAC loads are proposed to follow the target power by adjusting the indoor temperature set-point. Unlike other control strategies, the strategy determines the control signal, including temperature set-point and adjustment time, by analysing the DR target power and outdoor temperature. DR strategies under different DR scenarios are analyzed, including load reduction, load increase and load recovery after DR control. Particularly, the RACs control strategy beyond DR potential is established and proved.

In order to adequately analyze the DR of the RAC loads in different situations, this paper designs a DR scenario of reducing load first and then increasing load, as shown in Fig. 6, and establishes a strategy of load recovery after DR.

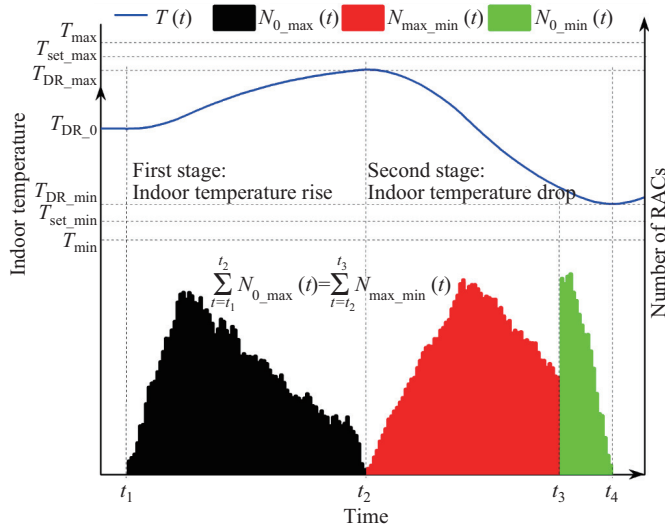


Fig. 6. The control targets within the DR potential.

A. CASE 1: Control Target Within DR Potential

Assuming the DR target power of RAC loads is $P_{DR-1}(t)$ and the outdoor temperature is $T_o(t)$.

The first step is to calculate the average indoor temperature $T(t)$ during the DR period.

According to (6), the initial average temperature T_{DR-0} is before DR can be calculated. Then the average indoor temperature $T(t)$ can be calculated by (15). As shown in Fig. 6, the initial, maximum and minimum temperature of $T(t)$ is denoted by T_{DR-0} , T_{DR-max} and T_{DR-min} , respectively, where $[T_{DR-min}, T_{DR-max}] \in [T_{min}, T_{max}]$.

The second step is to generate a control signal of each RAC load, which includes the temperature set-point and adjustment time.

As previously analyzed, the principle of the RAC loads participating in the DR program control is to change the operational power by adjusting the temperature set-point. By adjusting the temperature set-point of each RAC load, the indoor temperature changes follow the curve $T(t)$, which needs to satisfy:

$$\sum_{i=1}^N (T_{set,i}(t) - T_{set,i}(t - \Delta t)) = N(T(t) - T(t - \Delta t)) \quad (19)$$

Equation (19) describes an equation satisfied by the real-time adjustment of indoor temperature settings, but it is impossible to adjust the air conditioning system minute by minute in a practical application. In general, the fewer adjustments the better. So when $T(t)$ rises or falls, adjust the temperature set-point in place for one time. Therefore, first determine the temperature set-point that needs to be adjusted, and then calculate the number of RAC loads that need to be adjusted at each time point.

Since the temperature set-points of the RAC loads are generally integers, the upward and downward temperature set-points, $T_{set-max}$ and $T_{set-min}$, can be calculated by

$$T_{set-max} = \lceil T_{DR-max} \rceil = \left\lceil \max_{t \in \mathcal{T}} T(t) \right\rceil \quad (20)$$

$$T_{set-min} = \lfloor T_{DR-min} \rfloor = \left\lfloor \min_{t \in \mathcal{T}} T(t) \right\rfloor \quad (21)$$

where $\lceil \cdot \rceil$ means upward rounding and $\lfloor \cdot \rfloor$ means downward rounding.

After determining the adjustment value of the RAC indoor temperature, the next step is to determine the number of RAC loads adjusted at each time point according to (19).

In order to illustrate the control strategies in this paper, a typical scenario of DR is designed, as shown in Fig. 6. In the first stage $[t_1, t_2]$, it is necessary to raise the indoor temperature set-point to $T_{set-max}$ to reduce the air conditioning load. Let $N_{0-max}(t)$ denote the number of RAC loads adjusted to $T_{set-max}$ from initial temperature at time t . In the second stage $[t_2, t_4]$, the indoor temperature is adjusted to $T_{set-min}$, the RAC loads whose temperature set-point is adjusted to $T_{set-max}$ are prioritized, the number of adjustments are expressed as $N_{max-min}(t)$. If all the RAC loads which are set to $T_{set-max}$ have been adjusted to $T_{set-min}$, the unadjusted RAC loads in the first stage need to be set to $T_{set-min}$ to meet the demand, and the number is denoted by $N_{0-min}(t)$. The specific calculation is as follows.

As the residential houses are generally similar, the differences of each RAC load are ignored during the DR control process. For convenience of writing, define:

$$T_{rate}(t) = T(t) - T(t - \Delta t) \quad (22)$$

During the first stage $[t_1, t_2]$, the average indoor temperature rises. The number of RAC loads adjusted to $T_{set-max}$ at time t are:

$$N_{0-max}(t) = \left\lceil \frac{NT_{rate}(t)}{T_{set-max} - T_{DR-0}} \right\rceil \quad (23)$$

where $\lceil \cdot \rceil$ means rounding. Then we can randomly select $N_{0-max}(t)$ RAC loads to adjust the temperature set-point from the initial temperature to $T_{set-max}$ at time t . In the first stage, the total number of RAC loads adjusted to $T_{set-max}$ are calculated as follows:

$$N_{up} = \left\lceil \frac{N(T_{DR-max} - T_{DR-0})}{T_{set-max} - T_{DR-0}} \right\rceil \quad (24)$$

During the second stage $[t_2, t_4]$, the RAC load will be adjusted to $T_{set-min}$. First, in the time period $[t_2, t_3]$, the RAC load whose temperature set-point has been changed to $T_{set-max}$ is adjusted. The number of RAC loads adjusted to $T_{set-min}$ at time t are:

$$N_{max-min}(t) = \left\lceil \frac{NT_{rate}(t)}{T_{set-min} - T_{set-max}} \right\rceil \quad (25)$$

The total number of RAC loads adjusted to $T_{set-min}$ at time t are:

$$N_{down}(t) = \left\lceil \frac{N(T(t) - T_{DR-max})}{T_{set-min} - T_{set-max}} \right\rceil \quad (26)$$

In particular, $N_{down}(t-1) < N_{up}$ and $N_{down}(t) > N_{up}$, are shown as t_3 in Fig. 6. At time t_3 , the number of RAC loads adjusted to $T_{set-min}$ are comprised of two parts. The number of first part RAC loads adjusted from $T_{set-max}$ to $T_{set-min}$ are:

$$N_{max-min}(t) = N_{up} - N_{down}(t-1) \quad (27)$$

Meanwhile, the number of the remaining parts of the RAC loads adjusted from the original temperature set-point to $T_{\text{set_min}}$ are:

$$N_{0_min}(t) = \left\lceil \frac{NT_{\text{rate}}(t) - N_{\text{max_min}}(t)(T_{\text{set_min}} - T_{\text{set_max}})}{T_{\text{set_min}} - T_{\text{DR_0}}} \right\rceil \quad (28)$$

Secondly, in the time period $[t_3, t_4]$, the total number of RAC loads adjusted to $T_{\text{set_min}}$ over N_{up} , $N_{0_min}(t)$ can be calculated as: by

$$N_{0_min}(t) = \left\lceil \frac{NT_{\text{rate}}(t)}{T_{\text{set_min}} - T_{\text{DR_0}}} \right\rceil \quad (29)$$

After calculating the number of RAC loads that should be adjusted at different times, we can select the corresponding number of RAC loads to implement the control strategy. In the selection process, users should be selected to avoid multiple choices of the same user, and to avoid a user being adjusted for a long time.

It should be noted that indoor temperature rises need a certain period of time, the temperature adjustment time should be corrected forward, and the correction time depends on the speed of indoor temperature changes.

B. CASE 2: Control Target Beyond DR Potential

In CASE 2, the DR target power of the RAC loads is $P_{\text{DR_2}}(t)$, and other conditions are the same with CASE 1. In CASE 2, the DR strategy also includes two steps, calculating $T(t)$ and generating control signals.

The average indoor temperature $T(t)$ will exceed the user comfort range calculated according to (15). Therefore, in this case, the key for the DR strategy is to calculate $T(t)$, which within the acceptable range, will ensure the minimum error between the total power of the RAC loads and the DR target.

Setting the power of the RAC loads at $P_{\text{DR}}(t)$, the DR optimization objectives is:

$$\begin{aligned} \min \quad & \int_{t \in T} |P_{\text{DR}}(t) - P_{\text{DR_2}}(t)| dt \\ \text{s.t.} \quad & T(t + \Delta t) = T(t) + \frac{-P(t) + (T_o(t) - T(t))\mathcal{G}}{\mathcal{C}} \Delta t \\ & T(t) \in [T_{\text{min}}, T_{\text{max}}] \end{aligned} \quad (30)$$

Without loss of generality, we assume that power reduction exceeds DR potential. The indoor temperature is bounded by the upper limit of the acceptable temperature, and the indoor temperature will be up to T_{max} , as shown in Fig. 7. In the indoor temperature rising stage, there are 3 strategies to control the RAC load power. Strategy 1: The aggregated power decline over-adjustment in the early stage, that is $P_{\text{DR}}(t) < P_{\text{DR_2}}(t)$, as the green line shown in Fig. 7; Strategy 2: The aggregated power decline meet-adjustment in the early stage, that is $P_{\text{DR}}(t) = P_{\text{DR_2}}(t)$, as the blue line shown in Fig. 7; Strategy 3: The aggregated power decline under-adjustment in the early stage, that is, $P_{\text{DR}}(t) > P_{\text{DR_2}}(t)$, as the pink line shown in Fig. 7. DR optimization objective values are S_1 , S_2 , and S_3 , respectively. The solid lines represent the power of the RAC loads. The dash lines denote the indoor temperature. P_0 , P_1

are the RACs' power when the average indoor temperature is stable at $T_{\text{DR_0}}$ and T_{max} , respectively. P_2 is the DR target power.

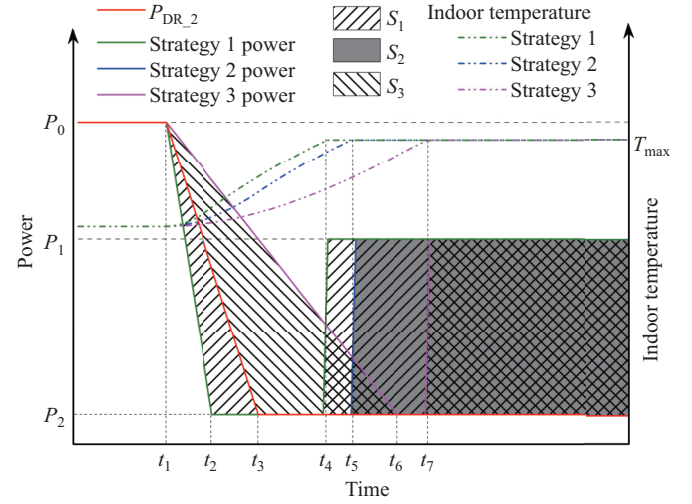


Fig. 7. The different control targets beyond the DR potential.

Strategy 2 is the most optimal control strategy, which is proved as shown in the Appendix. In Strategy 2, the indoor temperature $T(t)$ is calculated according to (15), if $T(t) > T_{\text{max}}$ or $T(t) < T_{\text{min}}$, then we set $T(t) = T_{\text{max}}$ or $T(t) = T_{\text{min}}$.

The second step is to generate a control signal, which is similar to CASE 1.

C. Load Recovery After DR

In response to demand, indoor temperature will deviate from the user's normal setting temperature. After DR, the user's setting temperature needs to return to the previous level. At this time, it may cause obvious power fluctuations, especially during peak load rebound.

In order to avoid the impact of this situation on the power grid, the response recovery strategy can be formulated according to (15) and (18). If the temperature level is restored within a short time, the fluctuation of the aggregated power of the RAC loads become more intense. Therefore, it is necessary to choose the appropriate recovery strategy.

According to the analysis of Section III, the recovery power is related to the rate of indoor temperature recovery. There are two strategies: one is to determine the aggregated power of the RAC loads during the recovery process and then calculate the indoor temperature $T(t)$; the other is to determine the recovery duration, and then calculate the indoor temperature $T(t)$. For the second strategy, the aggregated power needs to be supervised during the recovery process according to (18). In this paper, we adopt the first load recovery strategy. And then the power of the RAC loads is recovered by the DR strategy proposed in this section.

V. SIMULATION RESULTS

A. Base Data

In order to verify the accuracy and effectiveness of the ARAC modeling, identification methods and DR strategies are

proposed in this paper. We select 120,000 RAC loads, and the first-order ETP model parameters are calculated as shown in Table I.

TABLE I
PARAMETERS OF RAC LOADS

Parameters	Value range	Parameters	Value range
$G/(kW/^\circ C)$	[0.16, 0.21]	$T_{set}/^\circ C$	[24, 26]
$C/(kW \cdot h/^\circ C)$	[0.13, 0.23]	$\delta/^\circ C$	1
$\eta P/kW$	[6.5, 7.5]	η	[2.6, 3]

120,000 first-order ETP models are randomly generated by using the parameters of the RAC loads shown in Table I. When the outdoor temperature is different, which is primarily between 31–38°C, we use the Monte Carlo method to simulate different temperature settings and operational states (the indoor temperature will be adjusted randomly under certain probabilities) of the 120,000 RAC loads and obtain 200 data sets of the RACs power. Each set of data has 240 power points, the time slot is 1 minute, and $|\theta| \leq 0.003$. Then these data are utilized for parameter identification.

B. Verification of ARAC Model and Parameter Identification

The parameters of the ARAC model are primarily G and C as described in Section II. First, we identify the parameter G . Then the parameter C is identified later.

The identification result of parameter G is shown in Fig. 8. The black spots denote power calculated by the Monte Carlo simulation. The red line is the identification result. The identified value of G is 7,787.7 kW/°C, and the calculated value by (8) is 7,774.4 kW/°C. The relative identification error is 0.17%.

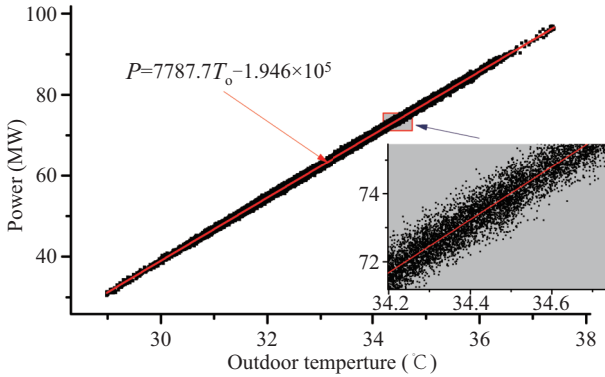


Fig. 8. The identification simulation of parameter G .

Next, we use the identified G to further identify C . First, we evaluate the average indoor temperature according to (10), as the blue line shown in Fig. 9. Secondly, we identify the parameter C according to (13) and (14). The final identified result of parameter C is 7,774.2 kW·h/°C, and calculated value by (7) is 7,724.05 kW·h/°C. The relative identification error is 0.65%.

In order to verify the accuracy of the ARAC model and its parameter identified in this paper, we evaluate the RACs' power and compare with the power simulated by the Monte Carlo simulation, as shown in Figs. 10 and 11.

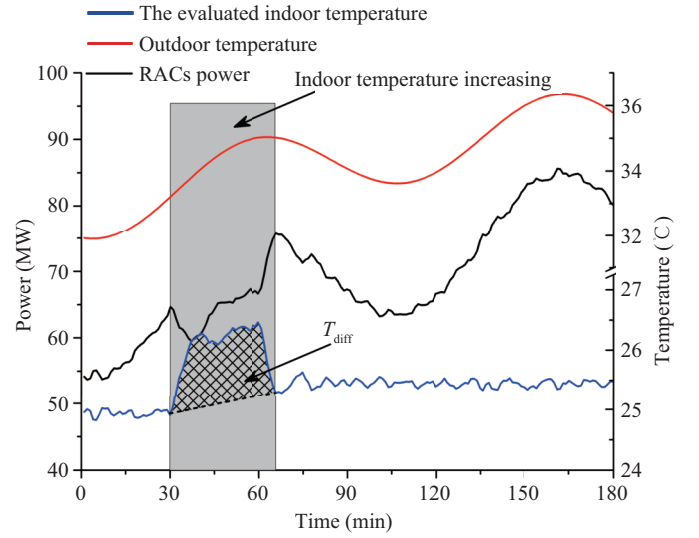


Fig. 9. The identification simulation of parameter X .

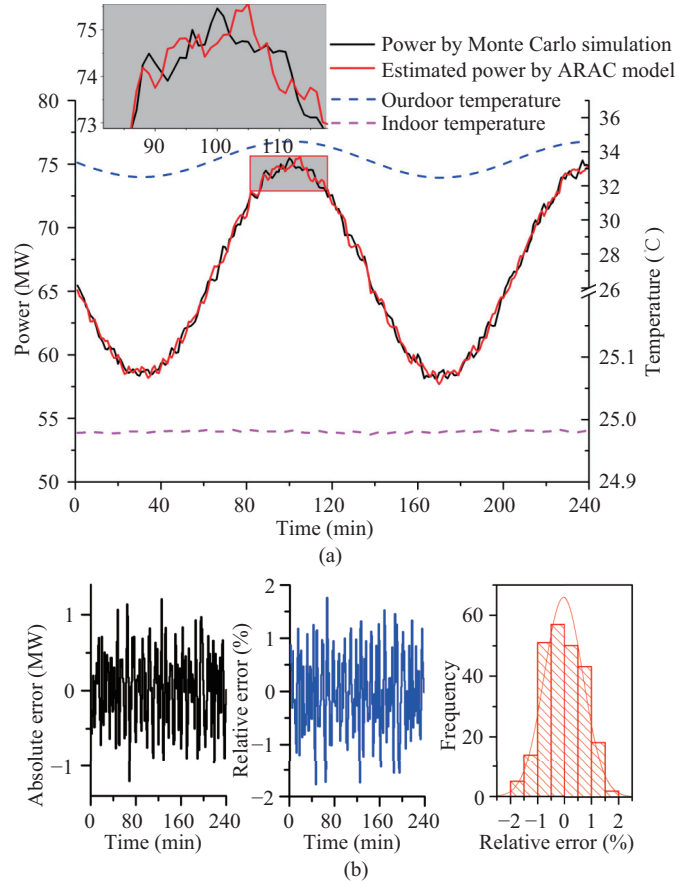


Fig. 10. The evaluation results by identified ARAC model when indoor temperature remains stable, (a) RACs power evaluation, (b) Evaluation error.

The black line in Figs. 10 and 11 is the aggregated power of the RAC loads obtained by the Monte Carlo simulation, and the red line is the power evaluated by the ARAC model. It can be seen that the ARAC model and the parameter identification method proposed in this paper can accurately estimate the RACs' power, which sets the foundation for RAC loads to

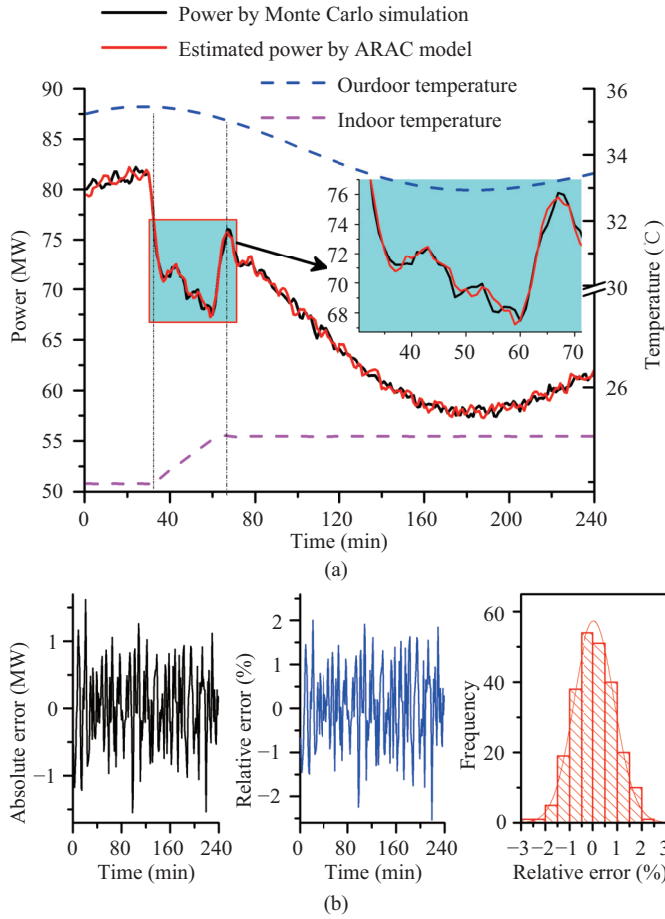


Fig. 11. The evaluation results by identified ARAC model when indoor temperature changes. (a) RACs power evaluation. (b) Evaluation error.

participate in DR programs.

C. Analysis and Verification of RACs' DR Characteristics

We can get instantaneous characteristics of average indoor temperature changes of RAC loads by (17) as shown in Fig. 12, and the proportional (T_{rate}) to the aggregated power of RAC loads and the differences between outdoor temperature and average indoor temperature, respectively.

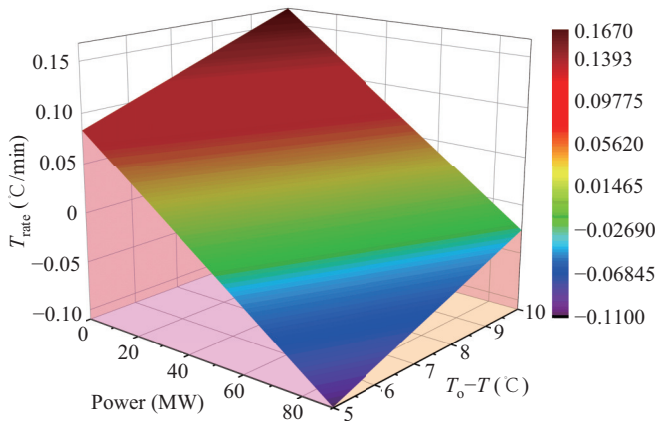


Fig. 12. DR characteristics of RAC loads.

Figure 13 shows the DR characteristics of RAC loads under specific aggregated power and outdoor temperature conditions. Fig. 13(a) and Fig. 13(b) show the curve of the aggregated power and outdoor temperature.

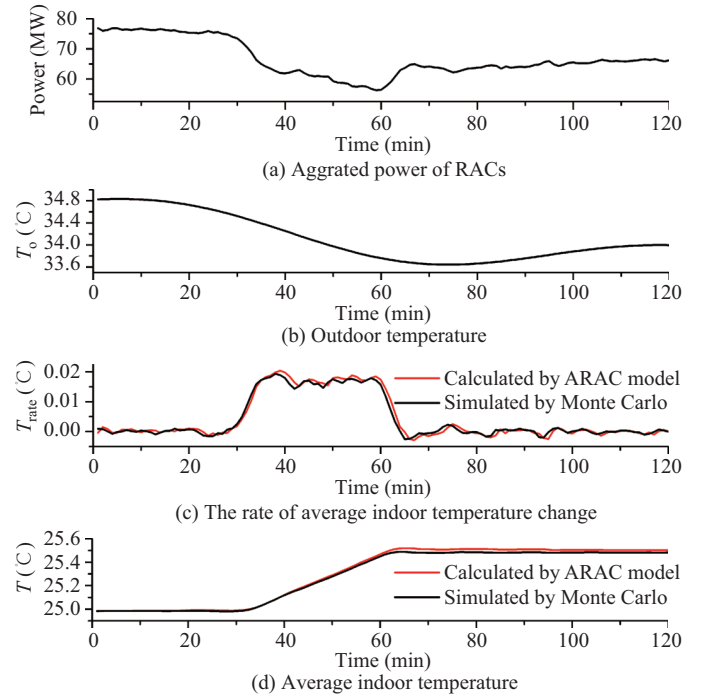


Fig. 13. The verification of DR characteristics. (a) Aggregated power of RACs. (b) Outdoor temperature. (c) The rate of average indoor temperature change. (d) Average indoor temperature.

In Fig. 13(c), we show the rate of average indoor temperature change, and the average indoor temperature curve is displayed in Fig. 13(d). The black line is obtained by the Monte Carlo simulation, and the red line is calculated by (17).

This process of indoor temperature analysis is the dotted arrows for the supplier to calculate $T(t)$ in Fig. 5, and also the first step in DR strategies to calculate $T(t)$.

D. Simulations of RACs DR Control Strategies

In order to verify the control strategy proposed in this paper, we carried out a DR scenario in which power is first reduced and then increased. The DR of RAC loads is usually in the period of centralized use, and the DR period is set to 180 minutes. Considering the degree of DR constrained by users' comfort, we conducted two cases to achieve control targets within and beyond the DR potential. The acceptable indoor temperature range is $[23, 27]^\circ\text{C}$.

E. CASE 1: Control Target Within DR Potential

In CASE 1, the DR target of the RAC load is shown in Fig. 14.

Figure 15 shows the indoor temperature under CASE 1. The black line is the outdoor temperature curve during the DR period. The red line is the average indoor temperature calculated by (17) and the blue line is the average indoor temperature executed by the DR strategies proposed in this

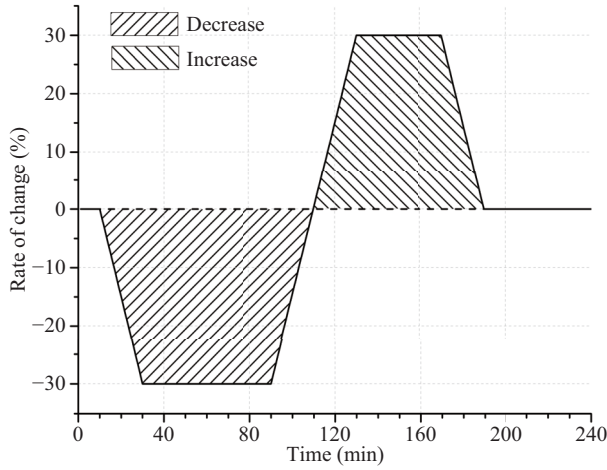


Fig. 14. DR target of RACs power change rate in CASE 1.

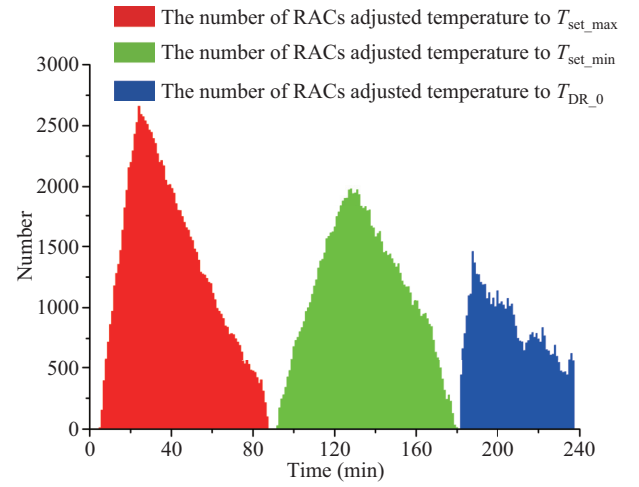


Fig. 16. DR control strategies in CASE 1.

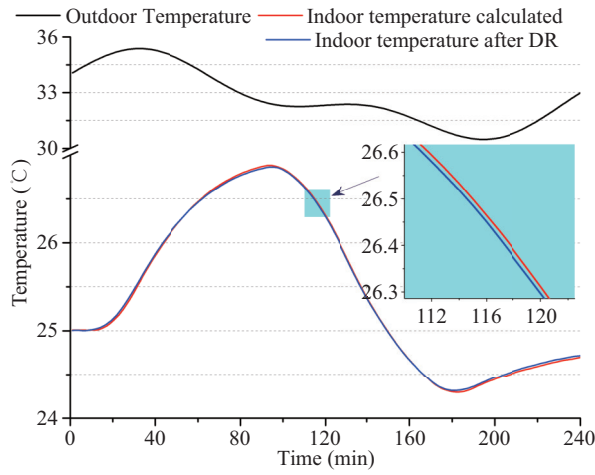


Fig. 15. Average indoor temperature curve in CASE 1.

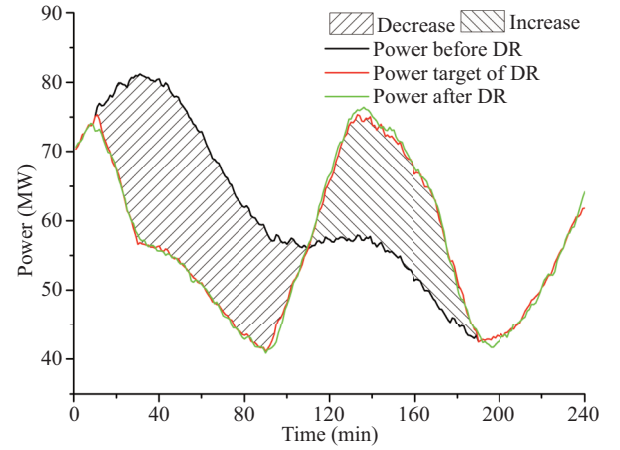


Fig. 17. Aggregated power curve of RAC loads in CASE 1.

paper. It can be determined that the $T_{\text{set_max}}$ is 27°C , $T_{\text{set_min}}$ is 24°C and T_{DR_0} is 25°C .

Figure 16 shows the number of RAC loads adjusted at different stages in CASE 1. The red bars are the number of RAC loads whose temperature set-point is adjusted to 27°C . The green bars are the number of RAC loads whose temperature set-point is adjusted from 27°C to 24°C . The blue area is the load recovery after DR, and the bars are the number of RAC loads that are restored to their original temperature setting.

Figure 17 shows the aggregated power curve of RAC loads in CASE 1. The black line is the power before DR. The red line is the DR power target according to Fig. 14. The green line is the RACs' power curve after DR control.

It can be seen from Fig. 18 that the average indoor temperature error is primarily distributed in $[-0.02, 0.03]^{\circ}\text{C}$, and the aggregated power error is in $[-1, 1]$ MW. Therefore, the DR control strategies satisfies the DR requirements.

F. CASE 2: Control Target Beyond DR Potential

In CASE 2, the ratio of power change is shown in Fig. 19, which is two times that of CASE 1.

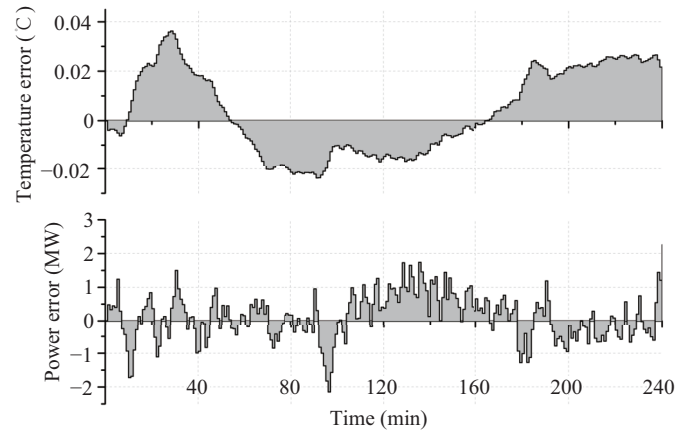


Fig. 18. The error of DR control in CASE 1.

In the first step, the average indoor temperature $T(t)$ is calculated by (17). At the 41st minute, $T(t)$ reaches the upper limit of acceptable temperature, so it is set to 27°C , as shown in Fig. 20. It can be seen from Fig. 20, $T_{\text{set_max}}$ is 27°C , $T_{\text{set_min}}$ is 23°C and T_{DR_0} is 25°C . The control strategy of the second step is similar to that of CASE 1. Simulation results are shown in Figs. 20–23.

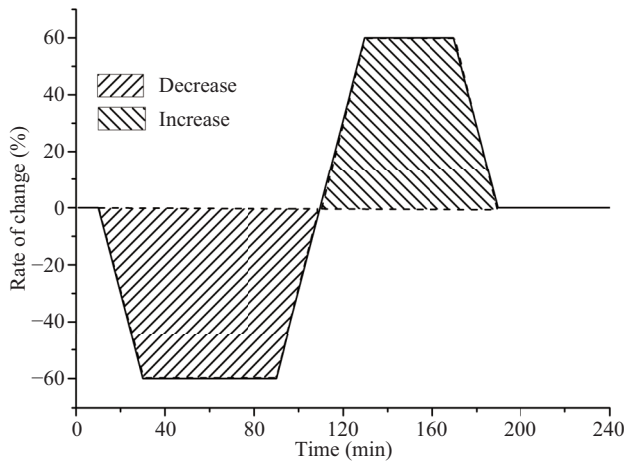


Fig. 19. DR target of RACs power change rate in CASE 2.

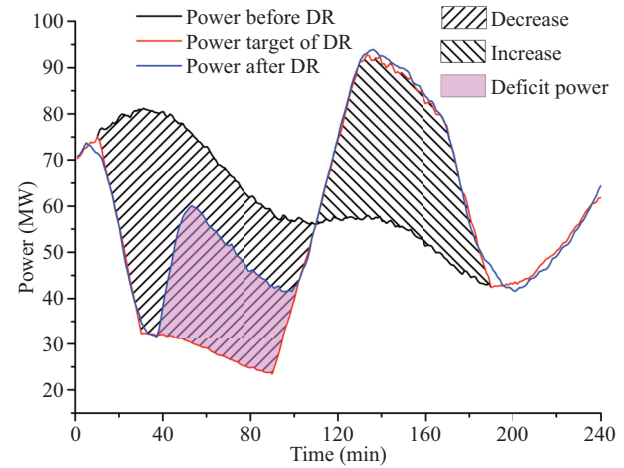


Fig. 22. The aggregated power curve of RAC loads in CASE 2.

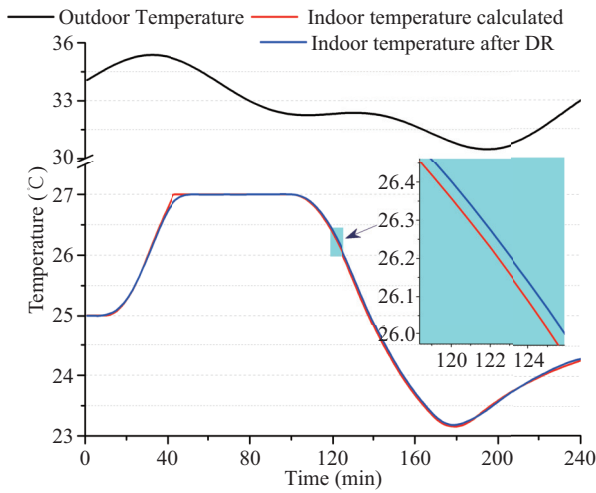


Fig. 20. The average indoor temperature curve in CASE 2.

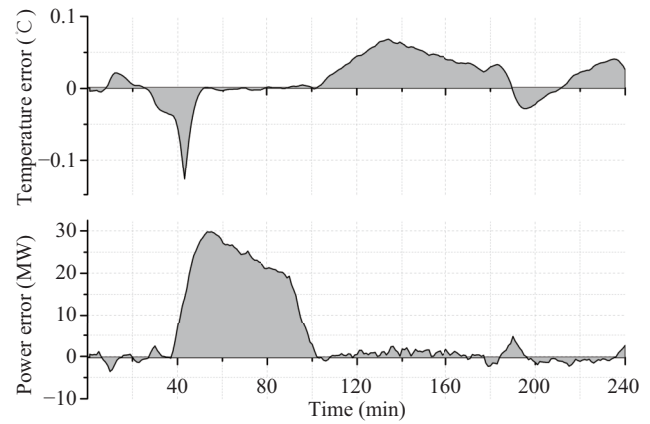


Fig. 23. The error of DR control in CASE 2.

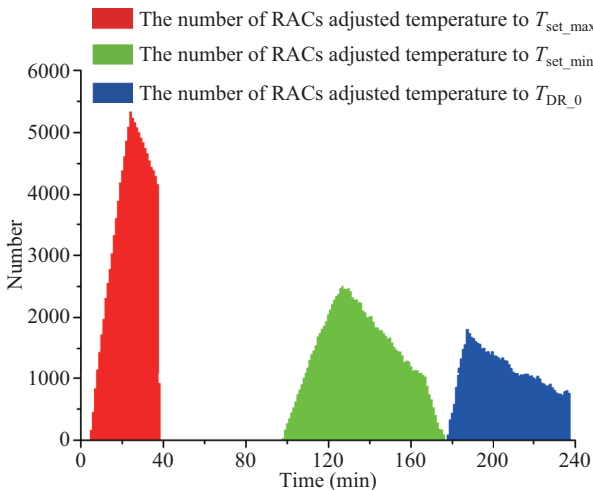


Fig. 21. The DR control strategies in CASE 2.

Since the DR potential of RAC loads is exceeded during the load reduction stage in CASE 2, the indoor temperature of each RAC load reaches $T_{\max}$ 27°C at the 41st minute and is held until the 102nd minute. During this period, there is a big gap between the aggregated power after DR control and the

DR target. It can be seen from Fig. 24 that the average indoor temperature error is primarily distributed in $[-0.05, 0.05]^{\circ}\text{C}$, and the aggregated power is $[-3, 3]$ MW, except for the deficit period.

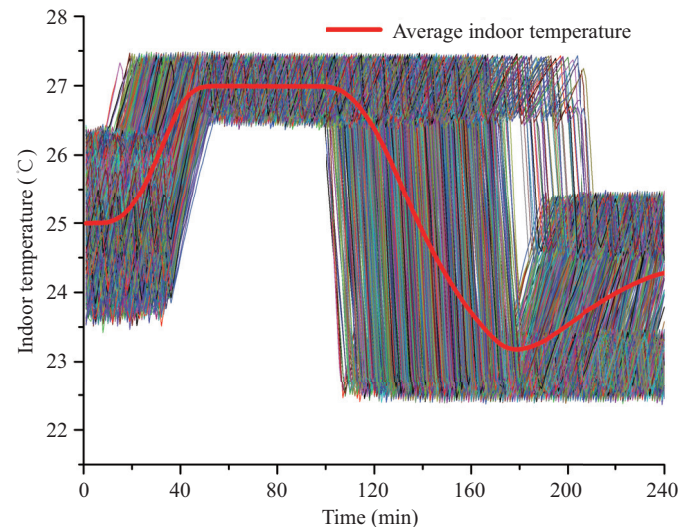


Fig. 24. Indoor temperature curves of 1,000 RAC loads randomly selected from CASE 2.

In this paper, the DR control signal is formulated by calculating the indoor temperature during the DR period. In the calculation process, the acceptable range of indoor temperature settings is considered to ensure the user's need for the indoor temperature. Fig. 24 shows the indoor temperature curves of 1,000 RAC loads randomly selected from CASE 2. We can see that the control strategy can ensure the comfort of the users.

From the above simulations of the DR control strategy, we can see that the DR control strategy of RAC loads proposed in this paper can effectively control RAC loads by adjusting the temperature set-point. The control strategy proposed in this paper only needs to obtain the total power of the RAC loads and outdoor temperature, and send the temperature adjustment set-point and adjustment time to each RAC load. This strategy avoids calculating a single RAC model, which greatly reduces the calculation burden, and does not need to obtain the operational state and indoor temperature, which reduces communication burden during the DR process and protects user privacy. Therefore, it is preferred in large-scale DR programs.

VI. CONCLUSION

In this paper, we establish an ARAC model, provide an identification method of ARAC model parameters based on RACs' power and outdoor temperature. We then analyze DR characteristics of RAC loads based on an ARAC model. Further, we propose DR control strategies of large-scale RAC loads. Finally, the model and method are verified and analyzed.

The ARAC model proposed in this paper avoids the calculation of a single RAC model. The ARAC model describes the relationships among aggregated power, indoor temperature, and outdoor temperature. In addition, the DR control strategies proposed in this paper only send the temperature adjustment values and adjustment time to each RAC load, which reduces the data collection and communication costs and avoids users' privacy issues, and are suitable for large-scale RAC loads to participate in DR programs.

The DR control strategy proposed in this paper is implemented through a DLC scheme, and the impacts of dynamic price on users are not considered. In order to enable users to autonomously participate in the DR program, the DR control strategy of RAC loads, considering real-time prices, will be studied in the near future. At the same time, the impact of the uncertainties of users' behaviors and the outdoor environment on the RACs' participation in DR will also be analyzed.

APPENDIX

It can be seen from Fig. 5, as the RACs' power when employing Strategy 1 drops more rapidly than that of Strategy 2, and the objective value of the DR is $S1 > S2$.

In Strategies 2 and 3, due to $P_{DR}(t) \geq P_{DR,2}(t)$, the objective function can be rewritten as:

$$\min \int_{t \in \mathcal{T}} P_{DR}(t) dt - \int_{t \in \mathcal{T}} P_{DR,2}(t) dt \quad (A1)$$

which is equivalent to:

$$\min \int_{t \in \mathcal{T}} P_{DR}(t) dt \quad (A2)$$

Combined with (10), we can obtain:

$$\int_{t \in \mathcal{T}} P_{DR}(t) dt = \mathcal{G} \int_{t \in \mathcal{T}} (T_o(t) - T(t)) dt - \mathcal{C} (T_{\max} - T_{DR,0}) \quad (A3)$$

$$= \mathcal{G} \int_{t \in \mathcal{T}} T_o(t) dt - \mathcal{G} \int_{t \in \mathcal{T}} T(t) dt - \mathcal{C} (T_{\max} - T_{DR,0}) \quad (A4)$$

Therefore the objective function is equivalent to:

$$\max \int_{t \in \mathcal{T}} T(t) dt \quad (A5)$$

Since the power under Strategy 2 is smaller than Strategy 3 in the early period, the average indoor temperature rises more rapidly. The same conclusion can be obtained from Fig. 5, that is, $S2 < S3$. In summary, Strategy 2 is the optimal control strategy.

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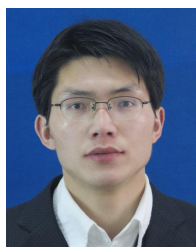


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