ISSN 2004-2965 Energy Proceedings, Vol. 19, 2021

International Conference on Applied Energy 2021
Nov. 29 - Dec. 5, 2021, Thailand/Virtual
Paper ID: 397

A consensus-based distributed control method of residential inverter air conditioners for fair utilization of demand flexibility resources

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ABSTRACT

The wider or even full adoption of electric vehicles and renewable energy sources threatens conventional power systems and affects energy reliability. Residential air conditioning (AC) systems can serve as significant demand flexibility resources by shifting electricity consumption between different periods. However, coordinating multiple diverse and dispersed ACs with different dynamics and capacities in residential buildings is still a grand challenge. Existing studies mainly focused on fixed-speed air conditioners with on-off states only. Moreover, most control strategies are centralized and face user privacy and computational and communicational overhead concerns.

This study proposed a consensus-based distributed control strategy to allocate the demand response tasks fairly to multiple inverter air conditioners. First, a mathematical model with lumped thermal parameters is established to describe inverter air conditioners' thermodynamic and electrical behaviors. Then, a combination of weighted consensus and average consensus-based modification algorithms is adopted to prioritize the DR-participation rate of inverter air conditioners with different capacities and dynamics. The control variable is the temperature setpoint of each inverter air conditioner. Finally, a building with five inverter air conditioners is simulated under a virtual demand response signal. Simulation results validated the effectiveness of the consensus-based distributed control scheme, which is scalable with the plug-and-play feature. As a result, the inverter air conditioners could effectively and efficiently respond to external DR signals.

Keywords: inverter air conditioner, passive thermal storage, consensus-based, distributed control, demand flexibility, fair utilization

NONMENCLATURE

Abbreviations	
DR	Demand response
IAC	Inverter air conditioner
WCC	Weighted consensus control
ACM	Average consensus-based modification
SoC	State of Charge
Symbols	
C_a	Heat capacity of air in the room
$P_{DR,n}^{t}$	Power adjustment task allocated to the *n*th agent at time *t*
T_{set}, n	Indoor temperature setpoint of the *n*th IAC
$\varepsilon_n^{c/d}$	Contribution correction factor of *n*th IAC to uniformly use AC flexibility
β	Weight consensus on DR participation rates

1. INTRODUCTION

The wider or even full adoption of electric vehicles (EVs) and renewable energy sources (RESs) will be the key elements driving the world towards the vision of net-zero carbon emissions. However, the high penetration of EVs and RESs will threaten the stability of conventional power systems and affect energy reliability. As the largest energy consumer and land user, buildings could enhance the power grid reliability and increase the installation capacities of distributed RESs by taking advantage of their passive and active demand flexibility resources (e.g., thermal energy storage).

Air conditioners (ACs) can shift large amounts of electricity consumption between different time periods and attract extensive attention among all flexible demand resources. The compressors of ACs have evolved from fixed speed to variable speed units, and the latter has gained a growing market share for their higher energy efficiency. Therefore, this paper focused on inverter air conditioners (IACs). Generally, IACs can be controlled by frequency adjustment [1–3] and temperature setpoint [4,5] changes. Since the direct frequency control requires significant hardware upgradation of existing devices, this study uses the indirect temperature setpoint control.

The control architecture divides the control strategies into centralized and distributed methods. For example, temperature priority-based control is a typical centralized control strategy for coordinating a large population of ACs [6–9]. The AC units are controlled based on a priority list determined by the difference between the temperature measurements and temperature setpoints. However, centralized controllers are often criticized for disclosing end-users ' privacy and inducing computational and communicational overhead. Thus, distributed control methods attract researchers' significant interests. For example, Hao et al. [4] proposed a distributed transactive control approach of commercial AC systems that uses market mechanisms to engage self-interested responsive loads for load balancing of the power grid. Recently, a few papers adopted consensus-based distributed control methods [10–12] to coordinate multiple residential air conditioners for grid voltage and load management. However, they all considered fix-speed ACs with on-off status only, and the control targets are the load aggregators. To the authors' best knowledge, rare literature adopted consensus algorithms to coordinate individual IACs for fair utilization of their flexible resources.

This study aims to develop a consensus-based distributed control method for fairly utilizing the demand flexibility resources offered by multiple residential IACs with different dynamics and capacities. The main contributions include *i.* a mathematical model that describes the dynamic operating characteristics of IACs, *ii.* a weighted consensus control algorithm that caters for different thermal storage capacities of rooms, *iii,* an average consensus-based estimation and modification algorithm that accounts for houses with different real-time thermal 'state of charge (SoC).' This study is advantageous over existing literature in 1) formulating a consensus-based distributed control method that relies on limited information exchange among neighboring IACs to fairly allocate the demand response (DR) tasks, 2) and investigating the operating characteristics of DR-engaged IACs neither AC aggregators nor fixed-speed air conditioners.

2. THERMODYNAMIC & *ELECTRICAL MODELS OF IACS*

The thermal dynamics of the rooms and IAC systems are modeled by ODE equations (1). The wall (T_m) and indoor air temperatures (T_a) are functions of internal and external heat transfers, such as internal heat gains (Q_i), solar gains (Q_s) and heat injected/removed by IACs (Q_{AC}) (2). The details are omitted here for space concerns, and the derivations can be obtained in [13,14]. Note that we assumed the IACs operate at cooling mode in this paper.

$$\begin{aligned} \dot{T}_a^t &= \frac{1}{C_a}(U_a[T_o^t - T_a^t] + U_m[T_m^t - T_a^t] + Q_a^t) \\ \dot{T}_m^t &= \frac{1}{C_m}(U_m[T_a^t - T_m^t] + Q_m^t) \end{aligned} \tag{1}$$

$$\begin{aligned} Q_a^t &= -(1 - f_{AC})Q_{AC}^t + (1 - f_s)Q_s^t + (1 - f_i)Q_i^t \\ Q_m^t &= -f_{AC}Q_{AC}^t + f_sQ_s^t + f_iQ_i^t \end{aligned} \tag{2}$$

where f_{AC}, f_s, and f_i are constant coefficients.

As for the electrical model of the IAC system, the relationships among electricity consumption (P_{AC}), the cooling capacity of IACs (Q_{AC}), and the operating electricity frequency of the compressor (f_{AC}) can be expressed as (3).

$$P_{AC}^t = k_1 f_{AC}^t + l_1, Q_{AC}^t = k_2 f_{AC}^t + l_2, f_{AC}^t \in [f_{AC}^{\min}, f_{AC}^{\max}] \tag{3}$$

In this context, f is locally adjusted to maintain the indoor temperatures near to setpoints, and k_1, l_1, k_2 and l_2 are constant coefficients. The frequency of IAC is controlled according to the difference between the actual and desired temperature. The frequency evolution is expressed as (4), where k_f is a constant coefficient.

$$\begin{aligned} f_{AC}^t &= f_{AC}^{t-1} + k_f \cdot (T_a^{t-1} - T_a^{set}) \\ f_{AC}^t &\in [f_{AC}^{\min}, f_{AC}^{\max}] \end{aligned} \tag{4}$$

3. CONSENSUS-BASED DISTRIBUTED CONTROLLER DESIGN

This section proposed a consensus-driven distributed control scheme to coordinate multiple IACs with different thermal storage capacities and unequal thermal states to fulfill the real-time DR requests from the system operator. The coordinated control combines the weighted consensus control (WCC) algorithm and the average consensus-based estimation and modification (ACM) algorithm. The WCC algorithm adjusts the temperature setpoints proportional to their thermal storage capacities. The ACM algorithm modifies the above setpoint adjustments by estimating the average 'SoC' of total IACs and generating modification factors in a distributed way to keep the thermal states of IACs close.

3.1 Agent-based modeling and networked control of multiple IACs

First, we developed an agent-based modeling and networked control framework for a building with multiple IACs. Assume that a DR-engaged building has *r* rooms, and each room installs an IAC. Each IAC is viewed as an agent with a local controller that adjusts the temperature setpoints to respond to external DR requests. Then, the multiple agents are linked together by a communication network, where the operations distributed at different agents are coordinated through information exchanges among neighboring agents.

Assuming the adjacent nodes can communicate with each other bidirectionally, the communication network for creating links among IACs can be expressed by an undirected graph $\boldsymbol{G}(\boldsymbol{V},\boldsymbol{E})$, where $\boldsymbol{V}=\{v_1,\ldots,v_r\}$ is a set of nodes, and $\boldsymbol{E}\subseteq\boldsymbol{V}\times\boldsymbol{V}$ is a set of edges. The total number of communication links in $\boldsymbol{E}$ is denoted by l_s. The set of neighbors of node *n* is denoted by $N_n=\{m|(v_n,v_m)\in\boldsymbol{E}\}$.

3.2 DR Participation Proportional to Thermal Storage Capacities: Weighted Consensus Control

Consider a building with multiple IACs receives a DR signal at time *t* to increase or decrease electricity consumption by the amount of dP_t. The building manager needs to allocate the DR request to each IAC $\mathbf{P}_{DR}^t=[P_{DR,1}^t,\ldots,P_{DR,n}^t,\ldots,P_{DR,r}^t]'$. Consequently, we have the constraint

$$\sum_{n=1}^{r}P_{DR,n}^{t}=dP_t \tag{5}$$

Each IAC or room has a thermal storage capacity γ^n. The goal of WCC is to achieve consensus on weighted DR participation, namely $\frac{P_{DR,n}^t}{\gamma^n}\longrightarrow\beta, n=1,\ldots,r$ for some constant β. Denote the state vector $\mathbf{P}_{DR}^t=[P_{DR,1}^t,\ldots,P_{DR,n}^t,\ldots,P_{DR,r}^t]'$, the weighting coefficient vector $\boldsymbol{\gamma}=[\gamma^1,\ldots,\gamma^r]'$, and the state scaling matrix $\boldsymbol{\Psi}=diag[1/\gamma^1,\ldots,1/\gamma^r]$. Let $\mathbf{I}$ be the column vector of all ones. Together with the constraint (5), the target of WCC is $\boldsymbol{\Psi}\mathbf{P}_{DR}^t\longrightarrow\beta\mathbf{I}$ subject to $\mathbf{I}'\mathbf{P}_{DR}^t=dP_t$. It follows from $\boldsymbol{\gamma}'\boldsymbol{\Psi}=\mathbf{I}'$ that $\beta=\frac{dP_t}{\boldsymbol{\gamma}'\mathbf{I}}=\frac{dP_t}{\gamma^1+\cdots+\gamma^r}$. The most important characteristic of this control strategy is that for all iterations $k\in\{1,\ldots,K\}$:

$$\sum_{n=1}^{r}P_{DR,n}^{1}=\ldots=\sum_{n=1}^{r}P_{DR,n}^{k}=\ldots\sum_{n=1}^{r}P_{DR,n}^{K}=\ldots=\sum_{n=1}^{r}P_{DR,n}^{t} \tag{6}$$

This means that the total DR offers of IACs with the network in all algorithm iterations are the same as the total initial values.

For a specified instant, the WCC algorithm is run for several iterations $k\in\{1,\ldots,K\}$ to achieve the convergence. In each iteration step, the DR participation amount is updated from $\mathbf{P}_{DR}^k$ to $\mathbf{P}_{DR}^{k+1}$ by the amount $\mathbf{u}^k$ (7).

$$\mathbf{P}_{DR}^{k+1}=\mathbf{P}_{DR}^{k}+\mathbf{u}^k \tag{7}$$

Then, $\mathbf{u}^k$ can be calculated using the control signal, p_n^{ij}, considering the information from the neighbor units [15,16]:

$$u_{DR,n}^{k}=-\sum_{(i,j)\in G}p_n^{ij}+\sum_{(j,i)\in G}p_n^{ji} \tag{8}$$

The control signal p_n^{ij}, is calculated by (9), which represents an estimated difference between weighted $P_{DR,i}^k$ and $P_{DR,j}^k$ [15].

$$p_n^{ij}=\frac{P_{DR,i}^k}{\gamma^i}-\frac{P_{DR,j}^k}{\gamma^j} \tag{9}$$

For better presentation of the above process, (7)-(9) can be written in the following compact matrix form [15]:

$$\begin{aligned}\mathbf{p}^k&=\mathbf{H}_2\boldsymbol{\Psi}\mathbf{P}_{DR}^k-\boldsymbol{\Psi}\mathbf{H}_1\mathbf{P}_{DR}^k=\mathbf{H}\mathbf{P}_{DR}^k\\ \mathbf{u}^k&=-(\mathbf{H}_2-\mathbf{H}_1)'\mathbf{H}\mathbf{P}_{DR}^k\end{aligned} \tag{10}$$

where both $\mathbf{H}_1$ and $\mathbf{H}_2$ are $l_s\times r$ matrices. If the communication link (v_i, v_j) is the *m*th link in E, then all the elements of *m*th row in $\mathbf{H}_1$ are zero except the *j*th element, which is one. All the elements of the *m*th row in $\mathbf{H}_2$ are zero except the *i*th element, which is one. $\boldsymbol{\Psi}$ is $diag[1/\gamma^1,\ldots,1/\gamma^r]$ and $\widetilde{\boldsymbol{\Psi}}$ is a $l_s\times l_s$ diagonal matrix whose *m*th diagonal element is $1/\gamma^j$, if the *m*th link in the $\boldsymbol{E}$ set is (v_i, v_j).

Through the above WCC algorithm, the total DR amount of the building requested by the system operator could be shared among all IACs proportional to their thermal storage capacities.

3.3 Modification Proportional to the IACs' Thermal SoC: Average Consensus Control

The WCC strategy in the last subsection only considers the thermal storage capacity of IACs without considering their thermal 'state of charge (SoC).' In practice, the thermal 'SoC' will be different due to building insulations and internal activities. Using only the WCC algorithm, some IACs may excessively use up the DR resources while other IACs may still have considerable flexibility capacity. Thus, the average consensus control algorithm is added to the WCC controller to adjust the DR participation rates such that the available storage capacity can be utilized more uniformly.

The main idea is to estimate the average thermal 'SoC' of all IACs in a distributed way. Then contribution correction factors are calculated using the estimated total average thermal 'SoC' to modify the setpoint adjustments obtained in the last subsection to keep the energy storage levels of IACs close as far as possible. The information discovery law is defined as [17]

$$x_i[k+1] = x_i[k] + \sum_{j \in N_i} d_{ij}(x_j[k] - x_i[k]) \tag{11}$$

where $i, j \in \{1, \dots, r\}$. $x_i[k]$ and $x_i[k+1]$ are the discovered information by the agent *i* at the *k* and *k*+1 iterations, respectively. d_{ij} is the communication coefficient between the neighbor agents *i* and *j* and N_i is the set of neighbor agents connected to agent *i*.

The information discovery law for the whole system can be modeled as a discrete-time linear system (12).

$$\mathbf{X}[k+1] = \mathbf{D}\mathbf{X}[k] \tag{12}$$

where $\mathbf{X}[k] = [x_1[k], \dots, x_n[k], \dots, x_r[k]]^T$ and $\mathbf{X}[k+1]$ are the discovered information vector at the *k* and *k+1* iterations, respectively, and $\mathbf{D}$ is a communication matrix. If the sums of $\mathbf{D}$'s rows and columns are equal to one and the eigenvalues of $\mathbf{D}$ satisfy $|\lambda_n| \leq 1$, then it can be proven that [17]

$$\lim_{k \to \infty} \mathbf{X}[k] = \lim_{k \to \infty} \mathbf{D}^k \mathbf{X}[0] = \frac{\mathbf{1} \cdot \mathbf{1}^T}{r} \mathbf{X}[0] \tag{13}$$

As [17], the $\mathbf{D}$ is determined by the *mean metropolis* method with the following law [18]

$$d_{ij} = \begin{cases} 2/(g_i + g_j + 1) & j \in N_i \\ 1 - \sum_{i \in N_i} 2/(g_i + g_j + 1) & i = j \\ 0 & otherwise \end{cases} \tag{14}$$

where g_i and g_j are the number of agents connected to agent *i* and *j*, respectively. According to (13), the average of dispersed quantities ($\bar{X}$) can be obtained in a distributed manner.

Denote the thermal 'SoC' of all IACs at *k*th iteration by $\mathbf{SOC}[k] = [SoC_1[k], \dots, SoC_n[k], \dots, SoC_r[k]]$ After estimating the average thermal 'SoC' ($\overline{SoC_n}$) by the average consensus algorithm above, the contribution correction factors of IACs are calculated based on rules (15) to keep the corresponding thermal SoC close.

$$\begin{aligned} \varepsilon_n^c &= \begin{cases} 0 & SoC_n > 1.0 \\ 1 - k^c \cdot \dfrac{(SoC_n - \overline{SoC_n})}{100} & SoC_n \leq 1.0 \end{cases} \\ \varepsilon_n^d &= \begin{cases} 0 & SoC_n < 0 \\ 1 + k^d \cdot \dfrac{(SoC_n - \overline{SoC_n})}{100} & SoC_n \geq 0 \end{cases} \end{aligned} \tag{15}$$

where k^c and k^d are coefficients that adjust the tolerance to the unequal thermal SoCs of IACs. The thermal 'SoC' of the IAC system is defined in (16) by viewing it as a thermal battery model [19].

$$SoC_n = \frac{C_{a,n}(T_n^{\max} - T_n^t)}{C_{a,n}(T_n^{\max} - T_n^{\min})} = \frac{T_n^{\max} - T_n^t}{T_n^{\max} - T_n^{\min}} \tag{16}$$

where $C_{a,n}$ is the heat capacity of the air in the *n*th room, T_n^{max} and T_n^{min} are the indoor temperature range to guarantee the end-user's comfort. T_n^t is the real-time indoor temperature measurement.

Finally, the temperature setpoint of *n*th IAC is given by (17), where $T_{set,n}^{DR}$ is the final adjusted setpoint, $T_{set,n}^{initial}$ is the initial setpoint, f_{tem} is a constant coefficient, and $P_{DR,n}^t$ is the power adjustment allocated to *n*th IAC, which is determined by the thermal storage capacity γ^n, thermal 'SoC' correction factors $\varepsilon_n^{c/d}$ and the weighted consensus of DR-participation rates β.

$$\begin{aligned} T_{set,n}^{DR} &= T_{set,n}^{initial} - f_{tem} \cdot P_{DR,n}^t \\ P_{DR,n}^t &= \beta \cdot \gamma^n \cdot \varepsilon_n^{c/d} \end{aligned} \tag{17}$$

4. SIMULATION AND RESULTS

4.1 Simulation Setup

Considering a building with five DR-engaged rooms and IACs, we built the agent-based modeling and networked control simulation model in MATLAB. Each IAC is modeled as an agent, and the five agents are linked by a communication network with ring shape topology, as shown in Fig. 1.

We assume the building will respond to the virtual DR signals in Fig. 2. The five IACs are characterized by the same parameters except for the heat capacities of air in the rooms, which are listed in Table 1. The control inputs are the temperature setpoints of each IAC at each control interval. The uncontrollable inputs include the outdoor temperature, internal heat gains, and solar gains. The IACs share the same outdoor temperatures while the internal heat gains are shifted circularly, and the solar gains are scaled for five IACs to account for their different occupancy, activities, and orientations.

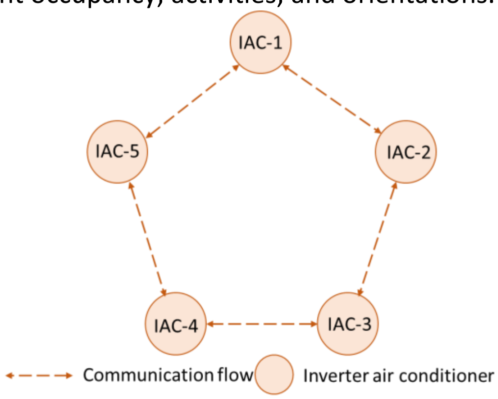


Fig. 1. Communication network among five IACs with ring shape topology

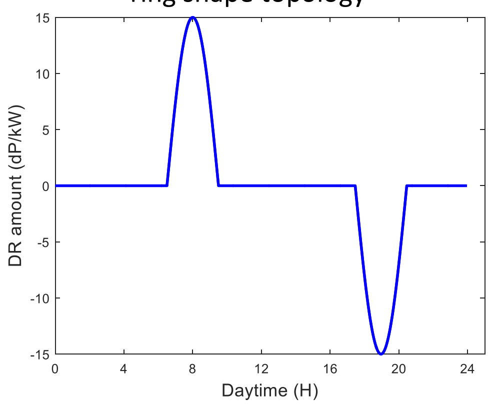


Fig. 2. Virtual DR signal for the building with five IACs

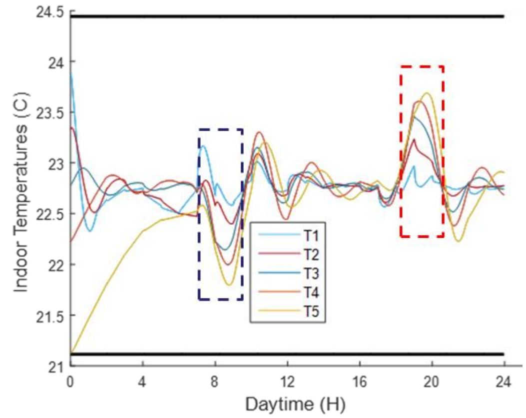
Table 1. Indoor air heat capacities of IACs (C_a in (1))

Units	IAC-1	IAC-2	IAC-3	IAC-4	IAC-5
Heat capacity of Indoor Air (Btu/F)	859	1718	2577	3436	4294

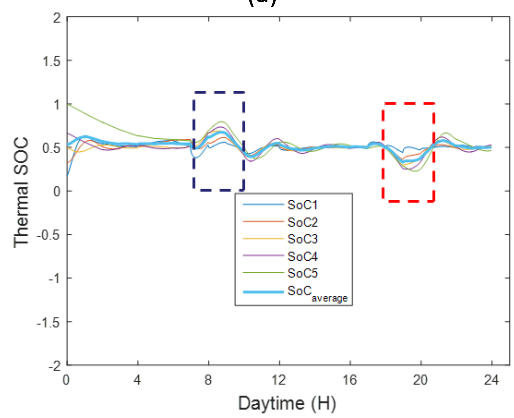
4.2 Results

Fig.3 shows the simulation results with the WCC algorithm only. Fig. 3(a) shows the 24-hour indoor temperature profiles. Since the IACs are operated at the cooling model, the indoor temperatures reduce around eight o'clock and increase around 19 o'clock to respond to the virtual DR signal in Fig. 2. Fig. 3(b) shows the corresponding individual and average thermal 'SoC' profiles according to the definition in (16). It is seen that the thermal 'SoC' values lie between zero and one, and the thermal 'battery' gets charged around eight o'clock and discharged around 19 o'clock. At time slots without DR request, the thermal 'battery' always maintains the thermal 'SoC' as nearly 0.5. Fig. 3(c) shows the individual 24-hour temperature setpoints control profiles of IACs.

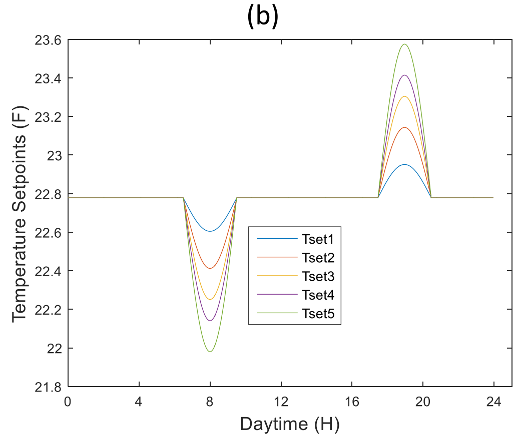
The setpoint adjustments of IACs are proportional to their indoor air heat capacities in Table 1.



(a)



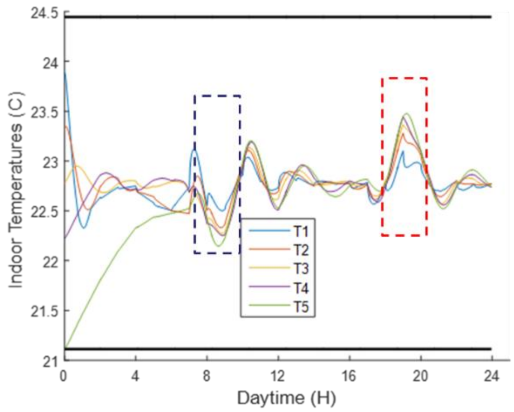
(b)



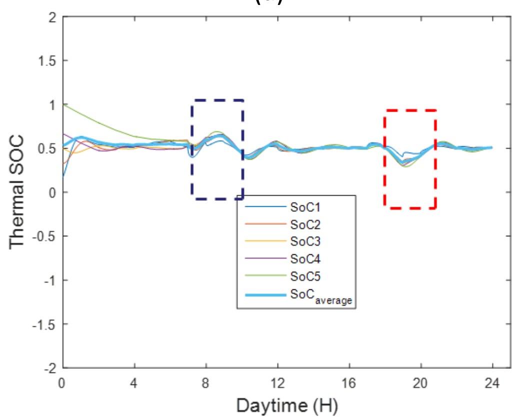
(c)

Fig. 3. Coordinated control with WCC only. (a) 24-hour indoor temperatures; (b) individual and average thermal 'SoCs'; (c) temperature setpoints of IACs.

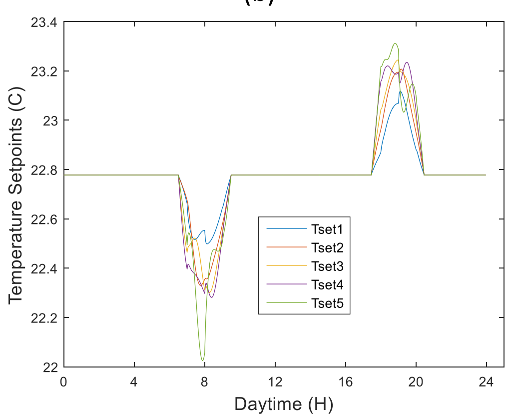
Fig.4 shows the simulation results with both WCC and ACM algorithms. The temperature profiles, thermal 'SoC' profiles, and the temperature setpoint profiles follow similar patterns in Fig. 3. The difference is that the discrepancies among individual temperature or thermal 'SoC' profiles of IACs are much smaller than in Fig. 3. This is accountable since the ACM algorithm modifies the DR participation rate of IACs based on their thermal 'SoC' to keep the thermal 'SoC' as close as possible.



(a)



(b)



(c)

Fig. 4. Coordinated control with WCC&ACM algorithms. (a) 24-hour indoor temperatures; (b) individual and average thermal 'SoCs'; (c) temperature setpoints.

This can be explained by equations (15). For example, if the real-time thermal 'SoC' of agent *n* (SoC_n) is lower than its estimated average thermal 'SoC' ($\overline{SoC}_n$), then $\varepsilon_n^c > 1$, which means the *n*th agent's contribution should be increased during the 'charging' mode. Conversely, if the real-time thermal 'SoC' of agent *n* (SoC_n) is large than its estimated average thermal 'SoC' ($\overline{SoC}_n$), then $\varepsilon_n^c < 1$, which means the *n*th agent's contribution would be reduced during the 'charging' mode. Consequently, the thermal 'SoC' profiles with WCC&ACM algorithms are closer to each other than the 'SoC' profiles with WCC control only.

Fig. 5 compares the profiles of the requested DR amount and the power adjustments provided by the WCC and WCC&ACM control strategies, respectively. It is seen that the WCC and WCC&ACM strategies could generally follow the DR requests from system operators and provide similar amounts of power adjustments. However, significant DR rebound effects appeared after DR periods, which should be further investigated to relieve the new power variations induced by the DR program.

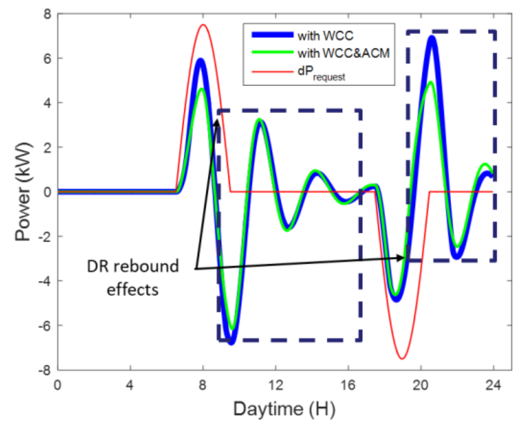


Fig. 5. Comparison among the requested DR amount and the power adjustments provided by the WCC algorithm and the WCC&ACM algorithm, respectively.

5. CONCLUSIONS

The inherent building thermal energy storage effect can be modeled as a virtual thermal 'battery' and dispatched similarly as an electrical battery. This study proposed a consensus-based distributed control scheme to engage residential rooms with different thermal 'battery' capacities and thermal 'SoCs' in the demand response program. The distributed control method comprises two sub-algorithms: weighted consensus control (WCC) and average consensus-based modification (ACM). The WCC algorithm allocates the DR task to each IAC proportional to their thermal storage capacities. The ACM algorithm generates average thermal 'SoC' estimations of all IACs for each IAC and produces modification factors to make the IACs' thermal 'SoCs' close as far as possible during DR periods. The most important implication is that the operations above are realized through information exchanges among neighbor units in a communication network with limited links and 'plug-and-play' features.

Five IACs connected by a ring shape communication network are simulated to validate the effectiveness of the proposed consensus-based distributed control method. Simulation results show the great promise of consensus algorithms in the fair real-time coordination and management of air conditioning systems and other demand flexibility resources. Further research should focus on reducing DR rebound effects and the probe of direct frequency control of IACs.

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