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A fully distributed robust optimal control approach for air-conditioning systems considering uncertainties of communication link in IoT-enabled building automation systems

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ABSTRACT

Internet of Things (IoT) technologies are increasingly implemented in buildings as the cost-effective smart sensing infrastructure of building automation systems (BASs). They are also dispersed computing resources for novel distributed optimal control approaches. However, wireless communication networks are critical to fulfill these tasks with the performance influenced by inherent uncertainties in networks, e.g., unpredictable occurrence of link failures. Centralized and hierarchical distributed approaches are vulnerable against link failure, while the robustness of fully distributed approaches depends on the algorithms adopted. This study therefore proposes a fully distributed robust optimal control approach for air-conditioning systems considering uncertainties of communication link in IoT-enabled BASs. The distributed algorithm is adopted that agents know their out-neighbors only. Agents directly coordinate with the connected neighbors for global optimization. Tests are conducted to test and validate the proposed approach by comparing with existing approaches, i.e., the centralized, the hierarchical distributed and the fully distributed approaches. Results show that different approaches are vulnerable against to uncertainties of communication link to different extents. The proposed approach always guarantees the optimal control performance under normal conditions and conditions with link failures, verifying its high robustness. It also has low computation complexity and high optimization efficiency, thus applicable on IoT-enabled BASs.

1. Introduction

Internet of Things (IoT) technologies, being rapidly developed, are increasingly implemented in buildings [1]. The IoT-enabled building automation systems (BASs) adopt IoT-based smart sensors as convenient and low cost information sources [2]. They can provide indoor air quality (IAQ) data [3] and energy loads [4] for occupants to inform about the current condition. They can also provide essential inputs to direct the control actions of building systems [5–7]. In addition, IoT-based smart sensors with advanced capabilities, e.g., data storage and processing, facilitate the realization of edge computing in smart buildings [8].

As one of the most important systems serving buildings, air-conditioning systems are operated to maintain a good indoor environment for ensuring the mental and physical health of occupants [9]. However, a considerable amount of energy is used to fulfill this task [10], as estimated to account for about 40% of the commercial building energy use [11]. The trade-off between the acceptable indoor environment and the minimized energy use can be found by developing optimal control strategies for air-conditioning systems, in which the multi-objective optimization problems are formulated and solved [12,13]. Ganesh et al. [14] formulated an objective function considering energy use, indoor ozone concentration, indoor PM2.5 concentration and indoor HCHO concentration. Zhai and Soh [15] formulated an objective function considering the energy use and Predictive Mean Vote (PMV). To solve the formulated multi-objective optimization control problems, different optimal control approaches have been investigated.

Centralized optimal control approaches have been mostly adopted. They are applicable to the current operation mode of BASs that the local information measured by sensors is transmitted to a central workstation for global optimization and determine optimal control set-points. IoT-based smart sensors only act as data source. Centralized optimal control approaches are vulnerable against individuals' failures [16], such as links failures between sensors and the central workstation. In IoT-enabled BASs, the information is transmitted via wireless communica-

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tion networks [17], in which inherent uncertainties exists [18]. One example is the uncertainties of communication link that communication networks are unpredictable to be under normal conditions or under conditions with link failure. Therefore, centralized optimal control approaches are vulnerable against link failure when they are implemented in IoT-enabled BASs, and there lacks a detailed investigation on how such a vulnerability would have impacts on the optimal control performance of air-conditioning systems.

As the counterpart, the relatively new distributed optimal control approaches solve the multi-objective optimization control problems by coordinating individual agents, in which local optimization are conducted [19]. Compared with the centralized optimal control approaches, the distributed optimal control approaches have better scalability and reconfigurability which are particularly beneficial for large-scale systems with flexible control objectives and system dynamics [24]. There are hierarchical distributed optimal control approaches and fully distributed optimal control approaches, depending on if there is a central coordinating agent facilitating coordination among local agents [20]. Hierarchical distributed optimal control approaches adopt central coordinating agents, which are at the global level, to connect all local agents together for global information exchange [21]. Fully distributed optimal control approaches treat all local agents equally and information is directly exchanged between connected local agents according to the preset communication topology [22]. Different distributed optimization algorithms are adopted in specific distributed optimal control approaches to solve the optimal control problems in a distributed manner. In IoT-enabled BASs, agents can be IoT-based smart sensors with limited computing capacities, according to the edge computing concept [23]. Although the coordination among multiple IoT-based smart sensors is realized via wireless communication networks, generally speaking, distributed optimal control approaches are robust against link failure and can handle uncertainties of communication link [16]. To be exact, the robustness depends on the specific distributed optimal control approaches and the algorithms adopted in each distributed optimal control approach.

Hierarchical distributed optimal control approaches have received a tremendous surge of interest and being increasingly investigated for air-conditioning systems in recent years. Li and Wang [24] proposed a multi-agent based hierarchical distributed approach for the optimal control of multi-zone dedicated outdoor air systems (DOASs). Agents were implemented on IoT-based smart IAQ sensors and the smart airflow meter. The alternating direction method of multipliers (ADMM) was used. Su and Wang [25] proposed an agent-based hierarchical distributed optimal control strategy for air-conditioning systems. The dual decomposition method was adopted to decompose the centralized optimization problem. Li et al. [26] proposed a real-time optimal control strategy for multi-zone variable air volume (VAV) air-conditioning systems. The ADMM was adopted to optimize the fresh air ratio of the supply air and the temperature set-point in the critical zone in a distributed manner. In hierarchical distributed optimal control approaches, if a link failure happens between a local agent and the central coordinating agent, the local agent will be isolated from the system. Due to the crucial roles of the central coordinating agent, the robustness of hierarchical distributed optimal control approaches is weak regardless of the adopted algorithms. And there lacks a detailed investigation on how this weak robustness would have impacts on the optimal control performance of air-conditioning systems.

Many fully distributed optimization approaches or algorithms have been proposed, and the robustness of fully distributed optimal control approaches depends on the algorithms adopted. Zhang and Chow [27,28] proposed the Incremental Cost Consensus (ICC) Algorithm, which was a leader–follower consensus-based algorithm, for the economic dispatch problem (EDP). To avoid the selection of a leader, Zhang et al. [29,30] proposed a two-level consensus-based algorithm for EDP, in which the lower level adopted the average consensus algorithm and the upper level adopted the ICC Algorithm. Li and Wang [31] adopted the two-level consensus-based algorithm to develop a fully distributed optimal control approach for air-conditioning systems. In these studies, a priori knowledge of the communication topology was needed. The unpredictable occurrence of link failure can change communication topologies with considerable uncertainties [16]. Therefore, it is inappropriate to adopt these algorithms in developing robust fully distributed optimal control approaches for air-conditioning systems considering uncertainties of communication link.

In contrast, without a priori knowledge of the communication topology, many fully distributed algorithms have been developed under time-varying communication topologies. Kingston and Beard [32] developed a fully distributed algorithm to solve the average-consensus problem under switching network topologies. Xu et al. [33] developed a fully distributed algorithm to solve the resource allocation problem under directed and time-varying communication topologies. It was applied to solve EDP in a smart grid environment. Yang et al. [34] proposed a fully distributed algorithm for EDP over the communication networks with time-varying communication topologies and communication delays. Although these algorithms can handle time-varying communication topologies, which can result from unpredictable link failure, many studies focused on pure algorithms development and applications in power systems. And no investigation has been made on developing robust fully distributed optimal control approaches considering uncertainties of communication link for air-conditioning systems and in the air-conditioning field.

This study therefore proposes a fully distributed robust optimal control approach for air-conditioning systems considering uncertainties of communication link in IoT-enabled building automation systems (BASs). This study has four major innovations. (1). A new fully distributed robust optimal control approach is developed to be implemented in IoT-enabled BASs with inherent uncertainties of communication link for optimally controlling multi-zone dedicated outdoor air systems (DOASs). (2). The impacts on the optimal control performance of DOASs are investigated when fully distributed optimal control approaches adopting different algorithms are implemented in BASs with inherent uncertainties of uncertain communication link. (3). The computation complexity, optimization efficiency and control performance of the proposed fully distributed robust optimal control approach are assessed to validate the applicability of the proposed approach to be deployed over IoT-enabled BASs. (4). The impacts on the optimal control performance of DOASs are investigated when centralized and hierarchical distributed optimal control approaches are implemented in IoT-enabled BASs with inherent uncertainties of communication link.

2. Description of system, problems and motivation

This section first describes multi-zone dedicated outdoor air systems (DOASs), which is a popular type of air-conditioning systems. Second, the mathematical formulation of the multi-objective optimization problem for optimal control of DOASs is presented. Third, uncertainties of communication link in IoT-enabled building automation systems (BASs) are identified by analyzing the on-site data.

2.1. Description of multi-zone dedicated outdoor air systems

The schematic of a DOAS is shown in Fig. 1. It is operated to supply each room with a certain amount of outdoor air, which is determined by considering the following two aspects. From the aspect of a single room, a large outdoor air volume is preferable due to its high efficiency in diluting indoor pollutants to improve IAQ. From the aspect of the primary air-handling unit (PAU), a small outdoor air volume is preferable so that the energy used for handling and delivering outdoor air can be reduced. Therefore, there is a trade-off problem in DOASs to ensure acceptable IAQ with minimized energy use. The outdoor air volume of individual rooms and PAU are the control variables to be optimized.

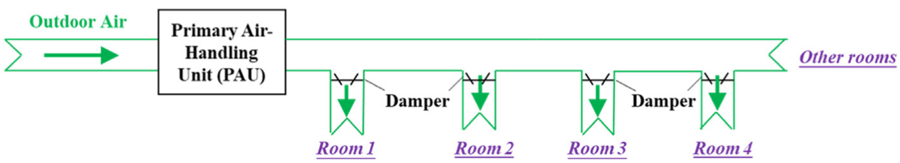

Fig. 1. Schematic of a multi-zone DOAS.

2.2. Formulation of the optimal control problem

The objectives of optimal control problem in DOASs are to maintain a satisfactory IAQ in individual rooms and minimize energy use of the PAU. The mass balance constraint should be met that the sum of outdoor air volume of individual rooms is equal to the outdoor air volume of the PAU, i.e., the outdoor air volume mismatch should be zero. Also, outdoor air volume of individual rooms and the PAU are constrained within the corresponding adjustable ranges. The objectives and constraints are formulated as

$$\min_{Q_i, Q_{Tot}} \alpha \cdot \sum_{i=1}^{n} IAQ_i(Q_i) + E(Q_{Tot}) \tag{1a}$$

$$\text{subject to } \sum_{i=1}^{n} Q_i - Q_{Tot} = 0 \tag{1b}$$

$$Q_i \in \left[Q_i^{min}, Q_i^{max}\right], i = 1, \dots n \tag{1c}$$

$$Q_{Tot} \in \left[Q_{Tot}^{min}, Q_{Tot}^{max}\right] \tag{1d}$$

where Q_i is the outdoor air volume of the room *i*, Q_{Tot} is the outdoor air volume of the PAU, α is the weighting factor, n is the number of rooms, $IAQ_i(\cdot)$ is the objective function of the room *i* to evaluate IAQ, $E(\cdot)$ is the objective function of the PAU to evaluate energy use, $Q_i{}^{min}$ and $Q_i{}^{max}$ are the lower and upper bounds of adjustable range for outdoor air volume of the room *i*, and $Q_{Tot}{}^{min}$ and $Q_{Tot}{}^{max}$ are the lower and upper bounds of adjustable range for outdoor air volume of the PAU. The objective functions of the room *i* and the PAU [24] are shown as

$$IAQ_i(Q_i) = (CO2_{amb} + \frac{G_{CO2} \cdot N_i}{Q_i})^2 \tag{2a}$$

$$E(Q_{Tot}) = \rho \cdot Q_{Tot} \cdot (h_{out} - h_{in})/COP + E_d \cdot \left(\frac{Q_{Tot}}{Q_d}\right)^2 \tag{2b}$$

where $CO2_{amb}$ is the CO_2 concentration of ambient air, G_{CO2} is the CO_2 generation rate by one occupant, N_i is the number of occupants in the room *i*, ρ is the air density, h_{out} is the outdoor specific enthalpy, h_{in} is the indoor specific enthalpy, *COP* is the overall coefficient of performance, E_d is the design fan power of the PAU, and Q_d is the design outdoor air volume of the PAU. It should be noted that N_i and h_{out} are time-varying while the other parameters are constants.

2.3. Uncertainties of communication link in IoT-enabled BASs

Uncertainties of communication link in IoT-enabled BASs are identified in the real case conducted in an office building of a Hong Kong campus [3]. This strenghthens the conclusions made by previous work [18] about the inherence of uncertainties in IoT-enabled BASs and justifies the necessity of our work about a robust approach. The IoT-based smart sensors were installed in three office rooms to collect indoor CO_2 concentration, which were then transmitted to the cloud server via a wireless communication network. Most of the time, communication networks were in normal conditions for data transmission. However, unexpected link failures happened. The on-site data of indoor CO_2 concentration in two days are shown in Fig. 2. Gaps, ranging from 0.5 to 9 h, mean that data failed to be transmitted to the cloud server due to link failures. Link failures can happen at any sensor at any time and last for any time length, thus they are unpredictable. Although uncertainties of communication link can be reduced by maintain networking hardware regularly, it is still worthy developing robust optimal control approaches which are invulnerable to link failures. Uncertainties of communication link have impacts on the optimal control performance of DOASs to different extents when implementing different optimal control approaches in IoT-enabled BASs. The specific impacts on the optimal control performance of DOASs when implementing these approaches are investigated in this study.

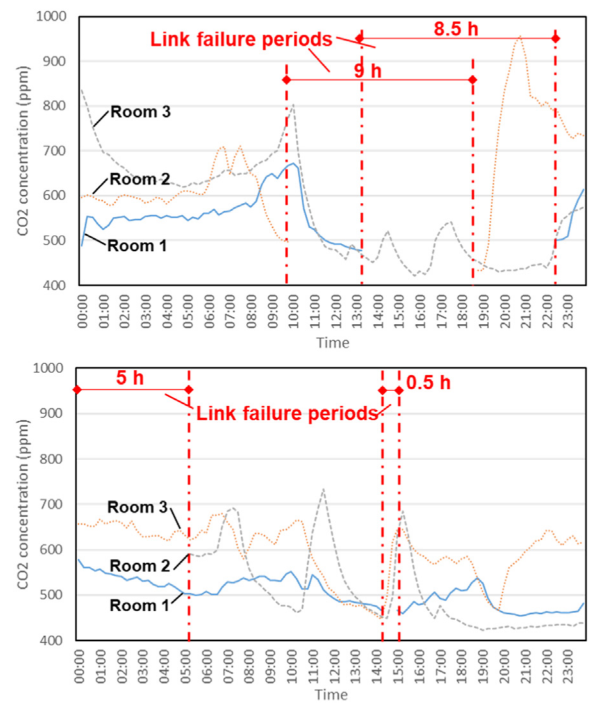

Fig. 2. On-site data measurement of indoor CO_2 concentration.

3. The proposed fully distributed robust optimal control approach

The distributed algorithm proposed in [34] is adopted in this study to develop a fully distributed robust optimal control approach for DOASs considering uncertainties of communication link in IoT-enabled BASs. The adopted algorithm can handle time-varying communication topologies which can result from the unpredictable occurrence of link failures, and the theoretical proof can be found in [34]. However, whether the proposed approach is applicable to be implemented in IoT-enabled BASs after considering the limited computing capacities of smart sensors still deserves investigating.

In the proposed approach, local agents directly communicate with the connected neighbors rather than through a central coordinating agent. An agent only needs to know those agents receiving its transmitted information. No prior knowledge of the communication topology is needed, including the number of agents in the system and the communication link between agents. There are $n + 1$ agents in this study, including n room agents and one PAU agent that are responsible for limiting indoor pollutant levels and reducing energy use respectively.

The incremental cost of the Room-i agent (λ_i) and the PAU agent (λ_{n+1}), defined as (3a) and (3b), are used as the consensus variables [27]. The optimized outdoor air volume of individual rooms and the PAU will be found when λ_i and λ_{n+1} converge to the same value.

$$\lambda_i = \frac{\partial IAQ(Q_i)}{\partial Q_i} \tag{3a}$$

$$\lambda_{n+1} = \frac{\partial E(Q_{Tot})}{\partial Q_{Tot}} \tag{3b}$$

At the start of each optimal control interval, the agent k (k = 1 to 7) initializes its variables $y_k(0)$ and $\upsilon_k(0)$. At each time step t (t>0), i.e., iteration, variables $\omega_k(t)$, $y_k(t)$, $\lambda_k(t)$, $\upsilon_k(t)$ and $\gamma(t)$ are updated locally as (4a)-(4f). Where, d_k is the out-degree of the agent k, which is the number of out-neighbors of the agent k [35]. The out-neighbors of the agent k are those agents receiving the transmitted information from the agent k. N_k^{in} is the in-neighbors of the agent k [35], from which the agent k receive information. D_k is a virtual outdoor air volume mismatch of agent k, such that $\sum_{i=1}^{n+1} D_i = 0$. a and b are constants. Then $y_k(t)$ and $\upsilon_k(t)$ are exchanged between the connected agents for another round of calculation in the next time step $t + 1$. When implementing distributed optimal control approaches in IoT-enabled BASs, the updating calculation and the information exchange at each time step are conducted at each sampling interval of individual IoT-based smart sensors [25]. The time step needed to achieve convergence should be smaller than the sampling times of individual IoT-based smart sensors in one optimal control interval.

$$\omega_k(t+1) = \frac{\vartheta_k(t)}{d_k(t)} + \sum_{j\epsilon N_k^{in}} \frac{\vartheta_j(t)}{d_j(t)+1} \tag{4a}$$

$$y_k(t+1) = \frac{y_k(t)}{d_k(t)} + \sum_{j\epsilon N_k^{in}} \frac{y_j(t)}{d_j(t)+1} \tag{4b}$$

$$\lambda_k(t+1) = \frac{\omega_k(t+1)}{y_k(t+1)} \tag{4c}$$

$$Q_k(t+1) = \min\left\{\max\left\{\lambda_k^{-1}(t+1), Q_k^{min}\right\}, Q_k^{max}\right\} \tag{4d}$$

$$\vartheta_k(t+1) = \omega_k(t+1) - \gamma(t+1)\left(Q_k(t+1) - D_k\right) \tag{4e}$$

$$\gamma(t) = \frac{a}{t+b} \tag{4f}$$

4. Arrangement of validation tests and implementation of control strategies

4.1. Test condition

A TRNSYS-MATLAB co-simulation testbed is established to conduct the test case. TRNSYS is responsible for characterizing the real-time CO_2 variation in six office rooms with different outdoor air volume which are the optimal solutions passed from MATLAB. The updating rules ((4a)-(4f)) for seven agents, i.e. six room agents (k = 1 to 6) and one PAU agent (k = 7), are programmed in MATLAB to solve the optimal outdoor air volume of individual rooms and the PAU in a fully distributed manner. The adjustable range of outdoor air volume of six rooms are the same, i.e., Q_i^{min}=11 L/s and Q_i^{max}=56 L/s (i = 1 to 6). The adjustable range of outdoor air volume of the PAU is between Q_{Tot}^{min}=0 and Q_{Tot}^{max}=336 L/s. The design fan power and the design outdoor air volume of the PAU are given as E_d=2.20 kW and Q_d=36 L/s. The weighting factor is α=1/30,000. The CO_2 concentration of ambient air is $CO2_{amb}$=400 ppm. The CO_2 generation rate by one occupant is G_{CO2}=0.25 l/min [36]. The number of occupants in individual rooms, N_i, are time-varying, which are shown as occupancy profiles in Fig. 3. The outdoor specific enthalpy, h_{out}, are time-varying, which are influenced by outdoor temperature and relative humidity in Fig. 3. The indoor specific enthalpy is h_{in}=57.07 kJ/kg. The overall coefficient of performance is COP=2.5. The initialized variables are $y_k(0)$=1 and $\upsilon_k(0)$=−10 (k = 1 to 7). Virtual outdoor air volume mismatch of individual rooms and the PAU are D_1=14 L/s, D_2=28 L/s, D_3=42 L/s, D_4=14 L/s, D_5=28 L/s, D_6=42 L/s and D_7=−168 L/s respectively. Parameters for updating $\gamma(t)$ are a = 10 and b = 1. Both the simulation time step and optimal control interval are one minute. The sampling interval of IoT-based smart sensors is one second.

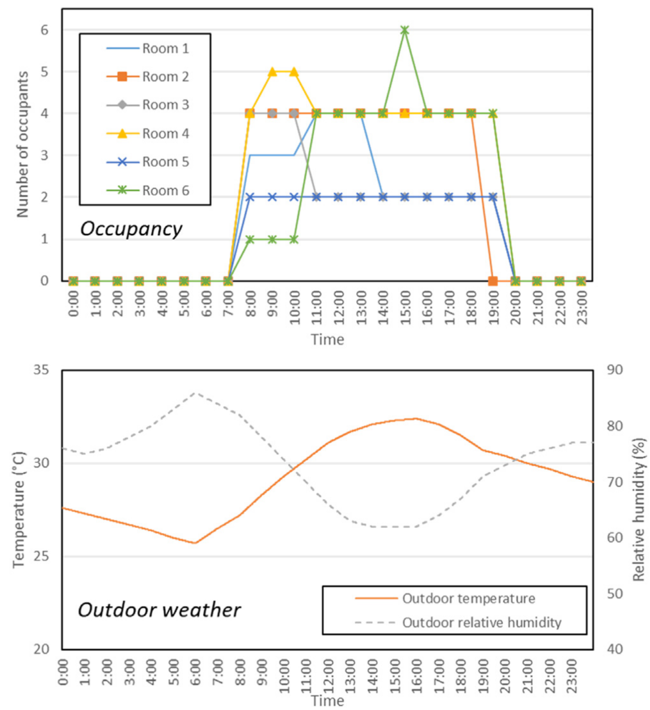

Fig. 3. Occupancy profiles and outdoor weather in the test case.

4.2. Implementation of the proposed and the existing optimal control approaches

The proposed and the existing optimal control approaches are implemented for multi-zone DOASs to test and compare the performance. The considered approaches are listed as follows.

- ***The proposed fully distributed robust optimal control approach.*** Fig. 4 shows the communication topology considering uncertainties of communication link in IoT-enabled BASs, i.e., the normal condition and the condition with link failures, when implementing the proposed fully distributed robust optimal control approach. As shown in Fig. 4(a), individual room agents and the PAU agent, connected into the fully connected topology and coordinate with each other directly. The conditions with link failures are assumed to occur, as shown in Fig. 4(b). Based on the observed link failure in the real case as shown in Fig.2, the link failure time lengths are assumed to be one hour (i.e., from 11:00 to 12:00) and eight hours (i.e., from 9:00 to 17:00) respectively to investigate the impacts of link failure time length on the optimal control performance of DOASs.
- ***The existing fully distributed optimal control approach.*** Similar to the proposed fully distributed robust optimal control approach, the existing fully distributed optimal control approach [31] has the same communication topology as shown in Fig. 4, and the same assumptions on the occurrence and the time length of link failures. However, by adopting a different algorithm, the existing approach requires a

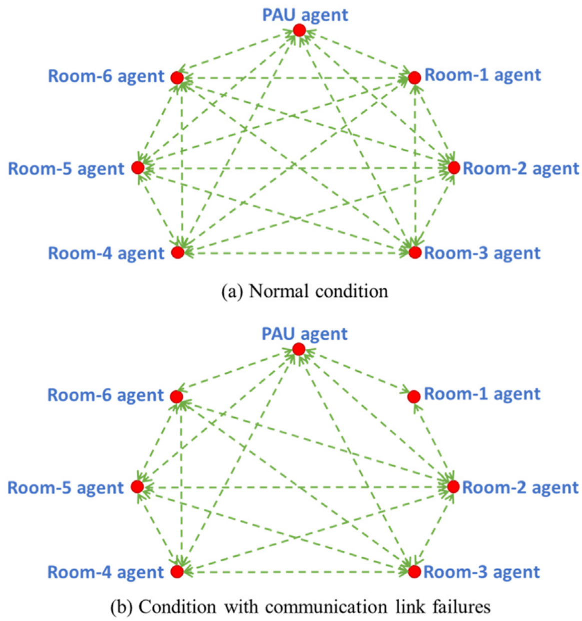

Fig. 4. Communication topology when implementing the existing and the proposed fully distributed optimal control approaches.

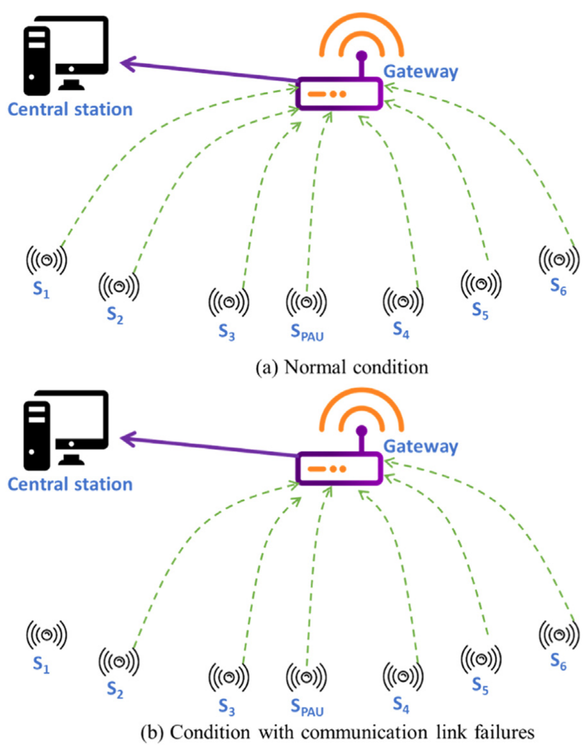

Fig. 5. Communication topology when implementing the existing centralized optimal control approach.

prior knowledge of the communication topology. This distinguishes it from the proposed one.

- ***The existing centralized optimal control approach.*** Fig. 5 shows the communication topology considering uncertainties of communication link in IoT-enabled BASs when implementing the existing centralized optimal control approach. Sensors 1 to 6 (S_1 to S_6) are installed in the room 1 to the room 6, and a sensor (S_{PAU}) is installed on the PAU. The measured information is transmitted to the central station via a gateway for global optimization [37]. The conditions with link failures are assumed to occur between S_1 and the gateway. There is the same assumption on the time length of link failures.

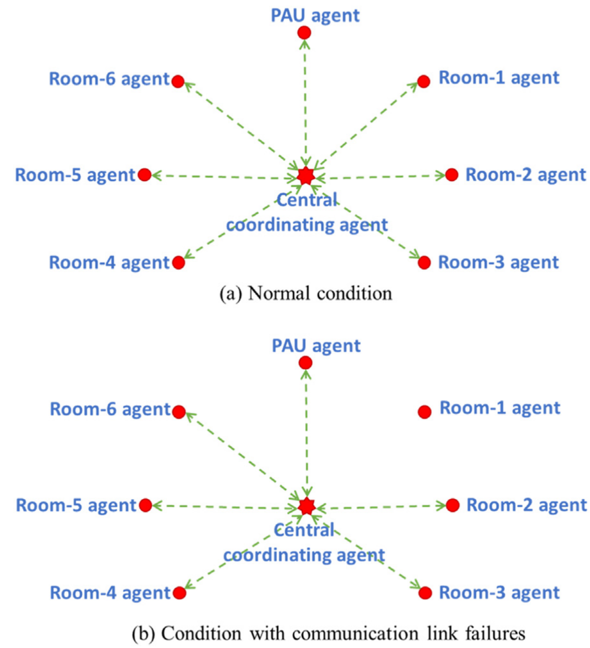

Fig. 6. Communication topology when implementing the existing hierarchical distributed optimal control approach.

- ***The existing hierarchical distributed optimal control approach.*** Fig. 6 shows the communication topology considering uncertainties of communication link in IoT-enabled BASs when implementing the existing hierarchical distributed optimal control approach. As proposed in previous work by this paper's authors [24], room agents and the PAU agent coordinate with each other via the central coordinating agent. The conditions with link failures are assumed to occur between the Room-1 agent and the central coordinating agent. There is the same assumption on the time length of link failures.

5. Test results and performance evaluation of the proposed approach

This section presents the performance of the proposed fully distributed robust optimal control approach when implemented in IoT-enabled BASs considering uncertainties of communication link for optimally controlling multi-zone DOASs. The performance of the proposed approach is evaluated both under normal conditions and conditions with link failures, by comparing it to three existing optimal control approaches.

5.1. Performance under normal conditions

Under normal conditions, the performance of the proposed fully distributed robust optimal control approach is evaluated in terms of the computation complexity, the optimization efficiency and the control performance. The computation complexity is assessed by a typical indicator of computation load, i.e. floating-point operations (FLOPs) for each optimization decision [25]. The optimization efficiency is assessed by the time steps needed to achieve convergence for each optimization decision. The control performance is assessed by comparing with a widely accepted benchmark, which is the "best" control performance given by the existing centralized optimal control approach.

For one optimization decision, the computation load of an agent using the proposed approach was 1040 FLOPs, which was smaller than 1960 FLOPs using the existing fully distributed optimal control approach

Table 1
Control performance comparison among different approaches.

Optimal control approach		Condition	$CO2_{Ave}$ (ppm)	$CO2_{Max}$ (ppm)	E_{DOAS} (kWh)
Existing	Centralized	Normal	795	903	36.96
		Link Failure (1 h)	796	906	36.91
		Link Failure (8 h)	794	918	37.03
	Hierarchical distributed	Normal	795	903	36.99
		Link Failure (1 h)	791	900	37.44
		Link Failure (8 h)	769	874	41.34
	Fully distributed	Normal	793	903	37.14
		Link Failure (1 h)	793	903	37.15
		Link Failure (8 h)	795	906	36.94
Proposed	Fully distributed robust	Normal	795	903	36.99
		Link Failure (1 h)	795	903	36.99
		Link Failure (8 h)	795	903	36.98

[31]. The computing capacity of IoT-based smart sensors widely used in buildings is about 160,000 FLOPs per second. Therefore, IoT-based smart sensors are more than enough for local optimization when using the proposed approach.

Under normal conditions, the proposed approach needed about 10 time steps to achieve convergence for one optimization decision, which was smaller than 20 time steps needed by the existing fully distributed optimal control approach. Since the sampling interval of IoT-based smart sensors is one second and the optimal control interval is one minute, the maximum time step is set to fifty in this study after adopting a safe factor of 1.2. Therefore, using the proposed approach, convergence can always be achieved before reaching the maximum time step to find the actual optimal values in each optimal control interval. The proposed approach is applicable and efficient to be implemented in IoT-enabled BASs, when communication networks are under normal conditions, for optimal control of multi-zone DOASs.

The control performance using these approaches in terms of the average CO_2 ($CO2_{Ave}$), maximum CO_2 ($CO2_{Max}$) and daily energy use of the DOAS (E_{DOAS}) are summarized in Table 1. Using the proposed approach, the average CO_2 was 795 ppm, the maximum CO_2 was 903 ppm and the daily energy use of the DOAS was 36.99 kWh. Thus the control performance was close to the benchmark. As validated in previous works by this paper's authors [24,31], the control performance given by the existing approaches were also close to the benchmark. The difference of control performance given by existing and proposed approaches was negligibly small.

5.2. Performance under conditions with link failures

Under conditions with link failures, the performance of the proposed fully distributed robust optimal control approach is evaluated in terms of the optimization efficiency and the control performance. The control performance of the existing centralized optimal control approach under normal conditions is used as the benchmark.

Under conditions with communication link failures, the proposed approach needed about 18 time steps to achieve convergence for one optimization decision, which was larger than that under normal conditions (i.e. 10 time steps). The unpredictable occurrence of communication link failures reduced the convergence speed but guaranteed accurate optimal values. In contrast, for existing fully distributed optimal control approach, the unpredictable occurrence of communication link failures resulted in convergence to incorrect values. On the other hand, although the time steps needed to achieve convergence for one optimization decision was increased, it was still smaller than the maximum time step (i.e., 50 time steps). Therefore, the proposed approach is applicable and efficient to be implemented in IoT-enabled BASs considering uncertainties of communication link for optimal control of multi-zone DOASs.

Fig. 7 and Fig. 8 show the optimized outdoor air volume of individual rooms using different optimal control approaches when IoT-enabled BASs are under conditions with one-hour and eight-hour link failures respectively. The periods with link failures are shown in shaded areas. The control performance are summarized in Table 1. Under conditions with link failures, regardless of lasting for short time length (one-hour) or long time length (eight-hour), the control performance given by the proposed approach was close to the benchmark. Specifically, under conditions with one-hour and eight-hour communication link failures, the average CO_2 were all 795 ppm, the maximum CO_2 were all 903 ppm and daily energy use of the DOAS were 36.99 and 36.98 kWh respectively. Due to the convergence to incorrect values, the control performance given by the existing fully distributed optimal control approach deviated from the benchmark. And the deviation increased as link failure time length increased. Therefore, compared to the existing fully distributed optimal control approach, the proposed approach offered better control performance, proving its robustness against uncertainties of communication link.

As shown in Table 1, due to the critical roles played by the central station and the central coordinating agent, the unpredictable occurrence of communication link failure made the control performance given by the existing centralized optimal control approach and the existing hierarchical distributed optimal control approach deviate from the benchmark. And the deviation increased as link failure time length increased. For the existing centralized optimal control approach, when under conditions with one-hour and eight-hour communication link failures, the average CO_2 were 796 and 794 ppm, the maximum CO_2 were 906 and 918 ppm and daily energy use of the DOAS were 36.91 and 37.03 kWh respectively. For the existing hierarchical distributed optimal control approach, when under conditions with one-hour and eight-hour communication link failures, the average CO_2 were 791 and 769 ppm, the maximum CO_2 were 900 and 874 ppm and the daily energy use of the DOAS were 37.44 and 41.34 kWh respectively.

On the other hand, the control performance deviation given by the existing centralized optimal control approach was smaller than that given by the existing hierarchical distributed optimal control approach. This results from different optimization processes using these two approaches. For the existing centralized optimal control approach, when link failure occurred between S_1 and the gateway, the central station conducts global optimization in a one-time effort using the most updated information from S_2-S_6 as well as S_{PAU} and the last updated information (before the occurrence of link failure) from S_1. For the existing hierarchical distributed optimal control approach, room agents and the PAU agent coordinate with others via the central coordinating agent in several iterations. When link failure occurred between the Room-1 agent and the central coordinating agent, the Room-1 agent was isolated from the whole multi-agent system and conducted local optimization without coordination. The outdoor air volume of the room 1 was optimized only focusing on maintaining a satisfactory IAQ, without considering the energy use minimization of the PAU. Regarding this, the outdoor air volume of the room 1 was determined as the upper bound of adjustable range for outdoor air volume of the room 1, as shown in Fig. 7 and Fig. 8.

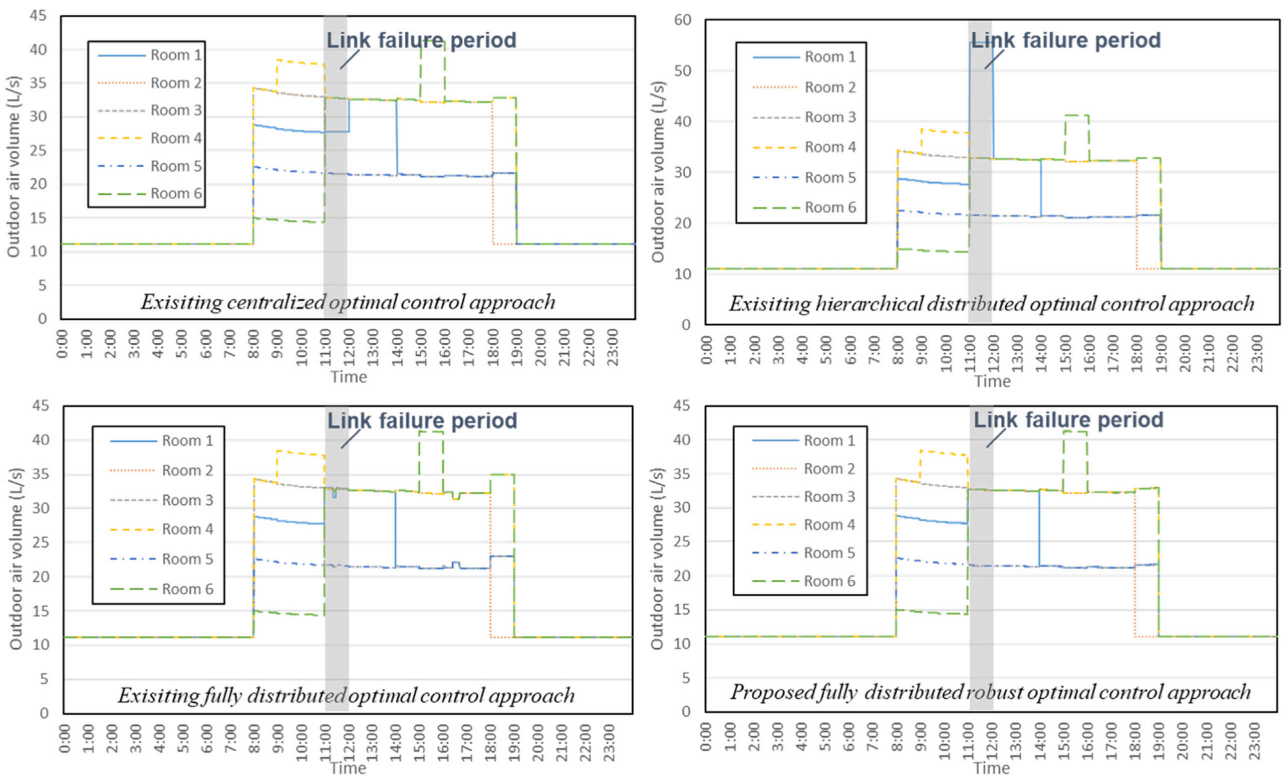

Fig. 7. Optimized outdoor air volume of individual rooms using different approaches under conditions with one-hour communication link failures.

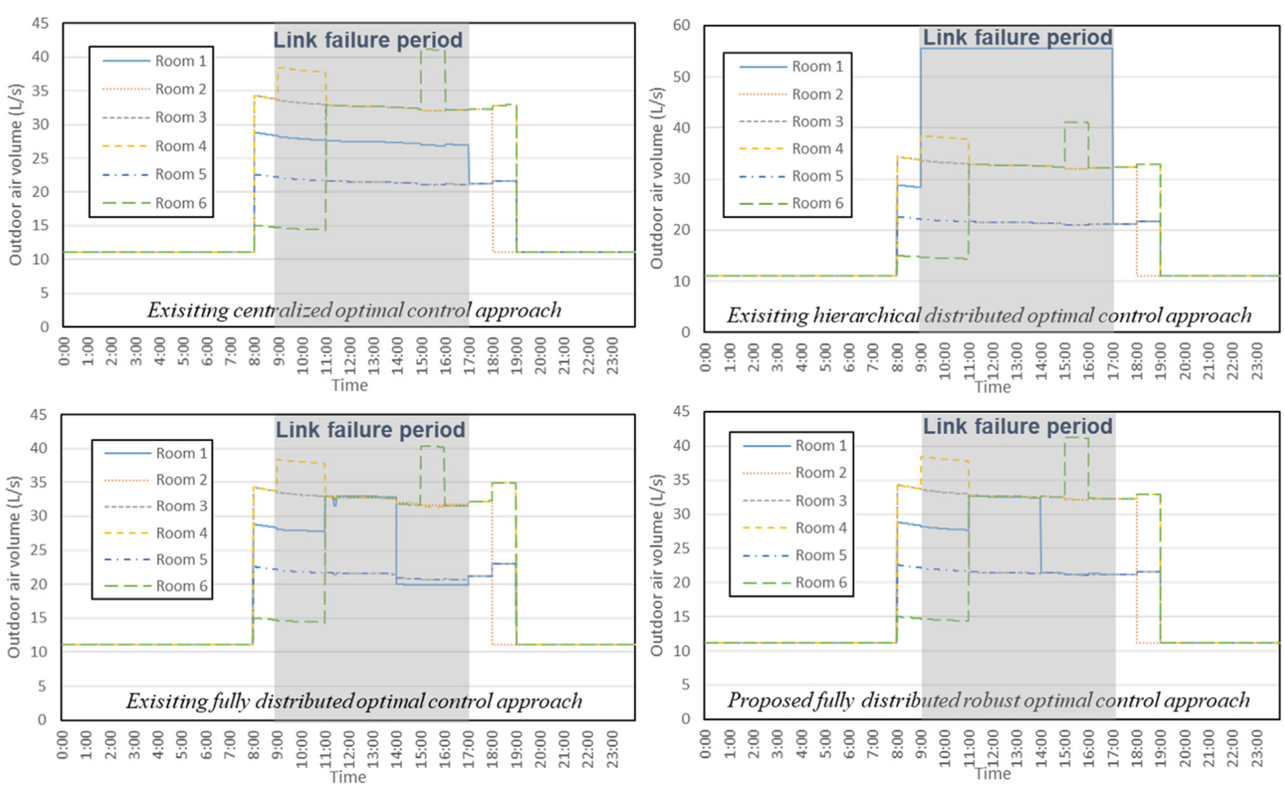

Fig. 8. Optimized outdoor air volume of individual rooms using different approaches under conditions with eight-hour communication link failures.

6. Conclusions

A fully distributed robust optimal control approach for air-conditioning systems considering uncertainties of communication link in IoT-enabled building automation systems (BASs) is proposed. A specific distributed algorithm is adopted that each agent only knows its out-neighbors, instead of a prior knowledge of the communication topology. Local agents directly coordinate with connected neighbors without needing the central station or the central coordinating agent. The TRNSYS-MATLAB co-simulation testbed is used to test the performance of the proposed approach when implemented in IoT-enabled BASs considering uncertainties of communication link, i.e., under normal conditions and under conditions with link failures. The proposed approach is validated by comparing with the existing centralized, the existing hierarchical distributed and the existing fully distributed optimal control approaches. Based on the experiences and results of the test case, conclusions can be summarized as follows:

- The proposed fully distributed robust optimal control approach has higher robustness than the existing fully distributed optimal control approach considering uncertainties of communication link in IoT-enabled BASs. The control performance given by the proposed approach was close to the benchmark both under normal conditions and conditions with link failure. However, the control performance given by the existing approach deviated from the benchmark under conditions with link failures.
- For one optimization decision, the proposed approach has lower computation complexity and higher optimization efficiency than the existing fully distributed optimal control approach. When using the proposed approach under normal conditions, the computation load of an agent was reduced from 1960 to 1040 FLOPs and the required number of time steps for convergence was reduced from about twenty to ten. Under conditions with link failures, the proposed approach guaranteed accurate optimal values, which was failed by using the existing approach.
- The proposed approach is applicable over the future IoT-enabled BASs, considering its low computation complexity and high optimization efficiency. The typical IoT-based smart sensors with computing capacity of 160,000 FLOPs per second and one-second sampling interval are enough to implement the proposed approach (with the computation load to be 1040 FLOPs and ten time steps for convergence).
- The robustness of the existing centralized and the existing hierarchical distributed optimal control approaches are both low, and the latter approach has even lower robustness. The control performance given by these approaches deviated from the benchmark under conditions with link failures. And the deviation increased as the link failure time length increased. The control performance deviation given by the centralized optimal control approach was smaller than that given by the hierarchical distributed optimal control approach.
- Considering its robustness against uncertainties of communication link, better scalability and reconfigurability, there is a promising application prospect of the proposed approach over current LAN-based field control networks or future IoT-enabled BASs as a distributed control architecture in building service systems. This is especially attractive for air-conditioning system control problems which are featured with huge amounts of inputs from large-scale sensor networks and flexible control objectives as well as system dynamics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Wenzhuo Li: Investigation, Methodology, Data curation, Validation, Software, Writing – original draft. **Rui Tang:** Conceptualization, Writing – review & editing. **Shengwei Wang:** Funding acquisition, Conceptualization, Writing – review & editing, Supervision.

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References

[1] K. Lawal, H.N. Rafsanjani, Trends, benefits, risks, and challenges of IoT implementation in residential and commercial buildings, Energy Built Environ. (2021).
[2] M. Jia, A. Komeily, Y. Wang, R.S. Srinivasan, Adopting Internet of Things for the development of smart buildings: a review of enabling technologies and applications, Autom. Constr. 101 (2019) 111–126.
[3] W. Li, C. Koo, S.H. Cha, T. Hong, J Oh, A novel real-time method for HVAC system operation to improve indoor environmental quality in meeting rooms, Build. Environ. 144 (2018) 365–385.
[4] R. Ford, M. Pritoni, A. Sanguinetti, B. Karlin, Categories and functionality of smart home technology for energy management, Build. Environ. 123 (2017) 543–554.
[5] K. Liu, J. Duangsuwan, Z. Huang, Intelligent agents enabling negotiated control of pervasive environments, Chiang Mai J. Sci. 38 (2011) 99–122.
[6] K. Nair, J. Kulkarni, M. Warde, Z. Dave, V. Rawalgaonkar, G. Gore, et al., Optimizing power consumption in iot based wireless sensor networks using Bluetooth Low Energy, in: 2015 International Conference on Green Computing and Internet of Things (ICGCIoT), IEEE, 2015, pp. 589–593.
[7] W. Li, C. Koo, T. Hong, J. Oh, S.H. Cha, S. Wang, A novel operation approach for the energy efficiency improvement of the HVAC system in office spaces through real–time big data analytics, Renew. Sustain. Energy Rev. 127 (2020) 109885–109900.
[8] F.-.J. Ferrández-Pastor, H. Mora, A. Jimeno-Morenilla, B. Volckaert, Deployment of IoT edge and fog computing technologies to develop smart building services, Sustainability 10 (2018) 3832.
[9] T. Ben-David, M.S. Waring, Impact of natural versus mechanical ventilation on simulated indoor air quality and energy consumption in offices in fourteen U.S. cities, Build. Environ. 104 (2016) 320–336.
[10] T. Ben-David, A. Rackes, M.S. Waring, Alternative ventilation strategies in U.S. offices: saving energy while enhancing work performance, reducing absenteeism, and considering outdoor pollutant exposure tradeoffs, Build. Environ. 116 (2017) 140–157.
[11] A. Ghahramani, K. Zhang, K. Dutta, Z. Yang, B. Becerik-Gerber, Energy savings from temperature setpoints and deadband: quantifying the influence of building and system properties on savings, Appl. Energy 165 (2016) 930–942.
[12] X. Wei, A. Kusiak, M. Li, F. Tang, Y. Zeng, Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance, Energy 83 (2015) 294–306.
[13] R. Tang, S. Wang, Model predictive control for thermal energy storage and thermal comfort optimization of building demand response in smart grids, Appl. Energy 242 (2019) 873–882.
[14] H.S. Ganesh, H.E. Fritz, T.F. Edgar, A. Novoselac, M. Baldea, A model-based dynamic optimization strategy for control of indoor air pollutants, Energy Build. 195 (2019) 168–179.
[15] D. Zhai, Y.C. Soh, Balancing indoor thermal comfort and energy consumption of ACMV systems via sparse swarm algorithms in optimizations, Energy Build. 149 (2017) 1–15.
[16] T. Yang, X. Yi, J. Wu, Y. Yuan, D. Wu, Z. Meng, et al., A survey of distributed optimization, Annu. Rev. Control 47 (2019) 278–305.
[17] D. Yu, Y. Xia, L. Li, D.-H. Zhai, Event-triggered distributed state estimation over wireless sensor networks, Automatica 118 (2020) 109039.
[18] X. Cao, J. Chen, Y. Xiao, Y. Sun, Building-environment control with wireless sensor and actuator networks: centralized versus distributed, IEEE Trans. Ind. Electron. 57 (2009) 3596–3605.
[19] R. Tang, H. Li, S. Wang, A game theory-based decentralized control strategy for power demand management of building cluster using thermal mass and energy storage, Appl. Energy 242 (2019) 809–820.
[20] R.R. Negenborn, J.M. Maestre, Distributed model predictive control: an overview and roadmap of future research opportunities, IEEE Control Syst. Mag. 34 (2014) 87–97.
[21] F. Lin, V. Adetola, Flexibility characterization of multi-zone buildings via distributed optimization, in: 2018 Annual American Control Conference (ACC), IEEE, 2018, pp. 5412–5417.
[22] F.E. Aliabadi, K. Agbossou, S. Kelouwani, N. Henao, S.S. Hosseini, Coordination of smart home energy management systems in neighborhood areas: a systematic review, IEEE Access (2021).
[23] A. Yousefpour, C. Fung, T. Nguyen, K. Kadiyala, F. Jalali, A. Niakanlahiji, et al., All one needs to know about fog computing and related edge computing paradigms: a complete survey, J. Syst. Archit. 98 (2019) 289–330.

[24] W. Li, S Wang, A multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering indoor air quality and energy use, Appl. Energy 275 (2020) 115371–115384.
[25] B. Su, S. Wang, An agent-based distributed real-time optimal control strategy for building HVAC systems for applications in the context of future IoT-based smart sensor networks, Appl. Energy 274 (2020) 115322–115335.
[26] W. Li, S. Wang, C Koo, A real-time optimal control strategy for multi-zone VAV air–conditioning systems adopting a multi-agent based distributed optimization method, Appl. Energy 287 (2021) 116605–116619.
[27] Z. Zhang, M.-.Y. Chow, Incremental cost consensus algorithm in a smart grid environment, in: 2011 IEEE Power and Energy Society General Meeting, IEEE, 2011, pp. 1–6.
[28] Z. Zhang, M.-.Y Chow, Convergence analysis of the incremental cost consensus algorithm under different communication network topologies in a smart grid, IEEE Trans. Power Syst. 27 (2012) 1761–1768.
[29] Z. Zhang, X. Ying, M.-.Y. Chow, Decentralizing the economic dispatch problem using a two-level incremental cost consensus algorithm in a smart grid environment, in: 2011 North American Power Symposium, IEEE, 2011, pp. 1–7.
[30] Z. Zhang, Y. Zhang, M.-.Y. Chow, Distributed energy management under smart grid plug-and-play operations, in: 2013 IEEE Power & Energy Society General Meeting, IEEE, 2013, pp. 1–5.
[31] W. Li, S Wang, A fully distributed optimal control approach for multi-zone dedicated outdoor air systems to be implemented in IoT-enabled building automation networks, Appl. Energy (2022) 308.
[32] D.B. Kingston, R.W. Beard, Discrete-time average-consensus under switching network topologies, in: 2006 American Control Conference, IEEE, 2006, p. 6.
[33] Y. Xu, K. Cai, T. Han, Z. Lin, A fully distributed approach to resource allocation problem under directed and switching topologies, in: 2015 10th Asian Control Conference (ASCC), IEEE, 2015, pp. 1–6.
[34] T. Yang, J. Lu, D. Wu, J. Wu, G. Shi, Z. Meng, et al., A distributed algorithm for economic dispatch over time-varying directed networks with delays, IEEE Trans. Ind. Electron. 64 (2016) 5095–5106.
[35] A. Nedić, A. Olshevsky, Distributed optimization over time-varying directed graphs, IEEE Trans. Automat. Contr. 60 (2014) 601–615.
[36] M.-.S. Shin, K.-.N. Rhee, E.-.T. Lee, G.-.J. Jung, Performance evaluation of CO 2 -based ventilation control to reduce CO 2 concentration and condensation risk in residential buildings, Build. Environ. 142 (2018) 451–463.
[37] M. Frei, C. Deb, R. Stadler, Z. Nagy, A. Schlueter, Wireless sensor network for estimating building performance, Autom. Constr. 111 (2020) 103043–103060.