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A multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering indoor air quality and energy use

Wenzhuo Li[1] *and Shengwei Wang* [1,*]

[1] Department of Building Services Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong.

Abstract:

A trade-off problem exists in ventilation systems to ensure acceptable indoor air quality (IAQ) with minimized energy use. It is often solved by the centralized optimization approach today. However, the dynamic operation conditions of ventilation systems and the changing expectations of users make the centralized optimal control not flexible and effective in responding to those dynamics and changes. Meanwhile, the distributed installation layouts of sensing and control networks provide appropriate application platforms for distributed optimal control. This paper therefore proposes a multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering IAQ and energy use by optimizing ventilation air volumes of individual rooms and primary air-handling unit (PAU). This distributed approach decomposes the complex optimization problem into a number of simple optimization problems. Distributed agents, corresponding to individual rooms and the PAU, are assigned to handle these decomposed problems. A central coordinating agent coordinates these agents to find the optimal solutions. Two control test cases under different outdoor weather conditions are conducted on a TRNSYS-MATLAB co-simulation testbed to validate the proposed multi-agent based distributed approach for optimal control by comparing with a baseline control approach and a centralized optimal control approach. Results of the distributed approach can provide almost the same outputs as the expected optimum given by the centralized optimal control approach. The experiences of implementing the proposed distributed approach show its effectiveness in solving complex optimization problems and optimizing multi-zone ventilation systems as well as good scalability and reconfigurability.

Keywords: Distributed optimal control, multi-agent system, distributed sensing and control network, indoor air quality, energy efficiency, multi-zone ventilation system.

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** Corresponding author: Shengwei Wang, email: beswwang@polyu.edu.hk*

1. Introduction

Indoor environment, in which occupants spend 80–90% of their lifetime [1], is one of the dominant routes affecting human's mental and physical health [2]. Indoor air quality (IAQ), one important aspect of indoor environmental quality (IEQ), is evaluated by indoor pollutant level, such as CO_2 [3], particulate matters (e.g. PM2.5) and VOCs (e.g. HCHO) [4]. Ventilation systems, as an important subsystem of heating, ventilation and air-conditioning (HVAC) system, are operated to maintain IAQ. However, ventilation systems contribute about 25% of HVAC energy use [5], which accounts for about 50% of building energy use [6]. Therefore, the goal of managing IAQ should be coupled with energy saving of ventilation systems.

Ventilation air volume, one of the major control parameters of ventilation systems, affects the pollutant dilution performance and energy use. Many previous studies therefore adopted multi-objective optimization approaches to determine the optimal ventilation air volume. Ganesh et al. [7] applied sequential methods, of which the objective function included energy use and indoor levels of pollutants (i.e., ozone, PM2.5 and HCHO) to determine the optimal air exchange rate. Kim et al. [8] used genetic algorithm (GA) and response surface methodology (RSM) to solve a multi-objective function, including CO_2, predicted mean vote (PMV) and total energy use, for optimizing the set-points of ventilation air volume, temperature and relative humidity. Das et al. [9] applied a multi-objective optimization approach to explore optimal ventilation rates by taking IEQ (i.e. PM2.5, ETS, radon, indoor temperature and mold growth) and energy savings into consideration. These studies applied centralized approaches for optimization, and approaches are possible in principle but are not convenient and effective to be implemented practically in real buildings. There are two major problems. First, it is difficult or inconvenient to collect and integrate the information of all systems and equipment in one device (i.e. central computer) [11]. Second, models of systems or equipment change with the indoor and outdoor conditions, and it is not convenient to update the models and the corresponding the overall performance estimate using objective functions [10].

On the other hand, the recent rapid development of Internet of Things (IoT) provides convenient and low cost interconnected smart sensing networks for building automation [14]. Since occupants are increasingly concerned about IEQ of spaces where they live in or work at, smart sensors act as information provisioning devices to collect IEQ data and inform occupants about the current IEQ [36]. If a deteriorated IEQ is detected, occupants would take relevant measures, such as opening windows. Alternatively, the building automation systems (BAS), such as ventilation systems, will take relevant control actions according to the preset control logics. Chen et al. [63] assessed different control schemes for the coordinated control of windows and the HVAC system. The advantages of the model predictive control (MPC) scheme were highlighted. Kim et al. [65] investigated the relationships between IEQ factors and occupants' behaviors as well as ventilation modes by analyzing the real datasets measured in experiments. Kim et al. [66] developed an automatic ventilation control algorithm based on indoor temperature, relative humidity, CO_2, TVOC, PM10, PM2.5, and occupants' ventilation behaviors. Li et al. [20] developed two event-driven control logics for removing excessive pollutants and preventing dew condensation. Certain events are predefined by setting thresholds for indoor temperature and CO_2. If such events are identified, certain actions would be conducted automatically, such as increasing ventilation air volume and dehumidification. This study only focused on local control in one room without stepping further into coordinated control among multiple rooms. In summary, given the distributed installation layout of future smart sensing networks or traditional BAS, a distributed control approach, which fully considers autonomy of individual single control loops and collaboration among multiple control loops, is needed.

The multi-agent system (MAS) paradigm [12], a relatively new approach, is a promising candidate for establishing distributed optimal control. Here, each agent is an autonomous entity [15] that can continually observe the environment, communicate with neighbors and make decisions towards its goals accordingly [16]. It is usually equipped with sensing modules (for gathering information), communication modules (for communication), and microprocessors (for making decisions) [17]. In an IoT-based system, heterogeneous IoT-based objects [18], such as smart sensors, embedded computers, smart actuators, and smart devices, build the foundation for the application of agent [19]. This is because agents can be easily defined by individual IoT-based object or a combination of IoT-based objects. When agents interact with each other for achieving their own goals rather than a common goal, a multi-agent system is formed [14]. Given the autonomy of single agent and collaboration among multiple agents, compared with centralized approaches, the multi-agent based distributed optimal control approach has the following benefits: (1) Good scalability: one central computer is substituted by a number of microprocessors embedded in different agents. Information of all associated systems and equipment collected in one control device is decomposed into a number of control devices (i.e. agents) [13]. Moreover, due to the plug-and-play manner of agents, it is easy to scale up/down the control problems and add/remove control objectives [24]. (2) Good reconfigurability: changing a component model requires local control reconfiguration only without the need of modifying the rest of the control system [22].

The multi-agent system paradigm has been applied in many domains, such as computer science and robotics, as an advanced technology [25]. Particularly, applications in automatic control of building systems are increasingly popular in recent years [30]. Wang et al. [26] developed a multi-agent control system to maximize indoor comfort with minimum energy use. The optimization parameters are set-points (of indoor temperature, illumination, and CO_2) and weights of different terms in an integrated comfort index (objective function). Yang and Wang [27] developed a multi-agent based user-centered control system to optimize the energy efficiency and indoor comfort. Personal agents were designed to identify users, learn occupants' preferences and present feedbacks, thus facilitating the interactions between occupants and environment. Cai et al. [28] established a general multi-agent control approach in the field of building energy system optimization. Such an approach was implemented in a cooling plant optimal control [31], thermal comfort maintaining [29], and demand response strategy [23]. Tang et al. [56] proposed the interactive demand side management strategies using game theory, which was one of the negotiation techniques for multi-agent systems. In the Stackelberg game, grid and buildings are players. Tang et al. [57] also proposed a game theory-based decentralized control strategy for power demand management of cluster-level buildings. Yu et al. [58] proposed an economic power dispatch strategy in smart grids by using a multi-agent based distributed consensus protocol. Wen et al. [59] proposed a two-stage economic power dispatch algorithm. At the first stage, the leader-following consensus-based initial power output allocation algorithm is executed to balance the power supply and demand. At the second stage, the distributed optimal dispatch problem is solved by the optimal power dispatch algorithm with adaptive parameters. Bünning et al. [60] introduced the framework of the agent-based control of building energy systems for the modelling language Modelica. Michailidis et al. [64] applied a novel, decentralized, agent-based, model-free Building Optimization and Control (BOC) methodology to a real building. Ventilation systems serving multiple rooms are complex systems, and their operation conditions are dynamic when considering variable indoor as well as outdoor conditions, and personalized occupants' preferences towards certain IAQ indicators. Although having appropriate features by applying multi-agent system paradigm (i.e. complexity and changeability) [21], there is a lack of an applicable multi-agent based distributed approach for optimal control of multi-zone ventilation systems.

This study therefore proposes a multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering both IAQ and energy saving by optimizing ventilation air volume for individual zones. This study has two major original contributions or innovations including: (1) A new multi-agent based approach is developed to solve the optimization problem of multi-zone ventilation systems by a distributed manner; (2) IAQ of individual rooms and energy use of primary air-handling unit (PAU) are integrated into the objective function to optimize the ventilation air volumes of individual rooms and PAU. The TRNSYS-MATLAB co-simulation testbed is used to simulate six rooms served by one PAU. To assess the scalability and reconfigurability of multi-agent based approach, typical test cases with different outdoor weathers are selected. The target indoor pollutant level and PAU energy use are considered to compare the control performance using different control approaches (i.e., baseline control approach, centralized optimal control approach, and multi-agent based distributed approach).

2. Proposed multi-agent based distributed approach for optimal control

This section first presents the schematic of the multi-agent based distributed approach to illustrate the coordination among distributed agents which aims at achieving the overall control objectives. Second, configuration of each type of agents is explained in section 2.2. Third, the mathematic formulation of the multi-objective optimization problem for multi-zone ventilation system is presented. At the end, a distributed optimization algorithm including its implementation is provided and elaborated.

2.1. Schematic of the multi-agent based distributed approach

The proposed multi-agent based distributed approach adopts a coordinator-user architecture [32], as shown in Figure 1. There are room agents as well as a PAU agent, associated to corresponding rooms as well as the PAU, and a central coordinating agent. Based on different functions and purposes, agents are classified into two levels. Room agents and a PAU agent are the users at the local level, and a central coordinating agent is the coordinator at the global level. The overall control objectives, including limiting indoor pollutant level and energy use minimization, are decomposed into several sub-objectives. Users are given with different sub-objectives to optimize. Specifically, the sub-objectives of limiting indoor pollutant level are assigned to room agents for solving the optimized ventilation air volume of each room agent (Q_i, i=1 to n), and the sub-objective of energy use minimization is assigned to the PAU agent for solving the optimized total ventilation air volume of the PAU agent (Q_{Tot}). The central coordinating agent at the global level facilitating the communication among other agents to achieve the overall control objectives.

In a word, the overall control goals of indoor pollutant level limiting and energy use minimization are achieved by interaction among distributed agents. Such a multi-agent based approach can be realized by several distributed optimization algorithms. In this study, alternating direction method of multipliers (ADMM) is used, and it is introduced later in section 2.4.2.

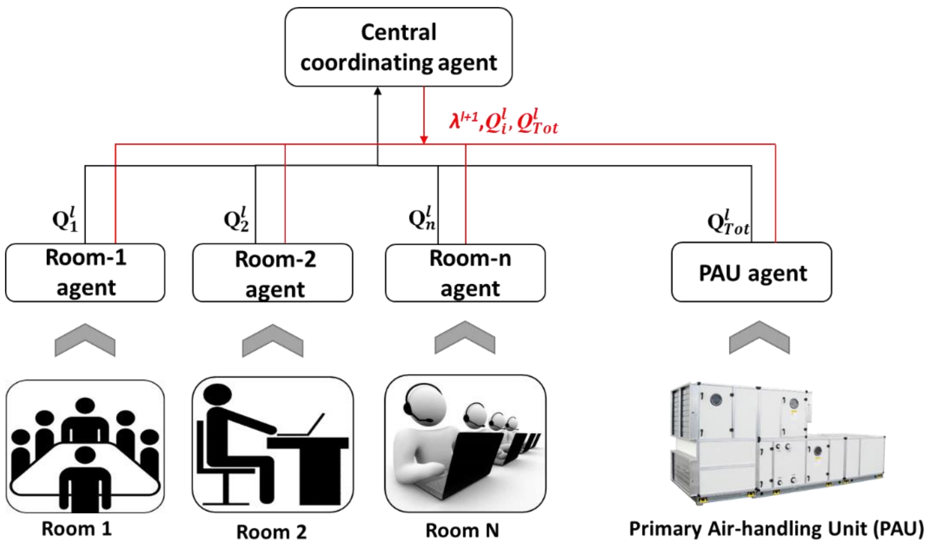

Figure 1. Schematic of proposed multi-agent based distributed approach for multi-zone ventilation systems

2.2. Agent configuration

The area framed in red in Figure 2 shows the configuration of Room-*i* agent. Each agent is implemented on a smart IAQ sensor. A smart IAQ sensor monitors the IAQ in each room (e.g. CO_2) with a constant time interval. It employs a model to predict the steady state pollutant concentration. The model is used in the objective function of individual room agents for optimizing their ventilation air volume (Q_i, i=1 to n). This model is introduced later in section 2.3.2. It exchanges information with the central coordinating agent. Specifically, it transmits its locally optimized ventilation air volume to the central coordinating agent. The received information includes two part. The first part consists of the locally optimized ventilation air volume of other agents, i.e. other room agents and the PAU agent. The second part consists of the updated parameter (i.e. λ).

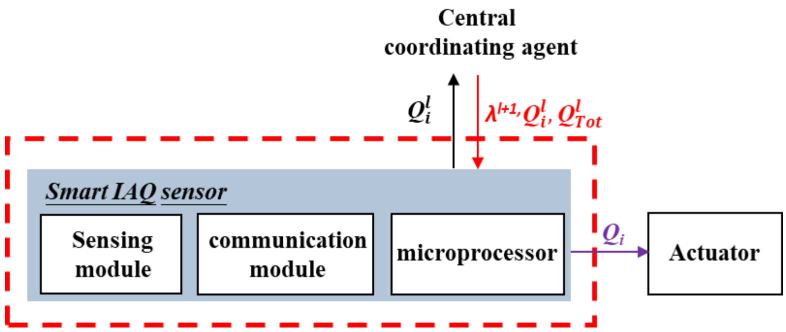

Figure 2. The configuration of Room-*i* agent

The area framed in red in Figure 3 shows the configuration of the PAU agent. The PAU agent is implemented on the smart airflow meter. The smart airflow meter monitors total ventilation air volume of PAU with a constant time interval. The energy use in PAU is mainly contributed by the chillers for providing cooling and PAU fans for delivering air flow [35]. It is worth noticing that not all the cooling of chillers is provided to the PAU. In fact, part of it is provided to other terminal equipment (e.g. fan-coil units (FCUs)). Therefore, in this study, the energy use by chillers only refers to the part to provide the cooling to the PAU. In this regard, the smart airflow meter employs models to predict the energy use of chillers ($E_{Chiller}$) and PAU fan (E_{Fan}). These models are used in the objective function of the PAU agent for optimizing its ventilation air volume (Q_{Tot}), which are introduced later in section 2.3.3. The PAU agent exchanges information with the central coordinating agent. Specifically, it transmits its locally optimized ventilation air volume to the central coordinating agent. The received information includes the locally optimized ventilation air volume of other room agents and the updated parameter (i.e. λ).

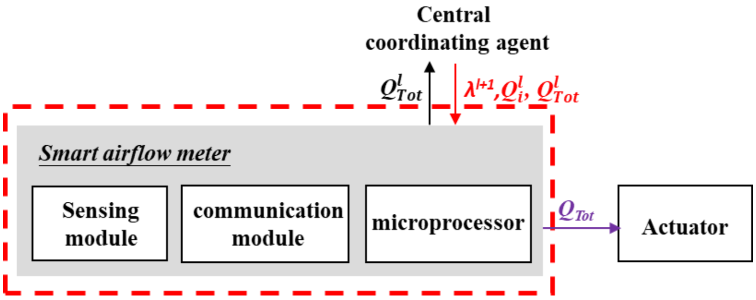

Figure 3. The configuration of the PAU agent

The central coordinating agent communicates with and coordinates other agents. As explained before, the ventilation air volumes of rooms (Q_i, i=1 to n) are optimized by corresponding room agents by limiting the pollutant level only. The total PAU ventilation air volume (Q_{Tot}) is optimized by the PAU agent to minimize its energy use. Therefore, a mass balance constraint, i.e. the sum of Q_i (i=1 to n) should equal to Q_{Tot}, may not be satisfied if room agents and the PAU agent are isolated without effective communication. The central coordinating agent receives the transmitted information from room agents and the PAU agent. With this information, it works as a data processor to ensure the satisfaction of the mass balance constraint by conducting relevant data processing (i.e. parameter updating). Meanwhile, it acts as a bridge through which one agent is able to get the needed information of other agents.

2.3. Multi-objective optimization of multi-zone ventilation system control

This section elaborates the mathematical formulation of the multi-objective optimization problem for multi-zone ventilation systems as well as mathematical models for predicting indoor pollutants and the energy use.

2.3.1. Objective function

The objective function is defined to quantify the performance of multi-zone ventilation systems considering the indoor pollutant level and energy use [61], as expressed in Equation (1). It consists of two sub-objectives, including $\sum_{i=1}^{\mathrm{N}} PL_i$, which considers the indoor pollutant level, and *E*, which considers the energy use. A weighting factor β is applied to combine the two sub-objectives into one overall objective. The task of control optimization is to minimize the overall objective to limit the indoor pollutant level and minimize the energy use [62]. The optimal ventilation air volume of individual rooms (Q_i) and the total PAU ventilation air volume (Q_{Tot}) are the control variables to be optimized. The mass balance constraint is shown as Equation (2).

$$\min_{Q_i, Q_{\mathrm{Tot}}} \mathrm{Obj} = \sum_{i=1}^{\mathrm{n}} PL_i + \beta \cdot E \tag{1}$$

subject to the constraint:

$$\sum_{i=1}^{\mathrm{n}} Q_i = Q_{\mathrm{Tot}} \tag{2}$$

2.3.2. Indoor pollutants

As CO_2 is one of the typical indoor pollutants, the excessive indoor pollutant level in a room (PL_i) is considered in terms of the steady-state CO_2 concentration ($CO2_i$) over a recommended limit, as shown in Equation (3). Where $CO2_{Limit}$ is the CO_2 limit (i.e. 800 ppm) prescribed in standard [33].

$$PL_i = \max\{0, CO2_i - CO2_{Limit}\}^2 \tag{3}$$

The steady-state CO_2 model is shown as Equation (4), which is derived from the mass balance equation of CO_2 in a space. Where, $CO2_{amb}$ (400 ppm) is the CO_2 concentration of ambient air. G_{CO2} is the CO_2 generation rate (0.25 l/min) by one occupant [3]. N_i is the number of occupants in a room.

$$CO2_i = CO2_{amb} + \frac{G_{CO2} \cdot N_i}{Q_i} \tag{4}$$

2.3.3. Energy use

As mentioned before, energy use in PAU (*E*) is calculated by summing up the equivalent chiller energy use for generating its required cooling ($E_{Chiller}$) [34] and its fan energy use (E_{Fan}), as shown in Equation (5).

$$E = E_{Chiller} + E_{Fan} \tag{5}$$

$E_{Chiller}$ is calculated according to Equation (6). Where, Q_{Tot} is the total ventilation air volume. h_{out} is the outdoor specific enthalpy. h_{in} is the indoor specific enthalpy. It is preset as a constant value, which is 57.07 kJ/kg corresponding to the indoor temperature of 25.5 °C and indoor relative humidity of 60%. *COP* is the overall coefficient of performance, and it is 2.5 in this study.

$$E_{Chiller} = Q_{Tot} \cdot (h_{out} - h_{in})/COP \tag{6}$$

E_{Fan} is calculated by Equation (7) according to the affinity laws [46]. Theoretically, the exponent in Equation (7) is 3 [46], but here it is set as 2 considering the varied fan efficiency and damper openings [46-48]. E_d is the design fan power. Q_d is the design ventilation air volume.

$$E_{Fan} = E_d \cdot \left(\frac{Q_{Tot}}{Q_d}\right)^2 \tag{7}$$

2.4. Realization of proposed multi-agent based distributed approach

This section elaborates how to realize the optimal control using the proposed multi-agent based distributed approach. The basic means is to decompose the centralized optimization problem concerned into a number of decomposed optimization problems to be processed in distributed agents. A specified algorithm is adopted to coordinate these agents to solve the global optimization problem in a distributed manner.

2.4.1. Centralized formulation of the optimization problem

As stated before, the centralized approach was widely existed in previous studies for optimal control of ventilation systems. The schematic of such an approach is illustrated in Fig. 4. The central control system collects all the required information from rooms, PAU and outdoor environment, including indoor occupancy, PAU parameters, and outdoor weather as well as outdoor CO_2 concentration. An online optimization technology or tool, such as Genetic algorithm (GA) is used to solve these optimization problems, based on the objective function presented in Section 2.3, which is deployed centrally in a control station. Using this centralized approach, the global optimum can be obtained since central control system solves optimization problem from an omniscient perspective. The outputs of this approach are considered as the “best”, which are used as the benchmark to assess the performance of other control approaches in this study.

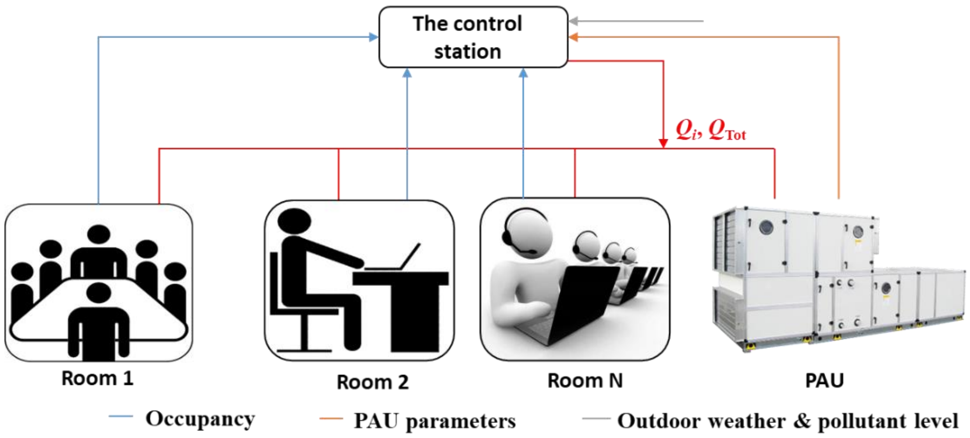

Figure 4. Schematic of typical existing centralized approach for the optimal control of multi-zone ventilation systems

2.4.2. Decomposition and distributed formulation of the optimization problem

Compared to the centralized approach, whose optimization tasks are conducted in one single location (i.e. one control station), each agent has its own objective function and optimization task when adopting the proposed multi-agent based distributed approach. The objective function of each agent can be formulated according to the original objective function in the centralized approach (i.e. Equations (1)) by using the decomposition theory. In fact, the decomposition theory provides the mathematical language to decompose the original problem into sub-problems [49]. In this study, ADMM is used, and it is widely used in areas of image restoration [50] and network resource allocation [51]. With this method, the original objective function in the centralized approach (Equation (1)) is reformulated into Equation (8) by adding terms including the constraint violation $\left(\sum_{i=1}^{\mathrm{N}} Q_i^l - Q_{Tot}^l\right)$, the Lagrangian ($\lambda$) and a penalty factor ($\rho$). Equation (8) can be assigned to different agents individually. The eventual objective function of a room agent is shown as Equation (9). The objective function of the PAU agent is shown as Equation (10). The central coordinating agent update the parameter, λ, by Equation (11) to ensure the satisfaction of the mass balance constraint. Where, l is the number of the iteration step.

$$\min_{Q_i, Q_{\mathrm{Tot}}}\left[\ \sum_{i=1}^{\mathrm{n}}(PL_i + E) + \lambda\left(\sum_{i=1}^{\mathrm{n}} Q_i - Q_{\mathrm{Tot}}\right) + \frac{\rho}{2}\left(\sum_{i=1}^{\mathrm{n}} Q_i - Q_{\mathrm{Tot}}\right)^2\right] \tag{8}$$

$$\min_{Q_i}\left[PL_i + \lambda\left(\sum_{\mathrm{m}=1,\mathrm{m}\neq i}^{\mathrm{n}} Q_m + Q_i - Q_{\mathrm{Tot}}\right) + \frac{\rho}{2}\left(\sum_{\mathrm{m}=1,\mathrm{m}\neq i}^{\mathrm{n}} Q_m + Q_i - Q_{\mathrm{Tot}}\right)^2\right] \tag{9}$$

$$\min_{Q_{\mathrm{Tot}}}\left[E + \lambda\left(\sum_{i=1}^{\mathrm{n}} Q_i - Q_{\mathrm{Tot}}\right) + \frac{\rho}{2}\left(\sum_{i=1}^{\mathrm{n}} Q_i - Q_{\mathrm{Tot}}\right)^2\right] \tag{10}$$

$$\lambda^{l+1} = \lambda^l + \rho \cdot \left(\sum_{i=1}^{\mathrm{N}} Q_i^l - Q_{Tot}^l\right) \tag{11}$$

2.4.3. Solution identification

After the decomposition and reformulation of the optimization problem, objective functions of room agents contain not only their original control objectives, i.e., indoor pollutant level limiting, but also additional terms, i.e. constraint violation. Similarly, the objective function of the PAU agent contains not only its original control objectives, i.e., energy use minimization, but also additional terms, i.e. constraint violation. ADMM conducts iterations to limit pollutant level, minimize energy use and reduce constraint violation gradually. The iteration stops until reaching convergence, which is judged by criteria of primal residual and dual residual [54]. In this study, the primary residual is calculated by Equation (12), and it reflects the abovementioned constraint violation. The dual residuals reflect the difference between the current and last values of each optimized variable, and they are shown as Equations (13) for room agents and (14) for the PAU agent. Where, ε_1 and ε_2 are the preset stopping threshold, and $\varepsilon_1=\varepsilon_2=0.001$ in this study.

$$\left(\sum_{i=1}^{\mathrm{N}} Q_i^l - Q_{Tot}^l\right)^2 \leq \varepsilon_1 \tag{12}$$

$$[\rho(Q_i^l - Q_i^{l-1})]^2 \leq \varepsilon_2 \tag{13}$$

$$[\rho(Q_{Tot}^l - Q_{Tot}^{l-1})]^2 \leq \varepsilon_2 \tag{14}$$

There are two major schemes [52], i.e, Gauss–Seidel ADMM with serial scheme and Jacobian ADMM with parallel scheme [53], to retrieve the information of other agents within one iteration. Gauss–Seidel ADMM uses Gauss–Seidel method as the iterative method. Using this method, agents conduct optimization in serial, and later agents use the updated information of former agents in the same iteration. On the other hand, Jacobian ADMM uses Jacobian method as the iterative method. Using this method, agents conduct optimization in parallel, and they perform their local optimization simultaneously. Each agent uses information of other agents updated in the last iteration rather than waiting for the updated information in the current iteration. Therefore, Jacobian ADMM with parallel scheme is more appropriate to be applied in the real application, and it is selected in this study.

Figure 5 shows the flowchart for the identification of the optimal ventilation air volumes of individual rooms (Q_i) and the total PAU ventilation air volume (Q_{Tot}) using Jacobian ADMM. At each iteration, each room agent optimizes its optimal ventilation air volume with the objective to limit its indoor CO_2 level. The PAU agent optimizes the total PAU ventilation air volume with the objective to minimize its energy use. These local optimizations are conducted in parallel. Each of these local optimizations handles a simple optimization problem involving a single variable to be optimized. Thus they are able to be performed at a local control device of limited capacity. Exhaustive method is used to solve these optimization problems. The central coordinating agent updates the parameter, λ, to reduce the constraint violation (i.e., to ensure the satisfaction of the mass balance constraint). Such iteration process will be stopped until the criteria of primal and dual residuals are met or the maximum iteration number is reached. The maximum iteration number is preset to be 100 in this study.

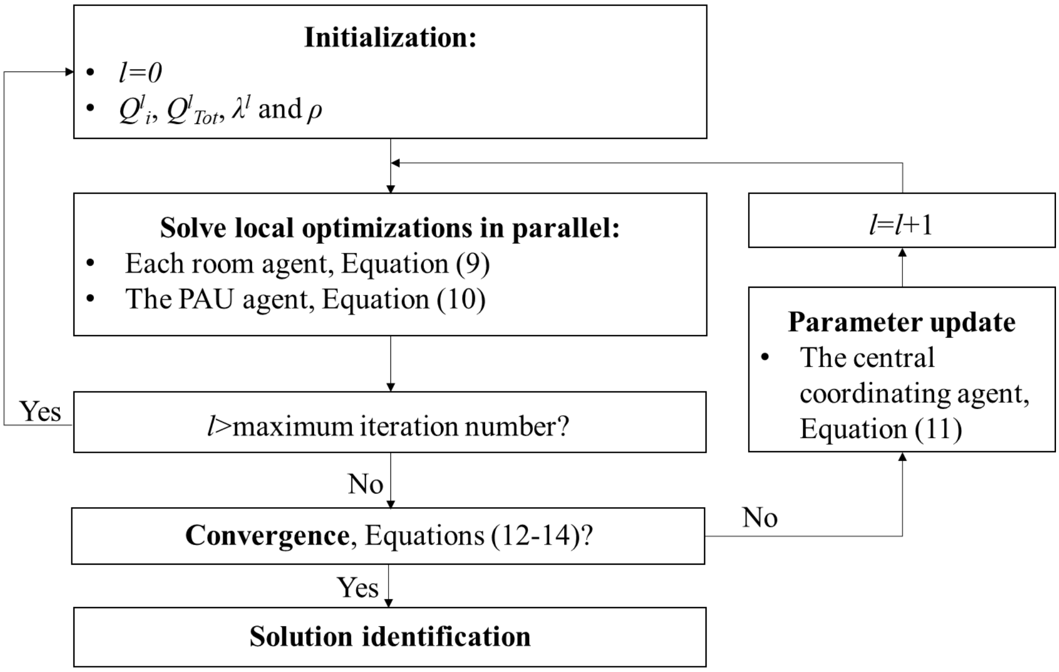

Figure 5. Flowchart for the identification of Q_i and Q_{Tot} using Jacobian ADMM

3. Validation test arrangement

To validate the proposed multi-agent based distributed approach for the optimal control of multi-zone ventilation systems, a TRNSYS-MATLAB co-simulation testbed is established as shown in Figure 6. In TRNSYS, six rooms, each with the size of 108 m^3 (9 m× 4 m× 3 m), are simulated to characterize the indoor real-time CO_2 variation under varying weather, occupancy and PAU control. These rooms are served by one PAU with the design fan power of 2.20 kW and design ventilation air volume of 336 L/s. The adjustable ranges for ventilation air volume in each room and total PAU ventilation air volume are 11-56 L/s and 0-336 L/s respectively. On the other hand, in MATLAB, a steady-state CO_2 model, an energy use model of PAU, and the real-time optimal controllers are programmed. The outputs of the controllers are ventilation air volume in each room and total PAU ventilation air volume. Both the simulation time step and optimal control interval are 1 min.

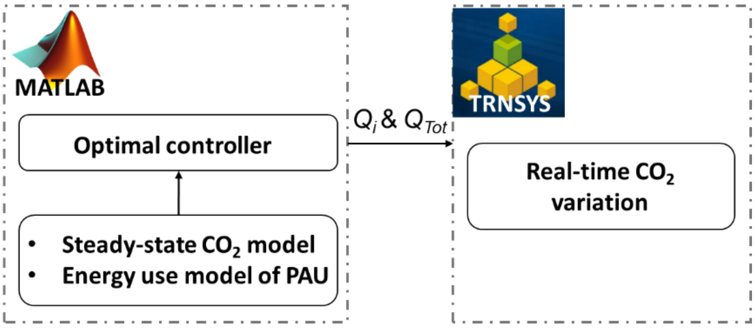

Figure 6. TRNSYS-MATLAB co-simulation testbed

Occupancy profiles and outdoor weather data from Hong Kong observatory are exogenous inputs to the controllers. Although the design number of occupants is 4, the actual occupancy changes over time [39]. Figure 7 shows the actual occupancy on a typical workday in six rooms, which are used in two cases to test the performance of different control approaches. Since the energy use of chillers varies with different outdoor weather conditions, simulation are conducted in two test cases with typical outdoor weather. Case 1 has a hot and humid day and Case 2 has a cool and dry day. Fig. 8 shows the outdoor temperature and relative humidity for these two cases.

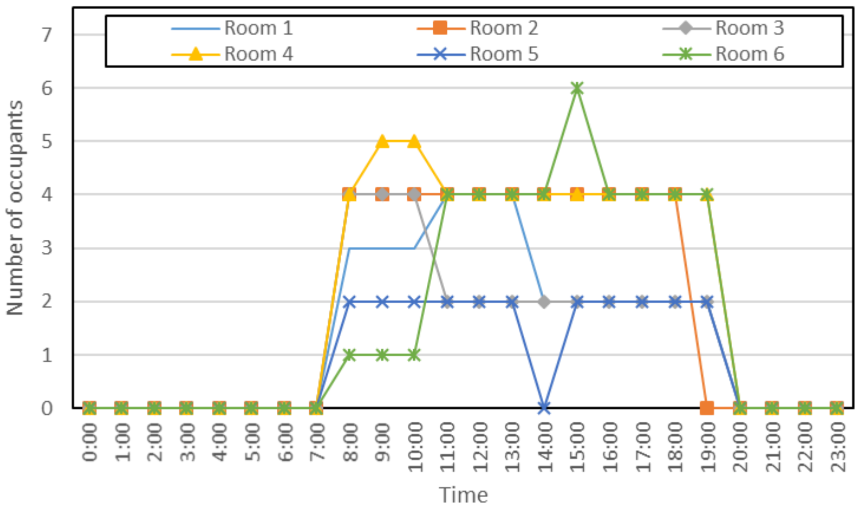

Figure 7. Actual occupancy profiles in individual rooms

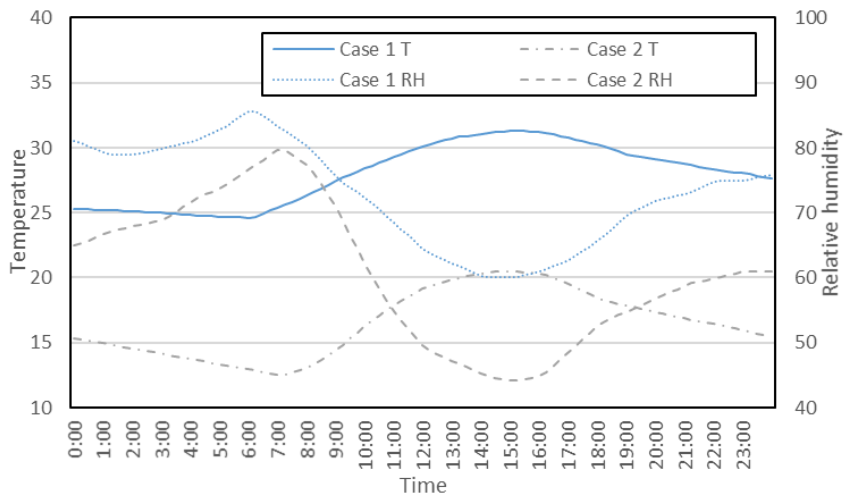

Figure 8. Outdoor temperature and relative humidity profiles in two test cases

Three control approaches for multi-zone ventilation systems are tested and compared, including baseline control approach, centralized optimal control approach, and multi-agent based distributed approach for optimal control.

- *Baseline control approach*: It is a commonly used control approach for multi-zone ventilation systems. No optimization is applied. Ventilation systems are operated according to a fixed schedule and design occupancy assumptions. During the period between 7:30 and 22:00 on workdays, ventilation air volume is determined based on room size and the design number of occupants [55]. During the period between 22:00 and 7:30 on workdays and the whole weekends, rooms are unoccupied, and ventilation air volume is determined only based on room size.
- *Centralized optimal control approach*: The ventilation air volume of rooms served by a PAU are optimized and controlled in a centralized manner, as illustrated in section 2.4.1.
- *Multi-agent based distributed approach for optimal control*: The ventilation air volume of rooms served by a PAU are optimized and controlled in a distributed manner by using the multi-agent based distributed approach, as proposed in this study.

4. Comparison of performance using different control approaches

This section presents and compares the performance of multi-zone ventilation systems controlled by using different control approaches in two test cases.

4.1. System performance using baseline control approach

According to the design occupancy and room size, the ventilation air volume is 22 L/s between 7:30 and 22:00 on workdays, and 11 L/s between 22:00 and 7:30 on workdays and the whole weekends. This operation schedule remains unchanged through the entire year. Since occupancy profiles in two test cases were the same, CO_2 in six rooms using baseline control approach were the same in both test cases, as shown in Figure 9. The maximum CO_2 are 1,123, 1,150, 1,069, 1,214, 771 and 1,332 ppm in six rooms respectively, as shown in Figure 10. The Hong Kong indoor environment standard considers the excellent level when indoor CO_2 is below 800 ppm and the good level when it is below 1,000 ppm [33]. Therefore, except Room 5, the maximum CO_2 in other rooms were too high to be acceptable.

In addition, an excessive pollutant index (*EPI*) is introduced in this study. It is defined as the Equation (15), i.e, the product of multiplying the real-time CO_2 ($CO2_{i,real}$) exceeding 800 ppm by its corresponding duration ($t_{>800}$). *EPI* reflects IAQ from both aspects of the instant CO_2 value and time duration. It is, therefore, a more comprehensive value for assessing IAQ. A higher *EPI* means lower IAQ considering the impact of excessive CO_2. As shown in Figure 11, *EPIs* were 70,740, 189,381, 36,622, 232,869, 0 and 176,528 ppm·min in six rooms respectively. It is worthy noticing that although Room 6 had the highest maximum CO_2 among six rooms, its IAQ was a little better than Room 4 which had the highest *EPI*.

Energy use of PAU varies under different weather conditions. As shown in Figure 12, it was 22.40 kWh in Case 1 with a hot and humid weather, and -16.87 kWh in Case 2 with a cool and dry weather. Here, the negative value indicates that free cooling of the PAU is activated and its reduction in chiller energy use is more than the fan energy use of the PAU itself.

$$EPI_i = \max\{0, CO2_{i,real-time} - 800\} \times t_{>800} \quad (15)$$

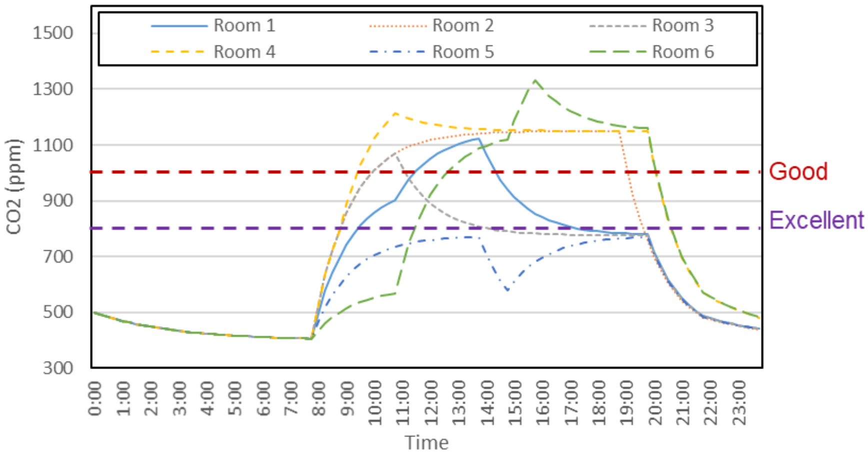

Figure 9. CO_2 concentration in six rooms using baseline control approach

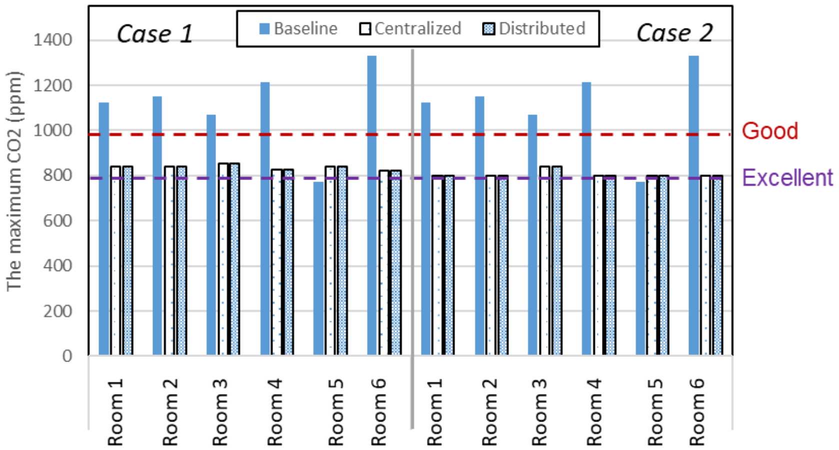

Figure 10. The maximum CO_2 in six rooms of two test cases using different control approaches

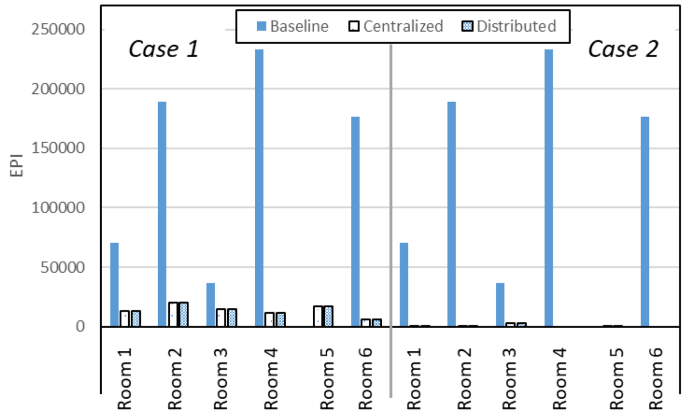

Figure 11. *EPI* in six rooms of two test cases using different control approaches

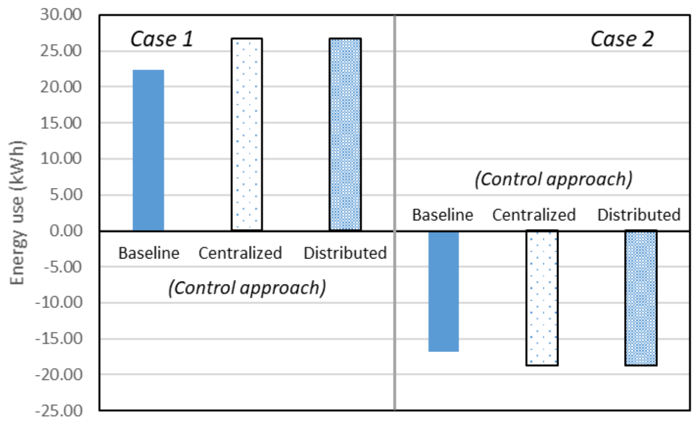

Figure 12. Energy use of PAU of two test cases using different control approaches

<u>4.2. System performance using centralized optimal control approach</u>

Figure 13 shows the optimized ventilation air volume of individual rooms in two test cases using the baseline control approach and centralized optimal control approach. Under the same occupancy and different weather conditions, the optimized ventilation air volume were different in two test cases. Results of Case 2 were significantly higher than that of Case 1, indicating that the free cooling was utilized much more efficiently.

The CO_2 concentrations and the *EPIs* of the six rooms in the two test cases are shown in Figures 10, 11, 14 and 15. The maximum CO_2 in Case 1 were 838, 839, 852, 827, 839 and 820 ppm in six rooms respectively. The maximum CO_2 in Case 2 were 801, 801, 842, 800, 801 and 799 ppm in six rooms respectively. In both test cases, the part exceeding 800 ppm was small and acceptable. As shown in Figure 11, *EPIs* of Case 1 were 13,260, 20,584, 15,019, 11,721, 16,873 and 6,285 ppm·min in six rooms respectively. *EPIs* of Case 2 were 45, 51, 3,154, 0, 44 and 0 ppm·min in six rooms respectively. Compared with the baseline control approach, the maximum CO_2 and *EPI* of Room 5 in two cases using centralized optimal control approach were increased slightly, but still within acceptable ranges. For other rooms, the maximum CO_2 were reduced significantly, and *EPIs* were reduced in the range between 58.99% and 96.44% in Case 1 and in the range between 91.39% and 100.00% in case 2, when compared with the baseline control approach. It can be observed that IAQ was improved considering the reduced maximum CO_2 and *EPIs*, and such improvement was much more significant in Case 2.

The energy use of the PAU of two test cases are shown in Figure 12. Compared with the baseline control approach, the energy use of the PAU was increased slightly (i.e., from 22.40 to 26.65 kWh or 19.01%.) in Case 1. The energy saving of using the centralized optimal control approach was increased from 16.87 to 18.78 kWh (i.e., 11.33%) in Case 2. In summary, the centralized optimal control approach performed well in finding a trade-off point between limiting indoor CO_2 concentration and minimizing the energy use.

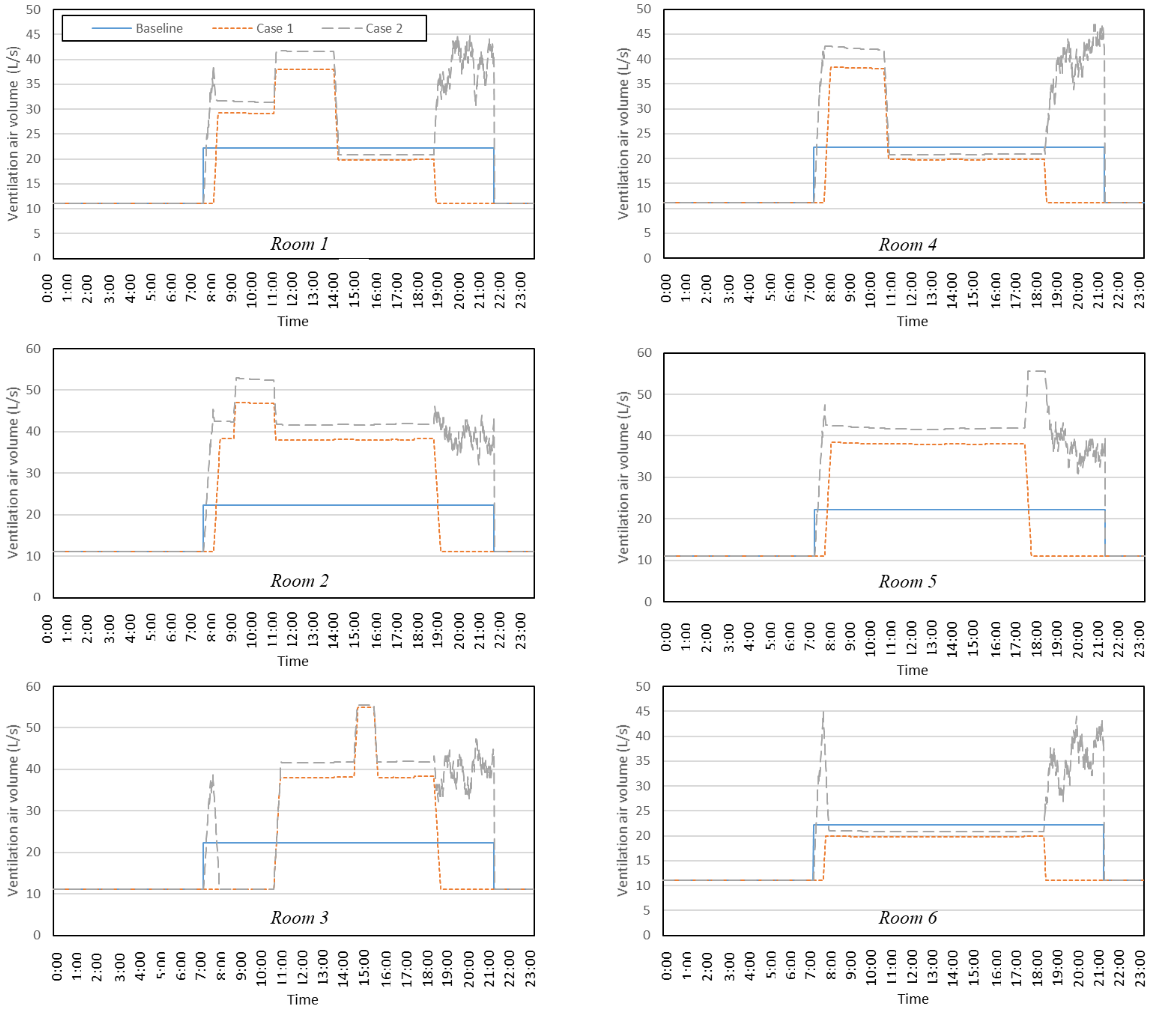

Figure 13. Optimized ventilation air volume of individual rooms in two test cases using baseline control approach and centralized optimal control approach

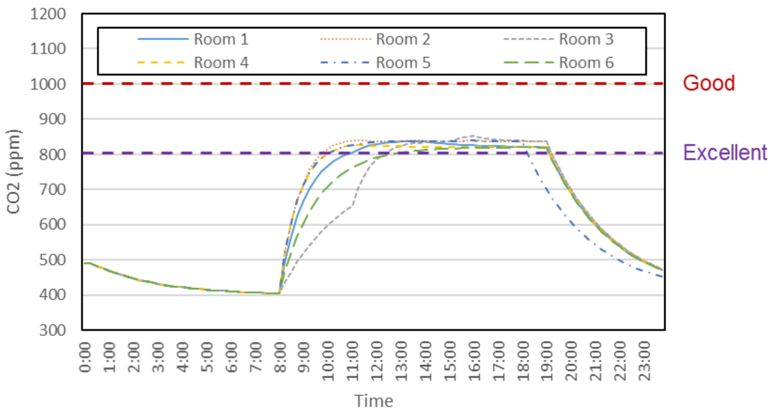

Figure 14. CO_2 concentration of individual rooms in Case 1 using centralized optimal control approach

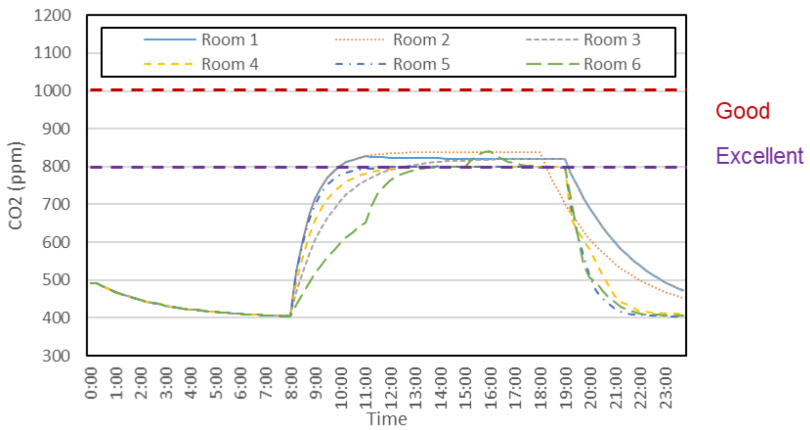

Figure 15. CO_2 concentration of individual rooms in Case 2 using centralized optimal control approach

4.3. System performance using the multi-agent based distributed approach for optimal control

To show the converging process clearly, the evolution of the ventilation air volume of individual rooms and the PAU in Case 1 at a particular point of time (i.e. 10:00) are depicted in Figure 16. Using the multi-agent based distributed approach for optimal control, the ventilation air volume of rooms and the PAU converged progressively to the global optimums given by the centralized optimal control approach. The constraint violation was diminishing below 0.01 within 20 iterations due to inter-agent coordination.

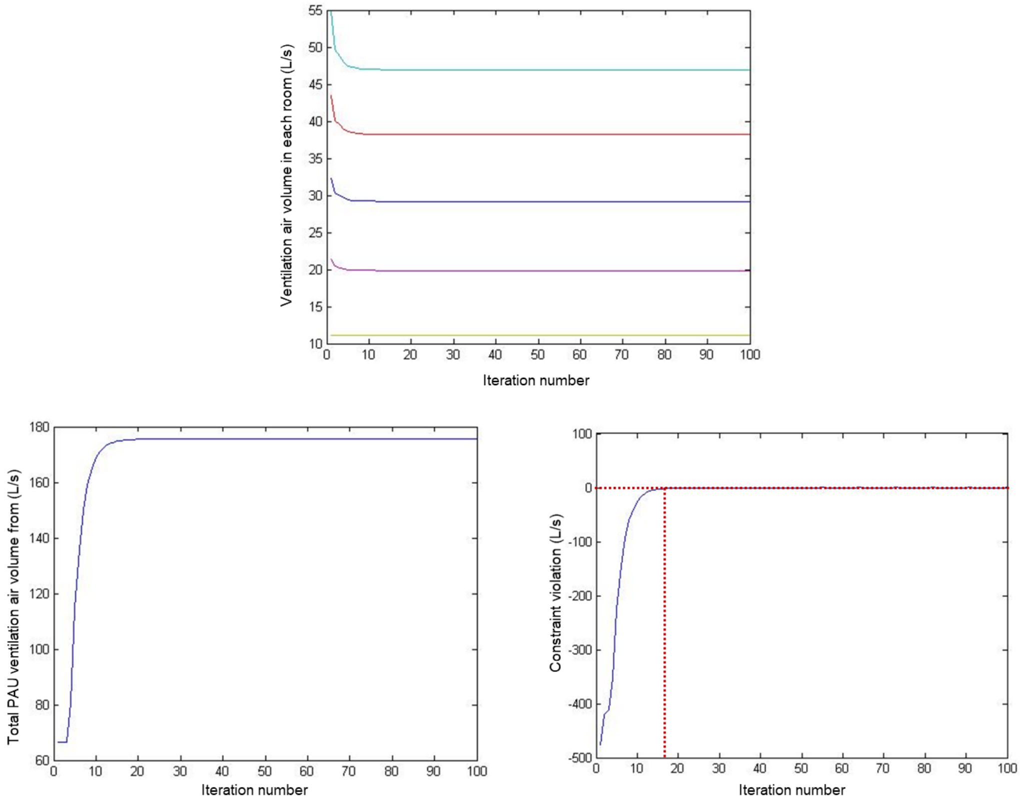

Figure 16. Results evolution of case 1 at 10:00 using multi-agent based approach for distributed optimal control

Figure 17 shows daily optimized ventilation air volume of individual rooms in two test cases using multi-agent based distributed approach for optimal control. As mentioned before, the stopping threshold and the maximum iteration number were preset to be 0.001 and 100 respectively. The optimized ventilation air volume given by multi-agent based distributed approach was nearly the same as that given by the centralized optimal control approach.

The maximum CO_2 concentrations and the *EPIs* of the six rooms in two test cases are shown in Figures 10, 11. The maximum CO_2 in Case 1 were 838, 839, 852, 827, 839 and 820 ppm in six rooms respectively. The maximum CO_2 in Case 2 were 801, 801, 842, 800, 801 and 799 ppm in six rooms respectively. In both test cases, the part exceeding 800 ppm was small and acceptable. As shown in Figure 11, *EPIs* of Case 1 were 13,260, 20,585, 15,020, 11,723, 16,874 and 6,285 ppm·min in six rooms respectively. *EPIs* of Case 2 were 45, 51, 3,154, 0, 44 and 0 ppm·min in six rooms respectively. Compared with the baseline control approach, the maximum CO_2 and *EPI* of Room 5 in two cases using multi-agent based distributed approach were increased slightly, but still within acceptable ranges. For other rooms, the maximum CO_2 were reduced significantly, and *EPIs* were reduced in the range between 58.99% and 96.44% in Case 1 and in the range between 91.39% and 100.00% in case 2, when compared with the baseline control approach. It can be observed that IAQ was improved considering the reduced maximum CO_2 and *EPIs*, and such improvement was much more significant in Case 2.

The energy use of the PAU of two test cases are shown in Figure 12. Compared with the baseline control approach, the energy use of the PAU was increased slightly (i.e., from 22.40 to 26.65 kWh or 18.99%.) in Case 1. The energy saving of using the multi-agent based distributed approach was increased from 16.87 to 18.78 kWh (i.e., 11.34%) in Case 2. In summary, the system performance, including maximum CO_2, *EPI* and energy use, using the multi-agent based distributed approach was nearly as good as that using the centralized optimal control approach.

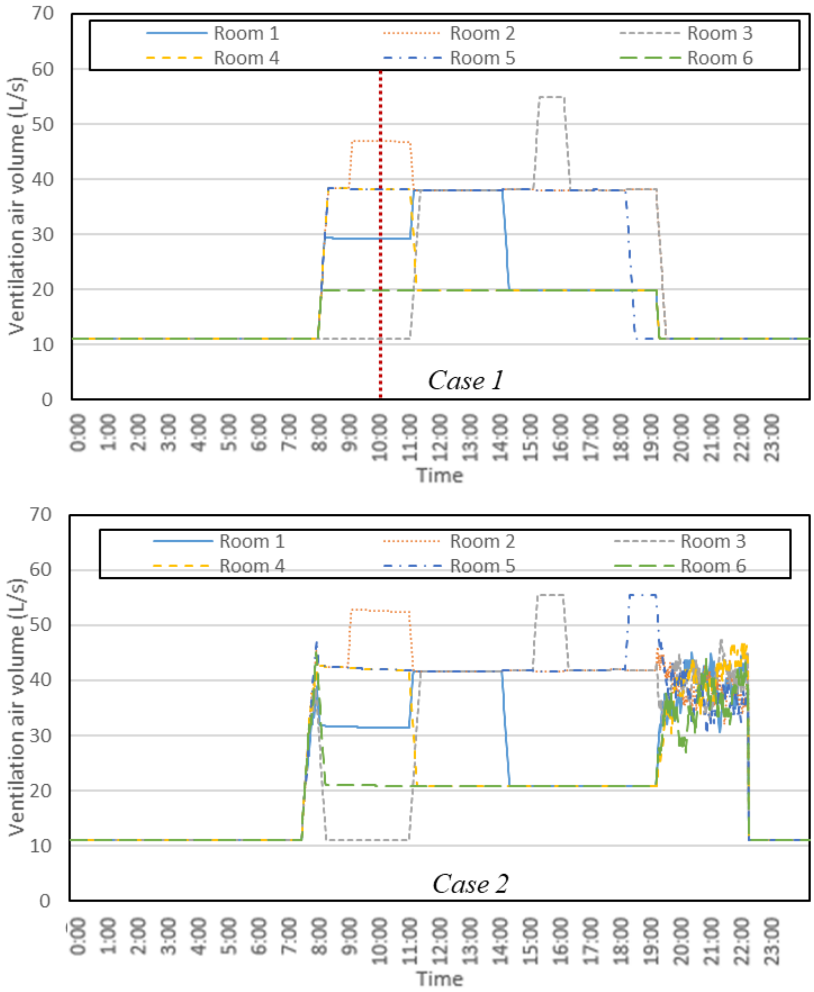

Figure 17. Daily optimized ventilation air volume of individual rooms in two test cases using multi-agent based distributed approach for optimal control

4.4. Discussion on the scalability and reconfigurability of the multi-agent based distributed approach

The benefits of good scalability and reconfigurability of the multi-agent based distributed approach are stated earlier. Such benefits are elaborated below in details by analyzing the implementation of this approach in the optimal control of multi-zone ventilation systems.

Good reconfigurability of multi-agent based distributed approach is an important advantage in resetting the optimal control strategies for multi-zone ventilation systems. It is also beneficial in providing enhanced robustness of the strategy in ever changing indoor and outdoor conditions. When the outdoor weather (i.e. outdoor condition) changes, the objective function of an optimization problem needs to be updated. The distributed optimal control approach takes different measures from that of the centralized approach. For the centralized optimal control approach, the term in the objective function regarding the energy use is deployed in the central station. Reseting or reconfiguration of this term needs to be done in the central station. The term regarding the indoor pollutant level is also deployed in the central station. This poses a failure risk to the entire control system. In contrast, using the multi-agent based distributed approach, the term in objective function regarding the energy use only needs to be reset in the PAU agent. This means that only the control agent of a component needs to be reconfigured without the need of modifying the entire control system when a component dynamic changes. Any local failure does not stop the operation of entire control system. Thus the resilience and robustness of the control system are improved.

Similarly, when the number of occupants (i.e. indoor condition) changes, the objective function of optimization problem also needs to be reset. Using the centralized approach, the term in objective function regarding the indoor pollutant level, being processed in the central control system, needs to be reset, while the term in objective function regarding the energy use is processed in the same location as well. This also poses a failure risk to the entire control system. In contrast, using multi-agent based distributed approach, the term in objective function regarding the indoor pollutant level only needs to be reset in one or more individual room agents if the associated component dynamics have changed. This also improves the resilience and robustness of the control system.

The enhanced scalability of the multi-agent based distributed approach is another important advantage for the optimal control of multi-zone ventilation systems, considering the flexibility in formulating the objective functions. One may appreciate the needs and benefits of diverse control in multi-zone ventilation systems. For instance, involving more rooms in a control system means more agents to be added. Selecting the pollutants to be considered by a room control agent according to users' concern means more terms to be added in agents. It means that the flexibility in scaling up/down control system and adding/removing terms in the optimization objective is of great advantage. In such cases, if using the centralized approach, the entire formulation of optimization task needs to be reconfigured. In contrast, if using the multi-agent based distributed approach, only the individual agent(s) need(s) to be reset or added/removed.

5. Conclusions

A multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering IAQ and energy use is proposed. The centralized multi-objective optimization problem is formulated and decomposed into distributed simpler problems, which are assigned to distributed local agents. Individual agents optimize their own objective functions and coordinate with each other to achieve the overall control optimization objectives in a distributed manner. The TRNSYS-MATLAB co-simulation testbed is used to test the performance of this control approach by comparing with a baseline control approach and a centralized optimal control approach. Based on the results of the online control tests, a few conclusions on the performance and the major advantages of the proposed distributed approach can be made/summarized as follows:

- The distributed optimal control approach is effective in finding the proper trade-off point between limiting indoor CO_2 concentration and minimizing PAU energy use (i.e., the optimal solution).
- The accuracy of the optimal solutions given by the distributed approach is very good when compared with target solutions given by the centralized approach in the test cases.
- The proposed distributed approach facilitates the complex control optimization problems being solved by field control devices collectively. A centralized optimization problem needs to be solved by certain complex algorithm in a control station of powerful capacity. By contrast, the decomposed optimization problems is simple and can be solved by simple algorithms in field control devices of very limited capacity.
- The proposed distributed approach has good scalability. With the ever changing indoor and outdoor conditions, resetting the corresponding agents rather than the whole system improves the resilience and robustness of the system.
- The proposed distributed approach has good reconfigurability. It is of great advantage to handle the flexibility in scaling up/down control system and adding/removing terms in the optimization objective for multi-zone ventilation systems.

The proposed multi-agent based distributed approach for optimal control of multi-zone ventilation systems is tested in simulation in this study. It would be beneficial to verify the effectiveness particularly the robustness of the proposed approach in on-site implementation. On-site test or experiment in real systems is needed in the future research prior to practical industrial applications.

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