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A real-time optimal control strategy for multi-zone VAV air-conditioning systems adopting a multi-agent based distributed optimization method

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Abstract: Determining the proper trade-off among thermal comfort, Indoor Air Quality (IAQ) and energy use is important for optimal control of air-conditioning systems. The number of optimization variables increases as systems become increasingly complex, as with multi-zone VAV (Variable Air Volume) air-conditioning systems, leading to large-scale mathematics programming challenges and inconveniences in the implementation of conventional centralized optimization strategies. This paper therefore proposes a real-time optimal control strategy adopting a multi-agent based distributed optimization method for multi-zone VAV air-conditioning systems. The proposed strategy consists of three novel schemes. First, a temperature set-point reset scheme adopts a linear rule to correlate the resetting of the temperature set-points in individual zones to simplify the optimization problem while applying proper optimization in individual zones. Second, a multi-objective optimization scheme optimizes the fresh air ratio of the supply air and the temperature set-point in the critical zone by formulating the multi-objective optimization problem. Third, a multi-agent distributed optimization scheme is developed to solve the optimization problem in a distributed manner, facilitating the deployment of local control devices of limited capacity. A TRNSYS-MATLAB co-simulation testbed is constructed to test and validate the proposed strategy. Test results show that the strategy is effective in properly balancing thermal comfort, IAQ and energy use while largely reducing programming challenges. The distributed optimization method can provide almost the same optimal outputs as conventional centralized optimization methods.

Keywords: Distributed optimal control, multi-agent system, thermal comfort, indoor air quality, energy efficiency, air-conditioning systems.

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1. Introduction

As most people spend 80–90% of their lifetime in buildings, Indoor Environment Quality (IEQ) is of vital importance to their mental and physical health [1]. Heating, Ventilation and Air-conditioning (HVAC) systems are provided to maintain a good indoor environment, including Indoor Air Quality (IAQ) and thermal comfort. However, HVAC systems account for about 50% of building energy use [2], which contributes to about 50% of total energy use worldwide [3]. Therefore, developing optimal control strategies for HVAC systems which reduce energy use and maintain both thermal comfort as well as IAQ has always been of great concern [4].

Multi-zone Variable Air Volume (VAV) air-conditioning systems, a popular type of HVAC system, have a large number of set-points in different control loops. These are determined during operation to optimize system performance. The fresh air ratio of the supply air and the temperature set-points of individual zones are often considered important optimization variables for typical control strategies, as shown in Figure 1. They are the main controlled variables determining the thermal comfort and IAQ of a zone. The supply air volume of each zone is controlled by its VAV terminal box to maintain the indoor air temperature at its set-point. The IAQ of a zone is determined by the pollutant level of indoor air, which is controlled by the fresh air intake. In a multi-zone VAV system, the fresh air intake of a zone is determined by the supply air volume to this zone and the fresh air ratio of the supply air. This is because all zones served by a VAV air-conditioning system share the same supply air, which is a mixture of outdoor air and recirculated air.

The fresh air ratio of the supply air and temperature set-points of individual zones can be determined in multiple ways. They can be set as fixed values based on the experiences of building operators. They can also be determined by referring to technical specifications and guidance, in which recommended values or basic calculation approaches are provided. For example, as an active response to the Paris Agreement, temperature set-points in indoor spaces are advised to be set between 24 and 26 °C by the Hong Kong SAR government [6]. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) recommends the fresh air ratio of the supply air be determined by the multi-zone equations approach [7]. However, these methods cannot guarantee optimal control performance in VAV air-conditioning systems with regards to thermal comfort, IAQ and energy use.

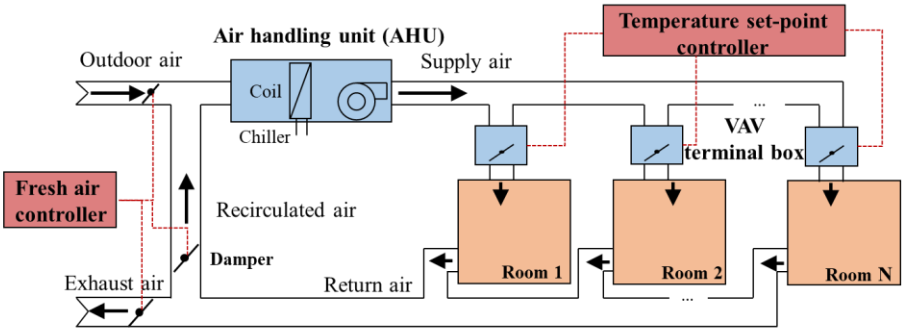

Figure 1. The typical configuration of multi-zone VAV air-conditioning systems

Optimal control strategies typically determine the set-points of control loops in HVAC systems by solving multi-objective optimization problems. Wei et al. [8] applied the Particle Swarm Algorithm (PSA) to solve a quad-objective optimization problem, including energy use, indoor air temperature, relative humidity, and CO_2 concentration level, to determine the set-points of the supply air temperature and the static pressure of an Air Handling Unit (AHU). Ganesh et al. [9] used sequential methods to solve an optimization problem, of which the objective function included energy use, indoor ozone, PM2.5 and HCHO, to determine the set-point of the air exchange rate. Zhai and Soh [10] optimized frequencies for a supply-air fan, compressor and water pump. The energy use and Predictive Mean Vote (PMV) were formulated into the objective function, which was solved through the sparse Firefly Algorithm (sFA) and sparse Augmented Firefly Algorithm (sAFA). Therefore, the fresh air ratio of the supply air and temperature set-points in individual zones can be optimally determined by formulating and solving multi-objective optimization problems with the concerned control objectives.

In multi-zone VAV air-conditioning systems, the number of optimization variables increases as the number of zones increases, which results in large-scale mathematics programming challenges [11]. First, the computational load can be high due to combinatorial explosion [12]. Second, the global optimum can be difficult to find, due to the non-convex optimization problem [13]. Many existing studies solve this problem by optimizing the controlled variables in the typical zone(s) only. The critical zone, requiring the highest fresh air ratio, is generally selected as the typical zone. Xu and Wang [14] proposed an adaptive Demand-Controlled Ventilation (DCV) strategy by integrating the dynamic occupancy detection, the multi-zone equations approach and the rule-based critical zone temperature set-point reset algorithm. Sun et al. [15] implemented this adaptive DCV strategy in a real building to validate its performance. Xu et al. [5] further improved the adaptive DCV strategy by formulating the multi-objective optimization problem for resetting temperature set-point in the critical zone. Wang et al. [16] proposed a ventilation strategy, in which the actual occupancy was detected by a Wi-Fi probe enabled occupancy sensing system. Two critical zones, requiring the highest and second highest fresh air ratios, were selected as the typical zones and used in the multi-zone equations approach. This simplification method reduces the number of optimization variables and reduces the programming challenges. However, it ignores the requirements of other non-typical zones, and possibly degrades system performance.

In many studies regarding the optimal control strategy of HVAC systems, the decision making process was centralized. The methods proposed in many studies were based on traditional Building Automation Systems (BASs), where information is transmitted to a central workstation for optimized decisions. However, as HVAC systems become increasingly complex, centralized control is not convenient and effective due to weaknesses in scalability and reconfigurability [17]. In contrast with centralized control, distributed control is appropriate for applications that are changeable and complex [18], such as building systems [19]. Although traditional BASs operate in a centralized manner, their distributed installation layout make it possible to implement distributed optimal controls. In addition, future BASs enabled by IoT-based smart devices are better suited for distributed optimal controls [20].

Distributed optimal controls require distributed optimization methods, for which the multi-agent system paradigm provides a promising implementation platform [21-23]. A complex problem, which is originally in a centralized form, is decomposed into several sub-problems, solved by properly designed agents in a distributed form. The optimum is reached through agent-to-agent coordination. Davarzani et al. [25] designed and implemented a multi-agent system framework for voltage and current constraint management of Medium Voltage (MV) feeders using the demand response at Low Voltage (LV) feeders. Su and Wang [39] proposed an agent-based distributed real-time control strategy for building HVAC systems, and investigated implementation issues including energy efficiency, optimization accuracy, convergence rate, computation complexities and computation loads. The proposed strategy was applied to a central cooling system, in which different components had different performances. Cai et al. [27] presented a general multi-agent control approach for building energy system optimization. It was implemented in two cases, including the optimal control of a chilled water cooling plant and a multi-zone direct expansion (DX) air-conditioning system. Concerning building indoor environment control, Wang et al. [24] proposed a multi-agent control system to manage building indoor energy and comfort. Four types of agent, including a switch agent, central coordinator-agent, local controller-agent and load agent, were defined. Kafuko and Wanyama [26] proposed a multi-agent system for minimizing total energy usage by adjusting the set-points of PID temperature controllers. A temperature agent and energy agent were presented at the local level, while an energy price agent, weather agent and supervisor agent were presented at the supervisory level. Li and Wang [40] presented a multi-agent based distributed approach for the optimal control of multi-zone ventilation systems. Ventilation air volumes of individual rooms and the Primary Air-handling Unit (PAU) were optimization variables for an acceptable IAQ with minimized energy use. The benefits of the proposed approach were discussed. Its good scalability is of vital importance with the ever changing indoor and outdoor conditions that only the corresponding agents rather than the whole system needs to be reset. Its good reconfigurability is of great advantage when handling the flexibility in scaling up/down control system and adding/removing terms in the optimization objective for multi-zone ventilation systems. The resilience and robustness of the system can be improved. Therefore, implementing real-time optimal control strategies for multi-zone VAV air-conditioning systems using multi-agent based distributed optimization methods is a promising direction for research.

This study therefore proposes a real-time optimal control strategy for multi-zone VAV air-conditioning systems adopting a multi-agent based distributed optimization method. The optimization variables involved in the optimization problem are the fresh air ratio of the supply air and the indoor air temperature set-point of the critical zone, while the supply air volume in individual zones is optimized by resetting their indoor air temperature set-points using a simplified approach. This proposed strategy has three major innovations. (1). A new temperature set-point reset scheme is adopted to reset temperature set-points in non-critical zones with reference to that of the critical zone. This scheme optimizes the supply air volume in individual zones without involving too many optimization variables, the primary cause of large-scale programming challenges. (2). A multi-objective optimization scheme integrates the thermal comfort and IAQ of individual zones and energy use in the multi-zone VAV air-conditioning system, maintaining satisfactory thermal comfort and IAQ while minimizing energy use. (3). A multi-agent based distributed optimization scheme is adopted to solve the optimization problem of multi-zone VAV air-conditioning systems in a distributed manner, facilitating deployment of the optimization problem to be solved on local control devices of limited capacity. To assess the control performance of the proposed real-time optimal control strategy for multi-zone VAV air-conditioning systems, five control strategies are tested and compared. A TRNSYS-MATLAB co-simulation testbed is developed to simulate six rooms served by the multi-zone VAV air-conditioning system for the above validation tests and comparison study.

2. The proposed control strategy

The proposed control strategy consists of three novel schemes, the temperature set-point reset scheme, the multi-objective optimization scheme and the multi-agent based distributed optimization scheme. The first two schemes form the new real-time optimal control method, elaborated in Section 2.1. The temperature set-point reset scheme and the multi-objective optimization scheme are explained in detail in Sections 2.2 and 2.3. Section 2.4 presents the multi-agent based distributed optimization scheme for solving the formulated optimization problem in a distributed manner.

2.1. An outline of the new real-time optimal control method

An outline of the new real-time optimal control method for multi-zone VAV air-conditioning systems are shown in Figure 2. In this method, the temperature set-point reset scheme applies a linear rule to correlate the resetting of the temperature set-points of individual zones. The temperature set-points of non-critical zones are reset with reference to that of the critical zone. Then the reset temperature set-points of individual zones are included in the multi-objective optimization scheme using a single optimization variable. The multi-objective optimization scheme aims to optimize the fresh air ratio of the supply air and the temperature set-point of the critical zone by formulating and solving the multi-objective optimization problem. The thermal comfort, IAQ and energy use of the VAV air-conditioning system are considered simultaneously in this scheme.

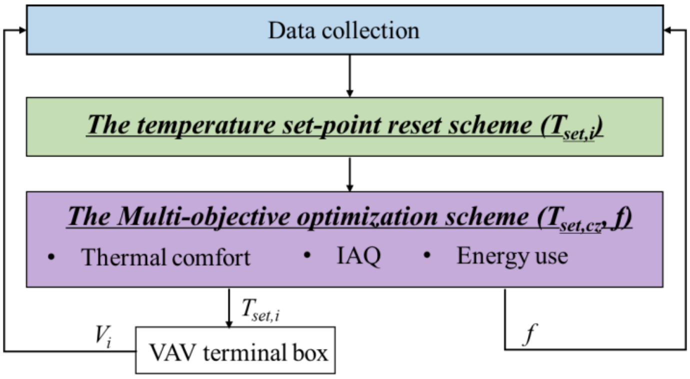

Figure 2. Outline of the new real-time optimal control method for multi-zone VAV air-conditioning systems

2.2. The temperature set-point reset scheme

Excessive CO_2 is a representative indoor pollutant [29, 32]. The zone with the highest CO_2 concentration level, if exceeding the prescribed level (i.e. 800 ppm), is considered the critical zone in this study. Higher CO_2 concentration level indicates inadequate fresh air intake. Undersupply and oversupply of fresh air intake both occur when the fresh air ratio of the supply air and the supply air volume of individual zones are no longer appropriate for current conditions. Therefore, the previous fresh air intake value needs to be re-determined or reset. Considering the energy conservation in a space, to meet the unchanged cooling load, the temperature set-points and the supply air volume of this zone are coupled together and they are adjusted to the opposite directions. In this regard, the previous fresh air intake value can be reset by adjusting the existing temperature set-point of an individual zone ($T_{set,i,k-1}$) with modification values ($\Delta T_{set,i,k}$), as shown in Equation (1). The adjustment range of temperature set-points of individual zones lies between 22 °C and 25 °C.

$$T_{set,i,k} = T_{set,i,k-1} + \Delta T_{set,i,k} \tag{1}$$

The temperature set-point reset scheme is proposed to correlate the modification values ($\Delta T_{set,i,k}$) of all non-critical zones with that of the critical zone by adopting a simplified linear rule. For each zone, the more CO_2 concentration level exceeds the prescribed level, the lower the temperature set-point is set in order to increase fresh air intake. The more CO_2 concentration level is below the prescribed level, the more fresh air intake could be reduced by resetting its temperature set-point higher. The temperature set-point resetting in multiple zones therefore follows a simple linear rule, as shown in Equation (2). The differences between CO_2 concentration levels in individual zones and the prescribed level (i.e. 800 ppm) are shown in Figure 3.

$$\Delta T_{set,i,k} = \frac{\Delta CO_{2,i,k}}{\Delta CO_{2,cz,k}} \cdot \Delta T_{set,cz,k} \tag{2}$$

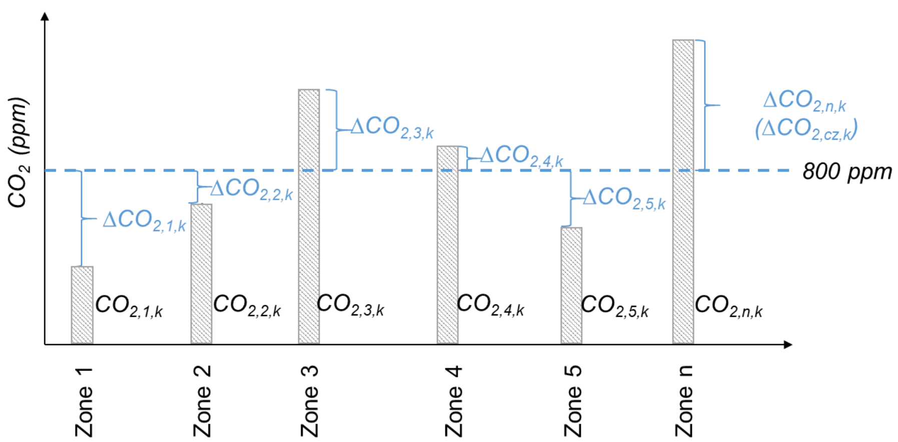

Figure 3. The differences between CO_2 of individual zones and the prescribed level

In this way, the temperature set-points of all non-critical zones are updated and reset with reference to that of the critical zone. These set-points are all included in the objective functions for the multi-objective optimization. Since the temperature set-points in all non-critical zones are functions of that of the critical zone, the number of optimization variables concerning zone temperature set-point to be solved in optimization is actually reduced to one. Thus the large-scale mathematics programming challenge is avoided.

2.3. Multi-objective optimization scheme - Formulation of the objective function

The multi-objective optimization scheme aims to optimize the fresh air ratio of the supply air and the temperature set-point of the critical zone. This is realized by formulating and solving the multi-objective optimization problem, in which three objectives are involved: thermal comfort, IAQ and energy use. The objective functions concerning thermal comfort, IAQ and energy use are presented below in this section. Using the weighted sum approach, the multi-objective optimization problem is converted into a single-objective one with the objective function expressed in Equation (3). Obj_{Th}, Obj_{IAQ} and Obj_E are the objective functions, concerning thermal comfort, IAQ and energy use respectively. α_{Th} and α_{IAQ} are the weighting factors. Their values are selected based on the relative importance of these control objectives. By trying different combinations of weighting factors, α_{Th} and α_{IAQ} to be 5×10^4 and 2×10^{-4} are able to obtain the relatively satisfactory system performance in terms of thermal comfort, IAQ and energy. Thus they are adopted in this study. The fresh air ratio of the supply air (f) and the temperature set-point of the critical zone ($T_{set,cz}$) are the two variables to be optimized. The search scopes of the optimized f and $T_{set,cz}$ are between 0 and 1 and between 22 °C and 24 °C, respectively. Here, the range of set-point is set low since the temperature set-point of the critical zone will be set lower to increase the supply air volume.

$$Obj = \alpha_{Th} \cdot Obj_{Th} + \alpha_{IAQ} \cdot Obj_{IAQ} + Obj_E \tag{3}$$

<u>*Thermal comfort*</u>*:* Thermal comfort is represented by PMV. It relates to air temperature, air velocity, air relative humidity, mean radiant temperature, clothing insulation and metabolic rate of the occupant, as calculated by Fanger's comfort equations [28]. PMV varies between -3 and +3. A PMV value of zero represents thermal neutrality. The objective function concerning thermal comfort (Obj_{Th}) is then assessed as shown in Equation (4). PMV_i is the PMV value in a zone. n is the number of zones.

$$Obj_{Th} = \sum_{i=1}^{n} PMV_i^2 \tag{4}$$

Indoor air quality: IAQ is represented by the concentration of CO_2 as the representative indoor pollutant [29, 32]. Due to metabolic processes, indoor CO_2 concentration level varies as the number of occupants changes. The objective function concerning IAQ (Obj_{IAQ}) is then assessed as shown in Equation (5). $CO2_i$ is the steady-state CO_2 concentration in the zone i, which is derived from the mass balance equation [31]. TH_{CO2} is the control threshold of CO_2 in the optimization scheme, which adopts the value of its prescribed level in the IAQ control standard [30].

$$Obj_{IAQ} = \sum_{i=1}^{n} \max\{0, (CO2_i - TH_{CO2})\}^2 \tag{5}$$

Energy use: The energy use here refers to the overall energy use of the multi-zone VAV air-conditioning system serving all the zones concerned. Specifically, energy use includes the energy used by the chiller plant to provide cooling to the zones and the AHU fan for delivering air flow to the zones [5], shown as Equation (6). E_T is the total energy use of the multi-zone VAV air-conditioning system. E_{Fan} is the fan energy use, which is calculated by the affinity laws [33, 34]. E_{Rest} is the energy used by the rest components of the multi-zone VAV air-conditioning system. It corresponds to the supply air temperature of 14 °C. The overall Coefficient of Performance (COP) including the pump and the chiller is assumed to be constant as 2.5 [5, 41].

$$E_T = E_{Fan} + E_{Rest} \tag{6}$$

2.4. The multi-agent based distributed optimization scheme

This section elaborates how to solve the formulated optimization problem using a multi-agent based distributed optimization scheme. First, the multi-agent system for distributed optimal control of multi-zone VAV air-conditioning systems is established. Then, the optimization problem is reformulated to multiple independent sub-problems that can be processed in corresponding agents. Finally, a detailed iteration process is used to find the solution of the reformulated optimization problem using a specific algorithm, which is described later in this section.

2.4.1 Establishment of the multi-agent system

The objective function presented in Equation (3) is the summation of multiple optimization objectives for multiple places, including thermal comfort and IAQ in individual zones as well as energy use for the air-conditioning system. This matches the multi-agent system paradigm well, in which multiple agents have the ability to solve their own objective functions and optimization tasks. Thus, a multi-agent system for distributed optimal control of multi-zone VAV air-conditioning systems is established as shown in Figure 4.

There are n VAV agents (corresponding to n zones), one AHU agent and one coordinating agent. VAV agents and the AHU agent solve their own objective functions to obtain their local optimization variables, i.e. the fresh air ratio of the supply air (f_i) and the temperature set-point of the critical zone ($T_{set,cz,i}$) with the search scopes of 0-1 and 22-24 °C respectively. The global optimization variables are the fresh air ratio of the supply air (f) and the temperature set-point of the critical zone ($T_{set,cz}$) that are finally used as optimal solutions used for the control of the VAV air-conditioning system. Therefore, the local optimization variables need to be as close as possible and finally converge to the global optimization variables. This is called the "consensus constraint", indicating that physical quantity can only have one value in one system. The coordinating agent aims to facilitate the agent-to-agent coordination and the satisfaction of the consensus constraint.

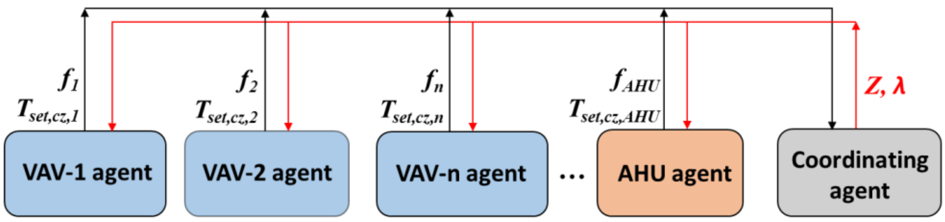

Figure 4. Schematic of the multi-agent system for distributed optimal control of multi-zone VAV air-conditioning systems

2.4.2 Decomposition and distributed formulation of the optimization problem

The objective function presented in Section 2.3 cannot be directly separated and assigned to agents individually. In other words, it is inapplicable to the established multi-agent system. Therefore, the augmented Lagrangian of Equation (3) is reformulated into Equation (7) by using the alternating direction method of multipliers (ADMM), which is one of the widely used distributed optimization algorithms [35-37]. Figure 5 shows a surface plot of the objective function at a given time. The convexity of the objective function within the search scopes guarantees the convergence of the ADMM.

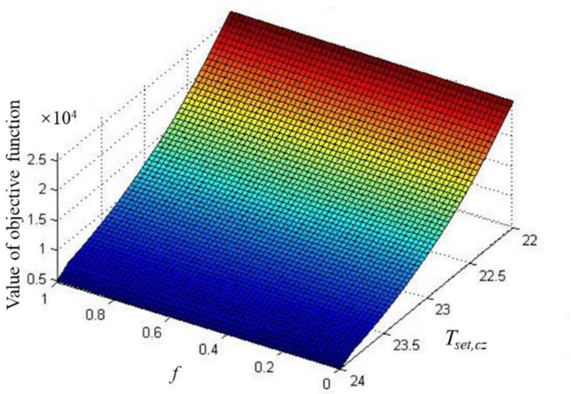

Figure 5. A surface plot of the objective function

Compared with Equation (3), the added terms aim to ensure the satisfaction of the consensus constraint. Equation (7) is the summation of multiple independent sub-problems which can be assigned to different agents individually. The objective function (i.e. the assigned sub-problem) of each VAV agent is shown as Equation (8). The objective function of the AHU agent is shown as Equation (9). The coordinating agent conducts data processing by Equations (10)-(11).

$$\alpha_{Th} \cdot Obj_{Th} + \alpha_{IAQ} \cdot Obj_{IAQ} + Obj_E + \lambda^T(X - FZ) + \frac{\rho}{2} \|X - FZ\|_2^2 \tag{7}$$

$$\left[\alpha_T \cdot {PMV_i}^2 + \alpha_{CO2} \cdot max[0, (CO2_i - TH_{CO2})]^2 + \frac{\rho}{2} \|X_i - F_i Z + \frac{\lambda_i^l}{\rho}\|_2^2\right] \tag{8}$$

$$\left[E + \frac{\rho}{2} \|X_i - F_i Z + \frac{\lambda_i^l}{\rho}\|_2^2\right] \tag{9}$$

$$Z^{l+1} = (F^T F)^{-1} F^T (X^{l+1} + \frac{\lambda^l}{\rho}) \tag{10}$$

$$\lambda^{l+1} = \lambda^l + \rho(X^{l+1} - FZ^{l+1}) \tag{11}$$

where, $\boldsymbol{\lambda}$ is the Lagrange multiplier vector. $\boldsymbol{\lambda}_i$ is the sub-vector of $\boldsymbol{\lambda}$ corresponding to an agent. $\boldsymbol{X}$ is the local optimization variable vector. $\boldsymbol{X}_i=[f_i,T_{set,cz,i}]^T$ is the local optimization variable vector of an agent. f_i is the optimized fresh air ratio by an agent. $T_{set,cz,i}$ is the optimized temperature set-point of the critical zone by an agent. $\boldsymbol{F}$ is a matrix indicating the relationship between the local optimization variable and the global optimization variable [27]. $\boldsymbol{Z}$ is the global optimization variable vector, i.e., $\boldsymbol{Z}=[f, T_{set,cz}]^T$. ρ is the penalty multiplier. l is the number of the iteration step.

2.4.3 Solution identification

In centralized optimization methods, the solution identification process is fulfilled in a one-time effort. In contrast, ADMM conducts several iterations to identify solutions for the optimization problems, as shown in Figure 6. In this study, Jacobian method is used as the iterative method [42]. Each agent uses information updated from the last iteration rather than waiting for the updated information from the current iteration, thus the local optimization is conducted in parallel. At each iteration, the local optimizations are solved by an exhaustive method. At the same time, each VAV agent optimizes the local optimization variables with the objective to maintain its PMV and CO_2 concentration level. The AHU agent optimizes the local optimization variables with the objective to minimize its energy use. The coordinating agent conducts data processing, including the global variables and the Lagrange multiplier vector, to make the local variables gradually converge to the global variables in order to ensure the satisfaction of the consensus constraint. The iteration process ceases when the criteria of primal and dual residuals are met or the maximum iteration number is reached [38]. In this study, $\boldsymbol{Z^0}$=[0, 23.5]^T, $\boldsymbol{\lambda^0}$=**0**, ρ=500, and the maximum iteration number is 30.

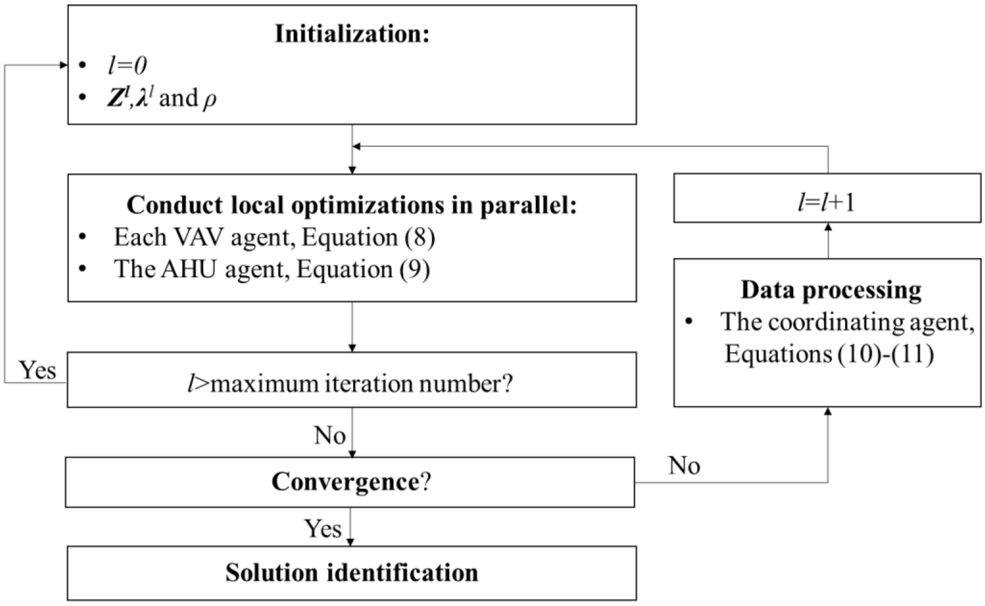

Figure 6. Flowchart for the solution identification using ADMM

3. Validation test arrangement

3.1. Test condition

Six rooms are considered zones in the test case, as shown in Figure 7. They are served by one multi-zone VAV air-conditioning system. Each room is served by one VAV terminal box. The temperature set-points of individual rooms and the fresh air ratio of the supply air are determined by different typical control strategies. Their performance is compared with the proposed strategy. The occupancy profiles on a typical workday in the six rooms are shown in Figure 8. The test case is conducted on a typical hot and humid day. Figure 9 shows the outdoor air temperature and relative humidity on the test day.

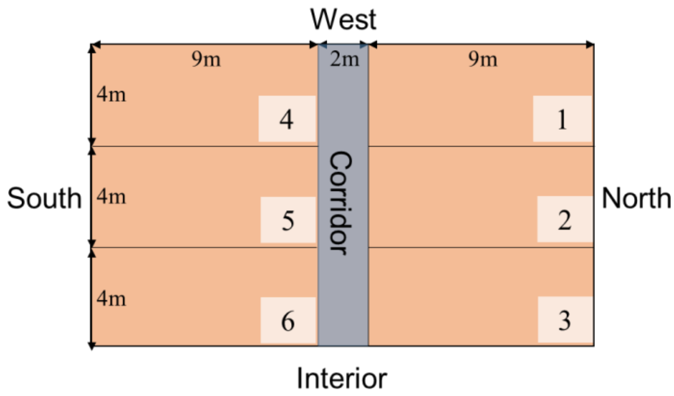

Figure 7. Layout of the test six rooms

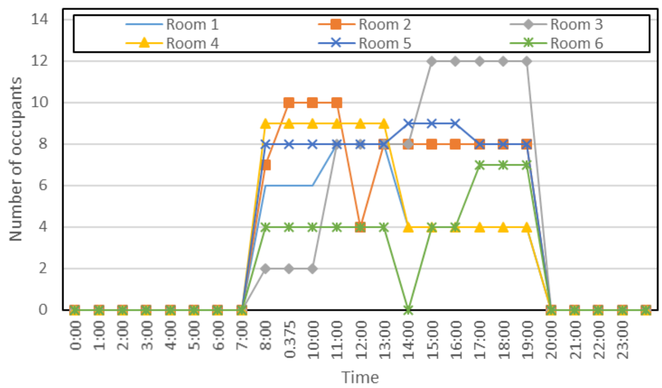

Figure 8. Occupancy profiles in individual rooms

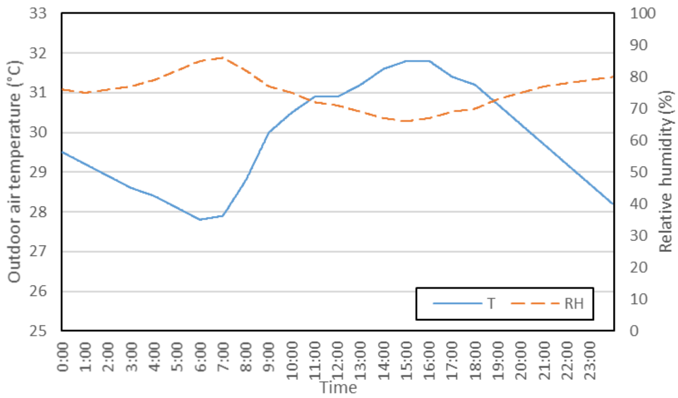

Figure 9. Outdoor air temperature and relative humidity on the test case

3.2. Control strategies used in comparison tests

Five control strategies (i.e. Strategies 1-5) for multi-zone VAV air-conditioning systems are tested and compared. A description of these strategies is given as follows.

Strategy 1 (fixed settings): A simple and classic control strategy for multi-zone VAV air-conditioning systems. No optimization is applied. Based on operational experience, the fresh air ratio of the supply air and temperature set-points of individual rooms are set as fixed values during the operation period. The fresh air ratio of the supply air is set to 0.25, and the temperature set-points of individual rooms are set to 24 °C.

***Strategy 2** (optimization applied to the critical room only)*: Optimization is conducted for determining the fresh air ratio of the supply air and the temperature set-point of the critical room. This strategy conforms to previous studies, in which optimization variables in the multi-zone area are represented by optimization variables of the critical zone only for simplicity. Specifically, temperature set-points of individual rooms are represented by the temperature set-point of the critical room. In summary, there are two optimization variables in the optimization problem, which is solved by an exhaustive method in a centralized manner.

***Strategy 3** (optimization applied to all rooms)*: Optimization is conducted for determining the fresh air ratio of the supply air and temperature set-points of all six rooms. The outputs of this strategy are considered as the "best" in terms of balancing thermal comfort, IAQ and energy use. This is because Strategy 3 considers all the possible optimization variables into optimization. Strategy 3 is used as the benchmark to assess the performance of other control strategies in this study. In summary, there are seven optimization variables in the optimization problem, which is solved by Genetic Algorithm (GA) in a centralized manner.

***Strategy 4** (proposed real-time optimal control method)*: According to the proposed real-time optimal control method (i.e. the temperature set-point reset scheme and the multi-objective optimization scheme), optimization is conducted for determining the fresh air ratio of the supply air and the temperature set-point of the critical room. In this case, there are only two optimization variables in the optimization problem, which is solved by an exhaustive method in a centralized manner.

***Strategy 5** (proposed full strategy):* The full optimal control strategy proposed in this study. It is very similar to Strategy 4, but the optimization problem is instead solved by the multi-agent based distributed optimization scheme. It adopts the exhaustive method and ADMM in a distributed manner.

3.3. TRNSYS-MATLAB co-simulation testbed

To validate the proposed control strategy for multi-zone VAV air-conditioning systems, a TRNSYS-MATLAB co-simulation testbed is constructed as shown in Figure 10. In TRNSYS, six rooms are simulated, with their layout, dimensions and occupancy profiles are shown in Figures 7 and 8. The variation of indoor air temperature and CO_2 concentration level are characterized when the multi-zone VAV air-conditioning system is controlled by optimal solutions determined in MATLAB. The supply air volume of the VAV terminal box in each room is adjustable in the range of 125-417 L/s. The PMV model, steady-state CO_2 model, AHU energy use model and real-time optimizers are programmed on MATLAB. For Strategies 1-4, models are integrated together and formulate an objective function, which is solved by one optimizer in a centralized manner. For Strategy 5, models and the ADMM are used to formulate objective functions for individual agents. Each agent is an optimizer, and they coordinate with each other to solve the overall control objective in a distributed manner. The AHU has the design fan power of 6.32 kW and design ventilation air volume of 3000 l/s. The outputs are the temperature set-point in each room ($T_{set,i}$) and the fresh air ratio of the supply air (f). Simulation time step and optimal control interval are both one minute.

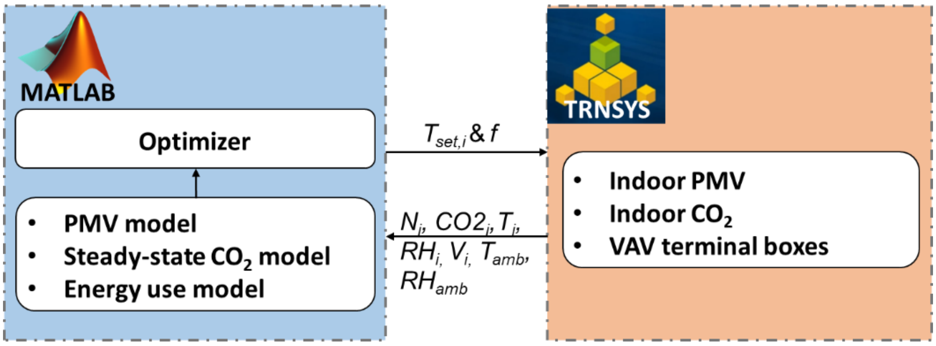

Figure 10. TRNSYS-MATLAB co-simulation testbed

4. Test results and comparison of system performance using different control strategies

This section presents the multi-zone VAV air-conditioning system performance controlled by the proposed real time optimal control strategy adopting a distributed optimization method in the test case, in comparison with that using other four reference control strategies.

4.1. System performance - Thermal comfort

The PMV in individual rooms and the distribution of absolute PMV during the occupied period (i.e. 8:00-18:00) in the test case using different control strategies are shown in Figures 11 and 12. Strategy 3 gave the lowest average absolute PMV among the control strategies, indicating it provided the best performance in maintaining thermal comfort conditions of all rooms close to thermal neutrality. Strategy 2 gave the second highest average absolute PMV, since only the identified critical room with temperature set-point resetting maintained its thermal comfort condition close to the thermal neutrality. The average absolute PMV given by Strategy 4 was between these two strategies (i.e., Strategies 2 and 3). Therefore, in terms of thermal comfort, Strategy 4 (the proposed real-time optimal control method) can be regarded as an improved version of Strategy 2 (optimization applied to the critical room only) as it gives better performance, closer to Strategy 3 (optimization applied to all rooms). The average absolute PMV of Strategy 5 was similar to that given by Strategy 4. The distributed optimization scheme can offer similar performance as that given by the centralized optimization method concerning thermal comfort. Thus the proposed full strategy (Strategy 5) offered satisfactory performance concerning thermal comfort.

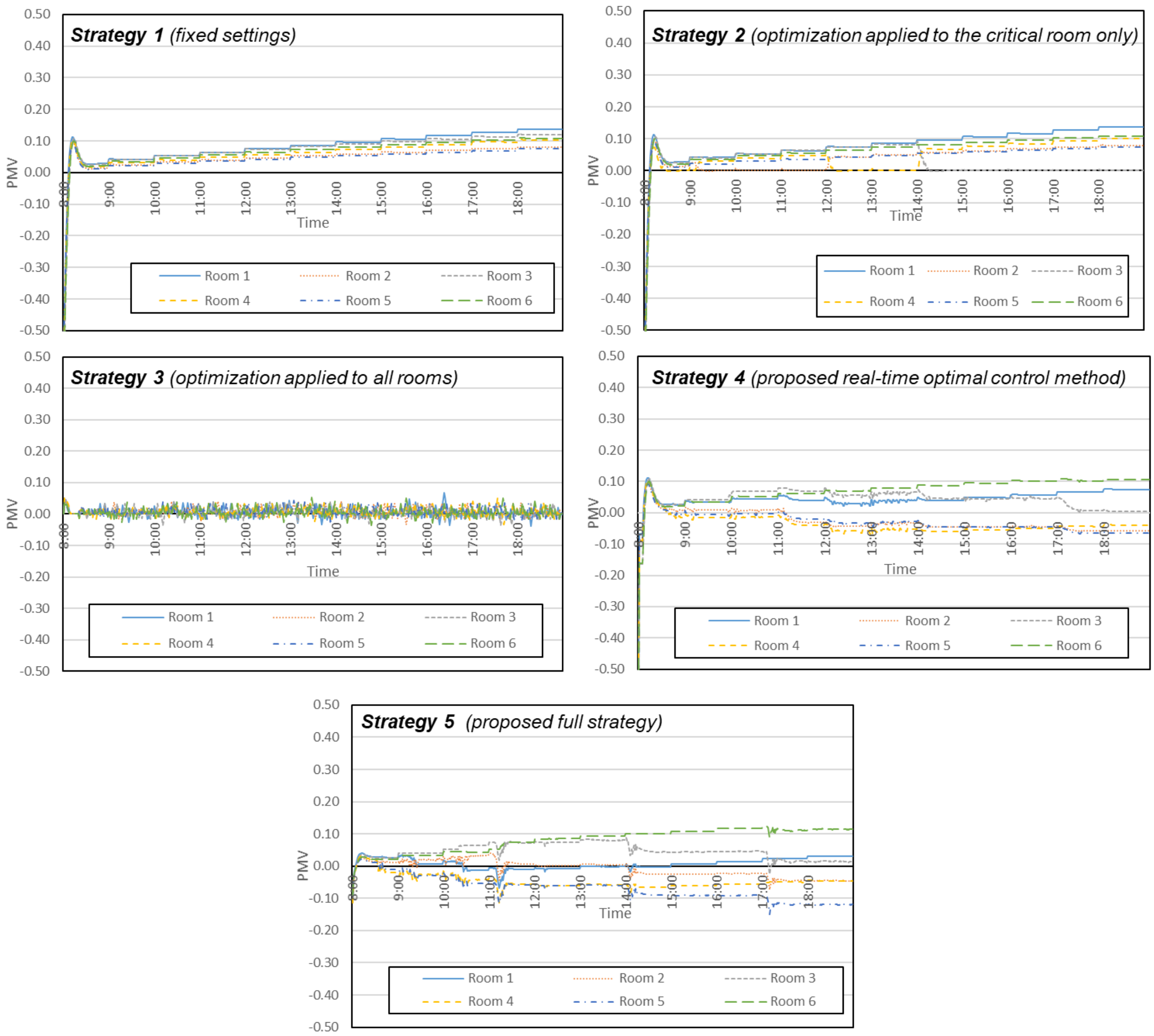

Figure 11. PMV in individual rooms using different control strategies

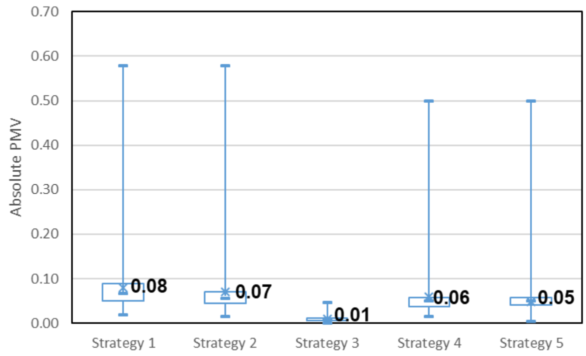

Figure 12. The distribution of absolute PMV during the occupied period (i.e. 8:00-18:00) in the test case using different control strategies

4.2. System performance - Indoor air quality

The CO_2 concentration level in individual rooms and the distribution of CO_2 concentration level during the occupied period (i.e. 8:00-18:00) in the test case using different control strategies are shown in Figures 13 and 14.. According to the Hong Kong indoor environment standard, the low (800 ppm) and high breakpoints (1000 ppm) for indoor CO_2 concentration level are used to differentiate between an 'excellent' CO_2 class and a 'good' CO_2 class [30]. Strategy 3 offered the lowest average CO_2, level at 800 ppm, which reaches the excellent class in the standard. The average CO_2 concentration level given by Strategy 4 was 807 ppm, which was slightly higher than that given by Strategy 3. Thus Strategy 4 (the proposed real-time optimal control method) offered satisfactory performance concerning IAQ, close to the output given by Strategy 3 (optimization applied to all rooms). Strategy 5 also gave an average CO_2 concentration level of 818 ppm, similar to that given by Strategy 4. This shows that the distributed optimization scheme can offer similar performance to the centralized optimization method concerning IAQ. Thus the proposed strategy (Strategy 5) can provide satisfactory IAQ.

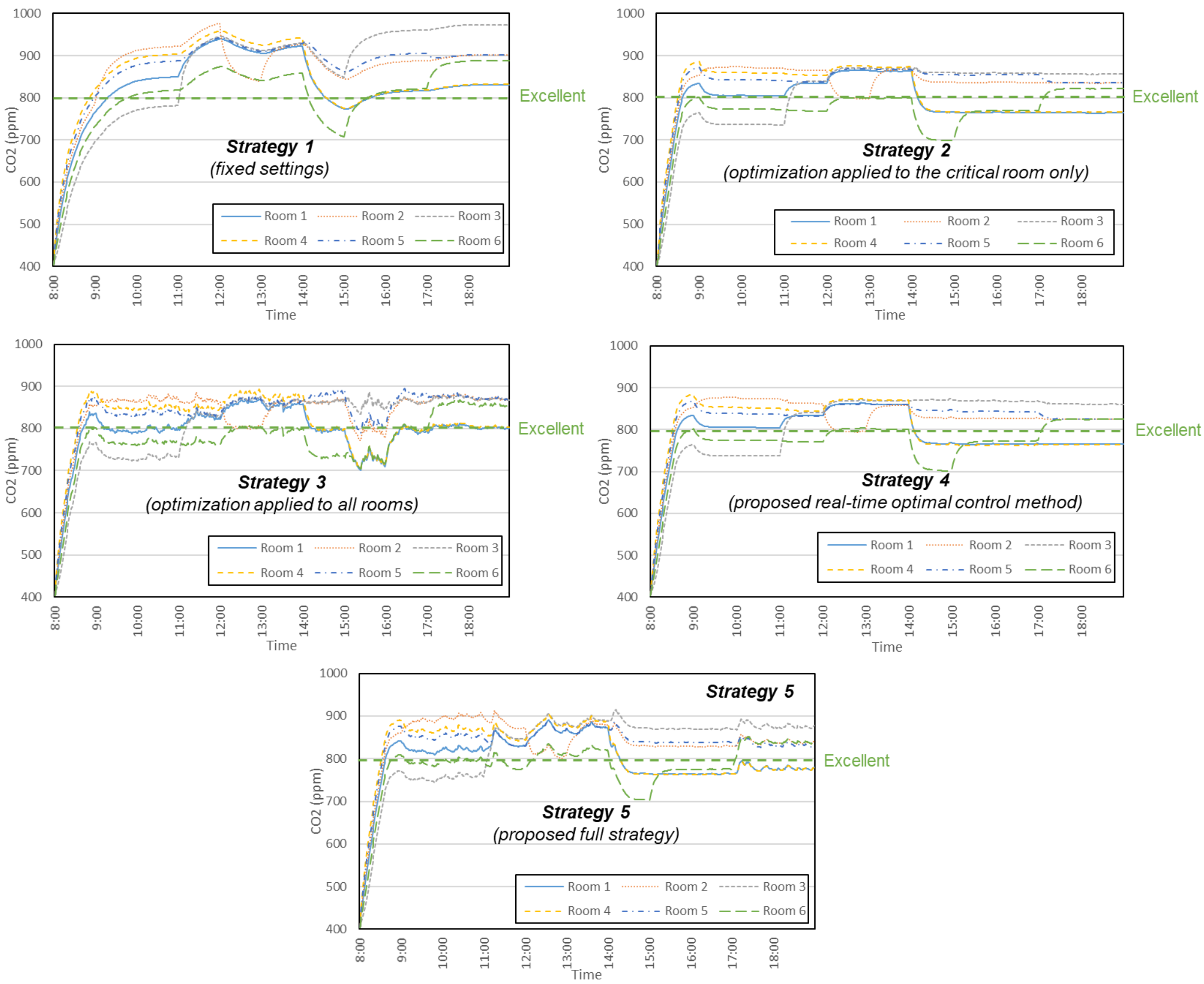

Figure 13. CO_2 concentration level in six rooms using different control strategies

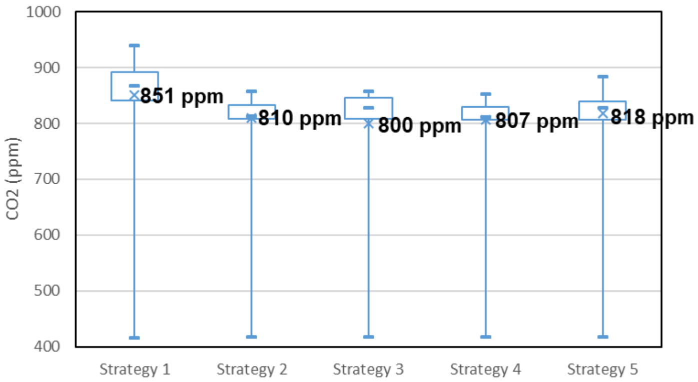

Figure 14. The distribution of CO_2 concentration level during the occupied period (i.e. 8:00-18:00) in the test case using different control strategies

4.3. System performance - Energy use

The energy use of the VAV air-conditioning system using different control strategies is shown in Figure 15. The strategies had similar energy use. Strategy 1 had the lowest energy use among all control strategies, 7% lower than that of Strategy 3. However, the need for proper indoor thermal and IAQ control under dynamic loading conditions is neglected due to the use of fixed set-points. The energy use of Strategy 4 was almost the same as that of Strategy 3. Thus, Strategy 4 (proposed real-time optimal control method) had an acceptable level of energy use, close to the output obtained by Strategy 3 (optimization applied to all rooms). The energy use of Strategy 5 was close to that given by Strategy 4, only 2% higher. This shows that the distributed optimization method can offer similar performance as the centralized optimization method concerning energy use. Thus the proposed strategy (Strategy 5) can offer satisfactory performance concerning energy use.

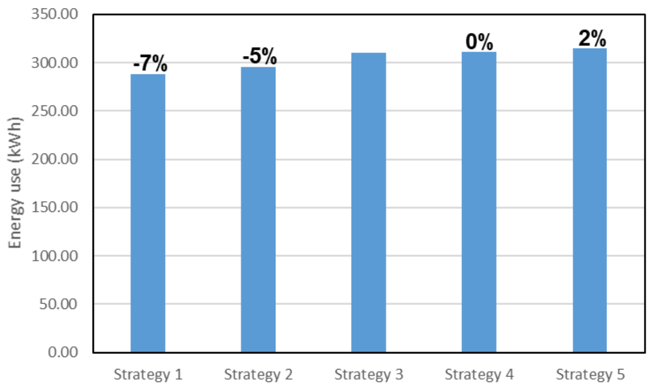

Figure 15. Energy use of VAV air-conditioning system of the test case using different control strategies

4.4. Summary of performance using different control strategies

Strategies 1-3 are current state-of-the-art. Strategy 4 adopts the proposed real-time optimal control method, i.e. the temperature set-point reset scheme and the multi-objective optimization scheme. Strategy 5 is the proposed full strategy, i.e. the real-time optimal control method and the multi-agent based distributed optimization scheme. The advantages of the proposed strategy can be justified through its similar performance with the current state-of-the-art in terms of maintaining thermal comfort and IAQ while minimizing energy use, and more importantly, the additional improvements in reducing the degree of challenge in programming as well as mathematical implementation and unique benefit in deploying the optimization task on local control devices of small capacity in a field control network. The performance of each strategy is summarized as follows.

The performance of Strategy 1 (fixed settings) highly depends on the intuition of building operators. In the test case, it had the lowest energy use at the cost of deteriorated thermal comfort and IAQ. If the temperature set-points of individual rooms and fresh air ratio of the supply air are preset without fully understanding the whole system, system performance may be even worse.

The performance of Strategy 3 (optimization applied to all rooms) was the "best" in terms of a slightly higher energy use but significantly improved thermal comfort and IAQ. However, the implementation of this strategy involves large-scale mathematics programming challenges in solving an optimization problem concerned for a multi-zone VAV air-conditioning system. The computational load is heavy, requiring up to 30 seconds on a PC, as shown in Figure 16, in the test case involving six rooms with a control interval of one minute. This is unaffordable for most buildings in practice, particularly if the VAV air-conditioning system serves more rooms. The strategy also cannot guarantee the global optimum, because as the number of optimization variables increases, the number of combinations increases. In this situation, the value of the objective function corresponding to one set of optimization variables can be close to that of another, and it is therefore not easy to find the global optimum. As shown in Figure 17, the optimized temperature set-points of individual rooms using Strategy 3 fluctuated significantly. The frequent change of control signals can be harmful to stability and shorten the life of the air-conditioning systems.

The performance of Strategy 2 (optimization applied to the critical room only) was worse than that of Strategy 3, since it had a slightly lower energy use but significantly worse thermal comfort and similar IAQ. However, there are no large-scale mathematics programming challenge for solving the optimization problem concerned. The computational load was quite small, at about 2 seconds as shown in Figure 16. The identified optimization variables are also more likely to the global optimum. As shown in Figure 17, the optimized temperature set-points of individual rooms using Strategy 2 was stable for a long period. This is beneficial for the stability and life of the air-conditioning systems.

The performance of Strategy 4 (proposed real-time optimal control method) in terms of balancing thermal comfort, IAQ and energy use was between that of Strategies 2 and 3. The degree of challenge in programming with regards to the optimization problem also lay in between them. The optimization of each individual step took 3 seconds on average as shown in Figure 16. This is slightly higher than Strategy 2, and significantly lower than Strategy 3. The optimized temperature set-points of individual rooms using Strategy 4 also kept stable, as shown in Figure 17. Therefore, Strategy 4 arguably combines the benefits of Strategies 2 and 3. The performance of the new real-time optimal control method in balancing thermal comfort, IAQ and energy use is satisfactory without significant programming challenges. It is worthy noticing that the results are based on a small size problem in buildings, i.e. six rooms. If more rooms are included to form a large size problem, which is a more realistic condition in buildings, the benefits of Strategy 4 can be more significant. As the number of rooms increases, the performance of Strategy 2 in terms of balancing thermal comfort, IAQ and energy use can be far worse than Strategy 4, because the requirements of more non-critical rooms are ignored. The performance of Strategy 3 in terms of degree of challenge in programming can be far worse than Strategy 4, because the combination number of optimization variables increases with exponential rate.

On the basis of Strategy 4, Strategy 5 (proposed full strategy) is further developed by replacing the centralized optimization method with the multi-agent based distributed optimization scheme. The system performance in balancing thermal comfort, IAQ and energy use was very close to Strategies 4 and 5. Meanwhile, as shown in Figure 16, the computational load is further reduced as the optimization for each step took only 1 second, which was even lower than that of Strategy 4 (3 seconds). It is worthy noticing that the computational load of Strategy 5 is estimated by recording the computation time of each agent rather than recording the total computation time of all agents. This simulates the computing time of the multi-agent based distributed optimization method implemented on multiple machines, which can be IoT-based smart devices with a certain computing power. As shown in Figure 17, the optimized solution using Strategy 5 was also relatively stable. Thus, the multi-agent based distributed optimization scheme can be regarded as a very promising alternative for the centralized optimization method. Therefore, adopting the proposed full strategy (Strategy 5) is the preferable means for the real time optimal control of air-conditioning systems, potentially providing an additional, unique benefit if the optimization task is deployed on local control devices of small capacity in a field control network. Before leaving factories, the component agent with specific control objectives can be integrated within local control devices by manufacturers. Thus the multi-agent based distributed optimization method can be setup in a plug-and-play manner.

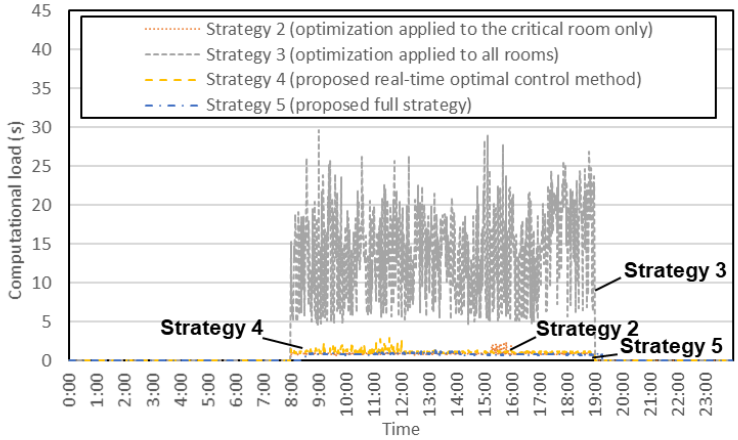

Figure 16. The computational load recorded for different control strategies

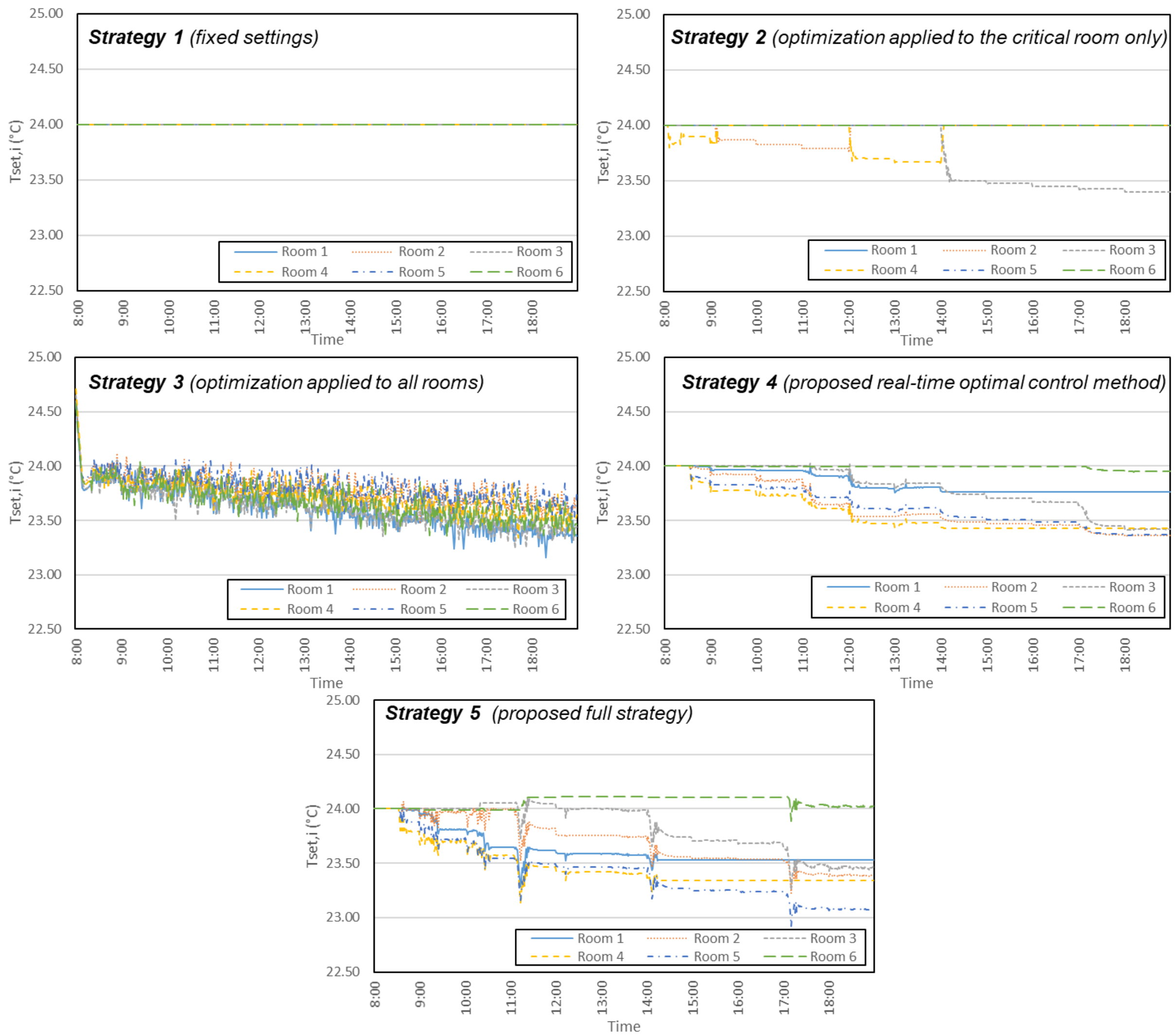

Figure 17. Temperature set-points of VAV terminal boxes in individual rooms using different control strategies

5. Conclusions

A real-time optimal control strategy for multi-zone VAV air-conditioning systems adopting a multi-agent based distributed optimization method is proposed. It consists of three novel schemes, the temperature set-point reset scheme, the multi-objective optimization scheme and the multi-agent based distributed optimization scheme. The temperature set-point reset scheme adopts a linear rule to correlate the resetting of the temperature set-points of individual zones to simplify the optimization problem, but yet to apply proper optimization to individual zones. The multi-objective optimization scheme optimizes the fresh air ratio of the supply air and the temperature set-point in the critical zone by formulating the multi-objective optimization problem, in which thermal comfort, IAQ and energy use are considered simultaneously. The multi-agent distributed optimization scheme is developed to solve the optimization problem in a distributed manner facilitating its deployment on local control devices of limited capacity. A TRNSYS-MATLAB co-simulation testbed is developed and used to test and validate the proposed strategy by comparing with different control strategies. Based on the experience and results of the tests, the conclusions can be summarized as follows:

- The new real-time optimal control method, i.e. the temperature set-point reset scheme and the multi-objective optimization scheme, is effective in finding the proper trade-off between maintaining thermal comfort and IAQ as well as minimizing energy use. By comparing the outputs of Strategy 4 (proposed real-time optimal control method) with that of Strategy 3 (the "best" output obtained by applying optimization to all rooms), Strategy 4 can offer similar energy use (i.e., nearly no difference), slightly higher average absolute PMV (i.e., increased from 0.01 to 0.06) and a similar average CO_2 concentration level (i.e., increased from 800 to 807 ppm).
- The proposed real-time optimal control method, i.e. the temperature set-point reset scheme together with the multi-objective optimization scheme, can alleviate large-scale mathematics programming challenges regarding the computational load and the stability of solutions. The computational load of a single optimization step using Strategy 4 was about 3 seconds, which was about 10 % of that using Strategy 3. The optimization variables determined by Strategy 4 were more stable compared with Strategy 3.
- The accuracy of the optimal solutions given by the proposed distributed optimization scheme is high when compared with that given by the centralized optimization method. Compared with Strategy 4, Strategy 5 (the proposed full strategy, i.e. the proposed real-time optimal control method together with the distributed optimization scheme) has slightly higher energy use (2%

greater), almost the same average absolute PMV (i.e., increased from 0.05 to 0.06) and a slightly higher average CO_2 concentration level (i.e., increased from 807 to 818 ppm).

- The proposed distributed optimization scheme can further reduce programming challenges. The computational load of an optimization step using Strategy 5 was about 1 second only, which was even lower than that of Strategy 4 (3 seconds). The optimized solution given by Strategy 5 was also stable. The distributed optimization scheme also allows for the optimization problem to be deployed and solved on local control devices of small capacity in a field control network.

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NOMENCLATURE

ADMM	The alternating direction method of multipliers
AHU	Air handling unit
BASs	Building automation systems
CO2	Steady-state CO_2 concentration
E	Energy use
F	A matrix indicating the relationship between the local optimization variable and the global optimization variable
HVAC system	Heating, ventilating and air-conditioning system
IAQ	Indoor air quality
IEQ	Indoor environment quality
PMV	Predicted mean vote
VAV	Variable air volume
Obj	Objective function
T_{set}	Temperature set-point
TH_{CO2}	Control threshold of CO_2
X	Local optimization variable vector
Z	Global optimization variable vector
f	Fresh air ratio of the supply air
l	The number of the iteration step
n	Number of zones

Greek letters	
Δ	Modification value
α	Weighting factor
$\boldsymbol{\lambda}$	Lagrange multiplier vector
ρ	Penalty multiplier
Subscripts	
E	Energy use
IAQ	Indoor air quality
T	Total
Th	Thermal comfort
cz	The critical zone
i	The i^{th} zone

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