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An agent-based distributed real-time optimal control strategy for building HVAC systems for applications in the context of future IoT-based smart sensor networks

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HIGHLIGHTS

- An agent-based distributed optimal control strategy for HVAC systems is developed.
- A complex optimization task is decomposed into simple subtasks deployed locally.
- Computation load is distributed over integrated IoT devices of limited capacity.
- A convergence acceleration method is developed to achieve optimization in real-time.
- It facilitates convenient plug-in of models of individual components in optimization.

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ABSTRACT

Existing studies on distributed optimal control of HVAC systems rarely consider the needs and constraints for practical applications and the deployment of control strategies on the physical building automation platforms. This paper proposes an agent-based distributed real-time control strategy for building HVAC systems with the objective to be deployed in the local control devices with limited programming and computation capacities, i.e. smart sensors integrated in future IoT-based field networks and local controllers in field networks of current LAN-based building automation systems. A complex optimization task with high computational complexity (i.e., computation code and computation load) is decomposed into a number of simple tasks, which can be handled by coordinating agents among the integrated local control devices. The computation task of an optimization decision is further distributed into a number of steps, each performed at a sampling interval of controllers. The test results show that the computation loads of all individual agents at each step were below 2000 FLOPs, which can be handled by the typical smart sensors using simple optimization codes and the number of iterations for each optimization decision was within 50, well below the convergence rate needed for optimal control with typical time interval of minutes. The proposed agent-based optimal control strategy is also convenient and effective to deal with multiple components of different performances and the optimization considering such performance deviations could reduce the overall energy consumption significantly.

1. Introduction

HVAC (heating, ventilation and air conditioning) systems for buildings consume huge amounts of energy [1] and therefore many researchers have made serious efforts to develop supervisory or optimal control strategies to improve energy efficiency of HVAC systems [2]. Lu et al. [3] proposed an optimal control strategy based on a modified genetic algorithm to minimize the total energy consumption of a HVAC system. Wang and Ma [4] presented a supervisory control strategy for a complex central chilled water system to improve the energy efficiency. This strategy was constructed for application in real central chilled water systems. Considering the need for control accuracy and computational complexity in practical applications, a hybrid optimization method called performance map and exhaustive search method was proposed to seek the optimal set-points. Wang and Jin [5] proposed a model-based optimal control strategy for VAV air-conditioning system using a genetic algorithm. Multi objectives with different weights were considered in the cost function, including thermal comfort, energy

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Nomenclature

Symbols

a_1-a_3	coefficients
b_1-b_6	coefficients
C	specific heat, kJ/ (kg K)
c_1-c_4	coefficients
Cap	Cooling capacity provided by chillers
COP	coefficient of performance
d_1-d_4	coefficients
f	objective function
g	constraint function
h	objective function of subproblem
M	flow rate, kg/s
N	number
P	power, kW
PLR	part load ratio
Q	hear transfer rate, kW
T	temperature, °C
X	value range
x	control variable

Greek symbols

α, β	step size
ε, δ	threshold value
λ, μ	Lagrange multiplier

Subscripts

a	air
chi	chiller
chws	supply chilled water
cof	coefficient
con	condenser
CT	cooling tower
cw	cooling water
cwo	cooling tower outlet water
des	design
f	frequency
in	inlet
nom	nominal
opt	optimal
out	outlet
rej	rejection
tot	total
wb	wet-bulb

consumption and indoor air quality. The test results of these control strategies show that the system energy efficiency could be improved significantly by adopting appropriate control strategies.

However, the centralized form of these optimal control strategies results in several drawbacks. Firstly, computation of performance prediction and searching optimal set-points of these strategies are performed in one central station, typically a central computer station, since the computation complexities of these supervisory or optimal control strategies are very high, especially for complex building HVAC systems. Secondly, these control strategies lack generality. Such centralized control strategies are designed for specific systems while the HVAC systems are different from each other due to the uniqueness of buildings. Furthermore, in this manner, it will be inconvenient and costly to adjust the centralized control strategies according to different target systems. Distributed control strategies is an effective means to overcome these drawbacks.

Recently, agent-based control for the distributed control of building HVAC systems has drawn increasing attention because of its scalability and modularity [6]. An agent can be defined as a physical or virtual entity which can perceive its environment, take actions to influence the environment according to its goals and tendencies [7]. Multiple agents can be integrated together to form a multi-agent system to achieve a common goal through coordination [8]. A number of studies have developed multi-agent systems for control of building HVAC systems [9]. Most of these studies focus on adjusting the set-points of building services systems including lighting and HVAC systems according to the information collected by agents, such as temperature, humidity [12] and occupant behavior [13], to achieve energy saving while maintaining comfortable indoor environment. Lymperopoulos and Ioannou [14] developed a distributed adaptive control strategy for buildings with multi-zone HVAC systems to realize temperature regulation. Hagras et al. [11] used agents embedded in rooms and offices to detect the presence of occupants and learn their preferences through their behaviors. Klein et al. [10], Yang and Wang [15] and Michailidis et al. [16] proposed multi-agent systems including human/personal agents which can collect information about the occupants' preferences and behaviors as the basis for control of HVAC and lighting systems.

A few researchers have also developed agent-based control strategies to improve the operational efficiency of HVAC systems. Kelly and Bushby [17], Treado [18] did some preliminary work to investigate the benefits and problems of employing intelligent agents to optimize the performance of building HVAC systems. The test results show that it is promising to use agents to optimize the performance of building HVAC systems in a distributed manner. Wang et al. [19] and Cai et al. [20] presented a general structure of the agent-based optimal control strategy for optimal control of HVAC systems. Both chose to decompose the optimization problem at system level into component level. Local optimization of each component is conducted by one corresponding agent and global optimization is achieved through coordinating these agents. Wang et al. [19] developed a model-free strategy based on decentralized evolutionary algorithm to search for the optimal set-points, while Cai et al. [20] chose to construct a model-based control strategy using subgradient or alternating direction multiplier method to solve the optimization problem. These studies propose the means to construct the agent-based optimal control strategies for building HVAC systems. The structure of the multi-agent system, the optimization technique for distributed optimization is provided.

However, these studies did not consider implementation issues and deployment of the agent-based optimal control strategies on physical platforms, especially the computation code and computation load distribution to ensure their feasibility, reliability and efficiency in practical applications. For the current Building Automation Systems (BASs), the agent-based distributed control strategies are preferably deployed over the local controllers connected with LAN-based field networks to realize distributed intelligence in order to enhance the control reliability in practical applications. Programming and computation capacities of these local controllers are limited and if computational complexity of each agent is high, the agent-based control strategies cannot be deployed on such platforms. For the future IoT (Internet of Things) sensor-based field networks or smart sensing networks, these issues need to be considered carefully in particular.

The Internet of Things, also called Internet of Everything, is recognized as one of the most important directions for future technology development and has been attracting vast attention from a wide range of application fields. With the increasing attention on the Internet of Things and the fast development of related technologies, the number of Internet connected devices is expected to exceed 50 billion by 2020 [29]. IoT refers systems of interrelated computing devices, mechanical and digital machines provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction [21,22]. Compared with Internet-based network, which allows communications between human to human and human to things, IoT establishes the communications of things to things [23]. In building automation field, the 'things' can be IoT sensors, smart sensors and local control devices attached to the building system components or spaces, which can perceive the environment, process data and execute control actions [24]. Today, IoT is used as an effective and convenient platform for decision making based on cloud computing or other central computation stations according to the information collected by the IoT devices [25]. A few studies show the realization of energy saving [26], indoor environment control [27], and demand response [28] based on IoT platform.

However, relying on the centralized computation for data processing and decision-making will result in heavy computation load, severe network traffic regarding the rapid increase in the number of IoT devices and therefore reduced control reliability. Implementing distributed intelligence in field-level devices connected within field networks for decision making instead of relying on centralized computation is an effective means to solve this problem. Currently, due to the limitations in computation capacities of IoT devices and inefficiency of communication among devices, it is still critical to realize distributed real-time optimal control based on IoT platform. But it will be practical to deploy the agent-based control strategy or other distributed intelligences in near future IoT platforms with the development of technologies and standards in field-level communication among IoT devices. In such platforms, the IoT or smart sensors and local control devices integrated in field networks should jointly undertake the optimization tasks. Due to the limited computation capacities and programming abilities of IoT devices, the computation load and the programming load of the agent-based control strategies should be considered carefully to ensure the feasibility in practical applications.

Besides, the means and potential advantages of agent-based control strategies used in dealing with same type of components with different performances are not addressed. The performance deviations of different components of the same type is a common issue in optimal control of building HVAC systems. It is very common that the same type of components with different performance are used in the same system and there often exist deviations among the same type components even when they are of the same model, and the deviations usually become larger as the components get older due to uncertain performance degradation and replacement of components. Ignoring the performance deviations could result in biased optimization results and reduced energy efficiency.

Therefore, this paper proposes an agent-based optimal control strategy for building HVAC systems. It considers the actual computation load distribution (both on physical platform and in time scale) and control program deployment on field controllers in current LAN-based field networks and the future IoT sensor-based field networks or smart sensing networks. It also considers the effectiveness of handling multiple components of different performances. A comprehensive case study is conducted to demonstrate the effectiveness and deployment of the proposed agent-based optimal control strategy for control optimization of a central cooling plant with multiple chillers and cooling towers. The computation load of individual agents and the information exchange frequency between smart control devices/sensors are investigated.

2. Proposed agent-based distributed optimal control strategy

2.1. Agent-based control framework and distribution of optimization tasks

Fig. 1 illustrates the decomposition and "physical distribution" of the proposed agent-based optimal control strategy for HVAC systems. A complex optimization task is decomposed into a number of simple tasks, which are handled by their corresponding agents and deployed over the associated local control devices. The control strategy is constructed on the basis of two types of agents, i.e., component agents and coordinator agents. The component agents act as the local optimizers of corresponding components based on the local measurements and information received from other agents. The coordinator agent is designed to coordinate the component agents since the local optimization results may be contradictory with each other due to the conflicts among the components. The information exchange among the agents is facilitated through the field networks.

Fig. 2 illustrates the "time-scale distribution" of computation for optimization by the proposed agent-based optimal control strategy compared with typical process control and conventional centralized optimal control strategies. In a typical process control, a control decision is made at each sampling interval (typically one second or more) because of the need for timely feedback. Computation task of each decision is simple, and can be completed by the local controllers within a short period of time. For typical centralized optimal control strategies, the computation of task for each optimization decision can be much more complex and is usually handled by the central PC stations or central control stations. When making an optimal control decision, the station collects the required data, performs optimization computation

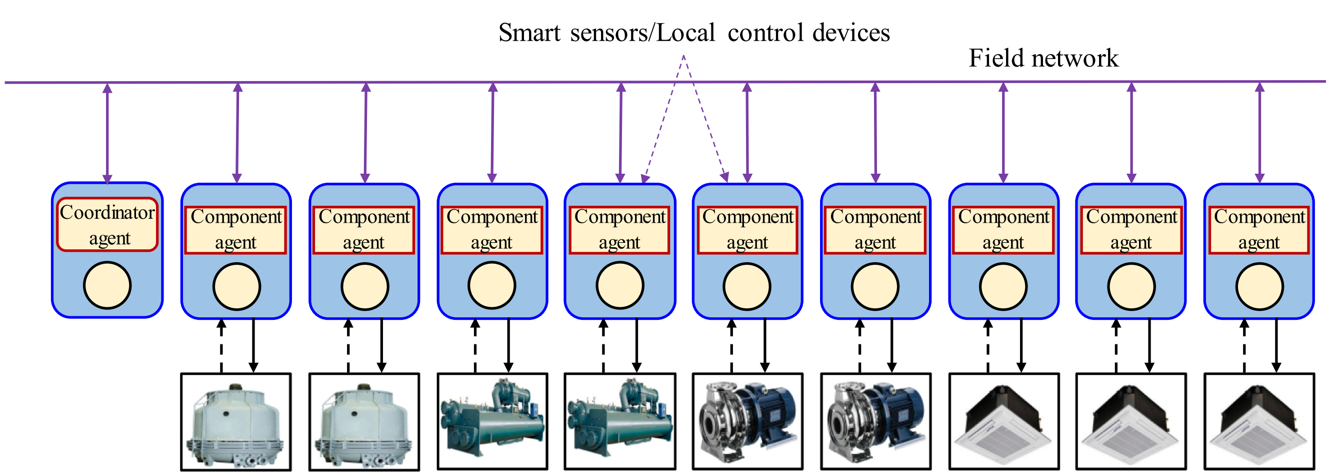

Fig. 1. The framework of the proposed agent-based optimal control strategy deployed in field networks.

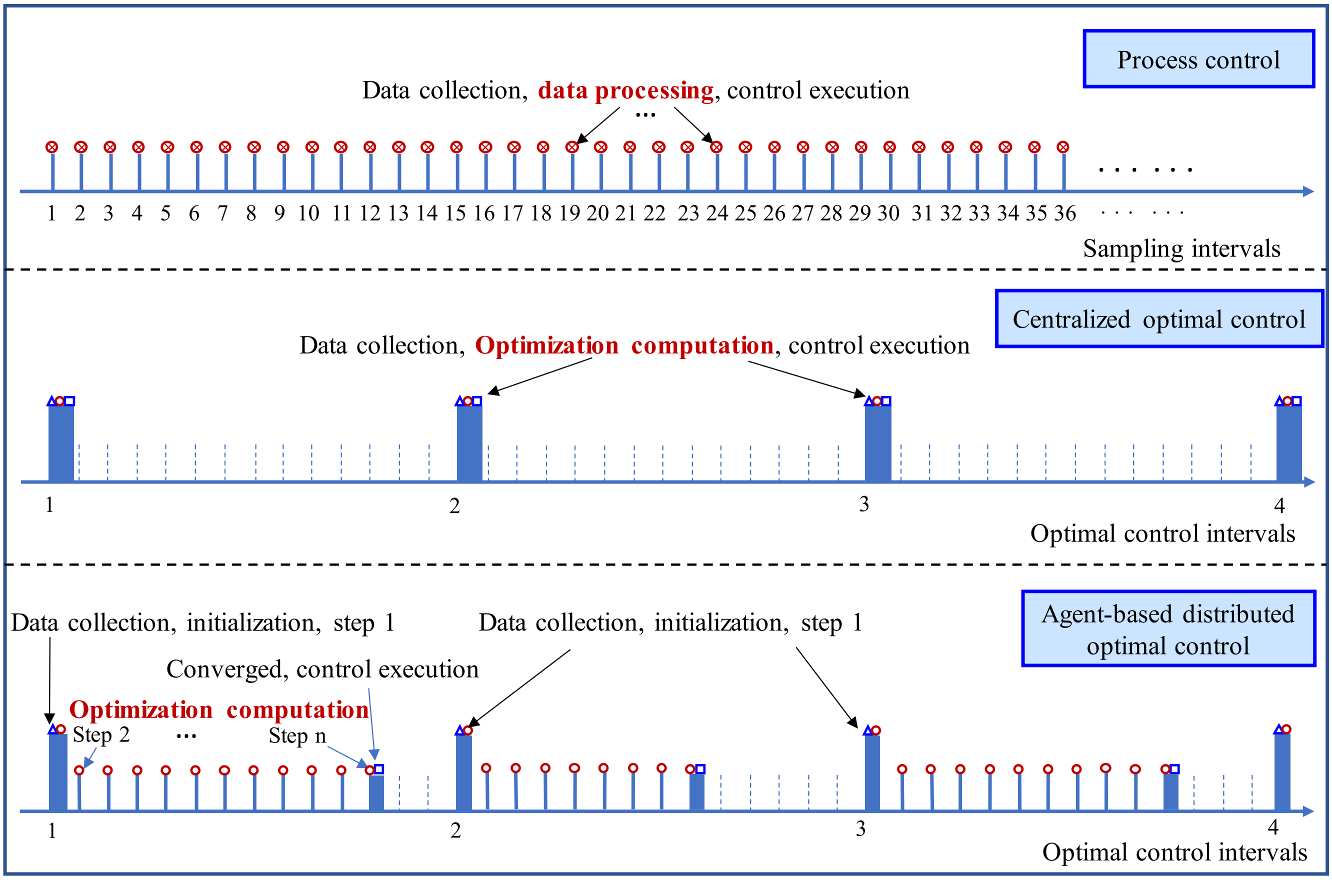

Fig. 2. Distribution of computation loads of different control schemes.

and executes (or sends out) the optimal decision consecutively. The optimal control interval is usually longer (i.e., minutes typically).

For the proposed agent-based optimal control strategy, computation load of an optimization is distributed to a number of steps in the time-scale. At each step, individual agents perform their relatively simple local optimizations/calculations for one iteration of the global optimization. This time interval of the steps is the sampling interval of the controllers. Once the global optimization is converged, the optimal decisions will be executed. In this manner, the proposed agent-based optimal control strategy can handle very complex optimization problems by decomposing them and then executing decomposed simple tasks over a number of steps in time-scale by a number of local control devices with limited computation capacities.

Decomposing the centralized control strategy from system level to component level also improves the generality and flexibility of the control strategy. The configurations of HVAC systems for different buildings are significantly different from each other because of the uniqueness of buildings. However, they are usually constructed using a number of basic and generic components, such as chillers, cooling towers and pumps. Therefore, for the proposed agent-based optimal control strategy, once the coordination mechanism is established, the entire control system can be constructed by simply integrating corresponding component agents in the smart sensors or local control devices. Such a control system can be easily reconfigured according to different configurations of target HVAC systems. The details of these agents are presented in Section 2.3.

2.2. Optimization problem decomposition

In order to realize agent-based control of HVAC systems, a system optimization problem needs to be formulated in a distributed manner instead of the traditional centralized manner. The optimization problem addressed in this study is to find the optimal set-points of control variables to minimize the system's power consumption. Due to coupling constraints among the components, variation in even one control variable usually influences power consumption of the entire system. Two typical control variables are the cooling tower outlet water temperature and the chilled water supply temperature. Increasing the cooling tower outlet water temperature results in reduction of the cooling tower power consumption while the efficiency of chillers decreases. Similarly, a higher chilled water supply temperature leads to lower power consumption by chillers while more chilled water is needed to provide enough cooling power, resulting in greater power consumption in chilled water pumps. Hence, the main issue for decomposing the “big” (global) optimization problem into “smaller” problems (subproblems) at component level is to deal with coupling constraints among the components. In this study, dual decomposition [30], which is suitable for the problem with a coupling constraint, is adopted to decompose the centralized optimization problem.

The centralized form of the optimization problem is expressed as Eq. (1) and the coupling constraints are expressed as Eq. (2). Where $f(\boldsymbol{x})$ represents the power consumption of one component in the system. $\boldsymbol{x}$ is the control variable of the corresponding component. $\boldsymbol{X}_i$ represents the range of values of $\boldsymbol{x}$ determined by constraints of the component.

$$\min_{\{\boldsymbol{x_i} \in \boldsymbol{X_i}\}} \sum_{i=1}^{n} f_i(\boldsymbol{x_i}) \tag{1}$$

$$\text{subjectto: } \sum_{i=1}^{n} \boldsymbol{g_i}(\boldsymbol{x_i}) \le \boldsymbol{b} \tag{2}$$

Based on Lagrange relaxation [31], the problem can be transformed into one without coupling constraint, as shown in Eq. (3).

$$L(\boldsymbol{x_i}, \lambda) = \sum_{i=1}^{n} f_i(\boldsymbol{x_i}) + \lambda^{\mathrm{T}}\left[\sum_{i=1}^{n} \boldsymbol{g_i}(\boldsymbol{x_i}) - \boldsymbol{b}\right] \tag{3}$$

The coupling constraint is added to the objective function as a penalty function, and $\lambda \geq 0$ is the Lagrange multiplier. The dual function is then formed as Eq. (4).

$$\theta(\lambda) = \underset{\{\boldsymbol{x_i} \in \boldsymbol{X_i}\}}{inf}\left\{\sum_{i=1}^{n} f_i(\boldsymbol{x_i}) + \lambda^{\mathrm{T}}\left[\sum_{i=1}^{n} \boldsymbol{g_i}(\boldsymbol{x_i}) - \boldsymbol{b}\right]\right\} \tag{4}$$

Then, the global optimization problem can be decomposed into a number of subproblems and a master/dual problem. Each subproblem deals with the optimization of an individual component with the given λ as expressed in Eq. (5).

$$\underset{\{\boldsymbol{x_i} \in \boldsymbol{X_i}\}}{min} f_i(x_i) + \lambda^{\mathrm{T}} \boldsymbol{g_i}(\boldsymbol{x_i}) \tag{5}$$

The master problem is presented by Eq. (6), which is to find the appropriate λ in order to prove that the optimal solutions of the subproblems obey the coupling constraints. Where, $h_i(\lambda)$ is the dual function obtained as the minimum value of the Lagrangian solved in Eq (5) for a given λ.

$$\underset{\{\lambda:\, \lambda \geq 0\}}{max} h(\lambda) = \sum_{i=1}^{n} h_i(\lambda) - \lambda^{\mathrm{T}} \boldsymbol{b} \tag{6}$$

It is worth noting that there exist certain requirements to guarantee that the results of the dual problems are equal to the original problem [32]. Since it highly depends on the values of the specific parameters in the objective functions, it is not discussed here.

2.3. Formulation of the agent-based optimal control strategy

The agent-based optimal control strategy is constructed by decomposing optimization problems concerned and the component agents are designed to solve the subproblems and the coordinator agent is designed to solve the master problem.

2.3.1. Component agents

As an optimizer of the corresponding component, a component agent consists of three parts: objective function, local constraints and optimization technique. The objective function is shown above (Section 2.2), which consists of power consumption of the component concerned and its corresponding penalty function. Power consumption of a component is predicted by a simplified component model. Local constraints are associated with characteristics of the component and the working conditions. Having the objective function and local constraints, an optimization technique is needed to search for the optimal solutions. Considering the limited programming and computation capacities of smart sensors and local control devices, it is not practical to use a complex optimization method such as the genetic algorithm. In this study, a computationally effective and easily implementable hybrid optimization technique, called PMES (performance map and exhaustive search) which was proposed by Ma and Wang [33], is adopted.

2.3.2. Coordinator agent

The coordinator agent is designed to coordinate the optimization of the component agents to guarantee the satisfaction of coupling constraints. It consists of two parts: convergence checking and parameter updating. The first part is to validate the convergence state of the global optimization through the coupling constraints. According to the optimization results from the component agents, the coordinator agent checks whether these results satisfy the coupling constraints or not, according to the convergence criterion, as shown in Eq. (7).

$$\sum_{i=1}^{n} g\{argmin_{x_i}[j_i(\lambda_k)]\} \leq b + \varepsilon \tag{7}$$

where, $\varepsilon > 0$ is a stopping threshold, the acceptable difference between the optimization results and the coupling constraints. If the criterion is met, it means the global optimization is converged and optimization results are indeed the optimal solutions. If not, the second part is activated to find the appropriate Lagrange multiplier by solving the master problem mentioned above, using a proper optimization technique. A commonly used technique in distributed optimization, the subgradient method [34], is adopted in this study. This method solves the problem by iteration as shown in Eq. (8).

$$\lambda_{k+1} = \lambda_k + \alpha\{\sum_{i=1}^{n} argmin_{x_i}[j_i(\lambda_k)] - b\} \tag{8}$$

where k is the number of iterations, α ($\alpha > 0$) is the step size which should be sufficiently small to ensure that the optimal λ can be found. At each iteration, λ is updated according to Eq. (8) and then sent to the component agents to generate new local optimization solutions.

2.3.3. Formulation of the proposed agent-based optimal control strategy

The proposed agent-based optimal control strategy is formulated by defining all component agents and the coordinator agent. The agent-based optimal control strategy obtains optimal results through coordinating these agents. At each iteration, the component agents first perform local optimizations with given initial λ and send the solutions to the coordinator agent. Then, the coordinator agent checks whether the convergence is reached or not. If not, the value of λ is updated and then sent to the component agents. This process is repeated until convergence is reached. The optimization tasks of each step mentioned in Section 2.1 are actually tasks of one iteration (Table 1). In addition, the complete process of the agent-based optimal control strategy includes the "initialization" at the first step and "control execution" at the last step as summarized in Table 1.

For practical implementation of the agent-based optimal control strategy in smart sensors or local control devices, computation complexity (i.e., computation code and computation load) of each agent and the number of iterations for one optimization need to be considered to guarantee the feasibility and reliability of the control strategy in actual implementation. The computation complexities of component agents can be reduced by using simplified component models, simple and effective optimization algorithm and reasonably small search ranges. Since the coupling components may have different requirements on the same control variables, the search range of the control variables can be limited by combining the local constraints in different

Table 1
The process of optimization of the agent-based optimal control strategy.

	Task
Initialization	The coordinator agent sends the λ_k^* which is the optimal solution from last optimization and the search range to component agents according to the collected data.
Iteration	(1). All component agents solve the local optimization problems with given λ_k^* and send optimization solutions $argmin_{x_i}[h_i(\lambda_k^*)]$ to the coordinator agent.
	(2). The coordinator agent updates the λ according to Eq. (8), and sends λ_{k+1} to component agents.
	(3). Repeat (1) and (2) until the convergence criteria Eq. (7) is satisfied.
Control execution	Component agents send control signals to corresponding components.

component agents. This should be done at the beginning of the optimization by the coordinator agent after collecting the local constraints provided by the component agents. There exists a maximum number of iterations for one optimization because of the expectation on the optimization interval and the limitation of sampling interval of the smart sensors or local control devices. Each iteration requires an update or data exchange between agents over the field networks. One second is a typical sampling interval for local control devices in current building automation systems. Considering that optimization interval for HVAC systems is typically at the scale of a minute, the upper limit of the number of iterations could be at the scale of hundred. For a given set of working conditions, the number of iterations needed is determined by the initial value of λ and the step size. Since the working conditions normally do not change significantly between two consecutive optimization intervals, using the λ, which leads to the convergence of the last optimization as the initial λ for current optimization, is a common method to reduce the number of iterations needed at each step. Finally, in case optimization results cannot be achieved within the upper limit of the number of iterations for an optimization decision, the component agents should prepare near-optimal solutions by adopting standby simple schemes.

It is worth noting that what is described here is the generic form of the agent-based optimal control strategy. For specific optimization problems, it needs to be customized or modified accordingly, to maximize the control performance.

3. Formulation of the agent-based optimal control strategy for a central cooling system considering performance deviation

To test the applicability of the proposed agent-based optimal control strategy and evaluate its performance in practical applications, a virtual central cooling system, which is constructed referring the actual system of the tallest building (i.e., ICC) located in Kowloon Station, is used for online tests. Deviation of performance among the components, a common phenomenon often ignored in existing centralized control strategies, is considered in the optimization strategy proposed by this study. The proposed agent-based optimal control strategy performs optimization in two stages. At the first stage, the optimal cooling tower outlet water temperature from towers is determined in order to minimize the total energy consumption of the central cooling system through coordinating cooling tower agents and chiller agents. At the second stage, temperature set-points for individual cooling towers are determined to minimize the total cooling towers energy consumption through coordinating the cooling tower agents.

3.1. Description of the central cooling system

A typical central cooling system (Fig. 3) is used for validation tests, which consists of three centrifugal chillers, three constant speed cooling water pumps and six cooling towers. Each chiller has a cooling capacity of 7235 kW with a COP of 5.6 at the rated working conditions, i.e., at the chilled water supply temperature of 5.5 °C, chilled water return temperature of 10.5 °C and condenser inlet temperature of 32 °C. The rated water flow rate and power load of the condenser cooling water pumps are 410.6L/s and 185 kW each, respectively. The nominal heat rejection capacity and power consumption of the six cooling towers are 5234 kW and 155 kW each, respectively. It is common that different types and sizes of components are used in the same cooling system and the performances of these components are largely different. Even if the nominal parameters of the same kind of components are the same, due to the unpredictable performance degradation or replacement, there are performance deviations among the components. In this study, the performance degradation of the cooling tower heat transfer efficiency is considered. For these six cooling towers, the first cooling tower is

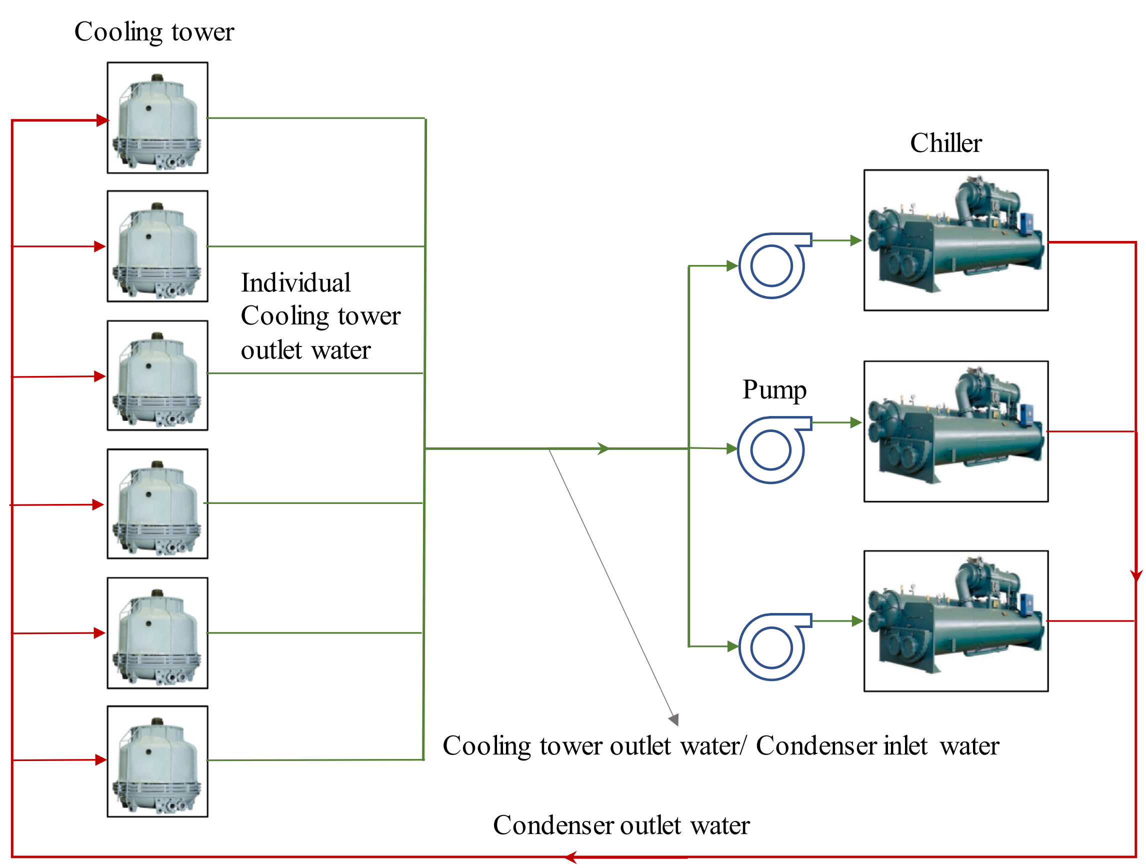

Fig. 3. Schematic of the central cooling system concerned.

assumed to be a new cooling tower with rated efficiency, and different degrees of performance degradation are assumed for the other five cooling towers. The heat transfer efficiencies of these five cooling towers are 95.3%, 89.1%, 84.5% 77.6% and 74.6% of the rated efficiency, respectively.

3.2. Optimization problem formulation and decomposition

3.2.1. The original centralized optimization problem

Cooling towers are responsible for rejecting the heat in the cooling water from chillers and regenerating cooling water at a lower temperature for chillers. For the central cooling system, the main control variable concerned in this study is the outlet water temperature from cooling towers. A lower temperature set-point results in more energy consumption by cooling towers and lower energy consumption by chillers, and vice versa. It is worth noting that the outlet water from cooling towers is mixed and then delivered to chillers. The objective of the traditional supervisory control strategy is to determine the optimal set-point of cooling tower outlet water temperature, i.e., condenser inlet water temperature, in order to minimize the total energy consumption of chillers and cooling towers. All cooling towers are assigned the same set-point. This is based on the assumption that the performance of all cooling towers in the system is almost the same.

Deviations between performances of cooling towers affect the optimal cooling tower outlet water temperature. Besides, it is obvious that for the same cooling tower outlet water temperature, assigning different set-points to different cooling towers according to the performance can achieve more energy saving compared with a single unified set-point. Hence, control variables of the supervisory control strategy that consider performance deviation are the individual cooling tower outlet water temperatures for the operating cooling towers. The optimization objective function can be then expressed as Eq. (9). Where, $P_{chi,j}$ and $P_{CT,i}$ are the functions of chiller power consumption and cooling tower power consumption, respectively. The formula of the two functions are shown in Section 3.3. There exist several constraints, i.e, Eqs (10–13), which mainly come from energy and mass balances as well as operational limitations of the cooling towers. The heat rejection by the cooling towers can be assumed to be equal to the sum of cooling load and power consumption of chiller compressors as shown in Eq. (10). The fan frequency of each cooling tower is bounded between 20 HZ and 50 HZ. Another constraint is lower bound of cooling tower outlet water temperature, which is 18 °C due to operational constraint of chillers, shown as Eq. (11). Since the cooling tower outlet water is delivered directly to the condenser inlets of chillers, and assuming the heat/cold loss in the pipelines and pump heat gain are ignored. The coupling constraint between the chillers and cooling towers is the cooling water temperature equals to the chiller condenser inlet water temperature, shown as Eq. (12). Another coupling constraint is the energy balance constraint, shown as Eq. (13). Where, M_{cw} is the mass flow rate of the cooling water and C is the specific heat.

$$\min_{\{Tcwoi\}} P_{tot} = \sum_{j=1}^{N_{chi}} P_{chi,j} + \sum_{i=1}^{N_{CT}} P_{CT,i} \tag{9}$$

Subject to: $\sum_{i=1}^{N_{CT}} Q_{CT,i} = Q_{load} + \sum_{j=1}^{N_{chi}} P_{chi,j}$ (10)

$$max(18,\ T_{cwoi,f=50HZ}) \le T_{cwoi} \le max(18,\ T_{cwoi,f=20HZ}) \tag{11}$$

$$T_{con,in} = T_{cwo} = \frac{1}{N_{CT}} \sum_{i=1}^{N_{CT}} T_{cwoi} \tag{12}$$

$$CM_{cw}(T_{con,out} - T_{con,in}) = CM_{cw}(T_{con,out} - T_{cwo}) = \sum_{i=1}^{N_{CT}} CM_{cwi}(T_{con,out} - T_{cwoi}) \tag{13}$$

3.2.2. Optimization problem decomposition

Adopting dual decomposition, the optimization problem can be formulated in a distributed manner. At the first stage, the objective is to achieve the optimal cooling tower outlet temperature (T_{cwo}), which equals to the condenser inlet water temperature ($T_{con,in}$). The sub-problems are expressed by Eqs. (14) and (15) and the master problem is presented by Eq. (16).

$$\underset{\{T_{con,in}\}}{Min} \sum_{j=1}^{N_{chi}} [P_{chi,j} - \lambda \bullet CM_{cwj}(T_{con,out} - T_{con,in})] \tag{14}$$

$$\underset{\{T_{cwoi}\}}{Min} \sum_{i=1}^{N_{CT}} [P_{CT,i} + \lambda \bullet CM_{cwi}(T_{con,out} - T_{cwoi})] \tag{15}$$

$$\lambda \bullet (T_{cwo} - T_{con,in}) = 0 \tag{16}$$

By solving these problems, the optimal cooling tower outlet water temperature (T_{cwo}) can be achieved. The second stage optimization is then conducted to find the individual optimal set-points for cooling towers in operation. The objective of the second stage optimization is to minimize the total power consumption of cooling towers while ensuring the outlet cooling water is at the optimal temperature. Eq. (17) represents the sub-problems and Eq. (18) represents the master problem.

$$\underset{\{T_{cwoi}\}}{Min} \sum_{i=1}^{N_{CT}} [P_{CT,i} + \mu \bullet CM_{cwi}(T_{con,out} - T_{cwo,i})] \tag{17}$$

$$\mu \bullet \left(T_{cwo,opt} - \frac{1}{N_{CT}} \sum_{i=1}^{N_{CT}} T_{cwoi} \right) = 0 \tag{18}$$

3.3. Agent definition

After decomposing the optimization problem, the agent-based optimal control strategy for the optimal control of the central cooling system can be constructed. The cooling tower agents, chiller agents and coordinator agent are designed to solve the sub-problems and the master problems. The optimization process of the two-stage optimization is the same as described above. After completing the first stage, the coordinator agent sends a new Lagrange multiplier μ and switches to the new convergence criteria and the new function for updating μ. Details of the agents in this control strategy are given below.

3.3.1. Chiller agent

The objective function of each chiller agent is shown as Eq. (19).

$$\underset{\{T_{con,in}\}}{Min} [P_{chi,j} + \lambda \bullet CM_{cwj}(T_{con,out} - T_{con,in})] \tag{19}$$

Where, $P_{chi,j}$ is the power consumption of chiller and it can be predicted by the simplified chiller model proposed by Stoecker [35]. Three main factors which influence the performance of chillers are considered: chilled water supply temperature (T_{chws}), condenser inlet cooling water temperature ($T_{\mathrm{con,in}}$) and part load ratio. As shown in Eq. (20), the impact of part load ratio is represented by the part load ratio coefficient (PLR_{cof}) and the impacts of T_{chws} and $T_{\mathrm{con,in}}$ are represented by a temperature coefficient ($Temp_{\mathrm{cof}}$). Eqs. (21) and (22) show the calculation of PLR_{cof} and $Temp_{\mathrm{cof}}$.

$$P_{chi} = Cap_{nom} \bullet COP_{nom} \bullet PLR_{cof} \bullet Temp_{cof} \tag{20}$$

$$PLR_{cof} = a_1 + a_2\left(\frac{Cap}{Cap_{nom}}\right) + a_3\left(\frac{Cap}{Cap_{nom}}\right)^2 \tag{21}$$

$$Temp_{cof} = b_1 + b_2 T_{chws} + b_3 T_{chws}^2 + b_4 T_{con,in} + b_5 T_{con,in}^2 + b_6 T_{chws} T_{con,in} \tag{22}$$

The parameters $a_1 - a_3$, $b_1 - b_6$ can be obtained from manufacturer or by curve-fitting using operations data. The local constraint is the cooling tower outlet water temperature should not be lower than 18 °C.

3.3.2. Cooling tower agent

The objective function of each cooling tower agent is shown as Eq. (23):

$$\underset{\{T_{cwoi}\}}{Min}[P_{CT,i} - \lambda \bullet CM_{cwi}(T_{con,out} - T_{cwoi})] \tag{23}$$

It is worth noting that, although the Lagrange multipliers of the penalty function in the two stages are different, the forms of the objective functions of the cooling tower agents are the same. Where, power consumption ($P_{CT,i}$) of the cooling tower fan can be calculated using Eq. (24).

$$P_{CT} = P_{CT,des}\left[d_1 + d_2\left(\frac{M_a}{M_{a,des}}\right) + d_3\left(\frac{M_a}{M_{a,des}}\right)^2 + d_4\left(\frac{M_a}{M_{a,des}}\right)^3\right] \tag{24}$$

To characterize the performance of cooling towers, the total heat transfer and power consumption need to be calculated. The total heat rejection can be calculated using the inlet air mass flow (M_a), return cooling water mass flow (M_w) and the temperature difference between the return cooling water and inlet air wet-bulb temperature. Wang and Ma [33] proposed a simplified method to calculate the heat transfer from the cooling water to the inlet air as shown in Eq. (25).

$$Q_{recj} = c_1 \bullet M_a^{c2} \bullet M_{cw}^{c3} \bullet (T_{con,out} - T_{wb})^{c4} \tag{25}$$

The parameters $c_1 - c_4$, $d_1 - d_4$ can be obtained from manufacture or by curve-fitting using operations data as well. In this study, $c_1 - c_4$ of the six cooling towers are obtained from curve-fitting based on the operations data of the cooling towers with different heat transfer efficiencies.

The cooling towers are also subject to the local constraint as shown in Eq. (26).

$$T_{cwoi,f=50HZ} \le T_{cwoi} \le T_{cwoi,f=20HZ} \tag{26}$$

3.3.3. Coordinator agent

Since master problems at the two stages are different, the convergence criteria and iteration functions for updating Lagrange multipliers at the two stages should be different. As aforementioned, the convergence criterion is used to check whether the coupling constraint is satisfied. According to coupling constraints at the two stages, the convergence state can be determined by Eqs. (27) and (28) respectively.

$$|T_{cwo} - T_{con,in}| < \varepsilon \tag{27}$$

$$\left|\frac{1}{N_{CT}}\sum_{i=1}^{N_{CT}} T_{cwoi} - T_{cwo,opt}\right| < \delta \tag{28}$$

Considering the accuracy of measurements, 0.05 °C is adopted as the threshold of the two optimizations. Adopting the subgradient method, Lagrange multipliers of the two stages can be updated through Eqs. (29) and (30) separately.

$$\lambda_{k+1} = \lambda_k + \alpha \bullet CM_{cw}(T_{cwo} - T_{con,in}) \tag{29}$$

$$\mu_{k+1} = \mu_k + \beta \bullet CM_{cw}\left(\frac{1}{N_{CT}}\sum_{i=1}^{N_{CT}} T_{cwoi} - T_{cwo,opt}\right) \tag{30}$$

Where α and β are the step sizes which can change the value of the penalty function, and their values significantly influence convergence of the entire optimization process. Through analyzing the objective function, the approximate searching range can be found, and the final value of the step size can be achieved by trial and error. The values of α and β are 3.5×10^{-8} and 5.0×10^{7} respectively in this study.

4. Test results and performance evaluation of the proposed control strategy

The optimization accuracy and computation load/efficiency of each agent and the entire control strategy are tested and analyzed to evaluate the feasibility, efficiency and reliability of the proposed agent-based optimal control strategy. Optimization accuracy indicates the ability of the strategy to find the optimal set-points for the components in order to minimize the system power consumption. This is a common criterion for evaluation of the control strategies. Considering the deployment of the agent-based optimal control strategy on the physical automation platforms, the computation load of individual agent needs to be considered since computation capacities of smart sensors and local control devices are limited. The optimization efficiency of the entire control strategy, indicated by the number of required iterations, is the other key issue concerning the ability of physical automation platforms for deployment of the distributed optimal control strategy. As aforementioned, since the sampling interval of the smart sensors/local control devices in BASs can be one second typically and assuming an optimization interval of five minutes, the number of iterations for each optimization should be obviously or surely less than three hundred. In order to improve the reliability of the control strategy, a method which can accelerate convergence of optimization by properly resetting the initial value of the Lagrange multiplier is proposed for this study. Moreover, energy performance of the agent-based optimal control strategy is evaluated by comparing it with other two control strategies applied in the same central cooling system for buildings. The building central cooling system is constructed in TRNSYS platform using detailed dynamic models to simulate the realistic performance of the system.

4.1. Control accuracy

To evaluate the accuracy of the proposed agent-based optimal control strategy, a centralized control strategy using Genetic Algorithm (GA) is constructed for comparison. Since the models and search range significantly influence the optimization results, the same simplified models and the same search range of the control variables are used for the two control strategies. Three typical working conditions of the central cooling system are selected to test the performance of the two control strategies: spring, mild-summer and sunny-summer.

Tables 2 and 3 show details of the selected working conditions and the corresponding optimization test results of the two control strategies. It can be seen that the total power consumption of cooling towers and chillers was almost the same under the two control strategies, which means that the proposed distributed control strategy is able to find the optimal cooling tower outlet water temperature set-point as the GA-based centralized control strategy. Moreover, the outlet water temperature set-points assigned to different cooling towers by the two control strategies were also similar. This indicates that the proposed agent-based optimal control strategy can achieve the optimal temperature set-points for individual cooling towers successfully, according to their respective performances.

Table 2
Test conditions of three typical days.

Seasons	*Spring*	*Mild-summer*	*Sunny-summer*
Load (kW)	4784.19	13914.80	17828.06
N_{ch}	1	2	3
N_{ct}	2	4	6
T_{db}(°C)	21.43	30.98	31.78
T_{wb}(°C)	18.62	25.20	26.90
M_{cw}(L/s)	410.60	821.20	1231.80

Table 3
Test results and comparison of two control strategies.

Optimization results	Spring		Mild-summer		Sunny-summer	
	Agent-based control	*GA-based control*	*Agent-based control*	*GA-based control*	*Agent-based control*	*GA-based control*
P_{ch}(kW)	861.18	861.17	2572.40	2572.88	3684.42	3689.11
P_{ct}(kW)	30.11	30.12	114.14	113.65	162.33	157.59
$P_{ch} + P_{ct}$(kW)	891.29	891.29	2686.54	2686.53	3846.75	3846.71
T_{cwo}(°C)	24.52	24.52	32.94	32.94	35.61	35.67
T_{cwo1}(°C)	24.42	24.42	31.93	32.01	34.02	34.10
T_{cwo2}(°C)	24.62	24.62	32.73	32.72	34.82	34.88
T_{cwo3}(°C)	–	–	33.33	33.31	35.42	35.52
T_{cwo4}(°C)	–	–	33.73	33.73	35.92	35.98
T_{cwo5}(°C)	–	–	–	–	36.32	36.42
T_{cwo6}(°C)	–	–	–	–	37.12	37.12

4.2. Computation complexity and optimization efficiency

To evaluate the computational effectiveness (i.e., feasibility, efficiency and reliability) of the agent-based optimal control strategy deployed in field control networks, computation loads of individual agents and the number of iterations for each optimization decision are assessed. For one optimization decision, a number of iterations are needed to achieve convergence. At each iteration (also a step of optimization computation in this study), each agent conducts its local optimization according to the information received at the current step and update its optimization outputs which to be used by other agents.

For assessing computation loads of individual agents, the floating-point operations (FLOPs) are counted and used as a performance indicator of the strategy. For cooling tower and chiller agents, computation loads are affected by the models and the search ranges of the control variables. The search ranges of the first stage optimization in the tests are set as 4 K, which is ± 2 K around the current set-point of the cooling tower outlet water temperature. At the second stage to optimize set-points of the outlet water temperatures for individual cooling towers, the search ranges for the cooling tower agents are also set as 4 K, but they are ± 2 K around the current cooling tower outlet water temperature set-point achieved at the first stage optimization. Results of computation loads are shown in Table 4. For cooling tower agents at each step, the numbers of FLOPs for the optimization of each agent were 945 at the both the stages Optimization of the chiller agents is activated at the first stage only. The number of FLOPs of each chiller agent was 1150 at each step. For the coordinator agent, the computation load was much smaller at each step, i.e., 19 FLOPs only. The CPU speed of a typical microcontroller used currently in smart sensors can be 16 MIPS (million instructions executed per second). Usually, each floating-point operation needs to execute different numbers of instructions and is not larger than 100. Hence, typical smart sensors today can handle about 160,000 FLOPs per second, which is enough for local optimizations of the proposed strategy. For comparison, the computation load of the global optimization at the test working condition using GA is 252,286,555 FLOPs for each optimization decision. A typical smart sensor takes about 26 min even if it is used to conduct the proposed optimization only. Such a long time requirement makes it impossible for smart sensors to be used for real-time optimal control in the context of concerning computation speed alone.

The number of iterations required for optimization of the proposed agent-based optimal control strategy in dynamic working conditions over a year is also tested. During the test, the Lagrange multiplier which leads to convergence of the optimization in the previous time interval is used as the initial value of the current optimization. This can accelerate convergence of the current optimization since the working conditions of two consecutive optimization intervals usually does not change significantly. Fig. 4 shows the number of iterations of both stages for each optimization under dynamic working conditions over a year. It can be found that, except the first optimization trial, all optimizations were completed within 250 steps. This indicates that using the agent-based optimal control strategy, the agents can complete optimization for the central cooling system within five minutes in all working conditions tested. The distribution of the number of iterations needed for optimization at both stages are shown in Table 5. It can be seen that all optimizations at the second stage converged within 50 steps, mainly due to the fact that the performance deviations among the cooling towers change very slowly. More iterations were needed for the optimization at the first stage in some periods due to working conditions and large changes of condition variables, such as cooling load, wet-bulb temperature and dry-bulb temperature. Considering that the changes in working conditions in the real applications could be more complex, more steps might be needed to achieve convergence in some cases in reality. Moreover, if the agents are deployed in the smart sensors or local controllers in today's field network, the delays of communication might also result in that a larger sampling interval has to be used and therefore longer time is needed for convergence of optimization at each optimal control interval. Therefore, more efforts should be made to reduce the number of iterations required for the first stage optimization to improve the efficiency and reliability of the proposed control strategy in real applications.

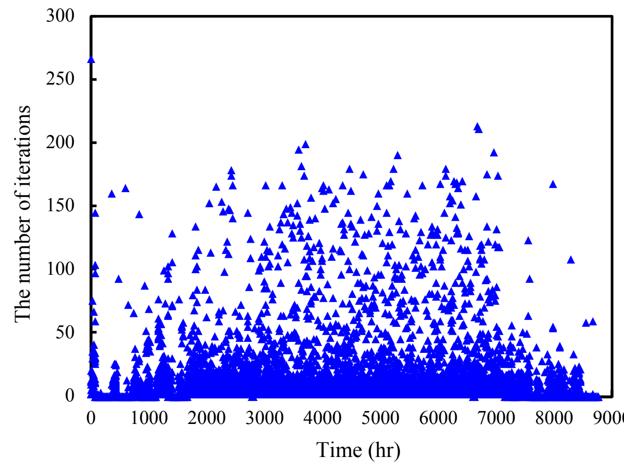

Fig. 4. The number of iterations for optimizations in the test year.

According to the convergence criterion of the first stage optimization, i.e., Eq. (27), convergence of the optimization is determined by the difference between the local optimization outputs of the chiller agents and those of cooling tower agents. By analyzing the variation of their local optimization outputs with the change of the Lagrange multiplier λ, a more effective method which is named convergence acceleration method, is developed in this study for reducing the number of iterations needed. At the first step of each optimization, the convergence

Table 4
The number of FLOPs of the agents at each iteration.

	Cooling tower agent	Chiller agent	Coordinator agent
Stage 1	945	1150	19
Stage 2	945	–	19

Table 5
The distribution of the of iteration numbers for the optimizations in the test year.

Range of iteration number		1–50	51–100	101–150	151–200	201–300
Accumulated number of cases	Stage 1	8371	266	133	43	1
	Stage 2	8760	0	0	0	0

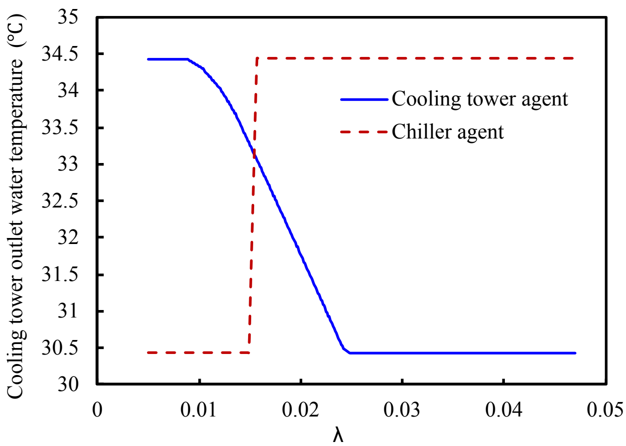

Fig. 5. Evolutions of the optimization results of chiller and cooling tower agents.

acceleration method recalculates the initial value of λ (a convergence acceleration λ, represented by $\lambda_{b,chi}$), which allows the local optimization outputs of the chiller agents equal to the boundary value of the current search range. Fig. 5 shows the evolution of local optimization outputs of the chiller agents and of cooling tower agents. It can be seen that local optimization outputs are bounded within the search range. Using the update function of the Lagrange multiplier (i.e., Eq. (29)), λ is updated according to the difference between the local optimization outputs of the chiller agents and of cooling tower agents. A key issue for reducing the number of iterations needed for optimization is to avoid the λ staying in the range where the local optimization outputs of the agents stabilize. In this case, local optimization outputs of the chiller

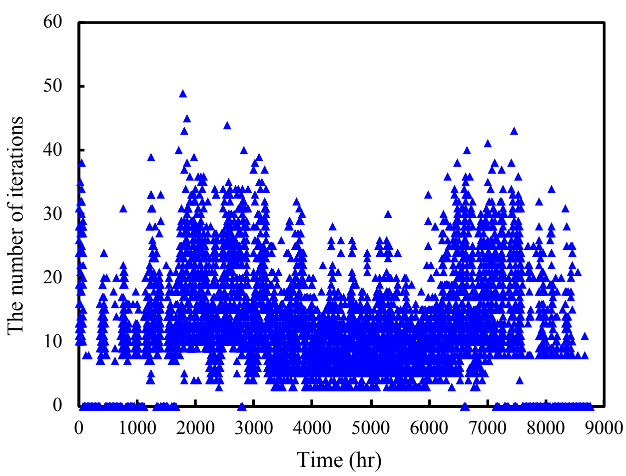

Fig. 6. The number of iterations needed for optimizations using the convergence acceleration method.

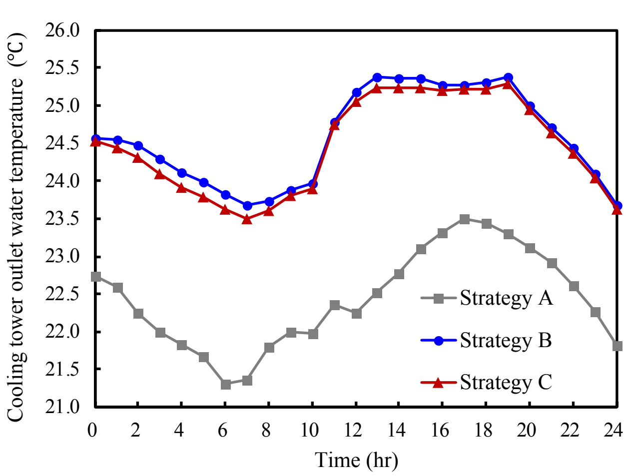

Fig. 7. Cooling tower outlet water temperature using different control strategies in the Spring day.

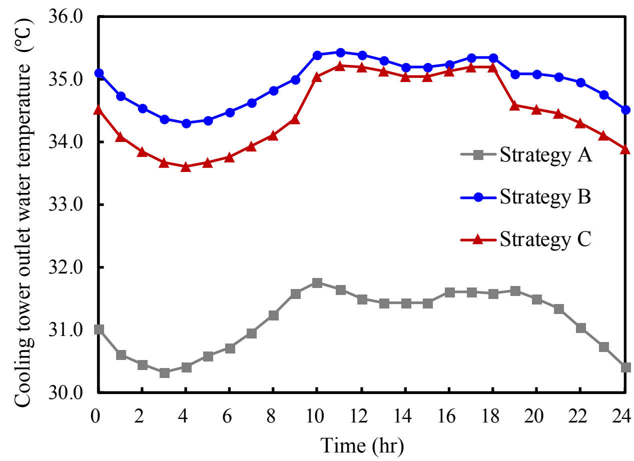

Fig. 8. The cooling tower outlet water temperature using different control strategies in the Summer day.

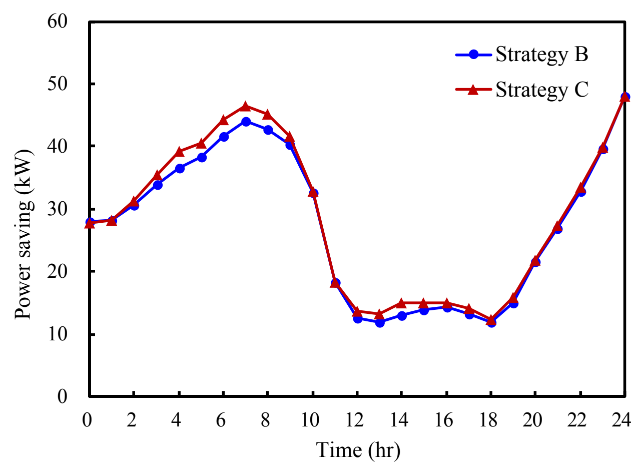

Fig. 9. Total power saving using different control strategies in the Spring day.

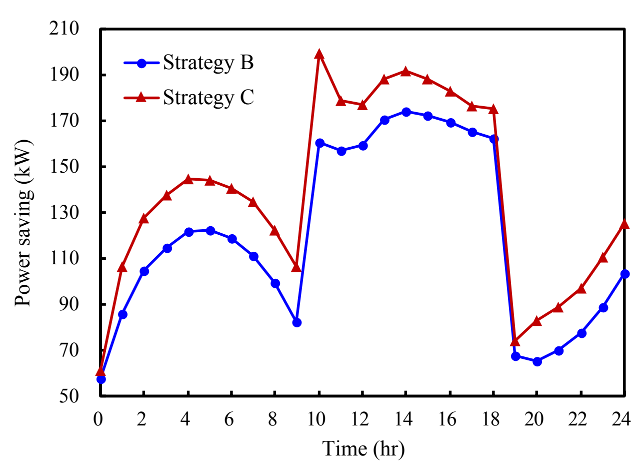

Fig. 10. Total power saving using different control strategies in the Summer day.

Table 6
Energy consumption* and savings using the three control strategies in the test days.

	spring			Summer		
	Consumption (kWh)	*Saving (kWh)*	*Saving (%)*	*Consumption (kWh)*	*Saving (kWh)*	*Saving (%)*
Fixed approach	21,312	–	–	75,313	–	–
Centralized	20,621	690.71	3.24	72,331	2982.36	3.96
Agent-based	20,595	716.57	3.36	71,852	3461.11	4.60

*: Energy consumption refers to the total energy consumption of chillers and cooling towers.

agents vary much faster than those of the cooling tower agents. The objective function of the chiller agents is relatively simple. Therefore, there should be a feasible and effective means to speed up the convergence rate by finding the convergence acceleration λ ($\lambda_{b,chi}$) and setting it to be the initial value of λ for each optimization. Fig. 6 shows the number of iterations of the two stages using the proposed convergence acceleration method. It can be seen that the number of iterations needed for optimization in all test conditions was reduced to below 50, indicating that the proposed method is much more effective. Adopting the proposed convergence acceleration method, the convergence rate of the proposed agent-based optimal control strategy using the sampling interval of one second can marginally satisfy the optimization interval of one minute and surely satisfy the optimization interval of two minutes. Considering the communication delays in today's field networks, the selected optimization interval needs to be longer (such as 3 min) as the practically acceptable minimum sampling interval is larger.

4.3. Energy performance evaluation

To evaluate the energy effectiveness of the proposed agent-based optimal control strategy (Strategy C), energy performance of the proposed strategy is compared with that of the two typical control strategies (Strategy A and Strategy B) in terms of the total energy consumption of the chillers and cooling towers. Strategy A is a control strategy using fixed differential temperature, which is usually regarded as a near-optimal control strategy. A fixed temperature difference between the cooling tower outlet water and the wet-bulb temperature is adopted. A differential temperature of 5 K is suggested usually and it is used in this study too. Strategy B is a centralized optimal control strategy based on exhaustive search without considering performance deviations among the cooling towers. For Strategy B, energy efficiency of all cooling towers is assumed to be the same, which equals to the average efficiency of the cooling towers involved. These three control strategies are tested in the central cooling system during a typical Spring and a typical Summer day. The building cooling load on the typical Spring day is between 3,311 kW and 6,442 kW, and the wet-bulb temperature ranges from 16.73 °C to 18.39 °C. On the typical Summer day, the building cooling load is between 10,295 kW and 17,552 kW and the wet-bulb temperature ranges from 25.32 °C to 26.76 °C.

Fig. 7 and Fig. 8 present profiles of the measured cooling tower outlet water temperatures using the three control strategies on a Spring day and a Summer day, respectively. It can be found that the outlet water temperatures of cooling towers using Strategy B and Strategy C were higher than that using Strategy A. Using Strategy B, the cooling tower outlet water temperature was slightly higher than that using Strategy C. Since the cooling load was low on the Spring day, the actual efficiency of the two cooling towers in operation was higher than the average efficiency of all cooling towers. Fig. 9 and Fig. 10 present the power savings of the central cooling system using Strategy B and Strategy C compared with that of using Strategy A on the Spring and Summer day, respectively. The system was more energy efficient when using both Strategy B and Strategy C, while the system was the most energy efficient when the proposed strategy (Strategy C) was used.

Energy consumption of the central cooling system using the three control strategies in the test days is listed in Table 6. On the Spring day, energy saving achieved by using Strategy C was slightly higher than that of using Strategy B. The use of Strategy B achieved an energy saving of 690.7 kWh, which accounts for 3.24% of the total energy consumption. The use of Strategy C achieved an energy saving of 716.6 kWh, which accounts for 3.36% of the total energy consumption. On the Summer day, the energy saving achieved by using Strategy C was obviously higher than that of using Strategy B. The use of Strategy B achieved an energy saving of 2,982.4 kWh (3.96%) and the use of Strategy C achieved an energy saving of 3,461.1 kWh (4.60%).

To assess the need for and effects of optimal set-points for individual cooling towers in case of performance deviations, another test is conducted. Energy performance of cooling towers with individual optimal

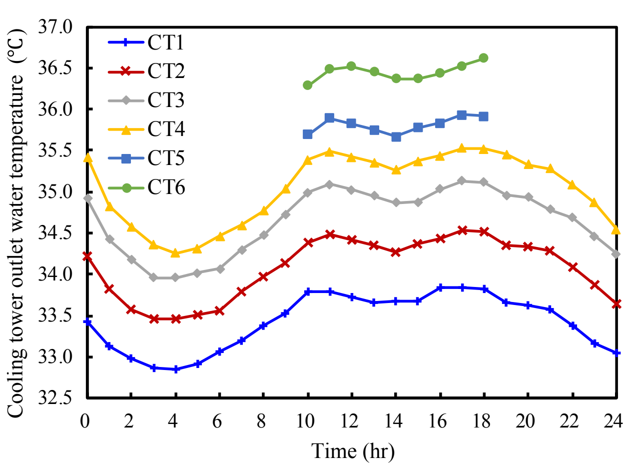

Fig. 11. Individual cooling tower outlet water temperature using the proposed strategy.

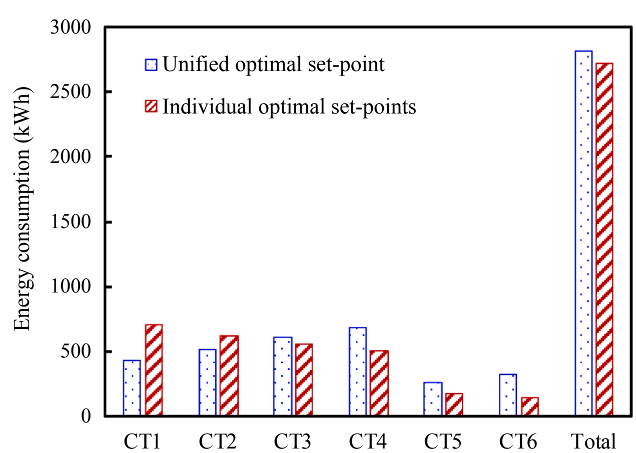

Fig. 12. Energy consumption of cooling towers using unified optimal set-point and individual optimal set-points.

set-points for cooling towers is compared with that using a unified optimal set-point for all cooling towers. Fig. 11 shows the outlet water temperatures of individual cooling towers using the proposed strategy, Strategy C, on the Summer day. Fig. 12 shows the total energy consumption of the cooling towers with individual optimal set-points and the unified optimal set-point on the same day. It can be seen that the outlet water temperatures of cooling towers with higher efficiency were controlled to be lower and more heat rejection loads were assigned to them as their speeds were controlled to be higher. By assigning different optimal set-points to individual cooling towers, total energy consumption of the cooling towers was reduced when producing cooling water of the same temperature for chillers, which accounts for 3.58% of the total energy consumption of the cooling towers.

5. Conclusions

An agent-based optimal control strategy is proposed for deployment in smart sensors integrated in future IoT-based field networks and local controllers in field networks of current LAN-based building automation systems in order to achieve distributed optimal control of building HVAC systems. A number of component agents and a coordinator agent are designed to deal with the simple tasks assigned to them after applying dual decomposition to an original complex optimization task by decomposition. The optimal decisions can be achieved by coordinating the control agents. The performance and implementation issues (i.e., energy efficiency, optimization accuracy and convergence rate, computation complexities and particularly computation loads of individual agents) of the proposed agent-based optimal control strategy, when deployed over the physical platforms of building automation systems, are assessed by tests on a simulated central cooling plant. According to the results and experiences of the implementation and validation tests, the following conclusions can be drawn:

- The agent-based optimal control strategy is able to effectively find the optimal set-points which can be found by the GA-based centralized control strategy. The convergence rate of the proposed agent-based optimal control strategy can well satisfy the optimal control interval as needed in normal application practice when adopting the proposed convergence acceleration method. The number of iterations needed for optimization in the test working conditions was below 50 and the optimization decisions can be made for an interval of minutes if the optimization computation for each iteration is performed at each sampling of controller with a typical sampling interval of one second.
- The codes of individual agents are very simple and acceptable for smart sensors or local control devices since a simple and effective optimization algorithm (i.e., hybrid performance map and exhaustive search) is adopted when the complex optimization task is decomposed into simple subtasks.
- Smart sensors and local control devices should be able to handle their corresponding local optimization tasks since the computation load of an optimization decision is also distributed to a number of steps in the time-scale. Computation loads of individual agents at each step were all less than 2000 FLOPs, well below computation capacities of typical smart sensors today.
- The proposed agent-based optimal control strategy is convenient and effective to deal with multiple components of different performances and it can achieve significant energy saving compared with conventional optimal control and near-optimal control strategies. It achieved energy savings of 716.57kWh (3.36%) and 3461.11 kWh (4.60%), for the central cooling system, on the Spring and Summer test days respectively, compared with the near-optimal control strategy. By considering performance deviations among the cooling towers, the proposed strategy achieved 3.58% energy savings for the cooling towers on the Summer test day.

It is worth noting that when considering performance deviations among the different components, an effective online calibration method is needed to capture the performance degradations of the components. The online calibration method applicable for the agent-based optimal control strategy needs further investigation.

CRediT authorship contribution statement

Bing Su: Data curation, Investigation, Methodology, Software, Writing - original draft. **Shengwei Wang:** Funding acquisition, Methodology, Project administration, Supervision, Writing - review & editing.

Declaration of Competing Interest

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

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