AGENT-BASED DISTRIBUTED REAL-TIME OPTIMAL CONTROL FOR BUILDING HVAC SYSTEMS IMPLEMENTED ON IOT PLATFORMS

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Agent-based Distributed Real-time Optimal Control for Building HVAC Systems Implemented on IoT Platforms

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no materials previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

__________________(Signed)

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ABSTRACT

Abstract of thesis entitled: Agent-based distributed real-time optimal control for building HVAC systems implemented on IoT platforms

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HVAC systems for buildings consume huge amounts of energy, many researchers have made serious efforts to develop real-time optimal control or supervisory control strategies to enhance system energy efficiency. However, the centralized form of the existing optimal control strategies results in several drawbacks, including the lack of generality and flexibility and the dependency on central computation stations. On the other hand, with the rapid development of related technologies, Internet of Things (IoT) has been attracting increasing attention in various industries, including its applications in building automation systems (BASs). The implementation of a large amount of IoT devices enables new applications and improves the existing ones but also brings new challenges in network traffic and system reliability. Distributed optimal control strategies offer effective means to avoid the drawbacks of centralized optimal control strategies and have the potential to be implemented on the field level of BASs to reduce the network traffic and increase control reliability. However, 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. The following problems and challenges when developing the distributed optimal control strategies for real applications are not well

addressed: *i.* the computation loads of the optimization tasks need to be distributed appropriately to allow them to be handled by local devices; *ii.* convergence of the optimization needs to be achieved within the required optimal control interval; *iii.* the impacts of information delays on control performance need to be investigated; *iv.* distributed optimal control strategies developed should have the capability of reducing the impacts of information delays. This PhD study, therefore, aims to develop agent-based distributed real-time optimal control strategies for the building HVAC systems concerning the deployment on the local controllers of current LAN-based field control networks and the smart sensors of future IoT-enabled field control networks.

To address the first challenge, agent-based distributed real-time optimal control strategies are proposed concerning the distribution of the computation load among physical devices and in time-scale. A complex optimization task with high computational complexity (i.e., computation code and computation load) is decomposed into a number of simple tasks, and the corresponding agents are constructed for solving them. Adopting edge computing, a computing paradigm using the distributed computing resources of field IoT devices, these agents are implemented on the integrated local devices. This is an effective means for dealing with the network traffic caused by the centralized structure and rapid growth of IoT devices. The computation task of an optimization decision is further distributed into a number of steps, each performed at a sampling interval of the local devices. Adopting these two distribution schemes, the computation loads of all individual agents at each step were below 2000 FLOPs, allowing them to be handled by the typical smart sensors using simple optimization codes. A convergence acceleration method is proposed to speed up the convergence of the distributed optimization. Adopting this method, the number of iterations for each optimization decision was within 50, well below the convergence rate needed for optimal control with the 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. The optimization considering such performance deviations could reduce the overall energy consumption significantly.

Information delays refer to the time delays in information exchange between devices integrated in communication networks. They could affect the performance of distributed optimal control, but are rarely concerned in HVAC field. This study investigates and quantifies the impacts of information delays on the performance of distributed optimal control strategies for HVAC systems through theoretical analysis and case studies, including a typical central cooling plant and a typical multi-zone air-conditioning system. The uncertain information delays are modelled by a Markov chain according to the characteristics of communication networks. Their impacts are quantified by comparing the performance of the distributed optimal control strategies involving the information delays with ideal performance. Results show that information delays significantly affected the convergence rate and control accuracy of the distributed optimal control strategies. These delays resulted in a difference in optimized cooling tower outlet water temperature of up to 0.6 K and a number of iterations of up to180 (about nine times than in ideal conditions). Test results indicate the necessity of considering the impacts of information delays when developing distributed optimal control strategies for HVAC systems.

To reduce the impacts of information delays on the performance of the distributed optimal control strategies, a delay-tolerant control method is proposed. It reduces the impacts of information delays through synchronizing the local optimization results used for convergence determination and adaptively resetting the step-size used for updating the Lagrange multiplier. The purpose of synchronizing local optimization results is to reduce the impacts of information delays on the accuracy of the optimization results. The purpose of setting the step-size adaptively is to reduce the impacts of information delays on the convergence rate. The computation load of the proposed method is 40 FLOPs (floating-point operations), which can be handled by typical smart sensors. Test results show that the proposed delay-tolerant control method could effectively reduce the impacts of information delays on optimization accuracy and convergence rate, thereby improving the energy performance of the distributed optimal control strategy under conditions where delays occur.

To further validate and evaluate the proposed distributed optimal control strategy, a hardware-in-the-loop simulator is constructed as a realistic test environment for the distributed optimal control strategies being implemented on real control devices. Being implemented on a wireless IoT sensor network integrated in the simulator, the applicability and the performance of the proposed strategy are validated and evaluated. The experience and test results show that the IoT sensing network has the capacity to implement the distributed optimal control strategy and handle the decomposed optimization tasks effectively. The energy performance of the proposed distributed optimal control strategy is almost the same as that using the perfect solutions.

To conclude, the proposed distributed optimal control strategies are applicable in the local IoT devices of field control networks and they are effective in improving system energy efficiency. For the current BASs, these strategies could broaden the applications of the optimal control of HVAC systems, by using the distributed computation resources of digital controllers integrated in field control networks. For the future BASs, they provide an approach to fully utilize the IoT-enabled field control networks for the optimal control of HVAC systems and support the development and applications of the emerging IoT technologies in the building automation industry.

PUBLICATIONS ARISING FROM THIS THESIS

Journal Papers

2020 **Bing Su**, Shengwei Wang. (2020). 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. Applied Energy, 274,115322.

2021 **Bing Su**, Wenzhuo Li, Shengwei Wang. (2021). Impacts of uncertain information delays on distributed real-time optimal controls for building HVAC systems deployed on IoT-enabled field control networks. Applied Energy, 300, 117383.

2021 **Bing Su**, Shengwei Wang. (2021). A delay-tolerant distributed optimal control method concerning uncertain information delays in IoT-enabled field control networks of building automation systems. Applied Energy, 301, 117516.

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NOMENCLATURE

a_1-a_3, b_1-b_6, c_1-c_4, d_1-d_4	coefficients
C	specific heat, kJ/ (kg K)
Cap	cooling capacity provided by chillers
CO2	CO_2 concentration, ppm
Conv	convergence status
COP	coefficient of performance
E	energy
f	objective function
g	constraint function
h	objective function of subproblem
INp	indoor pollution index
Ld	length of information delay
M	flow rate, kg/s
Md	maximum possible delay length
N	number
Obj	objective value
P	power, kW
PLR	part load ratio
Q	hear transfer rate, kW
R, *S*	function
SI	sampling interval
T	temperature, ℃
t	time cost, s
X	value range
x	control variable

Subscripts

a	ambient air

chi	chiller
chws	supply chilled water
co	coordinating agent
cof	coefficient
com	communication process
con	condenser
cpt	computation process
ct	cooling tower
cw	cooling water
cwo	cooling tower outlet water
des	design
f	frequency
fan	fan of PAU
G	generation
in	inlet
Limit	upper limit
nom	nominal
opt	optimal
out	outlet
rej	rejection
syn	synchronization
tot	total
u	uniform
wb	wet-bulb

Greek symbols

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

CHAPTER 1 INTRODUCTION

This chapter presents an outline of this thesis in the following three sections. The background and motivation of this study are introduced in Section 1.1. The aim and objectives are presented in Section 1.2. Section 1.3 shows the organization of this thesis and gives a brief description of each chapter.

1.1 Background and motivation

Global climate change has attracted increasing attention and cities across the globe are acting to reduce carbon emissions. Reducing energy consumption is an important and effective means for facilitating carbon neutrality. Buildings consume a large amount of energy which accounts for 30%-40% of total primary energy globally (Duić et al., 2013). In Hong Kong, the percentage is up to 70% of primary energy and the heating, ventilation and air conditioning (HVAC) system consumes over 32% electric energy (EMSD, 2020). Therefore, improving the energy efficiency of building HVAC systems is an effective means to reduce energy consumption.

Many researchers have made serious efforts to develop supervisory or optimal control strategies to improve the energy efficiency of HVAC systems (Wang and Ma, 2008). Optimal control can improve energy efficiency by systematically seeking the optimal values of control variables. 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 optimal control strategies are designed for specific systems while HVAC systems are different from each other due to the uniqueness of buildings. In this manner, it will be inconvenient and costly to adjust the centralized optimal control strategies according to different target systems. Distributed optimal control strategies are effective to overcome these drawbacks.

The Internet of Things (IoT), also called Internet of Everything (IoE), 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 (Xu et al., 2014). With the increasing attention on the IoT and the fast development of related technologies, the number of Internet connected devices will exceed 28 billion by 2022 (Cisco Annual Internet Report, 2019). In the building automation fields, it is a trend to endow the building electrical and mechanical devices with intelligence through embedding IoT devices on them. These devices form different building services subsystems (e.g., air-conditioning and lighting systems) of different scales. These embedded IoT devices form the monitoring and control networks of the building services subsystems, and they also form the field monitoring control networks of the Building Automation Systems (BASs) when integrated. Making effective use of these IoT devices at the field level to optimize the operation of the building services subsystems locally is an idea that practitioners would naturally generate. It would not only improve the energy efficiency and indoor environment using edge computing resources but also enhance the efficiency and reliability of local optimization and decision-making by handling them locally at field level without the need of sending massive field data to/from the remote cloud or central stations. However, most of the existing studies on the use of

IoT in buildings only focus on the use of the environmental monitoring data of IoT sensors for simple control of building services devices/systems, such as the ON/OFF control of lighting and air-conditioning systems. The optimal control of the building services subsystems, which aims to determine the optimal settings according to certain objectives, still relies on central data processing and optimization at a high level. The effective means for the full utilization of the local IoT devices for optimization and decision-making of the subsystems at the field level are still missing.

Although centralized data processing and optimization can achieve the optimal control of the building services subsystems, it increases the network traffic and reduces the reliability of system optimization. For the optimal control of a subsystem, usually the data of subsystems in other locations are not needed. When using the centralized structure, all the data obtained by the edge devices need to be transmitted to and analysed in the cloud or on central stations. This leads to unnecessary data transmission and could result in server network traffic. As estimated by cisco, the global annual network traffic will reach 4.8 zettabytes by 2022 (Cisco Annual Internet Report, 2019). Moreover, relying on a central computation station or cloud reduces the system reliability, as the optimizations of the local subsystems rely on both the operation of the central stations (or cloud) and local control (or IoT) devices including higher level communication networks and field control networks. In order to solve these problems, researchers have proposed various distributed computing paradigms, such as fog computing, edge computing and mist computing in IT fields (Yousefpour et al., 2019). The main idea of these computing paradigms is to use low-level devices for decision-making and optimization tasks. In this manner, some data can be analysed and used locally. Therefore, the network traffic and dependence on the cloud or central stations can be reduced, and the distributed field computing resources can be effectively utilized (i.e., local controllers of current LAN-based field control networks and smart sensors of future IoT-enabled field control networks). However, the existing literature contains no information on the distributed optimal control methods and strategies for HVAC systems considering such important current and future application scenarios. This PhD study, therefore, addresses these important problems and urgent needs, and the main challenges of the study are summarised.

i. Since the capacities (program memory for implementing the program and random access memory (RAM) for conducting computation/optimization) of the smart sensors/local devices are limited, the optimization tasks assigned to each local device needs to be simple enough to be handled. Therefore, a centralized optimization problem needs to be decomposed into a number of simple subproblems and appropriated distributed optimization method is needed to solve the decomposed problems.

ii. The impacts of information delays on the performance of distributed optimal control strategies for building HVAC systems need to be investigated and quantified. Information delays refer to the time delays in information exchange between devices integrated in communication networks. They could affect the performance of distributed optimal control, but are rarely concerned in HVAC fields.

iii. The means to deal with the impacts of information delays on the performance of distributed optimal control for HVAC systems is needed. The information delays could affect the optimization process of the distributed optimization and therefore reduce the reliability and energy performance of the distributed optimal control strategies. It is necessary to develop simple and effective means to reduce these impacts for applications of distributed optimal control strategies.

iv. Experimental validation is important and necessary for applicability verification and performance evaluation of the proposed distributed optimal controls strategies. It is necessary to construct an experimental rig to validate the proposed strategies by implementing them on the real sensor nodes of IoT sensing networks.

1.2 Aim and objectives

This PhD study aims to develop agent-based distributed real-time optimal control strategies for the building HVAC systems concerning the deployment on the local controllers of current LAN-based field control networks and the smart sensors of future IoT-enabled field control networks. It is accomplished by addressing the following objectives and research tasks:

i. Propose a framework and distribution scheme for the developed agent-based distributed real-time optimal control strategy. The issues on the "physical distribution" of the optimization tasks and "time-scale distribution" of the computation loads are addressed.

ii. Develop an agent-based distributed real-time optimal control strategy for building HVAC systems to be deployed on field control networks. The multiple components of different performances are effectively handled, and the energy saving is achieved. The implementation issues, when deploying the developed strategy over the physical platforms of BASs, are assessed.

iii. Quantify impacts of information delays on the performance of the distributed optimal control strategies. The qualitative analysis and quantitative assessment considering different HVAC systems are conducted. Critical factors which significantly affect the impacts of the information delays are investigated. The impacts of information delays on different distributed optimization methods are investigated.

iv. Develop a delay-tolerant method for reducing the impacts of information delays on the performance of distributed optimal control of HVAC systems. The computation load of the proposed method, when handled by smart sensors and local control devices, is assessed. The efficiency of the proposed method to reduce the impacts of information delays is investigated.

v. Develop a hardware-in-the-loop simulator as the test platform to test/validate the proposed distributed control strategies and control schemes. A virtual HVAC system and a physical control system are integrated.

1.3 Organization of this thesis

Chapter 1 introduces the background and the motivation of developing distributed optimal control strategies for the implementation on the field control networks. They are given by illustrating the drawbacks of conventional centralized optimal control strategies and the challenges brought by the development and applications of IoT technologies in the building automation field. The aim, main objectives and the organization of the thesis are also presented.

Chapter 2 presents a comprehensive literature review on the related existing studies, including the overview of the development and application of IoT in the building field, the existing research on distributed optimal control for HVAC systems, as well as the studies related to information delays in distributed optimization and feedback control. The research gaps are also summarised following the literature review.

Chapter 3 presents an agent-based distributed real-time optimal control strategy designed for the implementation on local control devices of field control networks based on proposed framework and distribution scheme. Dual decomposition is adopted to decompose the original centralized optimization problem into several subproblems and a master problem. PMES (performance map and exhaustive search), a computationally effective and easily implementable hybrid optimization technique, is adopted to solve the subproblems. The subgrdiant method is adopted to solve the master problem. The optimization accuracy and computation load/efficiency of each agent and the entire control strategy are tested and analysed to evaluate the feasibility, efficiency and reliability of the proposed strategy.

Chapter 4 investigates and quantifies the impacts of information delays on the performance of distributed optimal control strategies deployed on local devices of field control networks through theoretical analysis and case studies, including a typical central cooling plant and a typical multi-zone air-conditioning system. The uncertain information delays are modelled by a Markov chain according to the characteristics of communication networks. Their impacts are quantified by comparing the performance of the distributed optimal control strategies involving the information delays with ideal performance.

Chapter 5 presents a delay-tolerant method for reducing the impacts of information delays on the performance of distributed optimal control of HVAC systems. The proposed method reduces the impacts of information delays through synchronizing the local optimization results used for convergence determination and adaptively setting the step-size used for updating the Lagrange multiplier. The computation load of the proposed method is assessed to verify the applicability when implementing on local devices. The effectiveness of the proposed method is evaluated by comparing the energy performance of the delay-tolerant distributed optimal controls strategy with the strategy without the delay-tolerant scheme.

Chapter 6 presents the development of a hardware-in-the-loop simulator used as a realistic test environment for real control devices. The hardware-in-the-loop simulator consists of a virtual HVAC system and a physical control system interfaced through a USB hub. Being implemented on a wireless IoT sensor network integrated in the simulator, the applicability and the performance of the proposed strategy are validated and evaluated.

Chapter 7 summarizes the main contributions of this PhD study and gives recommendations for future research on the subject concerned.

The interconnection between the main chapters of the thesis is illustrated as shown in Figure 1.1. The framework and distribution scheme of the distributed optimal control strategies, which are used in all the developed distributed optimal control strategies, are presented in Chapter 3. The development of an agent-based distributed real-time optimal control strategy for building HVAC systems deployed on the field control networks is also presented in this chapter. The computation load, convergence rate and optimization accuracy of the proposed strategy when implementing in physical local devices are assessed. In Chapter 4 and Chapter 5, another essential issue in practical applications, i.e., the information delays, is addressed. The impacts of information delays on the performance of distributed optimal control strategies are investigated and quantified in Chapter 4, and a delay-tolerant method for reducing these impacts is proposed in Chapter 5. To further validate the applicability and evaluate the performance of the proposed distributed optimal control strategies, a hardware-in-the-loop simulator is constructed and the test results are presented in Chapter 6.

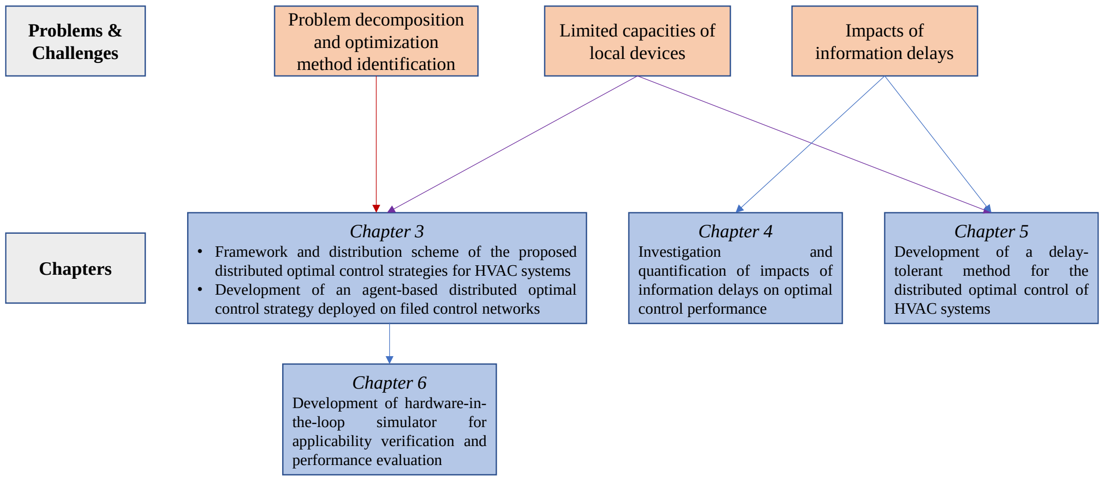


Figure 1.1 Organization of main chapters

CHAPTER 2 LITERATURE REVIEW

Real-time optimal control is efficient and essential for improving the energy efficiency of building HVAC systems. The centralized form of the existing optimal control strategies results in several drawbacks, including lack of generality, flexibility and rely on central computation stations. Using distributed optimal control strategies is an effective way to avoid these drawbacks. On the other hand, the rapid development and wide applications of IoT technologies enable new functions and improve the existing ones. It could have a major role in the building automation field of the next generation. But it also brings problems and challenges in network traffic and system reliability. Adopting the edge computing paradigm to make use of the computing resources of the large amount of local devices for optimization tasks is an effective means to address these problems. This chapter presents a comprehensive literature review on the existing centralized optimal control strategies, the development and applications of IoT technologies in the building field and the studies on the information delays in the control field. A summary of research gaps based on the literature review is also presented.

2.1 Development and applications of Internet of Things in building automation

BASs are responsible for maintaining the desired indoor environment through automatic monitoring and controlling the building services systems, including HAVC, lighting, security and fire systems (ASHRAE Guideline, 13–2015). The applications of the IoT technologies in the building automation field brings the opportunities of developing new functions and improving the existing services. The existing researches on the IoT applications in the building automation field can be divided into three categories, which are security management, indoor environment management and energy management.

For security management, data security (Rahman and Shah, 2016) and occupant safety (Piscitello et al., 2015) are the two main issues concerned by the researchers. Han et al. (2015) defined the security requirements for the IoT devices used in smart homes concerning the data privacy and the reliability and safety of the devices. The requirements are classified based on integrity, confidentiality and availability. Huth et al. (2015) proposed a new approach for secure deployment of IoT devices based on the physical properties of devices. Two key distribution technologies, which are Physical Unclonable Functions (PUF) and Physical Key Generation (PKG), are combined to ensure the confidentiality and authenticity of the IoT devices. Yoshigoe et al. (2015) investigated the privacy issue of IoT devices and illustrated the way of compromising user's privacy through simple network traffic analysis. Thang et al. (2011) proposed an architecture for the automated emergency alert services based on Internet Protocol Television (IPTV) platform.

For indoor environment management, the implementation of IoT devices enables more efficient and convenient means to enhance the occupant's comfort, which is the basic and essential concern of BASs. The large amount of IoT sensors improve the ability of real-time monitoring and controlling of BASs. Quan Pham et al. (2019) proposed a novel indoor environment monitoring system consists of multiple IoT sensors and the base station, using an EMI-free bidirectional visible light communication technology. The proposed monitoring system can measure the parameters of the indoor environment concerned, such as the CO_2 concentration, temperature and relative humidity. Marques and Pitarma (2017) developed an automatic system for indoor enviroment control using the monitoring data of IoT sensors, including the moisture, temperature and luminosity data. Bashir and Gill (2016) presents an integrated IoT Big Data Analytics (IBDA) framework for the storage and analysis of real-time data generated from the deployed IoT sensors. The framework is tested by using it for the automatical control of the oxygen level, luminosity and smoke/hazardous gases in different parts of the smart buildings according to the analysis of the obtained real-time smart data.

For energy management, the related research can be divided into two categories according to their aims, which are achieving energy saving and conducting demand response. The occupancy information is essential for energy saving methods or strategies and the IoT technologies enable convenient ways to obtain such information (Akkaya et al., 2015). Raj et al. (2019) investigated the energy saving potential of smart control of HVAC systems using the information from human motion detectors integrated in mobile phones. The results showed that the energy consumption of the compressor was reduced by 45%. Zou et al. (2018) proposed a novel device-free approach to realize occupancy detection and crowd counting using only WiFi enabled IoT devices. The proposed approach achieved 99.1% occupancy detection accuracy and 92.8% crowd counting accuracy without using extra infrared sensors, cameras or mobile devices. Elkhoukhi et al. (2019) presented a platform combining IoT technologies and a real-time machine learning approach for building energy management. An experimental test was conducted by deploying the proposed platform for the energy management of a laboratory. Almost 62% of energy saving was achieved by controlling the building services systems according to the estimated occupancy information. For the demand response, the bidirectional information exchange between the smart grid and the customers (i.e., buildings) is the essential issue. Wei et al. (2016) presented an IoT-based communication framework with a common information model to facilitate the development of demand response (DR) energy management system for industrial customers. Smart meters are getting increasing attention and are widely implemented with the development of smart grid technologies. By making use of the collected data and the computation recourses of smart meters, a number of methods and techniques are proposed to realize the energy management of buildings to provide demand response services (Yildiz et al., 2017).

The above review shows the development and main applications of IoT technologies in the building automation field. It can be found that the existing research mainly focuses on the improvement of the current building services by making use of the data obtained by smart sensors. As aforementioned, this could result in increased network traffic and reduced system reliability. Moreover, the research on the optimal control of building services systems/subsystems by using the local devices is missing.

2.2 Existing centralized optimal control strategies

Supervisory control or optimal control is an effective means of improving HVAC system energy efficiency. Many researchers have made efforts to develop optimal control strategies for building HVAC systems and most of them are in a centralized form. According to the optimization methods used, the optimal control strategies can be divided into two main categories, which are model-based methods and model-free methods (Wang and Ma, 2008). The main difference between the two methods is whether the system model for energy performance prediction is used in a control strategy.

For the model-based methods, the optimal control strategies seek for the optimal solutions which can minimize or maximize the objective concerned according to the model prediction. Lu et al. (2005) proposed an optimal control strategy based on a modified genetic algorithm (GA) to minimize the total energy consumption of an HVAC system. Ma and Wang (2009) 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 (2000) proposed a model-based optimal control strategy for a variable air volume (VAV) air-conditioning system using GA. Multi objectives with different weights were considered in the cost function, including thermal comfort, energy consumption and indoor air quality (IAQ). The test results of these control strategies show that the system energy efficiency could be improved significantly by adopting appropriate control strategies.

For the model-free optimal control methods, the pure learning methods received a lot of attention with the development of related technologies. Du et al. (2021) proposed a model-free optimal control strategy using the deep deterministic policy gradient method for the optimal control of a multi-zone residential HVAC system. Through learning from the continuous interaction with a simulated building environment, the proposed strategy reduced the energy consumption cost by 15% and reduced the comfort violation by 79%. Raman et al. (2021) proposed and implemented a model-free Reinforcement Learning (RL)-based optimal schedule for HVAC operation in a real home to reduce the energy cost while satisfying the occupants' requirements in comfort. 15% energy saving was achieved during the test period. Yuan et al. (2021)

proposed a model-free control strategy combining rule-based and RL-based control algorithms for the operation optimization of air-conditioning (AC) systems. The proposed strategy was applied in a VAV air-conditioning system and the test results show that 7.7% of total energy consumption was reduced.

These studies prove that developing appropriate optimal control strategies for building HVAC systems can effectively increase the system energy efficiency. However, the centralized form of these control strategies results in the lack of generality and flexibility.

2.3 Studies on agent-based distributed optimal control for building HVAC systems

Recently, agent-based control for the distributed control of building HVAC systems has drawn increasing attention because of its scalability and modularity (Bünning et al., 2017). An agent can be defined as a physical or virtual entity that can perceive its environment, take actions to influence the environment according to its goals and tendencies (Wooldridge and Jennings, 1995). Multiple agents can be integrated to form a multi-agent system to achieve a common goal through coordination (Schumacher, 2001).

A few researchers developed agent-based distributed optimal control strategies to improve the operational efficiency of HVAC systems. Kelly and Bushby (2012) and Treado (2010) did some preliminary works 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. Cai et al. (2016) and Wang et al.

(2019) 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 the system level into component level. Local optimization of each component was conducted by one corresponding agent and global optimization is achieved through coordinating these agents. Wang et al. (2019) developed a model-free strategy based on the decentralized evolutionary algorithm to search for the optimal set-points. Cai et al. (2016) chose to construct a model-based control strategy using the subgradient or alternating direction multiplier method (ADMM) to solve the optimization problems.

These studies propose a basic means of constructing agent-based optimal control strategies for HVAC systems. The structure of multi-agent systems and optimization techniques for distributed optimization are also provided. However, these studies did not consider the requirements and constraints in practical applications when the distributed control strategies are implemented on physical platforms, such as the convergence rate, computation load distribution and information delays.

2.4 Studies on the information delays in control systems and distributed optimization

The information delays refer to the time delays in the information exchange between different devices over communication networks.

2.4.1 Studies on the information delays in feedback control

In the control field, the impacts of information delays on the performance of networked feedback control loops have received attention from researchers and engineers since the 1980s, concerning the application scenarios of long-distance data transmission via local area networks and between controllers connecting sensors and control actuation devices (Doyle and Stein, 1979). With the rapid development of IoT technologies and field networks, more and more feedback control loops are established across standalone smart sensors and actuators as well as controllers integrated through communication networks (Ploplys et al., 2004). Therefore, such an information delays issue has received increasing attention in recent years. Lian et al. (2001) proposed a method for stability analysis of the feedback control of a multi-input and multi-output plant with varying network delays. Long et al. (2017) analysed the impacts of time-varying delays on the performance and stability of networked load frequency control systems. Nilsson et al. (1998) evaluated the performance of different control schemes with varying delays, assumed to be less than the sampling interval, and proposed a new scheme for handling these delays using timestamps. Their results show the necessity of accounting for information delays when designing the control scheme of feedback control systems.

2.4.2 Studies on the information delays in distributed optimization

Previous studies didn't consider the impacts of information delays on distributed optimization as they focused on "software distribution" (Nedic and Ozdaglar, 2009). Information exchange between different local control devices integrated in a field control network is essential in distributed optimal control. Thus, global optimization can be affected by information delays. In the optimization field, a few researchers have investigated the impacts of delays on distributed optimization algorithms and developed robust optimization algorithms capable of coping with communication delays as listed in Table 2.1. In these studies, information delays resulted in converging to incorrect values or failing to converge at all (Lobel and Ozdaglar, 2011). Tsianos and Rabbat (2011) proposed two ways to model constant delays and uncertain delays. They analysed the impacts of delays by involving the delay models in the distributed optimization algorithm and found that delays slowed down the optimization. Nedić and Ozdaglar (2010) investigated the convergence rate of a consensus problem using a common consensus algorithm under bounded delay conditions. By introducing additional delays to the subgradient projection algorithm, Lin et al. (2016) solved the distributed optimization problems with arbitrary bounded communication delays. The convergence characteristics of some other optimization algorithms, such as distributed subgradient projection algorithm (Lin et al., 2016), dual averaging update (Wang et al., 2015) and gradient push-sum method (Yang et al., 2017) are also investigated under information delays. Although these algorithms did achieve convergence in presence of information delays, the diminishing step-size was adopted, leading to a low convergence rate. For algorithms assuming a fixed step-size, Yang et al. (2017) demonstrated negative impacts on the convergence rate and optimization results due to information delays. Zhao et al. (2020) pointed out that there always exists a sufficiently small step-size that can guarantee the convergence of an algorithm under finite constant time delays. But using a small step-size could also reduce the convergence rate. Charalambous et al. (2015), therefore, proposed an algorithm achieving convergence in a small number of steps regardless delays exist or not. However, using this algorithm, the relatively high storage and computation capacity of the devices were required since all the historical data were stored in the agents and matrix calculation was needed. Therefore, this algorithm is not suitable to be used for the distributed optimal control strategy deployed over field control devices of limited storage and computation capacities.

Table 2.1 Summary of existing studies on delay-tolerant distributed optimization algorithms

Reference	Method	Drawbacks
Lobel and Ozdaglar, 2011	Distributed Subgradient Methods	Low convergence rate due to using dimishing step-size
Nedić and Ozdaglar (2010)	a common consensus algorithm	
Lin et al. (2016)	distributed subgradient projection algorithm	
Wang et al., 2015	dual averaging update	
Yang et al., 2017	gradient push-sum method	
Charalambous et al. (2015)	Distributed Finite-Time Average Consensus	High requirements in storage and computation capacity

The above review presents the existing research on the impacts of information delays on the distributed optimization algorithms. However, no existing study has considered the impacts of information delays on hierarchical distributed optimization algorithms such as the dual decomposition method and ADMM. Moreover, for other kinds of distributed optimization algorithms, only theoretical analysis has been conducted on the impacts of information delays. For the application scenarios concerned in this study, i.e., distributed online optimal control of HVAC systems deployed on local control devices integrated in BAS field control networks, no study considers the impacts of information delays. The existing algorithms and methods to eliminate or reduce these impacts are not applicable because of their low convergence rate and high requirements of storage and computation capacity.

2.5 Summary of research gaps

This chapter presents a comprehensive review on the existing studies concerning the following aspects. The development and applications of IoT technologies in the building automation field are illustrated. The existing centralized and distributed optimal control strategies are presented. The studies on information delays in the control field are presented. From the above review, the existing gaps can be summarized as follows:

i. Existing studies on distributed optimal control for building HVAC systems did not consider the requirements and constraints in practical applications when the distributed control strategies are implemented on physical platforms. The limited capacities of the local devices require simple programming code and small computation load.
ii. The impacts of information delays on hierarchical distributed optimization algorithms have not been investigated. No study can be found on the delays in distributed online optimal control of HVAC systems deployed on local control devices integrated in BAS field control networks.
iii. Existing delay-tolerant methods either could result in the low convergence rate or require high storage and computation capacity, which are not applicable in the scenarios concerned in this study, i.e., distributed real-time optimal control of HVAC systems deployed on local control devices integrated in BAS field control networks
iv. For the distributed optimal control of HVAC systems, most studies only conduct pure simulations to validate and evaluate the proposed strategies. However, the applicability validation and performance evaluation by implementing distributed optimal control strategies on the real sensor nodes of IoT sensing networks in the building automation fields cannot be found in the literature.

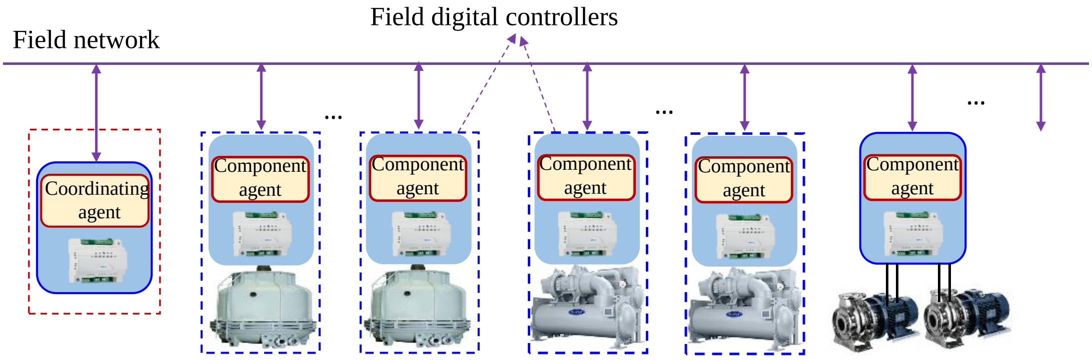
CHAPTER 3 DEVELOPMENT OF AN AGENT-BASED DISTRIBUTED REAL-TIME OPTIMAL CONTROL STRATEGY

This chapter presents the development of an agent-based distributed real-time optimal control strategy for building HVAC systems to be deployed on field control networks. Firstly, the framework and distribution scheme of the distributed optimal control strategies developed in this study are proposed to address the "physical distribution" of the optimization tasks and the "time-scale distribution" of the computation loads. They are essential for the implementation and application of the distributed optimal control strategies on integrated IoT smart sensors/devices or field controllers (denoted as "local control devices", below) of limited capacities. The agent-based distributed real-time optimal control strategy is proposed based on the proposed framework and distribution scheme. Dual decomposition is adopted to decompose the centralized optimization problem into several subproblems and a master problem. Multiple component agents and a coordinating agent are designed for solving these problems to get the optimal solutions. Section 3.1 presents the framework and distribution scheme of the proposed distributed optimal control strategies. Section 3.2 presents the decomposition of the centralized optimization problem. Section 3.3 formulates the distributed optimal control strategy with the constructed agents and presents the whole optimization process. The description of a validation case study concerning the performance difference of the components is presented in Section 3.4. The validation results and performance evaluation are presented in Section 3.5.

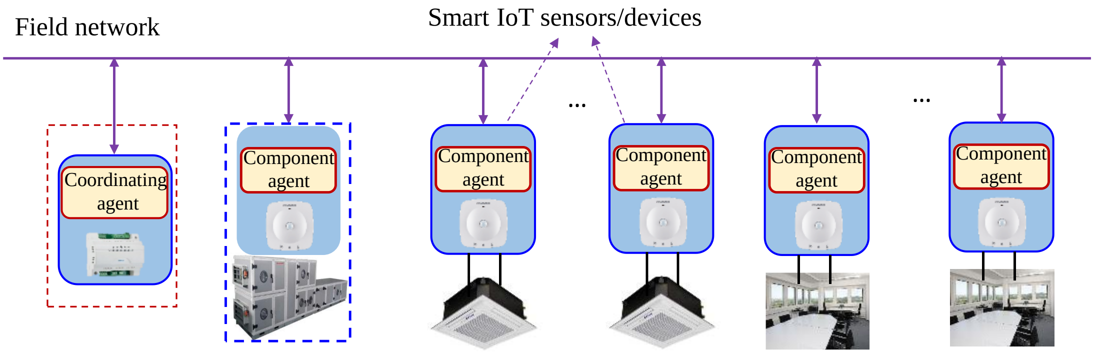
3.1 Framework and distribution scheme of the proposed distributed optimal control strategies

3.1.1 Framework of the distributed optimal control strategies

To achieve the “physical distribution”, a number of local optimization problems, each corresponding to a component or optimization objective, will be aggregated to represent a large optimization problem. The general configurations of distributed optimal control adopting multiple agents on the DDC field control networks of current BASs and the smart IoT sensor/device networks of future BASs are illustrated in Figure 3.1. One distributed optimal control strategy can then deal with a large optimization problem in a distributed manner through a number of agents, each responsible for solving a local optimization problem, and implemented on a corresponding local control device. Once a hierarchical distributed optimization algorithm is adopted, a coordinating agent will be needed. Distributed optimal control strategies will be developed for deployment on integrated local BAS control devices, for typical HVAC systems and subsystems, such as different configurations of the central cooling plants, of different configurations, all air systems of constant air volume (CAV) and variable air volume (VAV), and dedicated outdoor air systems (DOAS).



(A) Distributed optimal control deployed on DDC field control networks



(B) Distributed optimal control deployed on smart IoT sensor/device networks

Figure 3.1 Illustration of deployment frameworks of distributed optimal control of HVAC systems on current and future BASs

3.1.2 Distribution scheme of the computation loads in time-scale

Figure 3.2 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 typical process control, a control decision is made at each sampling interval (typically one second or more) because of the need for timely feedback. The computation task of each decision is simple and can be completed by the local controllers within a short time. For typical centralized optimal control strategies, the computation of a task for each optimization decision can be much more complex and is usually handled by the central personal computer (PC) stations or central control stations. When making an optimal control decision, the station collects the required data, performs optimization computation 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, the computation load of one optimization is distributed into 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.

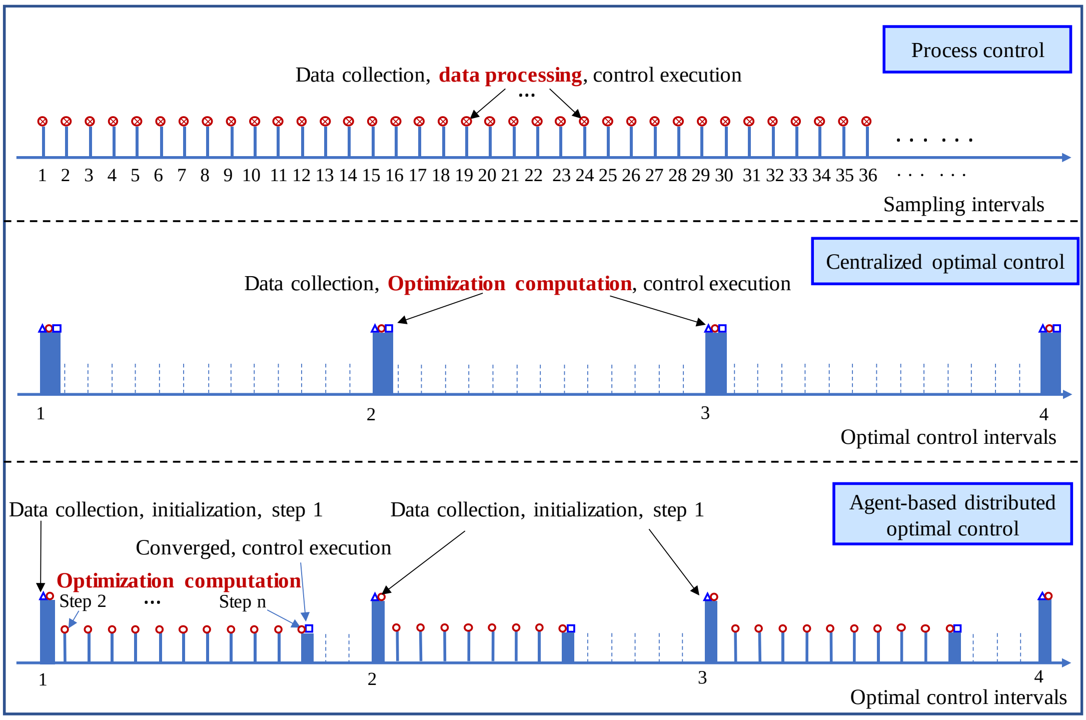


Figure 3.2 Distribution of computation loads of different control schemes

3.2 Decomposition of the centralized optimization problem

In order to realize agent-based control of HVAC systems, a system optimization problem needs to be formulated in a distributed manner instead of in a 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 the 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 the 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 the component level is to deal with coupling constraints among the components. In this study, dual decomposition (Palomar and Mung Chiang, 2006), 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 with coupling constraints is expressed as Eq. 3.1. Where *f(x)* represents the power consumption of one component in the system. $\boldsymbol{x}$ is the control variable of the corresponding component. $\boldsymbol{X}$ represents the range of values of $\boldsymbol{x}$ determined by constraints of the component. *g(x)* is the function of the constraints.

$$\begin{gathered}\min_{\{\boldsymbol{x_i} \in \boldsymbol{X_i}\}} \sum_{i=1}^{n} f_i(\boldsymbol{x_i}) \\ \text{subject to: } \sum_{i=1}^{n} \boldsymbol{g_i}(\boldsymbol{x_i}) \leq \boldsymbol{b}\end{gathered} \tag{3.1}$$

Based on Lagrange relaxation (Everett, 1963), the problem can be transformed into one without coupling constraint, as shown in Eq. 3.2. $\boldsymbol{\lambda} \geq 0$ is the Lagrange multiplier. The coupling constraint is added to the objective function as a penalty function.

$$L(\boldsymbol{x_i}, \boldsymbol{\lambda}) = \sum_{i=1}^{n} f_i(\boldsymbol{x_i}) + \boldsymbol{\lambda}^{\mathrm{T}}\left[\sum_{i=1}^{n} \boldsymbol{g_i}(\boldsymbol{x_i}) - \boldsymbol{b}\right] \tag{3.2}$$

The dual function is then formed as Eq. 3.3.

$$\theta(\boldsymbol{\lambda}) = \inf_{\{\boldsymbol{x_i} \in \boldsymbol{X_i}\}} \left\{\sum_{i=1}^{n} f_i(\boldsymbol{x_i}) + \boldsymbol{\lambda}^{\mathrm{T}}\left[\sum_{i=1}^{n} \boldsymbol{g_i}(\boldsymbol{x_i}) - \boldsymbol{b}\right]\right\} \tag{3.3}$$

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. 3.4.

$$\min_{\{\boldsymbol{x_i} \in \boldsymbol{X_i}\}} f_i(x_i) + \boldsymbol{\lambda}^{\mathrm{T}} \boldsymbol{g_i}(\boldsymbol{x_i}) \tag{3.4}$$

The master problem is presented by Eq. 3.5, which is to find the appropriate λ in order to prove that the optimal solutions of the subproblems obey the coupling constraints. Where, $h_i(\boldsymbol{\lambda})$ is the dual function obtained as the minimum value of the Lagrangian solved in Eq 3.4 for a given $\boldsymbol{\lambda}$**.**

$$\max_{\{\boldsymbol{\lambda}: \boldsymbol{\lambda} \geq 0\}} h(\boldsymbol{\lambda}) = \sum_{i=1}^{n} h_i(\boldsymbol{\lambda}) - \boldsymbol{\lambda}^{\mathrm{T}} \boldsymbol{b} \tag{3.5}$$

It is worth noting that there exist certain requirements to guarantee that the results of the dual problems are equal to the original problem (Boyd and Vandenberghe, 2004). Since it highly depends on the values of the specific parameters in the objective functions, it is not discussed here.

3.3 Formulation of the distributed optimal control strategy

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

3.3.1 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 3.1), which consists of the power consumption of the component concerned and its corresponding penalty function. The 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 technique 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 (2008), is adopted.

3.3.2 Coordinating agent

The coordinating 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 coordinating agent checks whether these results satisfy the coupling constraints or not, according to the convergence criterion, as shown in Eq. 3.6.

$$\sum_{i=1}^{n} g\{argmin_{x_i}[h_i(\lambda_k)]\} \leq b + \varepsilon \quad (3.6)$$

Where $\varepsilon > 0$ is a stopping threshold, the acceptable difference between the optimization results and the coupling constraints, k is the iteration step. 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 (λ) by solving the master problem mentioned above (Eq. 3.5), using a proper optimization technique. A commonly used technique in distributed optimization, the subgradient method (Palomar and Eldar, 2010), is adopted in this study. This method solves the problem by iteration as shown in Eq. 3.7.

$$\lambda_{k+1} = \lambda_k + \alpha\{\sum_{i=1}^{n} argmin_{x_i}[j_i(\lambda_k)] - b\} \tag{3.7}$$

Where α (α>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. 3.7 and then sent to the component agents to generate new local optimization solutions.

3.3.3 Optimization process of the distributed optimal control strategy

The proposed agent-based optimal control strategy is formulated by defining all component agents and the coordinating 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 the given initial λ and send the solutions to the coordinating agent. Then, the coordinating 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 3.2 are actually tasks of one iteration (Table 3.1). 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 3.1.

Table 3.1 The process of optimization of the agent-based optimal control strategy

	Task
Initialization	The coordinating agent sends the λ_k^* which is the optimal solution from the 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 coordinating agent.
	(2). The coordinating agent updates the λ according to

	Eq. 3.7, and sends λ_{k+1} to component agents.
	(3). Repeat (1) and (2) until the convergence criteria Eq. 3.6 is satisfied.
Control execution	Component agents send control signals to corresponding components.

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 algorithms 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 component agents. This should be done at the beginning of the optimization by the coordinating 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 BASs. Considering that the 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 hundreds. 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 that 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.

3.4 Description of the validation case study on a central cooling plant

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 to 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 individual cooling tower agents.

3.4.1 The central cooling plant

A typical central cooling system (Figure 3.3) 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 and a coefficient of performance (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 410.6 L/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 (Wang et al., 2010). 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 assumed to be a new cooling tower with rated efficiency, and different degrees of performance degradation is 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.

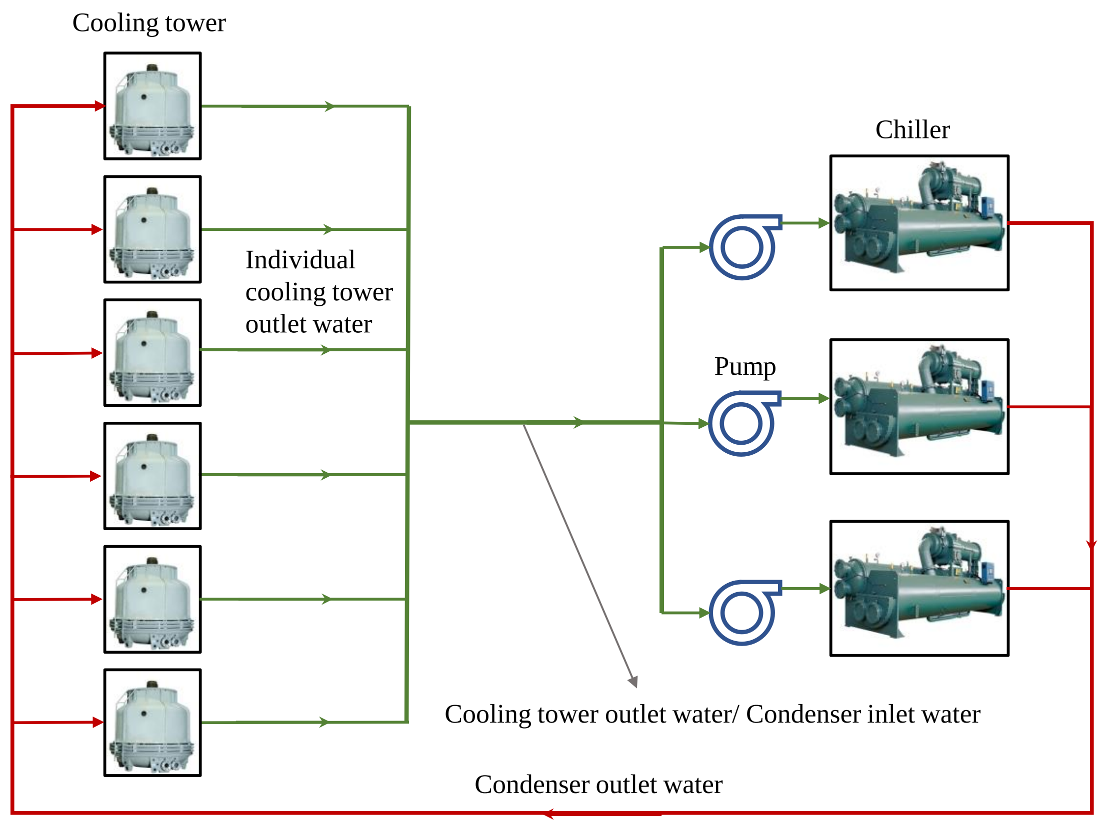


Figure 3.3 Schematic of the central cooling system concerned

3.4.2 Optimization problem formulation and decomposition

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 power consumption by cooling towers and lower power 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 power 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 individual cooling towers with different performance can achieve more energy saving compared with a single unified set-point. Hence, considering performance deviation, control variables of the supervisory control strategy are the individual cooling tower outlet water temperatures for the operating cooling towers. The optimization objective function can be then expressed as Eq. 3.8. Where, P_{tot} is the total power consumption of chillers and cooling towers, $P_{chi,j}$ and $P_{ct,i}$ are the functions of chiller power consumption and cooling tower power consumption, respectively. The formula of the two functions is shown in Section 3.3.3. There exists several constraints, i.e., Eqs 3.9-3.12, including energy and mass balances as well as operational limitations of the cooling towers. The heat rejection by the cooling towers (Q_{ct}) is assumed to be equal to the sum of cooling load (Q_{load}) and power consumption of chiller compressors as shown in Eq. 3.9. The fan frequency (f) of each cooling tower is bounded between 20 Hz and 50 Hz. Another constraint is the lower bound of cooling tower outlet water temperature, which is 18 °C due to operational constraint of chillers, shown as Eq. 3.10. The cooling tower outlet water is delivered directly to the condenser inlets of chillers, and the heat/cold loss in the pipelines and pump heat gain are assumed to be ignored. Therefore, the coupling constraint between the chillers and cooling towers is that the cooling water temperature equals the chiller condenser inlet water temperature, shown as Eq. 3.11. Another coupling constraint is the energy balance constraint, shown as Eq. 3.12. Where M_{cw} is the mass flow rate of the cooling water and C is the specific heat.

$$\min_{\{Tcwoi\}} P_{tot} = \sum_{j=1}^{N_{chi}} P_{chi,j} + \sum_{i=1}^{N_{ct}} P_{ct,i} \tag{3.8}$$

$$\text{Subject to: } \sum_{i=1}^{N_{ct}} Q_{ct,i} = Q_{load} + \sum_{j=1}^{N_{chi}} P_{chi,j} \tag{3.9}$$

$$max\left(18, T_{cwoi,f=50\ HZ}\right) \leq T_{cwoi} \leq max\left(18, T_{cwoi,f=20\ HZ}\right) \tag{3.10}$$

$$T_{con,in} = T_{cwo} = \frac{1}{N_{ct}} \sum_{i=1}^{N_{ct}} T_{cwoi} \tag{3.11}$$

$$CM_{cw}\left(T_{con,out} - T_{con,in}\right) = CM_{cw}\left(T_{con,out} - T_{cwo}\right) = \sum_{i=1}^{N_{ct}} CM_{cwi}\left(T_{con,out} - T_{cwoi}\right) \tag{3.12}$$

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. 3.13 and 3.14 and the master problem is presented by Eq. 3.15.

$$\underset{\{T_{con,in}\}}{Min} \sum_{j=1}^{N_{chi}} \left[P_{chi,j} - \lambda \cdot CM_{cwj}\left(T_{con,out} - T_{con,in}\right)\right] \tag{3.13}$$

$$\underset{\{T_{cwoi}\}}{Min} \sum_{i=1}^{N_{ct}} \left[P_{ct,i} + \lambda \cdot CM_{cwi}\left(T_{con,out} - T_{cwoi}\right)\right] \tag{3.14}$$

$$\lambda \cdot \left(T_{cwo} - T_{con,in}\right) = 0 \tag{3.15}$$

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. 3.16 represents the sub-problems and Eq. 3.17 represents the master problem.

$$\underset{\{T_{cwoi}\}}{Min} \sum_{i=1}^{N_{ct}} \left[P_{ct,i} + \mu \cdot CM_{cwi}\left(T_{con,out} - T_{cwo,i}\right)\right] \tag{3.16}$$

$$\mu \cdot \left(T_{cwo,opt} - \frac{1}{N_{ct}} \sum_{i=1}^{N_{ct}} T_{cwoi}\right) = 0 \tag{3.17}$$

3.4.3 Configuration of agents

After decomposing the optimization problem, the agent-based optimal control strategy for the optimal control of the central cooling system is constructed. The cooling tower agents, chiller agents and a coordinating agent are designed to solve the sub-problems and the master problems. The optimization process of the two-stage optimization is described above (Section 3.3.2). After completing the first stage, the coordinating agent sends a new Lagrange multiplier μ and switches to the new convergence criteria and the new function for updating μ. The objective function of cooling tower agents, chiller agents and the coordinating agent are given below in detail.

The objective function of each chiller agent is shown as Eq. 3.18.

$$\underset{\{T_{con,in}\}}{Min} \left[P_{chi,j} + \lambda \cdot CM_{cwj}\left(T_{con,out} - T_{con,in}\right)\right] \tag{3.18}$$

Where, $P_{chi,j}$ is the power consumption of chiller and it can be predicted by the simplified chiller model proposed by Stoecker (Stoecker, 1975). Three main factors which influence the performance of chillers are considered: chilled water supply temperature (T_{chws}), condenser inlet cooling water temperature ($T_{con,in}$) and part load ratio. As shown in Eq. 3.19, the impact of part load ratio is represented by the part load ratio coefficient (PLR_{cof}) and the impacts of T_{chws} and $T_{con,in}$ are represented by a temperature coefficient ($Temp_{cof}$). PLR_{cof} and $Temp_{cof}$ are calculated by Eqs. 3.20 and 3.21.

$$P_{chi} = Cap_{nom} \cdot COP_{nom} \cdot PLR_{cof} \cdot Temp_{cof} \tag{3.19}$$

$$PLR_{cof} = a_1 + a_2\left(\frac{Cap}{Cap_{nom}}\right) + a_3\left(\frac{Cap}{Cap_{nom}}\right)^2 \quad (3.20)$$

$$Temp_{cof} = b_1 + b_2T_{chws} + b_3T_{chws}^2 + b_4T_{con,in} + b_5T_{con,in}^2 + b_6T_{chws}T_{con,in} \quad (3.21)$$

Where Cap_{nom} is the nominal capacity of the chiller, *Cap* is the capacity used in operation, COP_{nom} is the nominal coefficient of performance. The parameters including $a_1 - a_3$ and $b_1 - b_6$ can be obtained from manufacturer or by curve-fitting using operation data. The local constraint is that the cooling tower outlet water temperature should not be lower than 18 °C.

The objective function of each cooling tower agent is shown as Eq. 3.22

$$\underset{\{T_{cwoi}\}}{Min}\left[P_{ct,i} - \lambda \cdot CM_{cwi}\left(T_{con,out} - T_{cwoi}\right)\right] \quad (3.22)$$

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. 3.23.

$$P_{ct} = P_{ct,des}\left[d_1 + d_2\left(\frac{M_a}{M_{a,nom}}\right) + d_3\left(\frac{M_a}{M_{a,nom}}\right)^2 + d_4\left(\frac{M_a}{M_{a,nom}}\right)^3\right] \quad (3.23)$$

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 (Ma et al., 2008) proposed a simplified method to calculate the heat transfer from the cooling water to the inlet air as shown in Eq. 3.24.

$$Q_{recj} = c_1 \cdot M_a^{c_2} \cdot M_{cw}^{c_3} \cdot \left(T_{con,out} - T_{wb}\right)^{c_4} \quad (3.24)$$

The parameters including $c_1 - c_4$ and $d_1 - d_4$ 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. 3.25.

$$T_{cwoi,f=50\ HZ} \leq T_{cwoi} \leq T_{cwoi,f=20\ HZ} \tag{3.25}$$

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. 3.26 and 3.27 respectively.

$$\left|T_{cwo} - T_{con,in}\right| < \varepsilon \tag{3.26}$$

$$\left|\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}} T_{cwoi} - T_{cwo,opt}\right| < \delta \tag{3.27}$$

Considering the accuracy of measurements, 0.05 °C is adopted as the threshold of the two optimizations (i.e., ε and δ). Adopting the subgradient method, Lagrange multipliers of the two stages can be updated through Eqs. 3.28 and 3.29 separately.

$$\lambda_{k+1} = \lambda_k + \alpha \cdot C \cdot M_{cw}\left(T_{cwo} - T_{con,in}\right) \tag{3.28}$$

$$\mu_{k+1} = \mu_k + \beta \cdot C \cdot M_{cw}\left(\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}} T_{cwoi} - T_{cwo,opt}\right) \tag{3.29}$$

Where α and β are the step sizes that can change the value of the penalty function, and their values significantly influence the convergence of the entire optimization process. Through analysing 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.

3.5 Validation test results and performance evaluation

The optimization accuracy and computation load/efficiency of each agent and the entire control strategy are tested and analysed to evaluate the feasibility, efficiency and reliability of the proposed agent-based distributed real-time 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 the evaluation of the control strategies. Considering the deployment of the proposed strategy on the physical automation platforms, the computation load of individual agents needs to be considered since the 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 the 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 that can accelerate the convergence of optimization by properly resetting the initial value of the Lagrange multiplier is proposed for this study. Moreover, the energy performance of the proposed strategy is evaluated by comparing it with the other two control strategies applied in the same central cooling system for buildings. The building central cooling system with the configuration descriped in Section 3.4.1 is constructed in the TRNSYS platform using detailed dynamic models to simulate the realistic performance of the system.

3.5.1 Control accuracy

To evaluate the accuracy of the proposed agent-based distributed real-time optimal control strategy, a centralized real-time optimal control strategy using a 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, i.e., spring, mild-summer and sunny-summer, are selected to test the performance of the two control strategies.

Tables 3.2 and 3.3 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 strategy is able to find the optimal cooling tower outlet water temperature set-point as the GA-based centralized real-time optimal 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 strategy can achieve the optimal temperature set-points for individual cooling towers successfully, according to their respective performances.

Table 3.2 Test conditions of three typical days

Seasons	*Spring*	*Mild-summer*	*Sunny-summer*
Load (kW)	4,784.19	13,914.80	17,828.06
N_{ch}	1	2	3
N_{ct}	2	4	6
T_{db} (℃)	21.43	30.98	31.78
T_{wb} (℃)	18.62	25.20	26.90
M_{cw} (L/s)	410.60	821.20	1231.80

Table 3.3 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_{cws} (℃)	24.52	24.52	32.94	32.94	35.61	35.67
T_{cws1} (℃)	24.42	24.42	31.93	32.01	34.02	34.10
T_{cws2} (℃)	24.62	24.62	32.73	32.72	34.82	34.88
T_{cws3} (℃)	-	-	33.33	33.31	35.42	35.52
T_{cws4} (℃)	-	-	33.73	33.73	35.92	35.98
T_{cws5} (℃)	-	-	-	-	36.32	36.42
T_{cws6} (℃)	-	-	-	-	37.12	37.12

3.5.2 Computation complexity and optimization efficiency

To evaluate the computational effectiveness (i.e., feasibility, efficiency and reliability) of the proposed agent-based distributed real-time optimal control strategy when 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 updates its optimization outputs which are 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 3.4. For cooling tower agents at each step, the numbers of FLOPs for the optimization of each agent were 945 at both 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 coordinating 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 minutes 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 the optimization of the proposed agent-based distributed real-time 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 the convergence of the current optimization since the working conditions of two consecutive optimization intervals usually does not change significantly. Figure 3.4 shows the number of iterations of both stages for each optimization under dynamic working conditions over a year. It can be found that, except for the first optimization trial, all optimizations were completed within 250 steps. This indicates that using the proposed 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 is shown in Table 3.5. 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 the 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.

According to the convergence criterion of the first stage optimization, i.e., Eq. 3.26, the 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 analysing 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 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. Figure 3.5 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. 3.28), 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 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. Figure 3.6 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 distributed real-time 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 minutes) as the practically acceptable minimum sampling interval is larger.

Table 3.4 The number of FLOPs of the agents at each iteration

	Cooling tower agent	Chiller agent	Coordinating agent
Stage 1	945	1150	19
Stage 2	945	-	19

Table 3.5 The distribution of the 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

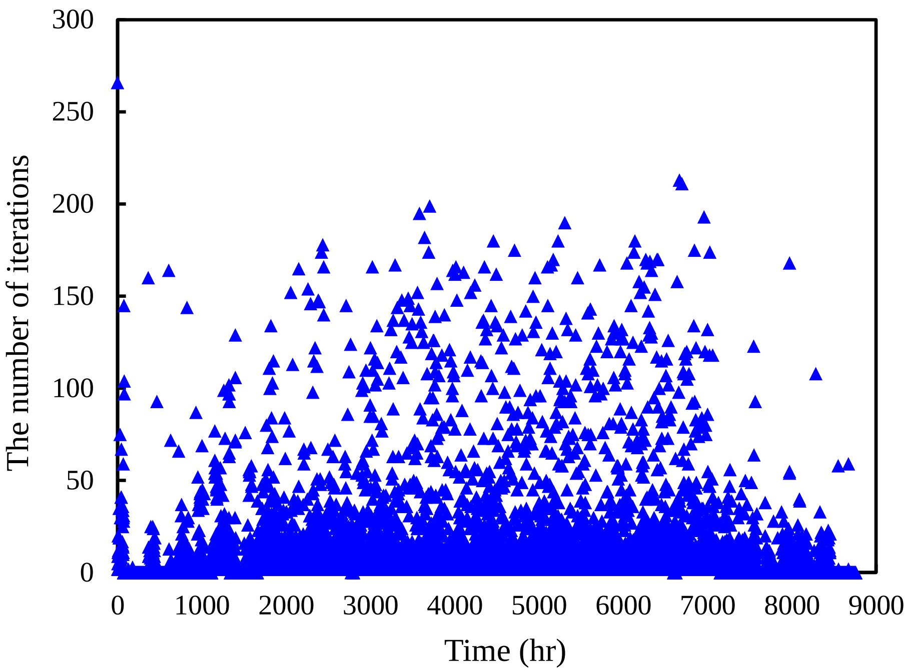


Figure 3.4 The number of iterations for optimizations in the test year

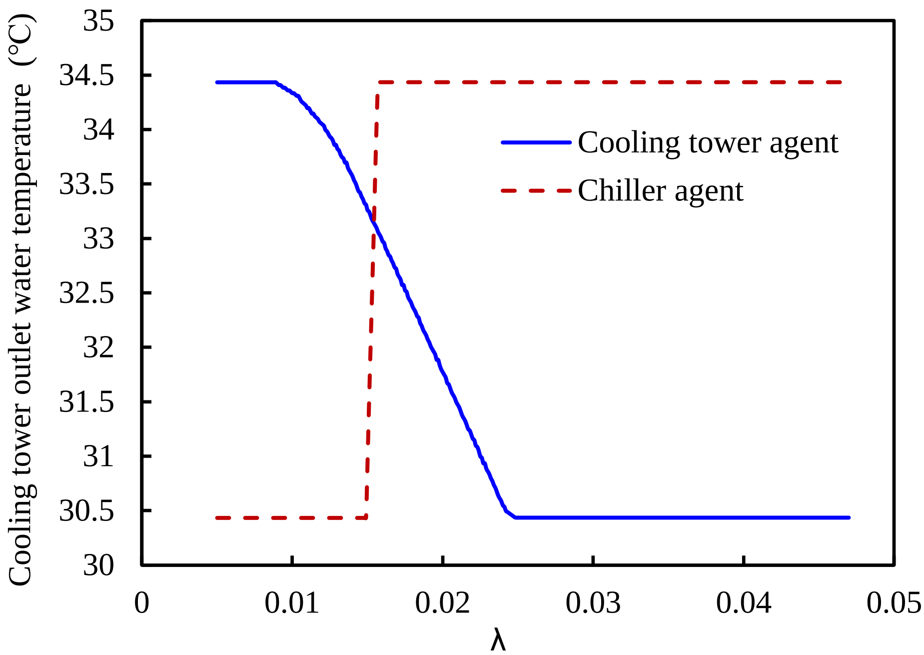


Figure 3.5 Evolutions of the optimization results of chiller and cooling tower agents

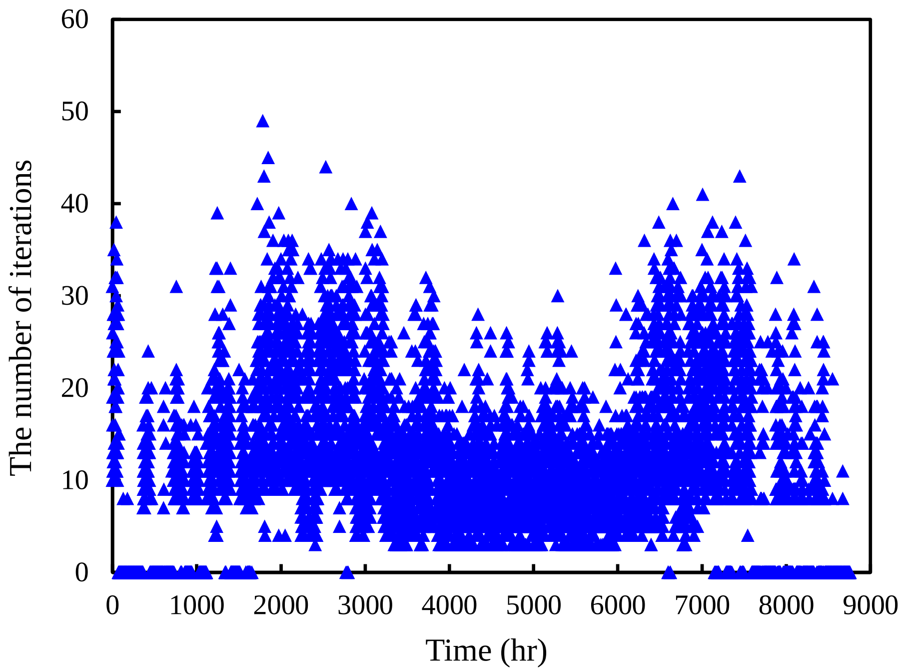


Figure 3.6 The number of iterations needed for optimizations using the convergence acceleration method

3.5.3 Energy performance

To evaluate the energy effectiveness of the proposed agent-based distributed real-time optimal control strategy (Strategy C), the 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, the energy efficiency of all cooling towers is assumed to be the same, which equals 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.

Figure 3.7 and Figure 3.8 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. Figure 3.9 and Figure 3.10 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 days, 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 3.6. 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%).

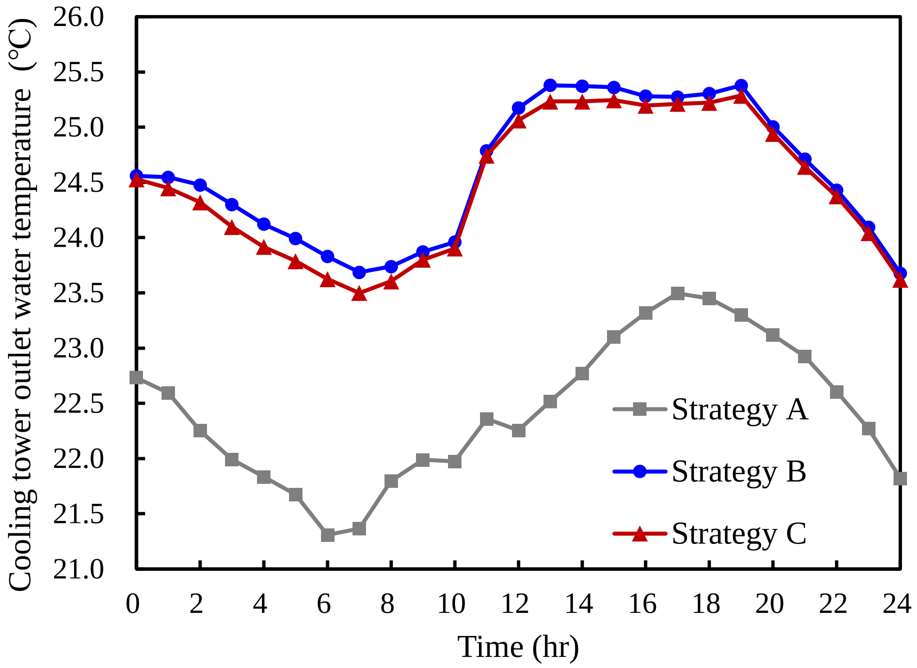


Figure 3.7 Cooling tower outlet water temperature using different control strategies in the Spring day

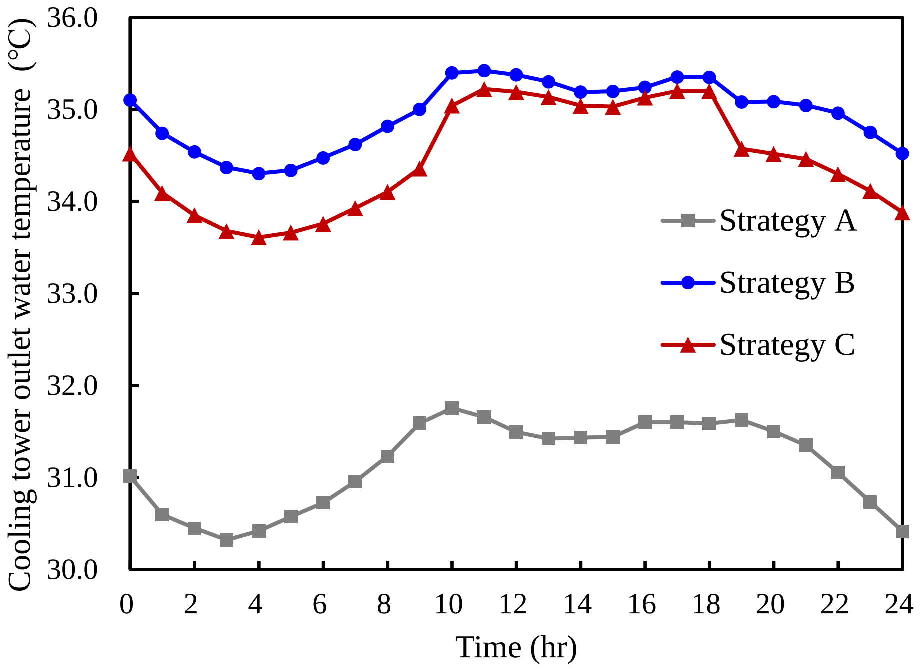


Figure 3.8 The cooling tower outlet water temperature using different control strategies in the Summer day

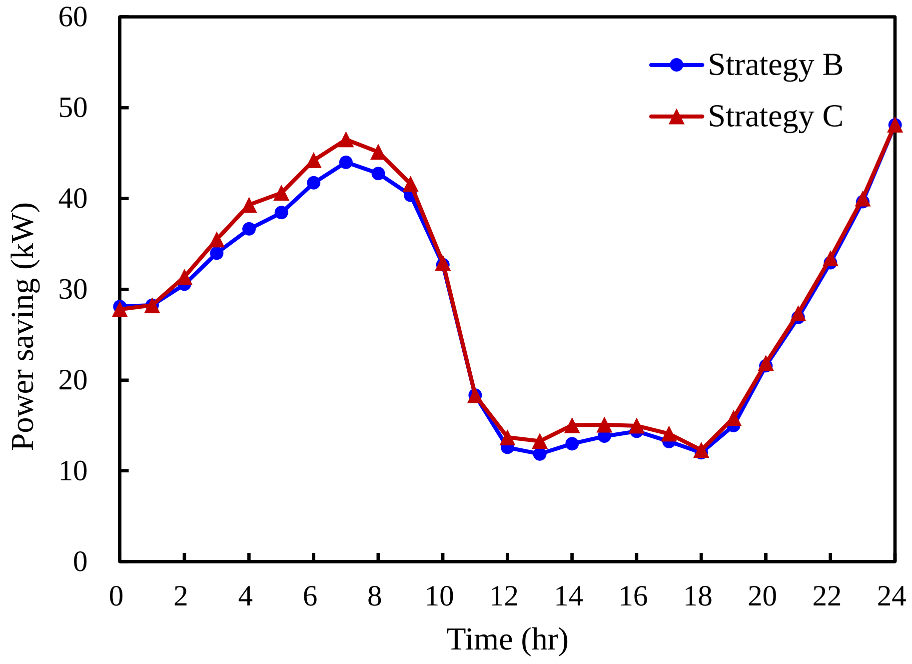


Figure 3.9 Total power saving using different control strategies in the spring day

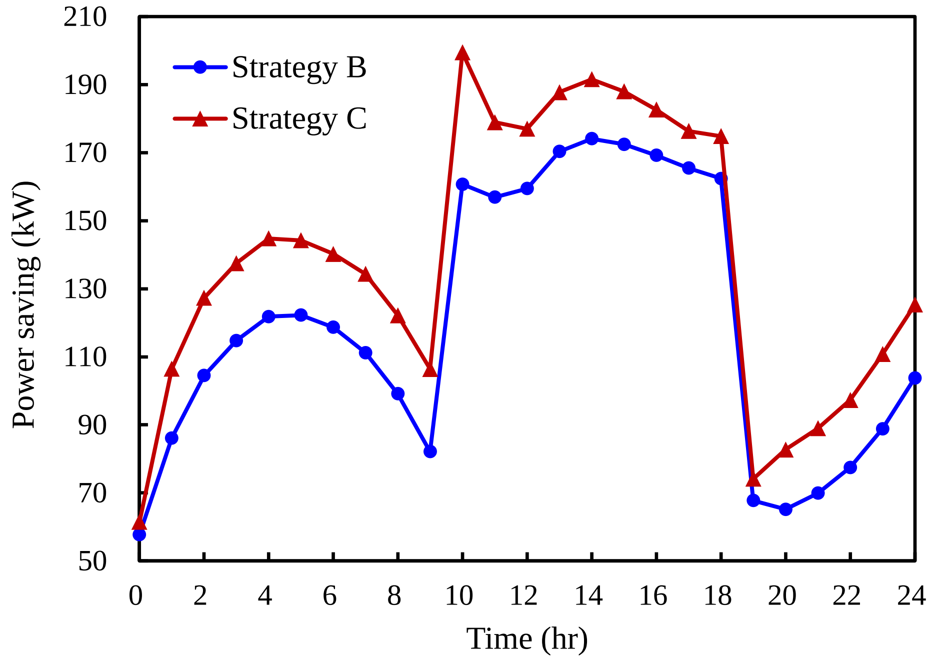


Figure 3.10 Total power saving using different control strategies in the summer day

Table 3.6 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	21312	-	-	75313	-	-
Centralized	20621	690.71	3.24	72331	2982.36	3.96
Agent-based	20595	716.57	3.36	71852	3461.11	4.60

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

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 set-points for cooling towers is compared with that using a unified optimal set-point for all cooling towers. Figure 3.11 shows the outlet water temperatures of individual cooling towers using the proposed strategy, Strategy C, on the summer day. Figure 3.12 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, the 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.

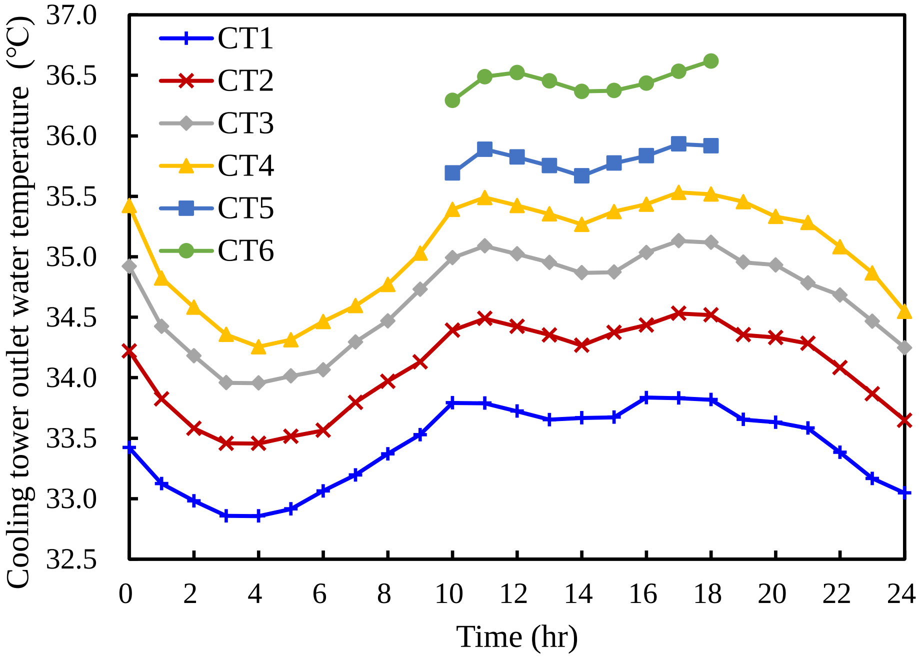


Figure 3.11 Individual cooling tower outlet water temperature using the proposed strategy

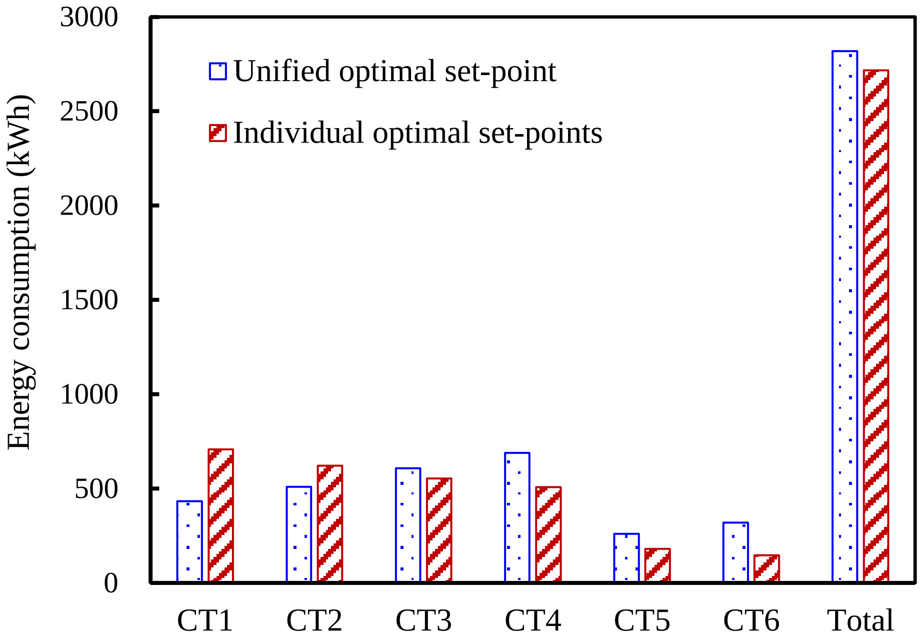


Figure 3.12 Energy consumption of cooling towers using unified optimal set-point and individual optimal set-points

3.6 Summary

The implementation framework and the computation load distribution of the proposed distributed optimal control strategies are proposed concerning the real applications in field control networks. An agent-based distributed real-time 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. 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 strategy, when deployed over the physical platforms of BASs, 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:

i. The proposed agent-based distributed real-time optimal control strategy is able to effectively find the optimal set-points which can be found by the GA-based centralized optimal control strategy. By adopting the proposed convergence acceleration method, the convergence rate of the proposed strategy can well satisfy the needed optimal control interval in normal application practice.

ii. 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.

iii. 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.

iv. The proposed agent-based distributed real-time 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.

CHAPTER 4 IMPACTS OF INFORMATION DELAYS ON THE PERFORMANCE OF DISTRIBUTED OPTIMAL CONTROL STRATEGIES

Since the distributed optimal control strategies obtain the optimal settings through coordination of multiple agents implemented on corresponding local control devices, information delays, which are the time delays in information exchange between devices integrated in communication networks, could affect the performance of distributed optimal control of HVAC systems. This chapter investigates and quantifies the impacts of information delays on the performance which are rarely concerned before. Section 4.1 illustrates and models the information delays in distributed optimization. Section 4.2 presents the qualitative analysis and quantitative assessment of the impacts on the distributed optimal control of a central cooling plant. Section 4.3 investigates and compares the impacts on the distributed optimal control strategies for a multi-zone air-cooling system using two distributed optimization methods. A summary is given in Section 4.4.

4.1 Description and modelling of information delays in distributed optimization

Figure 4.1 illustrates information exchange between control devices (or agents) in a synchronized network and how information delays of different lengths affect an optimization process. In ideal conditions, the actual information delays are less than the sampling interval (referred to as “regular delays” hereafter). Unless a delay larger than the sampling interval occurs, the intermediate local optimization results of the current sampling step can be used by other agents at the next sampling step. It is also possible that data is lost during communication as packet loss. In general, information delays are caused by the time cost of computation (t_{cpt}) and communication (t_{com}). Since the field controllers or devices generally sample the data from their buffers and process them periodically with a predefined sampling interval, the effective delay of the information exchange between controllers is discrete in terms of the number of sampling intervals. According to the time spent for these processes and the sampling interval (*SI*), the possible maximum information delay (*Md*) can be obtained using Eq. 4.1. It is worth noting that the field controllers or devices can store some received data in their buffers and will always use the latest available data. Therefore, packet loss will not result in a situation where no information is available for the use of an agent.

$$Md = \begin{cases} \left\lfloor \frac{t_{com}+t_{cpt}}{SI} \right\rfloor & (bounded\ delay) \\ +\infty & (packet\ loss) \end{cases} \tag{4.1}$$

Synchronizing the operation of multiple individual local controllers or devices is not easy in engineering practice (Ploplys et al., 2004). Normally, the controllers or devices in BASs operate at the same sampling interval, but their operation is not synchronized. In such conditions, even under regular delays, some devices can experience effective information delays of one sampling interval when receiving actual data from other devices.

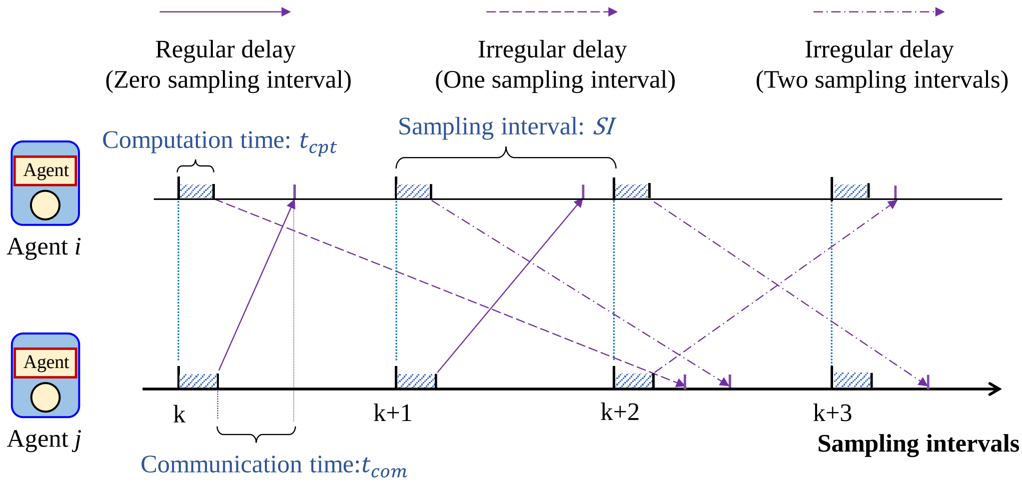


Figure 4.1 Information delays in the distributed optimization deployed among devices in a synchronized network

Markov chains are commonly used to model uncertain network delays since the current time delays are usually related to previous time delays (Lin Xiao et al., 2000). The Markov chain can be expressed by a state space and a transition probability matrix. The state space includes all possible values of the delays and the transition matrix gives the probabilities of the delays changing from one value to another value. In this study, the state space is set to [0, 1, 2] representing the possible lengths of effective information delays in terms of the number of sampling steps. A delay of zero steps represents a regular delay. The transition matrix is given in Eq. 4.2.

$$Tran = \begin{bmatrix} 0.4 & 0.6 & 0.0 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.4 & 0.4 \end{bmatrix} \tag{4.2}$$

Packet loss is also included in this model since local devices always use the latest available data. This is also the reason that the probability of transition from a delay of zero step to a delay of two steps is zero. This model will be used in the tests to quantify the impacts of information delays on the performance of distributed optimal control strategies in Sections 5.2 and 5.3.

4.2 Study on the distributed optimal control strategy for a central cooling plant

The central cooling plant and its distributed optimal control strategy involved in this test case are described in Section 3.4.

4.2.1 Qualitative analysis

Uncertain information delays can affect both the control accuracy and the convergence rate of distributed optimal control strategies. The impacts on control accuracy mean that the control strategy obtains the biased optimal results, which will result in the reduced energy efficiency of the target energy system. The impacts on convergence rate mean that more iteration steps are needed to achieve convergence of the optimization, which may result in convergence failure within the pre-set optimization interval. In this case, a simple near-optimal strategy would be adopted to generate set-points, which also results in the reduced energy efficiency.

To analyse the impacts of information delays on distributed optimization, formulas for the distributed optimization with information delays involved are formulated. It is worth noting that, since the optimization interval concerned in the real-time optimal control is short, usually in minutes, the system is assumed to be static during the optimization interval. The length of information delays is denoted as *Ld*. In this case, the objective is to find the optimal cooling tower outlet water temperature. At step k, the chiller agents and cooling tower agents update their local optimization results with the latest information available, as shown in Eqs. 4.3 and 4.4. The coordinating agent determines the convergence state and updates the multiplier according to Eqs. 4.5 and 4.6.

$$T_{con,k} = f_{chi}\left(\lambda_{k-Ld_{chico}}\right) \tag{4.3}$$

$$T_{cwo,k} = f_{ct}\left(\lambda_{k-Ld_{ctco}}\right) \tag{4.4}$$

$$Conv_k = g\left(T_{con,k-Ld_{cochi}}, T_{cwo,k-Ld_{coct}}\right) \tag{4.5}$$

$$\lambda_k = h\left(T_{con,k-Ld_{cochi}}, T_{cwo,k-Ld_{coct}}\right) \tag{4.6}$$

$$Conv_k = g\left[f_{chi}(\lambda_{k-Ld_{chico}-Ld_{cochi}}), f_{ct}(\lambda_{k-Ld_{ctco}-Ld_{coct}})\right] \tag{4.7}$$

$$\lambda_k = h\left[f_{chi}\left(\lambda_{k-Ld_{chico}-Ld_{cochi}}\right), f_{ct}\left(\lambda_{k-Ld_{ctco}-Ld_{coct}}\right)\right] \tag{4.8}$$

Where *chico* indicates the delay in the information exchange from chiller agent to coordinating agent. Using Eqs. 4.3 and 4.4, Eqs. 4.5 and 4.6 can be transformed into Eqs. 4.7 and 4.8, which show how the information delays affect the convergence determination and multiplier update respectively. The impacts of information delays on the multiplier update are illustrated in Figure 4.2. Compared with ideal conditions (only regular information delay exist), the scenarios with irregular information delays lead to faster Lagrange multiplier updates in the first several steps, finally converging to biased optimization results at a lower convergence speed. Similar phenomena in the distributed optimization of economic dispatch problems have been reported in previous studies (Tao Yang et al., 2015; Zhao et al., 2020).

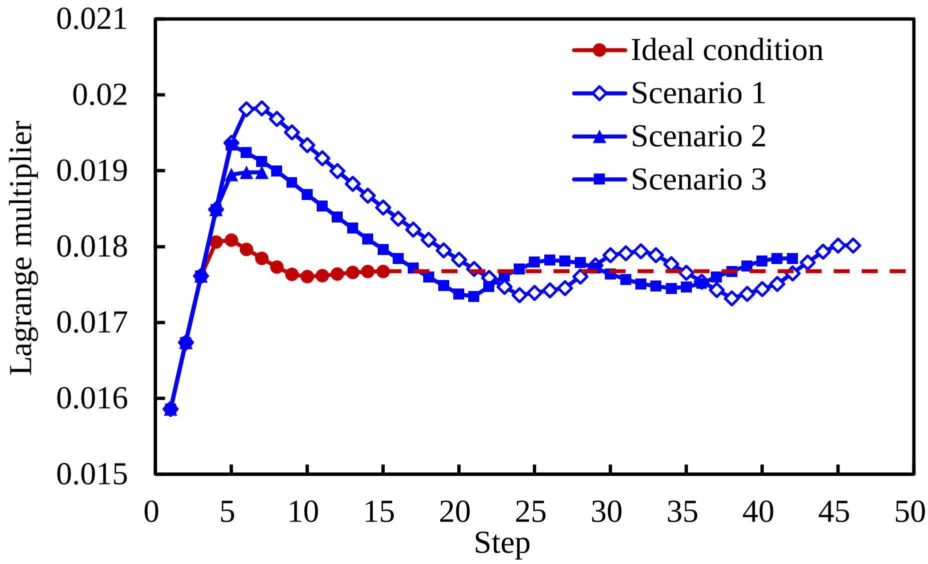


Figure 4.2 Evolution of the Lagrange multiplier

The impacts on the convergence determination are determined by the magnitude of delays during information exchange between chiller agents and the coordinating agent (i.e., Ld_{chi}=$Ld_{chico} + Ld_{cochi}$), and that between the cooling tower agents and the coordinating agent (Ld_{ct}=$Ld_{ctco} + Ld_{coct}$). According to Ld_{chi} and Ld_{ct}, information delays can be divided into two categories, 'uniform delay' ($Ld_{chi} = Ld_{ct}$) and 'nonuniform delay' ($Ld_{chi} \neq Ld_{ct}$). In scenarios with uniform delays, the local optimal results used for convergence determination by the coordinating agent are from the same iteration step. Therefore, if the coordinating agent sends the actual optimal result to the cooling tower agents when convergence is achieved, the uniform delay will not affect the optimization results. In scenarios with nonuniform delays, the coordinating agent determines the convergence state with the local optimization results of different iteration steps. As shown in Figure 4.3, due to the nonuniform delay, $T_{cwo,k-Ld_{ctco}}$ will be generated as the optimal value, which results in biased optimization results as shown in Eq. 4.9. Such impacts have not been reported in previous studies, since using the coordinating agent to determine convergence status is the mechanism only used in hierarchical distributed optimization algorithms.

$$bias = T_{cwo,opt} - T_{cwo,k-Ld_{coct}} \quad (4.9)$$

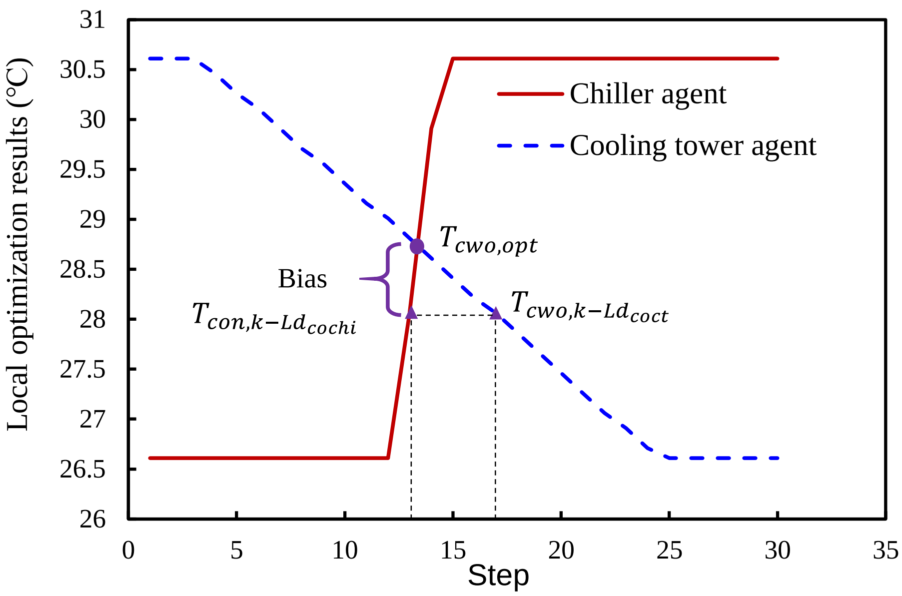
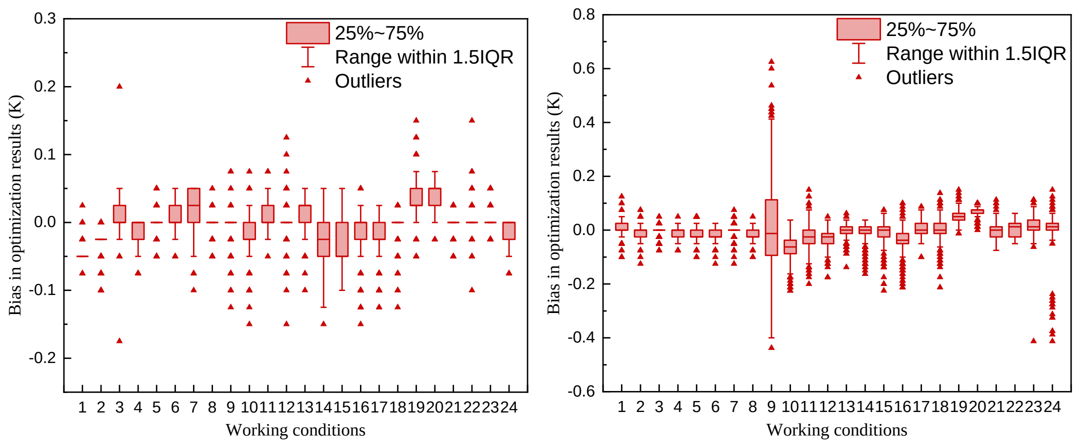


Figure 4.3 Impacts of nonuniform information delays on optimization results

4.2.2 Experimental and quantitative assessment

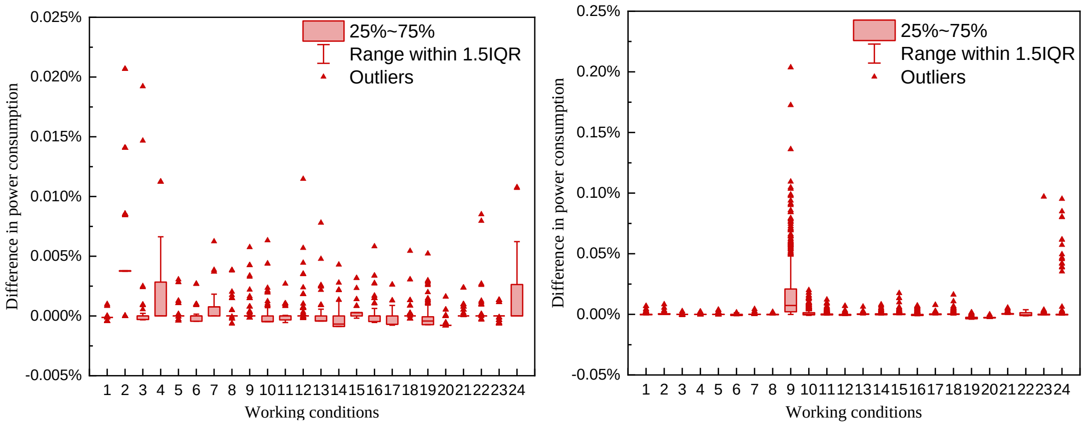
A distributed optimal control strategy for the central cooling plant was developed incorporating information delays to quantify their impacts. The delays were modelled using the Markov chain constructed in Section 4.1. In the tests, the optimization results, energy performance and the convergence rates of the distributed optimal control strategy were obtained and compared with those in ideal conditions. Twenty-four working conditions in a spring day and twenty-four working conditions in a summer day were chosen as the test conditions. Since the information delays are uncertain and information exchange is required at each iteration, during one global optimization interval, there can be hundreds of instances of information exchange with delays of different lengths. In order to present an overview of the impacts of information delays, 1000 simulations were conducted for each working condition in the tests.

Figure 4.4 shows the distribution of the biases in the optimization results in the spring and summer test conditions. The biases in the optimization results were very small in most optimizations, and the biases in the summer test conditions were larger than those in the spring test conditions. The maximum biases were 0.2 K and 0.6 K in the spring and summer test conditions respectively. As a result, the impacts on power consumption could be neglected in most optimizations, and the impacts at the summer test conditions were more obvious as shown in Figure 4.5. The maximum increase in power consumption was 0.02% and 0.2% in the spring and summer test conditions respectively. The impact on the convergence rate was obvious and remained similar in the spring and summer test conditions as shown in Figure 4.6. In ideal conditions, all the optimizations were completed within 40 steps, satisfying the one-minute optimization interval. However, due to information delays, the convergence rate was slowed in most optimizations. In the spring test conditions, convergence could not be achieved within one minute in 1,533 optimizations, accounting for 6.1% of the total. In the worst case, convergence was achieved after 216 steps, about seven times as many as in ideal conditions. In the summer test conditions, convergence could not be achieved within one minute in 1,652 optimizations, accounting for 6.6% of the total, and in the worst case, convergence was achieved after 182 steps, about nine times as many as in ideal conditions.



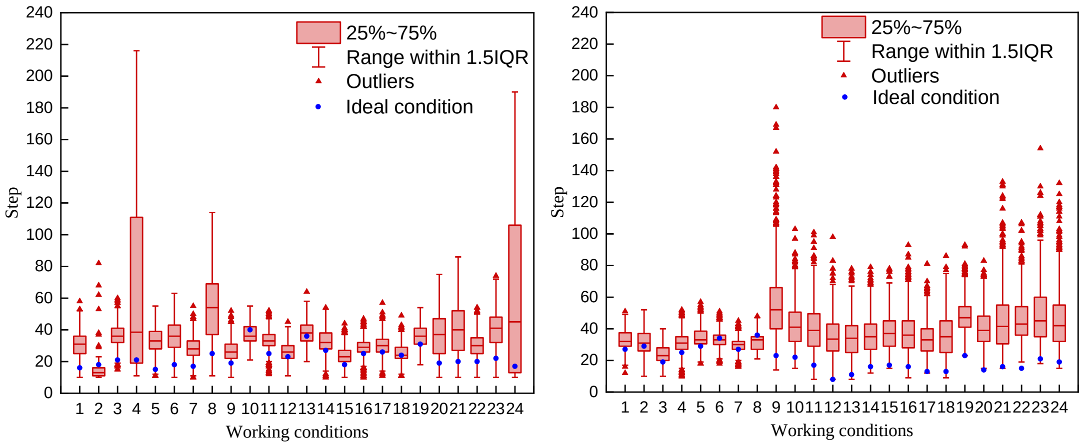
(a) Spring working conditions (b) Summer working conditions

Figure 4.4 Statistical distribution of the bias in optimization results under information delays



(a) Spring working conditions (b) Summer working conditions

Figure 4.5 Statistical distribution of the difference in system power consumption under information delays



(a) Spring working conditions (b) Summer working conditions

Figure 4.6 Statistical distribution of the iteration steps under information delays

4.2.3 Sensitivity analysis

Sensitivity analysis was also conducted to analyse the impacts of information delays. In this study, the length of information delays and the step-size for the update of the Lagrange multiplier are the main factors concerned, as shown in Eqs. 4.7 and 4.8. The control strategy was tested in scenarios with different types/lengths of information delays and step-sizes in various working conditions of a typical year. Three indicators were chosen to evaluate the impacts of information delays, including bias in the optimization results, increase in energy consumption and increase in iteration step numbers, by comparing with those in ideal conditions.

4.2.3.1 Effects of information delay length

To investigate the effects of the information delay length, the control strategy was tested in scenarios with constant information delays of different lengths. The tested uniform and nonuniform delay scenarios and the corresponding results are shown in Tables 4.1 and 4.2 respectively. In these tests, the step-size for the update of the Lagrange multiplier was set to 5×10^{-8}, reflecting ideal conditions. According to the convergence rate in ideal conditions, the optimal control interval was set to one minute. If the convergence cannot be achieved within the pre-set control interval, a near-optimal approach will be adopted, i.e., the cooling tower outlet water temperature will be set to 5 K higher than the current wet-bulb temperature.

According to the results of the tested uniform delay scenarios, the impacts of the uniform delay increased dramatically with increases in delay length. As delay length increased from 1 sampling interval to 4 sampling intervals, the average bias in optimization results increased from 0.05 K to 0.44 K and the total energy consumption increase rose from 7,853.3 kWh to 37,397.2 kWh (i.e., from 0.06% to 0.28%). As aforementioned, the uniform delay will not affect the optimization results if convergence can be achieved. The increase of these impacts was caused by the increasingly slowed convergence rate. The average increase of iteration steps rose from 9 to 33 and the number of non-convergence optimizations increased from 306 to 2,986 (i.e., from 4.50% to 43.92%) as the delay length grew.

Table 4.1 Statistical performance data of optimal control strategy under different uniform delays

Uniform delays	Ld_{ct}=1 Ld_{chi}=1	Ld_{ct}=2 Ld_{chi}=2	Ld_{ct}=3 Ld_{chi}=3	Ld_{ct}=4 Ld_{chi}=4
Average bias in optimization results (K)	0.05	0.23	0.30	0.44
Maximum bias in optimization results (K)	2.20	2.48	2.93	3.03
Total energy consumption increase (kWh)	7,853.3	18,589.9	27,518.2	37,397.2
Increase ratio of total energy consumption	0.06%	0.14%	0.21%	0.28%
Average increase of iteration step numbers	9	20	28	33
Number of non-convergence optimizations	306	1163	2145	2986

According to the results of the tested nonuniform delay scenarios, the value of Ld_{chi} had the largest effects on the impacts of the information delays. This is because the impacts of the information delays on the local optimization of chiller agents are more obvious than those on the local optimization of cooling tower agents. The tested scenarios include two groups: in one group Ld_{chi} was larger than Ld_{ct} and in the other group it was smaller than Ld_{ct}. Under the same lengths of the information delays, the impacts in the $Ld_{chi} > Ld_{ct}$ scenarios were larger than those in the $Ld_{chi} < Ld_{ct}$ scenarios. In scenarios where $Ld_{chi} > Ld_{ct}$, the impacts of information delays increased with the increase of difference between Ld_{chi} and Ld_{ct} as well as the sum of these two delays. In the scenario where [Ld_{ct}=0, Ld_{chi}=1], the impacts on the optimization results and convergence rate were the lowest, and in the scenario where [Ld_{ct}=3, Ld_{chi}=4], the impacts were the largest. In these two scenarios, the average biases in optimization results were 0.04 K and 0.45 K, the total energy consumption difference was 3868.1 kWh and 36581.0 kWh (0.06% and 0.28%), and the number of non-convergence optimizations was 184 and 2959 (2.71% and 43.53%) respectively. In the scenarios where $Ld_{chi} < Ld_{ct}$, the impacts of the information delays did not always increase with the increase of the difference or the sum of the delays. In the scenarios where Ld_{chi}>0, the impacts of the information delays almost decreased with the increase of the delays among the cooling tower agents and the coordinating agent (Ld_{ct}). This is because the increase in the difference of delays reduces the number of non-convergence optimizations. In the scenarios where all optimizations converged, i.e., the scenarios where Ld_{chi}=0, the increase in the delays among the cooling tower agents and the coordinating agent (Ld_{ct}) led to the increase in the impacts on optimization results.

Table 4.2 Statistical performance data of optimal control strategy under different nonuniform delays

Ldct<Ldchi	Dif = 1				Dif = 2			Dif = 3		Dif=4
	Ldct=0 Ldchi=1	Ldct=1 Ldchi=2	Ldct =2 Ldchi=3	Ldct=3 Ldchi=4	Ldct=0 Ldchi=2	Ldct=1 Ldchi=3	Ldct=2 Ldchi=4	Ldct=0 Ldchi=3	Ldct=1 Ldchi=4	Ldct=0 Ldchi=4
Average bias in optimization results (K)	0.04	0.19	0.32	0.45	0.17	0.32	0.44	0.30	0.45	0.44
Maximum bias in optimization results (K)	2.20	2.48	2.75	2.98	2.48	2.68	2.97	2.68	2.80	2.80
Total energy consumption increase (kWh)	3,868.1	16,338.4	26,877.1	36581.0	13,923.0	26,184.6	34,782.5	23,065.7	35,108.3	33539.3
Increase ratio of total energy consumption	0.03%	0.12%	0.20%	0.27%	0.10%	0.20%	0.26%	0.17%	0.26%	0.25%
Average increase in iteration step numbers	8	20	28	33	19	27	32	26	32	31
Number of non-convergence optimizations	184	1091	2033	2959	901	1891	2794	1642	2710	2582
Ldct>Ldchi	Ldct=1 Ldchi=0	Ldct=2 Ldchi=1	Ldct=3 Ldchi=2	Ldct=4 Ldchi=3	Ldct=2 Ldchi=0	Ldct=3 Ldchi=1	Ldct=4 Ldchi=2	Ldct=3 Ldchi=0	Ldct=4 Ldchi=1	Ldct=4 Ldchi=0
Average bias in optimization results (K)	0.01	0.02	0.14	0.29	0.015	0.04	0.13	0.03	0.05	0.04
Maximum bias in optimization results (K)	0.14	1.67	2.48	2.68	0.33	1.44	2.27	0.36	1.46	0.36
Total energy consumption increase (kWh)	23.4	1,549.1	13,725.6	26,317.9	107.6	1,605.2	11,930.0	225.8	1,296.4	413.3
Increase ratio of total energy consumption	0.00%	0.01%	0.10%	0.20%	0.00%	0.01%	0.09%	0.00%	0.01%	0.00%
Average increase in iteration step numbers	1	8	19	28	1	8	18	-1	8	-1
Number of non-convergence optimizations	0	63	818	1916	0	58	707	0	38	0

4.2.3.2 Effects of step-size

To investigate the effects of the step-size for the update of the Lagrange multiplier on the impacts of information delays, the control strategy was tested with different step-sizes. Tests were conducted in two scenarios with typical information delays and the corresponding statistical results are shown in Table 4.3 and Table 4.4 respectively. The first scenario involves uniform delays with the largest sum of delays where [Ld_{ct}=4, Ld_{chi}=4], and the other scenario involves nonuniform delays with the largest difference of delays where [Ld_{ct}=0, Ld_{chi}=4]. The step-size varies from 1×10^{-8} to 5×10^{-8} with an increment of 1×10^{-8}.

It can be seen that the best choice of the step-size in ideal conditions, i.e., 5×10^{-8}, was not the best choice when information delays exist. Using an appropriate step-size can reduce the impacts of information delays on the optimization results and the convergence rate. The best choice of step-size was 2×10^{-8} under both test scenarios, as it had the least impacts on the convergence rate and a negligible impact on optimization results. In the two test scenarios, the average increase of iteration step numbers was 18 and 17, and the number of non-convergence optimizations was 397 and 350 (5.84% and 5.15%) respectively.

Table 4.3 Statistical performance data of optimal control strategy using different step-sizes under uniform delays

Step-size	1×10^{-8}	2×10^{-8}	3×10^{-8}	4×10^{-8}	5×10^{-8}
Average bias in optimization results (K)	0.47	0.08	0.27	0.36	0.44
Maximum bias in optimization results (K)	2.93	2.20	2.80	2.82	3.03
Total energy consumption increase (kWh)	23,449.7	6,924.6	22,719.9	28,743.7	37,397.2
Increase ratio of total energy consumption	0.18%	0.05%	0.17%	0.21%	0.28%
Average increase of iteration step numbers	30	18	25	29	33
Number of non-convergence optimizations	3,198	397	1,514	2,262	2,986

Table 4.4 Statistical performance data of optimal control strategy using different step-sizes under nonuniform delays

Step-size	1×10^{-8}	2×10^{-8}	3×10^{-8}	4×10^{-8}	5×10^{-8}
Average bias in optimization results (K)	0.48	0.08	0.26	0.39	0.44
Maximum bias in optimization results (K)	2.97	2.48	2.70	2.80	2.80
Total energy consumption increase (kWh)	23,941.6	6,409.5	21,115.4	30,507.4	33,539.3
Increase ratio of total energy consumption	0.18%	0.05%	0.16%	0.23%	0.25%
Average increase of iteration step numbers	30	17	25	28	31
Number of non-convergence optimizations	3,223	350	1,329	2,095	2,582

4.3 Study on the distributed optimal control strategy for a multi-zone air-conditioning system

4.3.1 Description of the multi-zone air-conditioning system

The second test case is the impacts of information delays on the distributed multi-objective optimal control of a multi-zone air-conditioning system with a dedicated outdoor air system (DOAS) using fan-coil units (FCU), as shown in Figure 4.7. The optimization objective is to minimize the energy consumption of the primary air handling unit (PAU) while maintaining indoor air quality (IAQ) through optimizing the ventilation air volume of individual rooms (Q_i) and the total PAU ventilation air volume (Q_{tot}). The objective function is shown in Eq. 4.10. n is the number of rooms, INp_i is the indoor pollution index in room i, E is the energy consumption, and γ is the weighting factor.

$$\min_{Q_i, Q_{Tot}} Obj = \sum_{i=1}^{n} INp_i + \gamma \cdot E \tag{4.10}$$
$$\text{subject to: } \sum_{i=1}^{n} Q_i = Q_{\text{tot}}$$

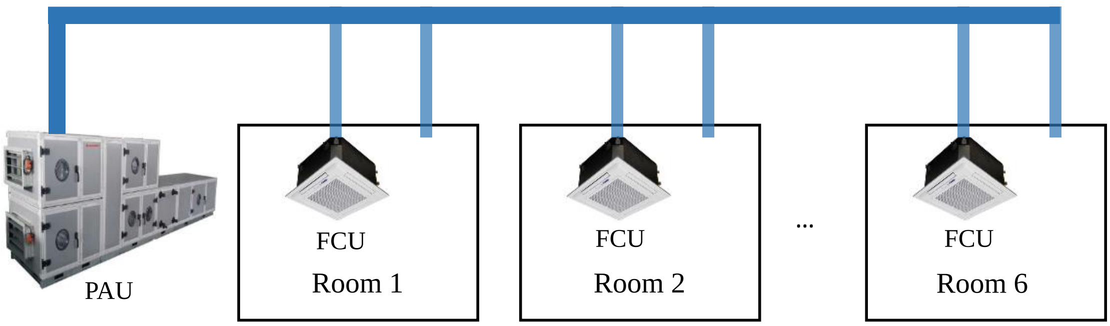


Figure 4.7 Schematic of the air conditioning system concerned

In this test case, CO_2 is the pollutant concerned. The pollution index is defined as Eq. 4.11, which is related to the difference between the steady-state CO_2 concentration ($CO2_i$) and the recommended limit ($CO2_{limit}$) of 800 ppm (Indoor Air Quality Management Group of the Government of the Hong Kong Special Administrative Region, 2003).

$$INp_i = \max\{0, CO2_i - CO2_{limit}\}^2 \tag{4.11}$$

The steady-state CO_2 concentration can be obtained according to the CO_2 concentration of ambient air ($CO2_a$) and the CO_2 generation of the occupants ($MCO2_G$) as shown in Eq. 4.12. N_i is the number of occupants in the room i.

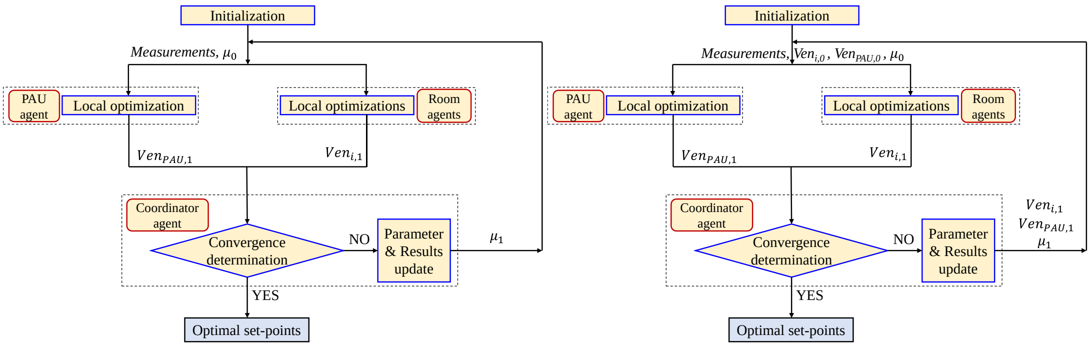
$$CO2_i = CO2_a + \frac{MCO2_G \cdot N_i}{Q_i} \tag{4.12}$$

The energy consumption of PAU (E) can be calculated through Eq. 4.13, it is the sum of the needed chiller energy consumption to generate the required cooling (E_{chi}) (Cheng et al., 2019) and the energy consumption of the fan (E_{fan}).

$$E = E_{chi} + E_{fan} \tag{4.13}$$

4.3.2 Formulation of the distributed optimal control strategies using different optimization methods

In this test case, two distributed optimization algorithms were adopted to formulate the distributed optimal control strategy, i.e., a subgradient method based on dual decomposition and the alternating direction method of multipliers (ADMM). The first one is simpler with lower computation load and communication load, while the second one requires weaker assumptions to guarantee convergence. The impacts of the information delays on the performance of the distributed optimal control strategies using the two algorithms were tested and compared. Figure 4.8 illustrates the optimization processes of the distributed optimal control strategies using the two methods. It can be found that the main difference is that, using ADMM, more information exchange between component agents and the coordinating agent is required. More detailed information regarding the control strategy can be found in (Li and Wang, 2020).



(a) Subgradient method (b) ADMM

Figure 4.8 Optimization process of the distributed optimal control strategies using different methods

4.3.3 Comparison on impacts of information delays using different optimization methods

In order to compare the impacts of the information delays on the performance of the two optimal control strategies, they were tested using the same uncertain information delays as well as the same critical condition with constant information delays. The uncertain information delays are modelled using the Markov chain constructed in Section 4.1, and the constant information delays are set to the possible maximum length, 2 sampling intervals. Eleven working conditions (working hours) in a spring day and eleven working conditions in a summer day were selected as the test working conditions. The occupancy profiles of the six rooms are shown in Figure 4.9.

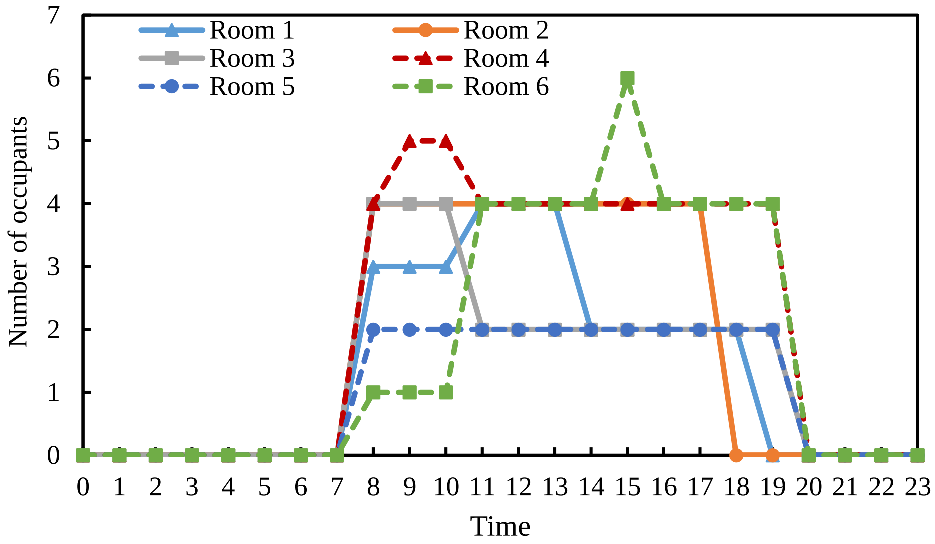
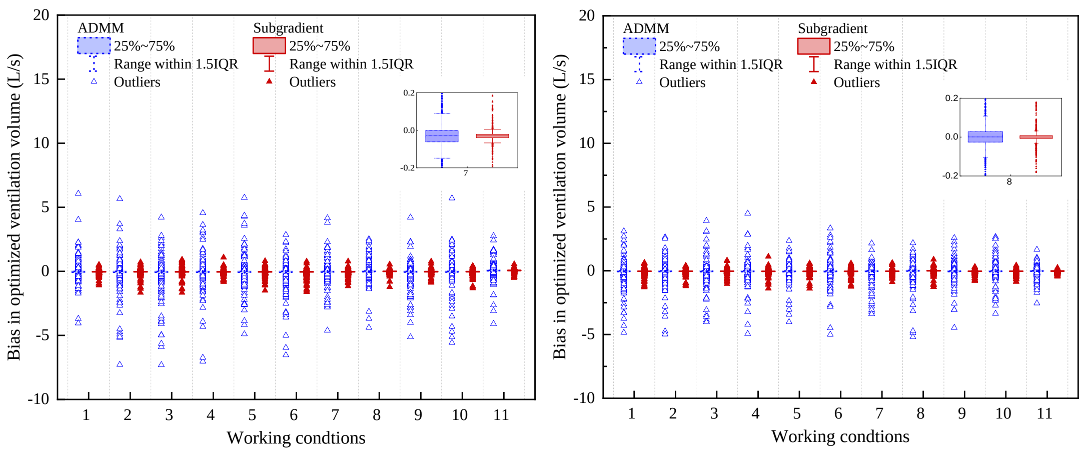


Figure 4.9 Occupancy profiles of the six rooms concerned

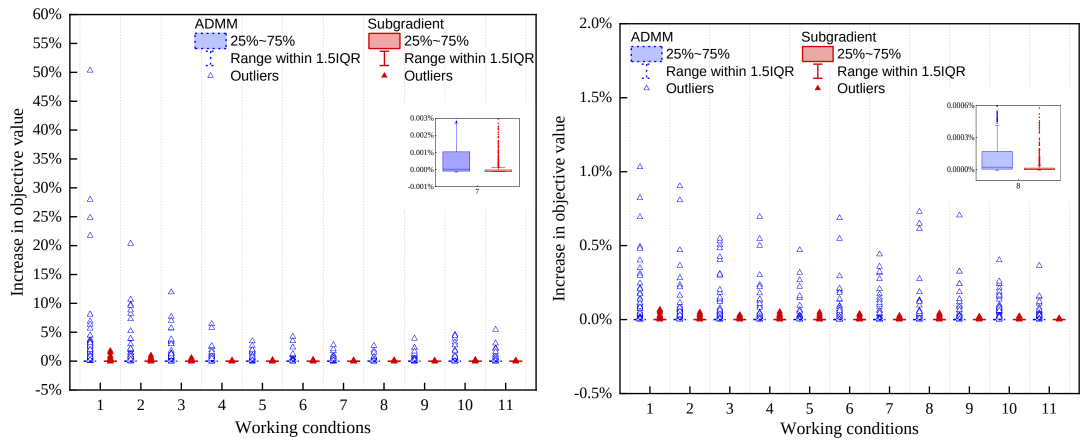
4.3.3.1 Impacts of uncertain information delays

The test results show that information delays had a larger impact on the control strategy using ADMM than when using the subgradient method. This is due to the fact that the amount of information exchange required by ADMM is larger than that required by the subgradient method. Figure 4.10 shows the impacts of the information delays on the optimization results of the two control strategies in spring and summer working conditions respectively. It can be found that the biases in the optimized ventilation air volume using ADMM was larger than that using the subgradient method. As a result, the increase in the achieved objective value using ADMM was larger than that using the subgradient method in the tests as shown in Figure 4.11. Using the subgradient method, in the spring and summer working conditions, the maximum biases in optimized ventilation air volume were 1.08 L/s and 1.11 L/s, and the maximum increase in the achieved objective values were 1.79% and 0.07% respectively. While using the ADMM, the maximum bias in optimized ventilation air volume was 6.07 L/s and 4.49 L/s, and the maximum increase in the achieved objective values was 50.33% and 1.03% respectively. The reason that the maximum increase in the achieved objective value in the spring working conditions was much larger is that the objective value achieved in the ideal condition was much smaller. Figure 4.12 shows the impacts of information delays on the convergence rate in the spring and summer working conditions respectively. The information delays resulted in the increase in the number of iteration steps in most of the test scenarios using the two methods, and the impacts on the strategy using ADMM was larger than that on the strategy using the subgradient method. In ideal conditions, the numbers of iteration steps using the ADMM and subgradient method were similar, around 20 steps in testing. With the information delays involved, in the spring and summer working conditions, the median of the iteration steps using ADMM was around 62 and the maximum number of iteration steps was 147 and 148 respectively. When using the subgradient method, the median of the iteration steps was around 40 and the maximum number of iteration steps was 51 and 59 respectively.



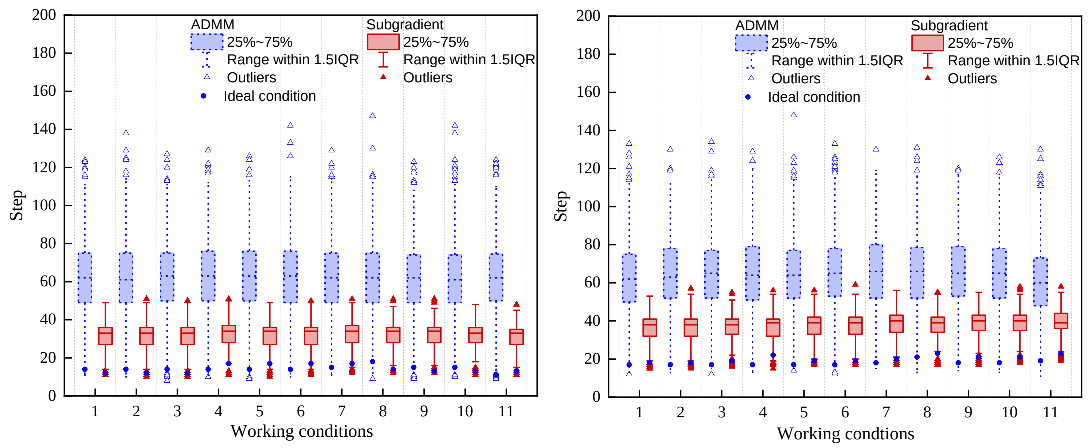
(a) Spring working conditions (b) Summer working conditions

Figure 4.10 Statistical distribution of the bias in optimized ventilation volume under information delays



(a) Spring working conditions (b) Summer working conditions

Figure 4.11 Statistical distribution of the difference in the objective value under information delays



(a) Spring working conditions (b) Summer working conditions

Figure 4.12 Statistical distribution of the number of iteration steps under information delays

4.3.3.2 Impacts of information delays under critical conditions

Both control strategies were tested on a typical year with constant information delays of two sampling intervals. According to the requirements of optimal control in practical applications and the convergence rate in ideal conditions, the optimal control interval was set to one minute in the tests. If convergence is not achieved within one minute, a simple ventilation strategy is adopted: the ventilation air volume is set to 22

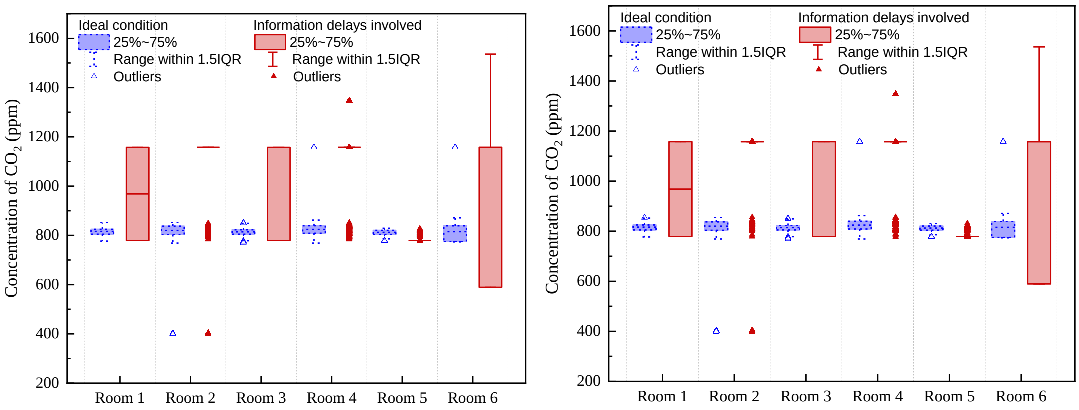
L/s for each room according to the design occupancy and room size. Table 4.5 shows the statistical results of the tests. The constant information delays affected ventilation volume and convergence rate of both control strategies, with the impacts on the control strategy using ADMM being larger. Using the subgradient method, the average biases in total ventilation volume and individual ventilation volume were 70.22 L/s and 1.23 L/s respectively. Using ADMM, the average biases in total ventilation volume and individual ventilation volume were 87.40 L/s and 2.16 L/s respectively. The average increases in the number of iteration steps of the two control strategies were similar (i.e., 41 and 43 respectively) while the number of non-convergence optimizations using ADMM was 3,927 (i.e., 97.81%), which is 148 larger than that using the subgradient method.

Table 4.5 Statistical performance data of two control strategies under constant information delays of two sampling intervals

Optimization algorithm	Subgradient method	ADMM
Average bias in total ventilation volume (L/s)	70.22	87.40
Maximum bias in total ventilation volume (L/s)	144.15	180.72
Average bias in individual ventilation volume (L/s)	1.23	2.16
Maximum bias in individual ventilation volume (L/s)	44.44	44.44
Average increase in iteration step numbers	41	43
Number of non-convergence optimizations	3,779	3,927

Figure 4.13 shows the distribution of the CO_2 concentration in the six rooms in the test working conditions using the set-points given by the control strategies using the subgradient method and ADMM respectively. It can be found that in ideal conditions, both control strategies successfully maintained CO_2 concentration around 800 ppm, the recommended upper limit, except for three non-convergence optimizations. Due to information delays, only the CO_2 concentration in Room 5 was maintained at around

800 ppm, and the CO_2 concentration in other rooms was much higher than the recommended upper limit in most of the test working conditions. This indicates that the control strategies failed to achieve a proper compromise between maintaining the IAQ and energy consumption due to the information delays, although the energy consumption when using the strategies under the information delays was reduced as shown in Figure 4.14.



(a) Subgradient method (b) ADMM

Figure 4.13 Statistical distribution of CO_2 concentration in six rooms using two control strategies under information delays

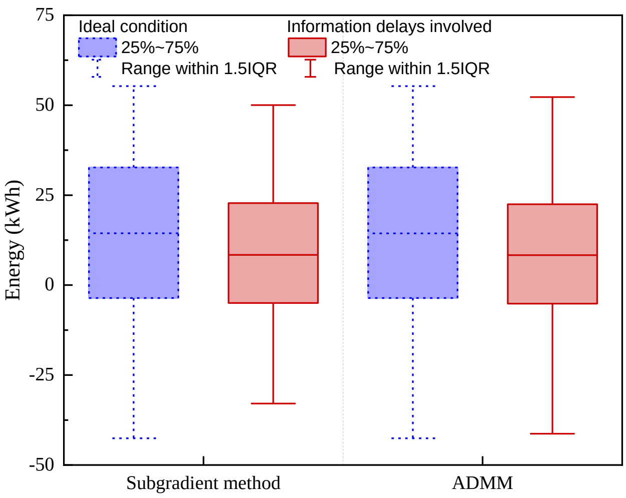


Figure 4.14 Statistical distribution of energy consumption using two control strategies under information delays

4.4 Summary

The impacts of information delays on the performance of distributed optimal control for HVAC systems deployed on field control networks are investigated through qualitative analysis and quantitative assessment using two case studies. The information delays are caused by the time cost of local optimization and the information exchange between devices as well as the asynchronous operation of different devices. Due to the information delays, the optimal control strategies resulted in biased optimization results or failed to achieve the optimization results within the pre-set optimal control interval. These impacts can result in reduced energy performance for the distributed optimal control strategies. The lengths of information delays and the step-size for the update of the Lagrange multiplier are two critical factors that could significantly affect the impacts of the information delays. When developing distributed optimal control strategies, considering these two factors could improve the reliability and energy performance. Moreover, the distributed optimal control strategy using the subgradient method shows greater robustness than when using ADMM under the same information delays. According to the test results and analysis, detailed conclusions can be drawn as follows:

i. Information delays could affect the performance of the distributed optimal control strategy significantly. Under uncertain information delays, the maximum bias of optimized cooling tower outlet water temperature was up to 0.6 K, the largest number of iteration steps increased to 180 (about nine times of that in ideal conditions), and the power consumption of the cooling plant was increased by 0.2%.

ii. The impacts of information delays increased dramatically with an increase in information delay length. With an increase in delay length from 1 sampling interval to 4 sampling intervals, the average bias in optimization results increased from 0.05 K to 0.44 K, the increase of annual energy consumption rose from 7,853.3 kWh to 37,397.2 kWh (0.06% to 0.28%) and the number of non-convergence optimizations increased from 306 to 2,986 (4.50% to 43.92%).
iii. The best step-size for the update of the Lagrange multiplier determined in ideal conditions is not the best choice when information delays exist. Proper selection of the appropriate step-size effectively reduces the impacts of information delays and therefore improves the energy performance. The annual energy consumption increase was reduced from 37,397.2 kWh to 6924.6 kWh (from 0.28% to 0.05%).
iv. The impacts of information delays on the performance of distributed optimal control strategies using ADMM is much larger than that using the subgradient method since ADMM requires more information exchange than the subgradient method. Under the same uncertain information delays, using ADMM and the subgradient method, the maximum biases in optimized ventilation air volume were 6.07 L/s and 1.08 L/s, and the maximum numbers of iteration steps increased from 18 and 17 to 147 and 51 respectively.

CHAPTER 5 DEVELOPMENT OF A DELAY-TOLERANT DISTRIBUTED OPTIMAL CONTROL METHOD CONCERNING UNCERTAIN INFORMATION DELAYS

Since the information delays could significantly affect the performance and reliability of distributed optimal control strategies, it is necessary to develop a delay-tolerant method to reduce these impacts. The existing delay-tolerant control methods proposed in the distributed optimization field are not applicable in the application scenarios concerned in this study, i.e., the distributed optimal control for building HVAC systems deployed on field control networks, either because of the low convergence rate or high storage and computation capacity requirements. This chapter, therefore, proposes a delay-tolerant control method to improve the robustness of the distributed optimal control strategy based on the analysis of the impacts of the information delays in Chapter 4 as well as the relevant research conducted by Zhao et. al. (Zhao et al., 2020). It is simple to be deployed on local control devices and is effective in reducing the impacts of information delays on optimization accuracy and the convergence rate. This chapter is organized as follows. Section 5.1 presents the outline of the proposed delay-tolerant method. The detailed description is shown in Section 5.2. Section 5.3 evaluates the performance of the proposed delay-tolerant method by testing it on the control of the central cooling plant. A summary of the work is presented in Section 5.4.

5.1 Outline of the proposed delay-tolerant control method

The proposed method reduces the impacts of the information delays by improving the operation process of the coordinating agent using the distributed optimization algorithm based on dual decomposition and the subgradient method illustrated in Section 3.2. The operation procedures of the coordinating agent using the conventional distributed optimization method and the proposed delay-tolerant control method are shown in Figure 5.1 and Figure 5.2 respectively. Using the conventional distributed optimization method, the coordinating agent directly uses the received local optimization results to determine convergence status, and update the Lagrange multiplier if convergence is not achieved. Using the proposed method, the results of the previous $2\times Ld_{max}+1$ steps will be stored and used, where Ld_{max} is the maximum delay length of one information exchange. In this way, $2\times Ld_{max}+1$ groups of local optimization results of different steps are available for the coordinating agent. The local optimization results are grouped according to the step information attached (one group corresponds to one step), and the number of optimization results in each group may not be the same due to packet loss and information delays. With the available optimization results, two schemes are introduced in the coordinating agent to reduce the impacts of information delays, i.e., "synchronization of local optimization results" and "adaptive step-size setting". The purpose of the synchronization of local optimization results is to reduce the impacts of information delays on optimization accuracy by ensuring that the local optimization results from the same step (denoted as "uniform results") are used to determine convergence. The purpose of the adaptive step-size setting is to reduce the impacts of information delays on the convergence rate by conservatively updating the Lagrange multiplier when delayed subgradient information is used.

The operation procedure of the coordinating agent using the proposed delay-tolerant control method, as shown in Figure 5.2, is further elaborated as follows. At first, the coordinating agent will check whether the latest group of local optimization results are all available or not. If all of them are available, they will be used to determine convergence. If some of them are not available, synchronization of the local optimization results is conducted to “obtain” uniform results for further optimization instead of waiting for the transportation of all optimization results. Waiting for all the latest optimization results to be received can be costly, especially when the number of agents is large due to uncertain delays. This scheme will “obtain” uniform results of a selected step by estimating the missing results. Then, these optimization results after synchronization are used to determine convergence. In such a way, the accuracy of the optimization results and convergence rate can be maintained under information delays. In the case that convergence is not achieved, the adaptive step-size setting scheme will be activated to reset the step-size for updating of the Lagrange multiplier according to the delay length of the uniform results instead of using the fixed step size determined in ideal conditions.

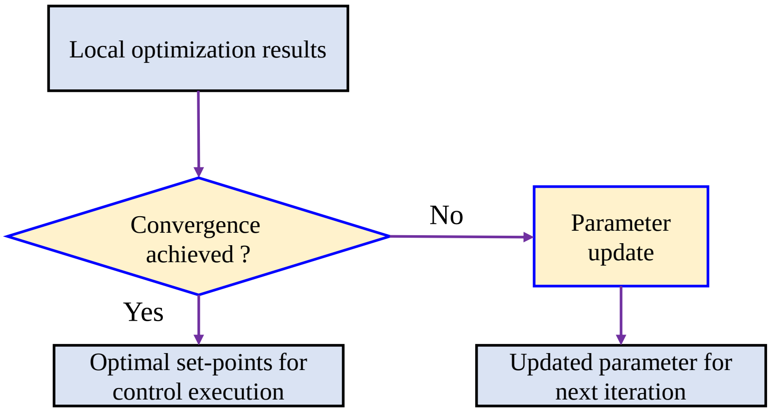


Figure 5.1 The operation procedure of the coordinating agent using conventional method

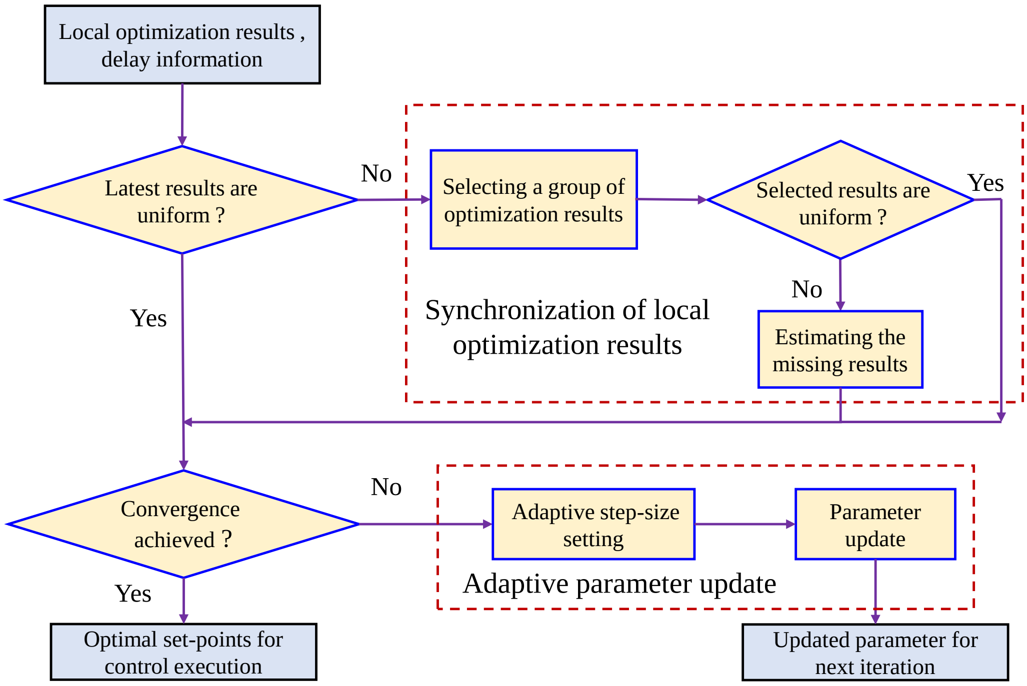


Figure 5.2 The operation procedure of the coordinating agent using the delay-tolerant control method

5.2 Detailed description of the proposed delay-tolerant control method

5.2.1 Synchronization of local optimization results

Synchronization of local optimization results is introduced to "obtain" uniform results for further optimization, in the case that the latest available local optimization results are not uniform. This synchronization process involves two major subtasks (shown in Figure 5.2), including a). selecting a group of local optimization results to be used for further optimization, and b). estimating the missing results of the selected group. The following criteria are used to select the group. First, the number of optimization results in each group (except the group with all the results available) is compared with the pre-set threshold. If the numbers in each of these groups are less than the pre-set threshold, the latest available uniform results will be used for further optimization. Another option is to use the latest available uniform results regardless of the situation, which can avoid the need to estimate missing data, but this is ineffective in reducing the impacts on the convergence rate. If the number of available optimization results in a group (e.g., the k-1 group) is equal to or larger than the pre-set threshold, the optimization results of this group will be selected for further optimization. It is possible that the number of available optimization results in more than one group (e.g., the k-1, k-2, and k-3 groups) can equal or exceed the threshold. In this case, the group of optimization results of the latest step will be used for further optimization. After the group is determined, an estimation process is conducted to estimate the missing data, as shown in Eq. 5.1.

$$\tilde{x}_{i,k-1} = \frac{\dot{x}_{j,k-1}}{\dot{x}_{j,k-Ld_i}} \times \dot{x}_{i,k-Ld_i} \tag{5.1}$$

k is the current step. $\tilde{x}_{i,k-1}$ is the estimated value of the optimization result of agent *i* at the k-1 step. $\dot{x}_{i,k-Ld_i}$ is the latest available optimization results of agent *i*. Ld_i is the delay length of the information used by agent *i*. $\dot{x}_{j,k-1}$ and $\dot{x}_{j,k-Ld_i}$ are the actual optimization results of agent *j* at k-1 step and k-Ld_i step respectively. This method is simple but effective when agent *i* and agent *j* are agents for local optimizations of the same type of components with similar characteristics. It is common that multiple components of the same type (e.g., chillers, pumps, and cooling coils) exist in an HVAC system or subsystem, providing a reliable reference for missing data estimation. For the group of optimization results that do not have available reference components, the group of data at this step will not be used and a group of data at the step of lower priority will be used instead.

5.2.2 Adaptive step-size setting

In the case where convergence has not yet been achieved, the Lagrange multiplier needs to be updated according to the local optimization results and sent to the other agents for the next iteration. A rule-based method is proposed to set the value of the step-size adaptively to improve the robustness of the optimization under uncertain delays. This method sets the appropriate step-size according to the delay length of the uniform optimization results, as shown in Eq. 5.2. α is the step-size. α_0 is the step-size determined in ideal conditions, $\alpha_m, \dots, \alpha_1, \alpha_0$ ($\alpha_m < \dots < \alpha_1 < \alpha_0$) are the step-sizes in conditions with different uniform delay lengths (Ld_u), n is the maximum information delay length.

$$\alpha = \begin{cases} \alpha_0, & Ld_u = 0 \\ \alpha_1, & 0 < Ld_u \leq 1 \\ & \dots \\ \alpha_m, & \mathrm{n - x} < Ld_u \leq n \end{cases} \tag{5.2}$$

The step-size for updating the Lagrange multiplier determines the update rate, which significantly affects the convergence characteristics of the optimization. The advantage of the proposed method is that it can ensure convergence being achieved at a satisfactory rate under uncertain information delays. Normally, the distributed optimization algorithms will use a fixed or diminishing step-size. The algorithm has a higher convergence rate using a fixed step-size than when using a diminishing step-size, while the robustness of the algorithm using a fixed step-size under uncertain information delays is worse. This is because using the fixed step-size determined in ideal conditions updates the Lagrange multiplier much faster than it should, interfering with the optimization process. It was proved that using a sufficiently small fixed step-size can ensure algorithm convergence (Zhao et al., 2020). Larger constant delays require smaller step-sizes. However, since delays are random in practical application, using the smallest step-size, determined according to the largest delay, can result in an unnecessarily low convergence rate.

5.3 Performance evaluation of the proposed delay-tolerant control method

To evaluate the performance of the proposed delay-tolerant control method, a distributed delay-tolerant optimal control strategy is formulated for the optimal control of the central cooling plant described in Section 3.3. A distributed optimal control strategy using the conventional distributed optimization method is constructed for comparison. These two control strategies were tested on a typical summer day with an optimization interval of two minutes. If optimal set-points cannot be found within two minutes, a simple near-optimal control strategy will be adopted: the cooling tower outlet water temperature will be set to be 5 K higher than the current wet-bulb temperature. Uncertain information delays were involved using the Markov chain model constructed in Section 4.1. In order to present an overview of the impacts of uncertain information delays, the test was repeated by one thousand times with random delay sampling on the test day.

5.3.1 Formulation of the distributed optimal control strategies

The distributed optimal control strategy without delay-tolerant strategy is the same as that described in Section 3.4. The formulation of the delay-tolerant distributed optimal control strategy is presented below.

Adopting the proposed delay-tolerant control method, the chiller agents and cooling tower agents are the same as those constructed using the conventional distributed optimal control strategy (Section 3.4). The parameters of the two proposed schemes (i.e., synchronization of the local optimization results and adaptive step-size setting) to be implemented in the coordinating agent needs to be identified. In this case, since the distributed optimization contains two stages, the parameters in the two stages need to be set separately. At the first stage, the optimization involves the chiller agents, cooling tower agents and coordinating agent. To synchronize the local optimization results, a group of local optimization results used for further optimization needs to be selected. Firstly, groups that the optimization results of the chiller agents are not available will be excluded. This is to avoid local optimization results of the chiller agents being estimated inaccurately in the scenario that only one chiller is in operation. Then, the number of cooling tower agent optimization results ($N_{syn,ct}$) in each group will be compared with the number of cooling towers in operation (N_{ct}). The groups that contain a sufficient number of local optimization results will be chosen, as shown in Eq. 5.3. Finally, the group of local optimization results of the latest step amongst the candidates will be used for further optimization. The missing optimization results of the cooling tower agents will be estimated according to Eq. 5.1.

$$N_{syn,ct} \geq \frac{N_{ct}}{2} \tag{5.3}$$

For the updating of the Lagrange multiplier in the case that the convergence is not achieved yet, the step-size will be set according to the delay length, as shown in Eq. 5.4.

$$\alpha = \begin{cases} 5 \times 10^{-8}, & Ld_u = 0 \\ 3 \times 10^{-8}, & 0 < Ld_u < 3 \\ 2 \times 10^{-8}, & Ld_u = 4 \end{cases} \tag{5.4}$$

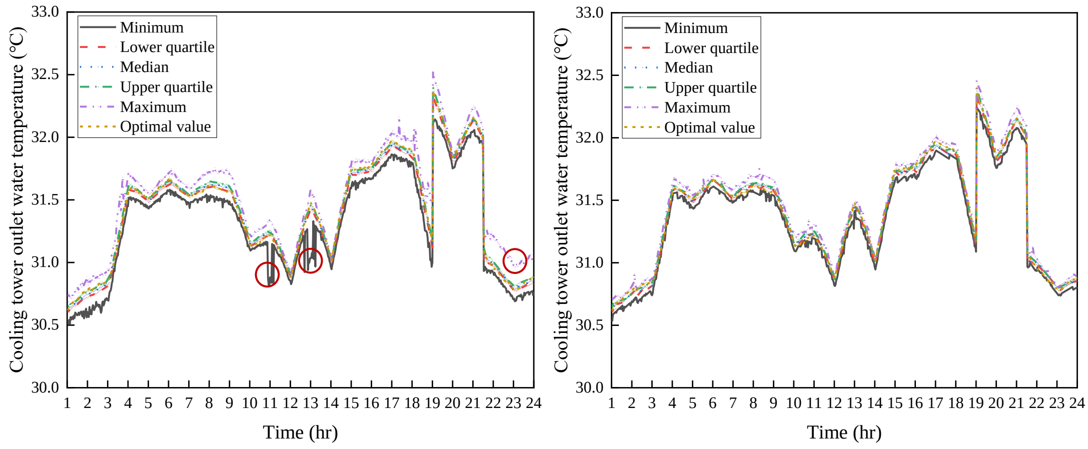
At the second stage, the optimization only involves the cooling tower agents and the coordinating agent. The group of local optimization results used for further optimization is determined in a similar way as the first stage. The threshold for determining whether there are sufficient number of optimization results in one group is also $\frac{N_{ct}}{2}$. The step-size is selected according to the delay length, as shown in Eq. 5.5.

$$\beta = \begin{cases} 5 \times 10^{-7}, & Ld_u = 0 \\ 3 \times 10^{-7}, & Ld_u > 0 \end{cases} \tag{5.5}$$

5.3.2 Applicability assessment and control performance evaluation

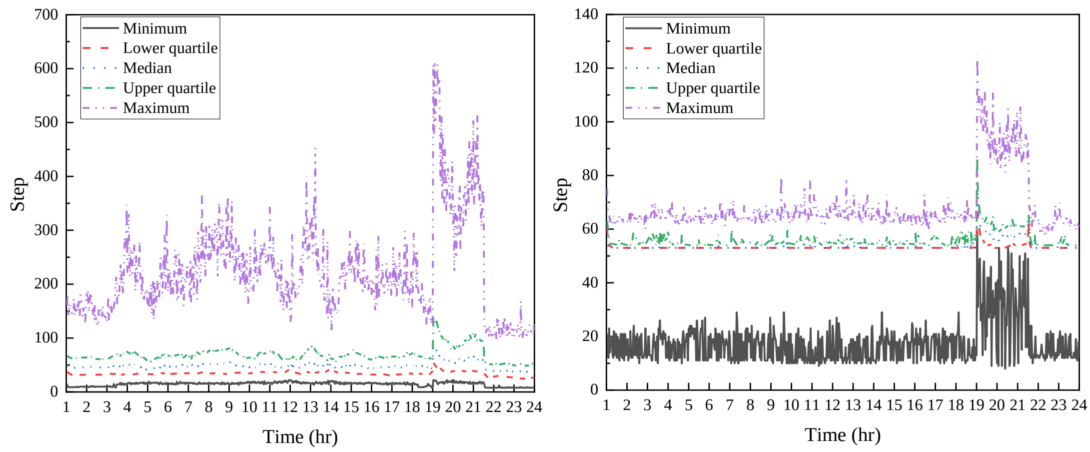
The computation load of the delay-tolerant strategy is assessed to validate the applicability of the proposed delay-tolerant control method in the distributed optimal control of HVAC systems deployed in local control devices integrated in the current LAN-based field control networks as well as future IoT-enabled ones. The floating-point operations (FLOPs) were counted and used as the performance indicator. Using the proposed delay-tolerant control method, the computation loads of the cooling tower agents, chiller agents and the coordinating agent at each iteration step were 945, 1,150 and 40 FLOPs respectively. Typical smart sensors with a CPU speed of 16 MIPS (million instructions executed per second) are able to handle these computation loads.

To evaluate the performance of the proposed strategy, the test results of the control strategy without a delay-tolerant scheme and the delay-tolerant control strategy are compared with the optimal set-points obtained in ideal conditions (i.e., the control devices operating synchronously without delays). Figure 5.3 shows the distribution of the set-points generated by the two control strategies and the optimal set-points obtained in ideal conditions (namely ideal set-points thereafter). The minimum value, lower quartile, median, upper quartile and maximum value of the set-points are shown. The delay-tolerant control strategy was more robust than the control strategy without a delay-tolerant scheme. Using the latter, the lower quartile, median and upper quartile of the optimization results were close to their optimal values. However, the biases between the minimum value or maximum value of the optimization results and the ideal set-points were large, and the maximum bias was up to 0.5 K. Using the delay-tolerant control strategy, all the set-points were much closer to the ideal set-points, and the maximum bias was only 0.2 K. Figure 5.4 shows the distribution of the convergence rate of the two control strategies in terms of iteration steps. The proposed method effectively reduced the impacts of information delays on the convergence rate of the distributed optimal control strategy. Using the control strategy without the delay-tolerant scheme, the maximum number of iteration steps mostly remained higher than 120, indicating that the convergence cannot be achieved within the pre-set optimal control interval. The largest iteration step in this case was over 600 steps (i.e., 10 mins). The number of non-convergent cases was 28,588 (4%). When using the proposed delay-tolerant control strategy, the convergence rate was much faster and more stable - the largest step was 135 (i.e., 2.25 mins) and only 4 cases (0.006%) did not achieve convergence within the optimal control interval during the tests.



(a) Strategy without delay-tolerant scheme (b) Delay-tolerant control strategy

Figure 5.3 Distribution of the generated set-points using different control strategies



(a) Strategy without delay-tolerant scheme (b) Delay-tolerant control strategy

Figure 5.4 Distribution of the number of iteration step using different control strategies

The daily energy consumption of the central cooling plant using the near-optimal set-points, the ideal set-points, the set-points generated by the control strategy without the delay-tolerant scheme and the delay-tolerant strategy are shown in Table 5.1. The energy consumption of the system using the near-optimal set-points is the baseline. The delay-tolerant control method significantly improved the energy performance of the control strategy when accounting for information delays. The daily energy consumption of the system using the set-points determined by the delay-tolerant control strategy was almost the same as that using the ideal set-points, offering energy savings of 0.46%. When using the set-points determined by the control strategy without a delay-tolerant scheme, less energy saving was achieved. In the worst case, energy savings were reduced by 312.82 kWh, accounting for 0.45% of total energy consumption and leaving it at 0.01% only.

It is worth noticing that although the saving rate is not very significant, at about 0.5%, the absolute savings are not low, and are achieved without any extra hardware investment. As there are different control variables in the energy system that could be optimized simultaneously, the collective energy savings of control optimization in buildings could be rather significant, particularly when optimization is widely used on both system, subsystem and field levels with the support of distributed intelligence.

Table 5.1. Daily energy consumption of the system using different set-points

	Near-optimal set-points	Ideal set-points	Control strategy without delay-tolerant scheme	Delay-tolerant control strategy
Maximum energy consumption (kWh)	69,340.06	69,020.32	69,333.14	69,022.41
Energy saving	-	0.46%	0.01%	0.46%
Average energy consumption (kWh)	69,340.06	69,020.32	69,042.64	69,020.30
Energy saving	-	0.46%	0.43%	0.46%

5.4 Summary

A simple and effective delay-tolerant control method is proposed to improve the performance of distributed optimal control strategies for building HVAC systems under information delays. The proposed method provides the means to deal with the impacts of information delays and addresses the needs to be implemented on field control devices. The applicability and performance of the proposed delay-tolerant control method when deployed in field control networks are assessed by tests on a simulated central cooling plant. According to the test results and analysis, more detailed conclusions can be drawn as follows:

i. Smart sensors and local control devices should be able to handle the computation load of the proposed delay-tolerant control method. The computation load of the cooling tower agents, chiller agents and the coordinator agent were 945, 1,150 and 40 FLOPs respectively, well below the capacity of typical smart sensors today.

ii. The proposed delay-tolerant control method effectively reduced the impacts of information delays on optimization accuracy. Using the proposed method, optimization results nearly equalled actual optimal values, and the maximum bias over all results was 0.2 K. Without a delay-tolerant scheme, the biases in optimization results were clearly larger, and the maximum bias over all results was 0.5 K.

iii. The proposed delay-tolerant control method effectively reduced the impacts of information delays on the convergence rate. Using the proposed delay-tolerant control method, almost all optimizations were converged within 120 steps (two minutes). Without a delay-tolerant scheme, the convergence rates were reduced due to information delays, and 4% of cases did not achieve convergence within 120 steps.

iv. The proposed delay-tolerant control method effectively improved the energy performance of the distributed optimal control under information delays. Using set-points determined through the delay-tolerant control strategy, the energy consumption of the system was almost identical to that using the ideal optimal set-points. When using the set-points determined without a delay-tolerant scheme, daily energy savings were reduced by 312.82 kWh, accounting for 0.45% of total energy consumption.

CHAPTER 6 DEVELOPMENT OF A HARDWARE-IN-THE-LOOP SIMULATOR FOR CONTROL STRATEGY VALIDATION AND VALIDATION RESULTS

Existing studies on the distributed optimal control of building HVAC systems mainly focus on the selection and customization of distributed optimization algorithms for developing distributed optimal control strategies. Validation and evaluation of these distributed optimal control strategies cannot be found in the literature when implementing them on the real sensor nodes of IoT sensing networks in the building automation field. This chapter, therefore, implements the proposed distributed optimal control strategy in Chapter 3 on multiple wireless sensor nodes to validate its applicability and conducts hardware-in-the-loop (HIL) simulations to evaluate its energy performance. The basic idea of hardware-in-the-loop simulation is to contain a part of real hardware in the simulation loop (Bacic, 2005). Compared with pure virtual (or digital) simulation, using the real hardware in the simulation could improve the validity. Section 6.1 presents the constructed hardware-in the loop simulator. Section 6.2 introduces the test arrangement. The test results and performance evaluation are shown in Section 6.3. A summary of the work and results is given in Section 6.4.

6.1 Description of the hardware-in-the-loop simulator

Figure 6.1 shows the architecture of the hardware-in-the-loop simulator constructed for the implementation and validation of the proposed distributed optimal control strategy. The hardware-in-the-loop simulator consists of a virtual HVAC system and a physical control system interfaced through a USB hub. The virtual HVAC system is simulated in TRNSYS, a commonly used dynamic simulation software platform in the building field, using detailed dynamic models. It is used to evaluate the energy performance of the control system. A time control component is designed to allow the simulated HVAC system to operate in real time. Therefore, it can realistically simulate the dynamic response of the HVAC system to the control actions. The control system consists of multiple sensor nodes. The distributed optimal control strategy consisting of multiple component agents and a coordinating agent is implemented on these sensor nodes. These sensor nodes connect to a Wireless Local Area Network (WLAN). The information exchange for the optimizations among the sensor nodes is realized through an access point. Firstly, all the information needed to be exchanged is sent to the access point. Then, the access point broadcasts the information from the coordinating node to the component nodes and send the information from the component nodes to the coordinating node. The USB hub works as the virtual and real interface for the information exchange between the virtual HVAC system and the real control system. The measurements obtained by the virtual sensors are sent to the real control network performing the optimization, and the optimized settings are sent to the virtual control devices for control execution. It is worth noticing that, in practice, the sensor nodes get the corresponding measurements using their sensing modules and the obtained optimized settings are sent to the corresponding local control devices for control executions.

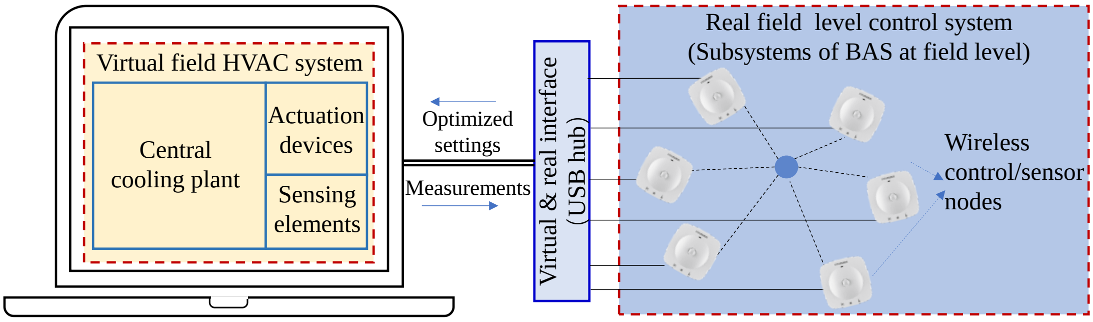


Figure 6.1 Architecture of the hardware-in-the-loop simulator.

Figure 6.2 presents an image of the experimental rig in operation. The computer is conducting the virtual HVAC system simulation and monitoring the operation of the real control system. The sensor nodes are conducting the optimization tasks. Each sensor node consists of a processor board and an ESP8266 WiFi module. The processor boards are Arduino Nucleo-32 boards which have 64KB RAM and 256KB program memory. Their CPU speed are 80 MHz which are the same with the typical current field controllers. During the tests, these sensor nodes conduct optimizations at the predefined optimization interval (i.e., two minutes). The virtual HVAC system operated in real time, it receives and executes the optimized settings. In this manner, the realistic operations and interaction of the HVAC system and control system are simulated and tested.

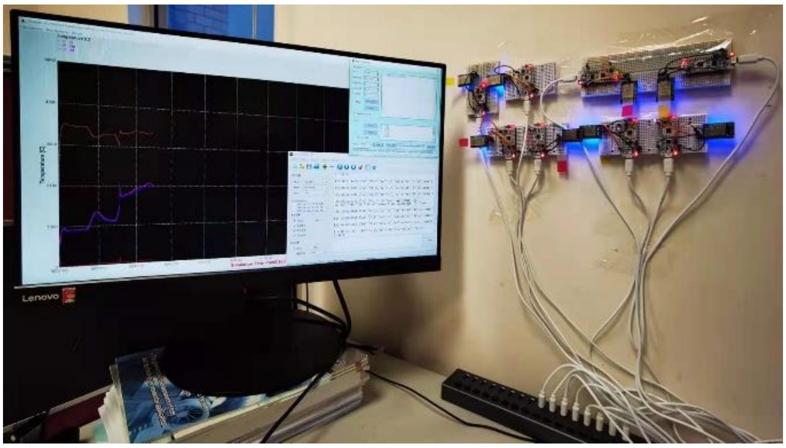


Figure 6.2 Image of the experimental rig in operation.

6.2 Communication protocol for information exchange

For the distributed optimal control strategies implemented in a computer or a computation station, it is simple for one agent to get the required information from the other agents. However, in the case when the distributed optimal control strategy is implemented on multiple smart sensor nodes, it is necessary to define a communication protocol for effective information exchange. The communication protocol defined and used in the wireless sensing network (WSN) is as follows:

{Node ID, Type, Request ID, Data}

Where the Node ID and Type are used for identifying the source of the data, the Request ID represents the iteration step and can be used for identifying the delays of the received information in terms of the sampling interval. Data refers to the local optimization results of the component node or the convergence status and Lagrange multiplier from the coordinating node.

6.3 Test results and performance evaluation

The applicability and energy performance of the proposed distributed optimal control strategy in Chapter 3 implemented on the IoT sensing network were tested on the constructed hardware-in-the-loop simulator. The central cooling plant described in Section 3.4 is simulated TRANSYS as the target system. The distributed optimal control strategy for the optimal control of the central cooling plant and the communication protocol are implemented on the real control system (i.e., WSN). The algorithm of the control strategy is the same as that described in Section 3.4.

6.3.1 Capability of IoT sensing networks for implementing the distributed optimal control strategy

To assess the capability of the IoT sensing network for implementing the distributed optimal control strategy, the required program memory and RAM consumption were verified. The required program memory for implementing the coordinating agent, chiller agent and cooling tower agent were 41,352 bytes (16.15% of the program memory of 256 K), 41,352 bytes (16.15%) and 45,576 bytes (17.80%), respectively. The RAM consumption were 2,932 bytes (4.58% of the RAM of 64 KB), 2,016 bytes (3.15%) and 2,016 bytes (3.15%), respectively. These are well below the capacities (i.e., program memory: 256 KB, RAM: 64 KB) of smart sensors constructed in this study. It is worth noticing that although the processor board used in this study is low cost and commonly used for IoT sensors, the processor board of some smart sensors might have much lower RAM and program memories. In these cases, the distributed optimal control strategy might not be applicable considering the memory sizes and RAM.

6.3.2 Capability of IoT sensing networks for the optimization tasks and optimization performance

To assess the capability of IoT sensing networks for conducting the optimization tasks, the CPU time consumed for conducting the local optimization tasks of each iteration step needs to be tested. For a sensor node, its basic tasks are sensing and communicating the measured variables at a given sampling interval. When implementing the distributed optimal control strategy, sensor nodes also need to handle the optimization tasks of one step within one sampling interval. For each sensor node, the optimization tasks include reading the information from other sensor nodes, parsing information and computation. Since the sensor nodes are single-threaded, these processes can only be executed in a single sequence, and the optimization tasks need to be completed within the sampling interval.

Table 6.1 shows the test results of the time for conducting the optimization tasks of one iteration step. According to the results, the chiller node and cooling tower node took the same time on reading information and parsing information, which were 8.6 ms and 0.4 ms, respectively. This is because the information received by the chiller and cooling tower nodes has the same size (around 100 bytes) and the baud rate of the sensor nodes are the same (115,200 bits/s). The coordinating node took more time on the reading information and parsing information, which were 30.2 ms and 3.3 ms, respectively. This is because that the coordinating node needs to deal with the information from all the other nodes and the information size is around 360 bytes. For the computation process, the coordinating node took the least time (0.3 ms) since no optimization task is involved. Whereas the cooling tower agent took the longest time, i.e., 27.6 ms. For conducting the whole optimization process, the overall time took by the sensor nodes were all less than 50 ms. In HVAC systems, the sampling interval is normally in seconds (two seconds in this study). Therefore, the sensor nodes have sufficient capability to conduct the optimization tasks.

Table 6.1 Time for conducting optimization tasks

Optimization tasks	Coordinating node	Chiller node	Cooling tower node
Reading information (ms)	30.2	8.6	8.6
Parsing information (ms)	3.3	0.4	0.4
Computation (ms)	0.3	3.2	27.6
Total process time (ms)	33.8	12.2	36.6

To assess the optimization performance of the distributed optimal control strategy implemented on the IoT sensing network, the optimization accuracy and convergence rate were verified. The optimization accuracy was assessed by comparing the optimization results obtained by the distributed optimal control strategy (implemented on the real wireless IoT sensing network) with the perfect optimization results obtained by exhaustive search (implemented in PC). Although using exhaustive search would cost a lot of time for searching the optimization results, it can definitely obtain the perfect optimal results. Table 6.2 shows the optimization results obtained by the proposed distributed optimal control strategy and the perfect optimal results of three typical working conditions, i.e., low load, medium load and high load. It can be found that the optimization results obtained by the proposed distributed optimal control strategy were almost the same as the perfect optimization results. This indicates that the proposed distributed optimal control strategy is effective in achieving optimal solutions.

Table 6.2 Optimization results using the proposed distributed optimal control strategy and the perfect settings

Optimization results	Low load		Medium load		High load	
	Proposed strategy	Perfect settings	Proposed strategy	Perfect settings	Proposed strategy	Perfect settings
P_{ch} (kW)	994	994	1902	1902	3289	3288
P_{ct} (kW)	30	30	60	60	106	106
$P_{ch} + P_{ct}$ (kW)	1,024	1,024	1,962	1,962	3,395	3,394
T_{cws} (°C)	33.90	33.90	33.21	33.20	33.43	33.42
T_{cws1} (°C)	33.85	33.85	33.10	33.10	32.65	32.65
T_{cws2} (°C)	33.95	33.95	33.15	33.10	32.90	32.95
T_{cws3} (°C)	-	-	33.25	33.20	33.30	33.25
T_{cws4} (°C)	-	-	33.35	33.40	33.65	33.65
T_{cws5} (°C)	-	-	-	-	33.95	33.95
T_{cws6} (°C)	-	-	-	-	34.10	34.05

The convergence rate of the proposed distributed optimal control strategy is another essential performance index, which is quantified using the iteration step of optimization. Figure 6.3 shows the iteration step of the optimizations during a twenty-four-hour test with an optimization interval of two minutes. It can be found that all the optimizations during the tests were converged within 14 iteration steps. As aforementioned, one iteration step is corresponding to one sampling interval of the sensor nodes. The convergence of all the optimizations can be reached within 28 seconds, well below the optimization interval. Therefore, it is quite safe for the proposed distributed optimal control strategy to satisfy the typical optimization interval for HVAC systems, even as short as one minute.

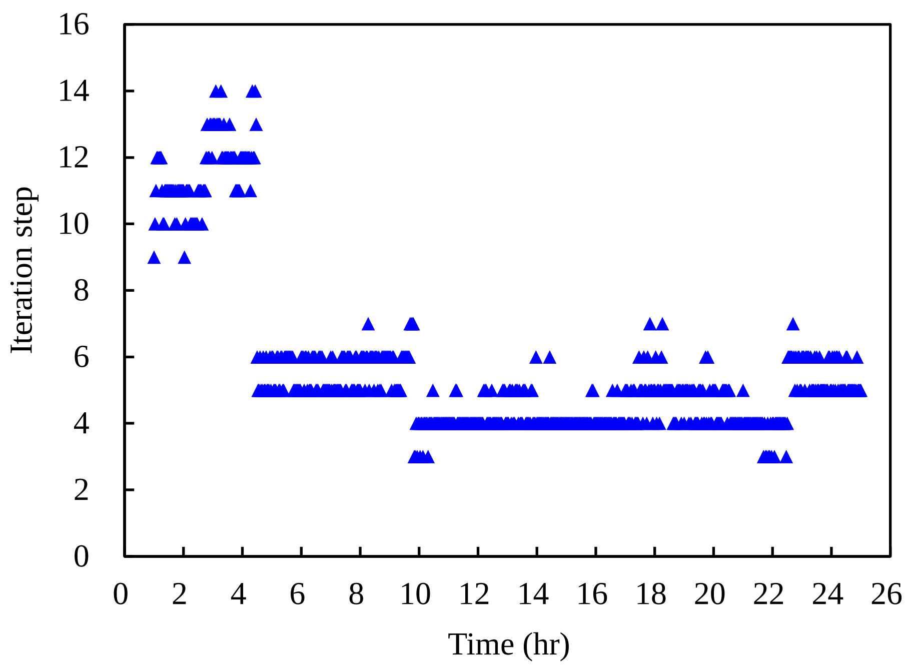


Figure 6.3 Convergence rate of the proposed distributed optimal control strategy.

6.3.3 Energy performance of the distributed optimal control strategy

To assess the energy performance of the distributed optimal control strategy, the energy consumption of the central cooling system using the proposed distributed optimal control strategy is compared with that of using the perfect solutions, a conventional centralized optimal control strategy and a near-optimal control strategy. The perfect solutions are the optimal individual cooling tower outlet water temperature obtained using exhaustive search. The centralized control strategy obtains the uniform cooling tower outlet water temperatures using exhaustive search without considering the load distribution among the cooling towers. The near-optimal control strategy uses fixed differential temperature. A fixed temperature difference, 5 K in this case, between the cooling tower outlet water and the wet-bulb temperature is adopted. The three control strategies were tested in the central cooling system during a summer day.

Figure 6.4 presents the cooling tower outlet water temperature using the four control strategies. It can be found that the outlet water temperatures of the cooling towers using the proposed strategy, perfect solutions and the centralized control strategy were obviously higher than that using the near-optimal control strategy. The cooling tower outlet water temperatures when using the proposed strategy were very close to the perfect solutions and the maximum difference was only 0.08 K. It can be found that, during 10:00 to 18:00, the cooling tower outlet water temperature using the centralized strategy was higher than that using the proposed strategy and perfect solutions, and the maximum difference was 0.2 K. This is because all the six cooling towers were in operation during this period and the centralized control strategy evenly distribute the cooling load among six cooling towers without considering the difference of their cooling efficiencies. Whereas, the proposed strategy and the perfect solutions addressed this issue during optimizations. Figure 6.5 presents the individual cooling tower outlet water temperature of the cooling towers in operation using the proposed strategy. It can be found that, the outlet water temperatures of the cooling towers with higher efficiency were controlled to be lower and more heat rejection loads were assigned to them.

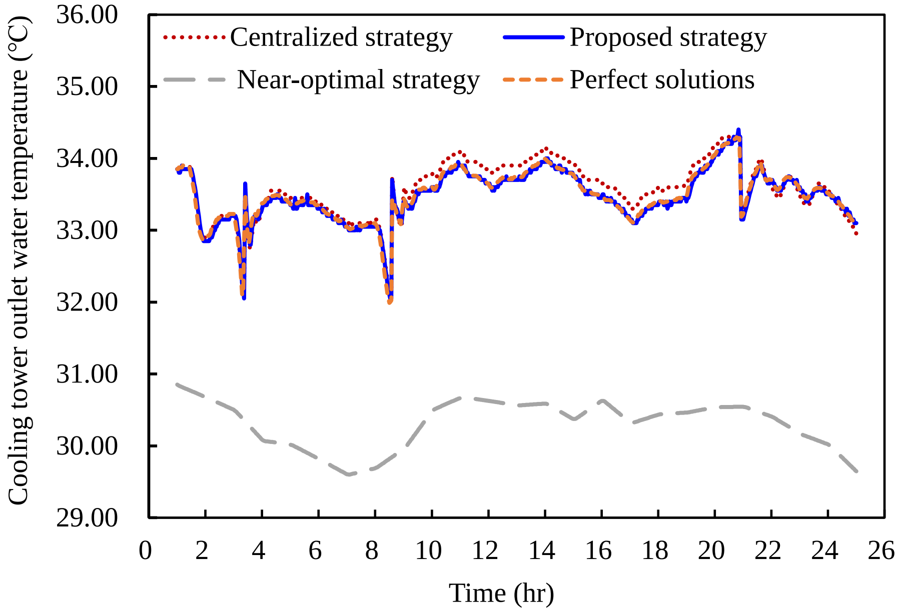


Figure 6.4 Cooling tower outlet water temperature using different control strategies.

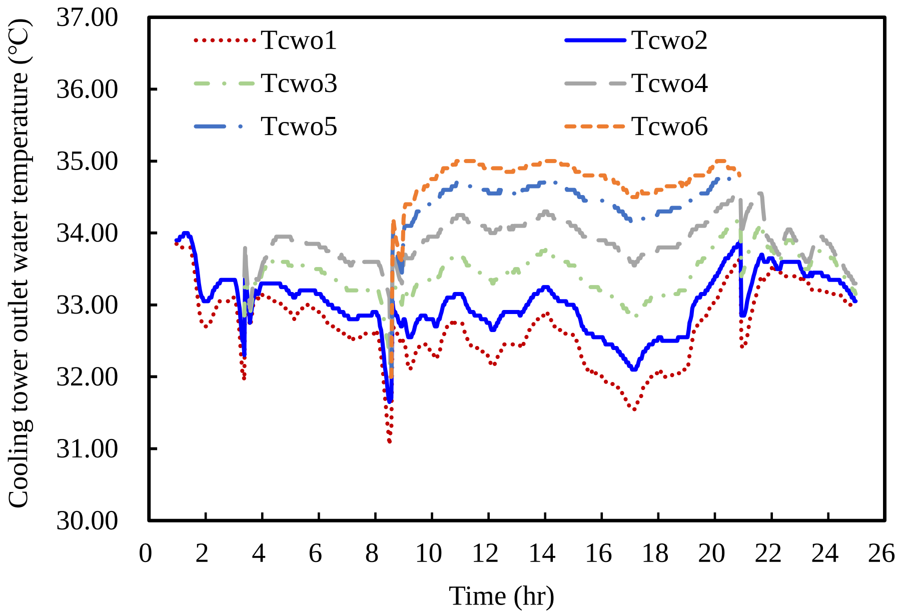


Figure 6.5 Individual cooling tower outlet water temperature using the proposed strategy.

Figure 6.6 presents the system power consumption when using the four control strategies. Both the centralized control strategy and proposed control strategy show better energy performance compared with the near-optimal control strategy. The system power consumption when using the two control strategies and the perfect solutions were very close. Table 6.3 presents the total system energy consumption in the test day when using the four control strategies. The total energy consumption when using the proposed control strategy and the perfect solutions was almost the same and a little higher than that using the centralized control strategy. Compared with the near-optimal control strategy, the total energy savings when using the perfect solutions, the proposed control strategy and the centralized control strategy were 7,576.23 kWh (7.76%), 7,573.34 kWh (7.75%) and 7,552.72 kWh (7.73%), respectively. The test results indicate that the proposed control strategy could achieve the same energy performance as the perfect solutions.

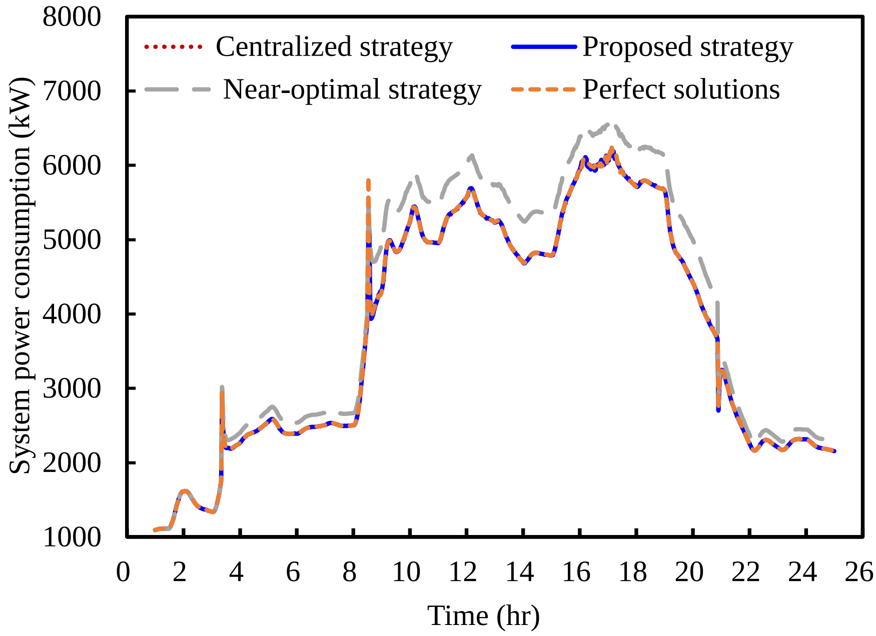


Figure 6.6 System power consumption using different control strategies.

Table 6.3 Daily Energy Consumption and Energy Saving using Different Control Strategies

	Energy consumption (kWh)	Energy saving (kWh)	Energy saving (%)
Near-optimal strategy	97,685	-	-
Centralized strategy	90,132	7,552.72	7.73
Perfect solutions	90,109	7,576.23	7.76
Proposed strategy	90,112	7,573.34	7.75

6.4 Summary

A hardware-in-the-loop simulator is constructed for the applicability verification and performance evaluation of the proposed agent-based distributed real-time optimal control strategy. The applicability of the distributed optimal control strategy is verified by implementing it on the physical sensor nodes of an IoT sensing network using typical processor boards commonly used by IoT devices today. According to the assessment, the smart sensors constructed in this study have the capability for implementing the proposed distributed optimal control strategy and conducting the optimization tasks. The required program memory and RAM for implementation account for 17.80% and 4.58% of the total capacities, respectively. These are well below the capacity of the constructed smart sensors. The required time for conducting the optimization tasks of one iteration step was less than 50 ms, which is well below the typical sampling interval of BASs. The optimization accuracy of the proposed distributed optimal control strategy is validated by comparing its optimization results with the perfect solutions. The needed iteration steps for obtaining the optimal solutions were within 14 steps, which can satisfy the optimization interval of minutes required by real-time optimal control of building HVAC systems. The energy performance of the distributed optimal control strategy is evaluated by comparing it with the perfect solutions and that of a centralized optimal control strategy. The test results show that the proposed distributed optimal control strategy achieved the similar energy performance as the perfect solutions and was even slightly better than that of the centralized strategy. Comparing with the near-optimal strategy, the daily energy saving was 7,573.34 kWh, which accounts for 7.75% of the total energy consumption of the central cooling system.

CHAPTER 7 CONCLUSIONS AND FUTURE WORK

This PhD study presented agent-based distributed real-time optimal control strategies for the building HVAC systems concerning the deployment on the local controllers of current LAN-based field control networks and the smart sensors of future IoT-enabled field control networks. The constraints and requirements in practical applications including the limited capacities of local devices, the required optimal control interval and the impacts of information delays are investigated. The proposed distributed optimal control strategy is further verified and evaluated by implementing it on the wireless sensor nodes of a constructed hardware-in-the-loop simulator.

This chapter presents the overall conclusions and recommendations, which is organized as follows. Section 7.1 presents a summary of the main contributions of this PhD study. Section 7.2 presents the conclusions on the work done during this study. The recommendations for future work are presented in Section 7.3.

7.1 Main contributions of this study

The main contributions of this PhD study are summarized as follows:

i. An agent-based distributed real-time optimal control strategy adopting edge computing is developed for optimal control of building HVAC systems at the field level. This strategy supports the development and applications of IoT technologies in the building automation field by providing an effective approach to realize the optimization of decision-making at the field level. Using this approach, the reliability of field-level optimizations and decision-making is increased since they do not rely on the central stations or cloud. The load of data transmission is significantly reduced by achieving the optimizations of subsystems locally at the field level using the field IoT/control devices.

ii. The proposed agent-based distributed real-time optimal control strategy reduces the efforts and cost of designing and reconfiguration for applications on systems of different configurations and scales. Since it can be designed by integrating software routines associated to building services devices and deployed on their embedded IoT devices or corresponding local controllers, allowing better generality and flexibility. It can broaden the applications of the optimal control of HVAC systems on current BASs, by using the distributed computation resources of digital controllers integrated in field control networks in the building automation industry.

iii. The impacts of information delays on the performance of distributed optimal control for HVAC systems deployed on field control networks are fully investigated and analysed. The necessity to eliminate or reduce these impacts when developing and implementing distributed optimal control strategies for HVAC systems in real applications are highlighted.

iv. The reliability and robustness of the proposed agent-based distributed real-time optimal control strategy in real applications is improved by developing a novel delay-tolerant method that can effectively reduce the impacts of information delays and is applicable in local devices.

v. The applicability and performance of the proposed distributed optimal control strategy are verified and evaluated by the experimental tests on a constructed hardware-in-the-loop simulator. A virtual HVAC system and a physical control system, consisting of wireless control/sensor nodes, are integrated. As distributed optimal control is increasingly investigated in recent years, besides the pure virtual (or digital) simulation, such a hardware-in-the-loop simulation method is effective and persuasive to validate the proposed distributed optimal control strategy.

7.2 Conclusions

On the agent-based distributed real-time optimal control strategy

- An agent-based distributed real-time 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 BASs to achieve distributed optimal control of building HVAC systems.
- The proposed agent-based distributed real-time optimal control strategy can effectively find the perfect solutions. Adopting the proposed convergence acceleration method, the convergence can be achieved within 50 iteration steps. The convergence rate of the proposed strategy can well satisfy the optimal control interval of minutes as needed in normal application practice.
- Smart sensors and local control devices are able to handle their corresponding 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 distributed real-time optimal control strategy is convenient and effective to deal with multiple components of different performances and it can achieve significant energy saving (3.58% of the total

energy consumption of the cooling towers) compared with conventional optimal control and near-optimal control strategies.

<u>On the investigation and quantification of the impacts of information delays</u>

- o Information delays in the information exchange among different local devices affect the optimization accuracy and convergence rate of distributed optimization and finally results in reduced energy performance. The maximum bias of optimized cooling tower outlet water temperature was up to 0.6 K, the largest number of iteration steps increased to 180 (about nine times of that in ideal conditions), and the power consumption of the cooling plant was increased by 0.2%.
- o The impacts of information delays increased dramatically with the increase in information delay length. With an increase in delay length from 1 sampling interval to 4 sampling intervals, the average bias in optimization results increased from 0.05 K to 0.44 K, the increase of annual energy consumption rose from 7,853.3 kWh to 37,397.2 kWh (0.06% to 0.28%) and the number of non-convergence optimizations increased from 306 to 2,986 (4.50% to 43.92%).
- o The best step-size for the update of the Lagrange multiplier determined in ideal conditions is not the best choice when information delays exist. Proper selection of the appropriate step-size effectively reduced the impacts of information delays and therefore improved the energy performance. The annual energy consumption increase was reduced from 37,397.2 kWh to 6924.6 kWh (from 0.28% to 0.05%).
- o The impacts of information delays on the performance of distributed optimal control strategies using ADMM is much larger than that using the subgradient method since ADMM requires more information exchange than the subgradient

method. Under the same uncertain information delays, using ADMM and the subgradient method, the maximum biases in optimized ventilation air volume were 6.07 L/s and 1.08 L/s, and the maximum numbers of iteration steps were 147 and 51 respectively.

<u>On the delay-tolerant distributed optimal control method</u>

- The proposed delay-tolerant distributed optimal control method, including two schemes of “synchronization of local optimization results” and “adaptive step-size setting”, can effectively reduce the impacts of information delays on the optimization accuracy and convergence rate.
- Smart sensors and local control devices are able to handle the computation load of the proposed delay-tolerant distributed optimal control method. The computation load of the cooling tower agents, chiller agents and the coordinating agent were 945, 1,150 and 40 FLOPs respectively, well below the capacity of typical smart sensors today.
- The proposed delay-tolerant distributed optimal control method effectively improves the energy performance of the distributed optimal control under information delays. Using set-points determined through the delay-tolerant control strategy, the energy consumption of the system was almost identical to that using the ideal optimal set-points.

<u>On the developed hardware-in-the-loop simulator</u>

- A hardware-in-the-loop simulator consists of a virtual HVAC system and a physical IoT sensing/control network is constructed for verification and evaluation of the proposed agent-based distributed real-time optimal control strategy. The applicability of the distributed optimal control strategy is verified by implementing it on the physical sensor nodes of an IoT sensing network using typical processor boards commonly used by IoT devices today.

- Since the complex optimization task is decomposed into simple subtasks, and they are solved by hybrid performance map and exhaustive search, a simple and effective optimization algorithm. The required program memory and RAM for implementation only account for 17.80% and 4.58% of the total capacities, respectively. These are well below the capacity of the constructed smart sensors.
- The smart sensors can handle the optimization tasks distributed in the sampling intervals. The required time for conducting the optimization tasks of one iteration step was less than 50 ms, which is well below the typical sampling interval of BASs.
- The proposed distributed optimal control strategy achieved the similar energy performance as the perfect solutions and was even slightly better than that of the centralized strategy. Comparing with the near-optimal strategy, the daily energy saving was 7,573.34 kWh, which accounts for 7.75% of the total energy consumption of the central cooling system.

7.3 Recommendations for future work

The major efforts of this PhD study have been devoted to developing the agent-based distributed real-time optimal control strategies for the optimal control of HVAC systems deployed on field control networks. The constraints and requirements in real applications including program size, computation load, convergence rate and information delays are addressed. In future studies, further efforts can be made on the following aspects to improve the quality of the research and to bring these methods into practical applications.

- Online calibration methods for improving the model accuracy of the model-based distributed optimal control strategies are needed. Model accuracy is essential for ensuring the performance of the model-based optimal control strategies. It is necessary to develop an effective and simple online calibration method to be implemented in local devices.
- The automatic model construction approach is worth to be developed for realizing the real plug and play of the distributed optimal control strategies. The distributed form of the proposed strategies can reduce the efforts on the design and reconfiguration of the strategy development, but the construction and commissioning of the equipment models are also time-consuming and laborious tasks in real applications. Combining the physical knowledge on the equipment and the machine learning methods could be an effective means to realize automatic model construction.
- The coordination methods at the higher level, i.e., between the different building services subsystems, when performing demand response (DR) are needed to be developed. Demand response is the action made by the demand side in response to the requirements of power grids. Buildings are expected to manipulate their power demand to provide different demand response services to maintain the balance between the supply side and demand side. The coordination of these subsystems can improve the capability of the buildings for providing these services while reducing the impacts on the indoor environment.
- On-site implementation and validation of the proposed distributed optimal control strategies are needed. The on-site tests are very important to identify the constraints in real applications such as the actual information delays in the real field control networks. The test results are essential for improving the reliability

and efficiency of the strategies. It is necessary and meaningful to make efforts on the field test of the proposed online control strategy in the practical buildings in future studies.

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