LI, Wenzhuo; LI, Hangxin; WANG, Shengwei. An event-driven multi-agent based distributed optimal control strategy for HVAC systems in IoT-enabled smart buildings. Automation in Construction, 2021, 132: 103919.

https://doi.org/10.1016/j.autcon.2021.103919

An event-driven multi-agent based distributed optimal control strategy for HVAC systems in IoT-enabled smart buildings

*Wenzhuo Li, Hangxin Li and Shengwei Wang**

Department of Building Services Engineering, Research Institute for Smart Energy, The Hong Kong Polytechnic University, Kowloon, Hong Kong.

Abstract: Smart buildings generally adopt a centralized optimal control for heating, ventilation and air-conditioning (HVAC) systems to improve the building system performance. As a crucial technology adopted in smart buildings, Internet of Things (IoT) based wireless sensor networks (WSNs) are promising platforms for implementing novel distributed optimal control to achieve distributed intelligence effectively. Such a future mist computing paradigm can be hindered by the limited energy resource of WSNs. The event-driven optimization method activates the optimization only when events occur. It can save the energy resource of WSNs, and thus pave the way for implementing the distributed optimal control architecture in IoT-based WSNs. This study therefore proposes an event-driven multi-agent based distributed optimal control strategy for HVAC systems for implementation in IoT-based battery-powered WSNs. The strategy consists of two novel schemes. First, an event determination scheme determines the event threshold by comprehensively considering the system performance and the total energy consumption of individual sensors implementing the distributed optimal control architecture. Second, an event-driven distributed optimization scheme solves the optimization problems with distributed optimization algorithms in IoT sensors of limited data processing capacity when an event occurs. Comparison and case studies are conducted to compare different strategies and validate the proposed strategy. Results show that different strategies require very different sensor energy consumption. The proposed strategy can provide satisfactory system performance while reducing the energy consumption of IoT sensors.

Keywords: Distributed optimal control, event-driven method, multi-agent system, mist computing, HVAC system, IoT-based wireless sensor network, sensor energy consumption.

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

1. Introduction

The Internet of Things (IoT) has attracted increased attention worldwide. It refers to objects with embedded computing devices that are able to connect to each other and exchange data using the Internet. IoT technology is increasingly applied in various domains, such as health, traffic, logistics, retail, agriculture, smart cities, smart metering, remote monitoring, and process automation [1]. Recently, in smart buildings, IoT-enabled services and applications [2,3] have been implemented to manage the indoor environment [4] and energy use of building systems [5]. A $70–150 billion and $200–350 billion economic impact are anticipated in offices and homes respectively [6]. IoT-based wireless sensor network (WSN) is a crucial technology adopted in smart buildings.

One of the critical issues for IoT-based WSNs, and especially battery-powered WSNs, is the limited energy resources available in individual sensors [7]. Given this, measures including reducing the sensor energy consumption and energy harvesting (extracting energy from the ambient environment) have been considered. Heinzelman et al. [8] proposed an energy-efficient communication protocol for wireless microsensor networks, Low-Energy Adaptive Clustering Hierarchy (LEACH), to distribute the load to all nodes and reduce global energy usage. LEACH was compared with the conventional protocols including the direct transmission, the minimum-transmission-energy, the multi-hop routing and the static clustering to demonstrate its superior performance. Elhoseny et al. [9] proposed a dynamic method to determine cluster heads and form sensor clusters using the genetic algorithm. The proposed method reduced the variance of remaining energy in individual sensors, thus extending network life. Roundy [10] investigated the conversion of ambient vibrations to electricity, which can be used by low power wireless electronic devices. Raghunathan et al. [11] investigated the key factors in designing solar energy harvesting wireless embedded systems. The performance of the solar energy harvesting module Heliomote was presented and evaluated through experiments.

As the counterpart of the widely adopted centralized optimal control approach, the relatively new distributed optimal control approach solves the optimization problem by coordinating individual agents in a distributed manner, which matches well with the distributed installation layout of IoT-based WSNs [12]. Besides their implementation in manufacturing [13] and chemical [14] fields, distributed optimal control architectures have been introduced into building systems, such as heating, ventilation and air-conditioning (HVAC) systems. Klein et al. [15] implemented a multi-agent comfort and energy system to reduce energy consumption and improve occupant comfort by coordinating building system device operations and occupant meeting schedules. Cai et al. [16] proposed and implemented a general multi-agent control approach in the distributed optimal control of a chiller plant and a multi-zone direct expansion (DX) air-conditioning system. Su and Wang [17] proposed and implemented an agent-based distributed optimal control strategy in a central cooling system. Several implementation issues including energy efficiency, optimization accuracy, convergence rate, computation complexities and computation loads were discussed. Li and Wang [18] proposed a multi-agent based distributed approach for the optimal control of multi-zone ventilation systems. According to the mist computing paradigm, the optimal control problem can be deployed and solved on IoT sensors of limited data processing capacity [19]. In IoT-based WSNs, sensor energy consumption differ based on whether a centralized or distributed optimal control architecture is used, which has not been fully discussed in previous studies.

When implementing distributed optimal control strategies in IoT-based battery-powered WSNs, reducing the operation frequency of sensors can reduce their energy consumption, thus assuring an acceptable battery replacement interval for sensors. IoT sensors can be operated with basic function (i.e. data collection) as well as advanced functions (i.e. communication, data analysis, computing and decision-making). Reducing the number of decisions needed through optimization can reduce the operation frequency of sensors. Conventionally, the proper set-points of control loops in HVAC systems can be determined with a time-driven optimization method [20]. The optimization action is driven in each time interval, a pre-determined fixed value. Compared to a shorter time interval, a longer time interval leads to less frequent optimization computation. Therefore, the energy resources of IoT-based battery-powered WSNs are less frequently used [21], but the optimization performance may be worse due to the untimely reaction to the various operating conditions [22]. For cases with stable operating conditions, a shorter time interval may not improve the optimization performance significantly but can waste the energy resources of the IoT-based battery-powered WSN, thus is not necessary [23]. The time interval is generally determined by experience, and thus cannot be used to ensure a proper trade-off between satisfactory optimization performance and minimized use of energy resource in IoT-based battery-powered WSNs.

In contrast with a time-driven optimization method, optimization can also be triggered when pre-determined events occur, which is referred as the event-driven optimization method. The event-driven method originates from discrete event systems [24], and it has been widely applied in many fields such as sampling [25] and estimation [26]. The event-driven optimization method, integrating the event-driven and optimization methods, was proposed by Cao [27,28], and is more flexible when handling uncertainties. Xu et al. [21] defined two events in the developed model-based periodic event-triggered mechanism (ETM) as a novel building operational optimization approach. Optimization actions were triggered if the actual occupied time was different from the predicted time or if the PMV value deviated from the comfortable range. The results using ETM showed a significant reduction in communication and computational resource usage, with acceptable system performance degradation compared to the time-triggered method. Wang et al. [23] defined two events for optimal control HVAC systems, part-load ratio (PLR) change and chiller on/off switching. The threshold for PLR change was determined by testing the energy saving percentage of different PLR changes (from 5% to 15%) compared to time-driven optimization. The event "PLR change by 7%" offered a relatively high energy saving percentage in cases, and thus was finally determined. Wang et al. [29] proposed the design approach to establish the event, policy and action space for event-driven optimization in HVAC systems. The performance score, combined with the energy and computation savings compared to the benchmark case, was used to determine the threshold of an event. Wang et al. [30] used the random forest (RF) to identify the relationship between the Euclidean distances of decision variables and state variables as well as their variations. State variables with higher percentage increases of the mean square error represented a higher importance, and thus were selected as events. Hou et al. [31] developed a systematic method, in which sensitivity analysis, linear regression and a comprehensive search were used, to determine the event/action space and the event-action map. By properly determining the events, it is expected to find a trade-off between the satisfactory optimization performance and minimized use of energy resource of the IoT-based battery-powered WSN, which has been rarely considered in previous studies.

This study therefore proposes an event-driven multi-agent based distributed optimal control strategy for HVAC systems for implementation in IoT-based battery-powered WSNs. It consists of two core schemes, including an event determination scheme and an event-driven distributed optimization scheme. This study has four major contributions. (1). A new event determination scheme is adopted to determine the event by comprehensively considering the system performance and sensor energy consumption in IoT-based battery-powered WSNs implementing the distributed optimal control architecture. (2). A new event-driven distributed optimization scheme is adopted to solve optimization problems using distributed optimization algorithms deployed in IoT sensors of limited data processing capacity only when events occur. (3). As IoT-based battery-powered WSNs become increasingly integrated in optimal control of building systems, sensor energy models are introduced into building field to estimate sensor energy consumption and to provide a reference for the effective use of the limited energy resources available in individual sensors. (4). A comparison is conducted between the centralized and distributed optimal control strategies in the aspects of sensor operation and energy consumption, the latter quantified both for each mode and in total for each sensor.

2. The proposed event-driven multi-agent based distributed optimal control strategy

This section first presents the optimal control problem of heating, ventilation and air-conditioning (HVAC) to be solved by the proposed strategy. Then, the outline of the event-driven multi-agent based distributed optimal control strategy is presented in section 2.2. Two core schemes, the event determination scheme and event-driven distributed optimization scheme, are illustrated in detail in sections 2.3 and 2.4.

2.1. Problem statement

The control objective of HVAC systems is to maintain a satisfactory indoor environment quality (IEQ) in individual rooms with minimized energy use of HVAC system. Using the weighted sum approach, the multi-objective optimization problem is expressed as the objective function in Equation (1). Where, n is the number of rooms, $Obj_{IEQ,i}$ is the objective function of IEQ in room i, β is the weighting factor, Obj_{HVAC} is the objective function of energy use of HVAC system. Different types of HVAC systems (e.g. Variable Air Volume (VAV) air-conditioning systems and dedicated outdoor air systems (DOAS)) are responsible for maintaining different IEQ indicators (e.g. indoor temperature and CO_2 concentration) by optimizing set-points of different control loops (e.g. temperature set-points and outdoor air volume of individual rooms). At the current stage, such an optimal control problem is solved by the central station in a centralized optimal control architecture. The optimization decision-making is conducted based on a time-driven optimization method. By contrast, the proposed strategy aims to solve this optimal control problem by IoT sensors of limited data processing capacity in a distributed optimal control architecture. The optimization decision-making is conducted based on an event-driven optimization method to save the energy resource of IoT sensors in battery-powered WSNs. Besides its novelty, the proposed strategy is also generally applicable for the optimal control of different types of HVAC systems.

$$Obj = \sum_{i=1}^{n} Obj_{IEQ,i} + \beta \cdot Obj_{HVAC} \tag{1}$$

2.2. Outline of event-driven multi-agent based distributed optimal control strategy

An outline of the proposed event-driven multi-agent based distributed optimal control strategy is shown in Figure 1. It is integrated with the event-driven optimization method and the distributed optimization method. By analyzing real-time operational data of the system, it is judged whether a pre-determined event has occurred. If no event occurs, no optimization will be conducted and the previous set-points of the system will be maintained. If an event occurs, optimization will be conducted to determine the optimal set-points of the system given specific control objectives for the current condition. Two core schemes, the event determination scheme and event-driven distributed optimization scheme, distinguish the proposed strategy from those proposed in previous studies. In the event determination scheme, an event is determined by considering the system performance and the sensor energy consumption in IoT-based battery-powered WSNs implementing the distributed optimal control architecture. In the event-driven distributed optimization scheme, if an event occurs, optimization will be realized by distributed optimization algorithms in IoT-based battery-powered WSNs.

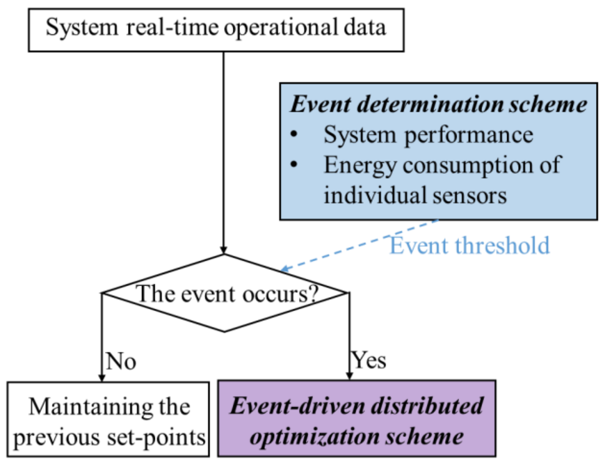


Figure 1. Outline of the event-driven multi-agent based distributed optimal control strategy

2.3. Event determination scheme

This section elaborates the formulation of the performance score, considering system performance and the total energy consumption of each sensor, to determine the event for the proposed strategy.

2.3.1. Performance score

The proposed strategy is based on the assumption that the more the current system state (S_k) deviates from the previous system state (S_{k-1}), the more the optimal current set-points of the system ($Opt.Set_k$) deviate from their previous values ($Opt.Set_{k-1}$). Thus, the necessity of optimization is increased. In this study, a change of system state is defined as an event [32]. In operation, if the deviation between measurements of the selected system state variable at previous and current sampling times (i.e. $\Delta S_k=|S_k-S_{k-1}|$) is greater than the preset event threshold, an event is detected.

If a large threshold is selected, the optimization will not be triggered frequently, which may result in degradation of system performance due to optimization delays. Under the distributed optimal control architecture, the optimization problem is solved by coordinating distributed agents on individual sensors. Thus, the sensor energy consumption can be reduced by reducing the optimization computations triggered. In contrast, if a small event threshold is selected, the optimization will be triggered frequently, improving system performance but increasing sensor energy consumption. Therefore, there is a trade-off problem in selecting the proper event threshold to ensure satisfactory system performance while minimizing sensor energy consumption.

A performance score (*PS*) is defined to quantify the performance of the optimal control strategy adopting a specific event threshold, as expressed in Equation (2). It consists of two parts. $\sum_{j=1}^{m} PS_{SYS,j}$ is the sum of *m* different system performance scores to evaluate the system performance. For the *j* system performance score, it is defined in section 2.3.2. PS_{sensor} is the sensor energy score used to evaluate sensor energy consumption. The objective is to minimize the performance score by selecting the best event threshold for the control strategy. The specific event threshold which allows the strategy offering the best performance score (i.e. the lowest *PS*) is identified as the best event threshold.

$$PS = \frac{1}{m+1}\left(\sum_{j=1}^{m} PS_{SYS,j} + PS_{sensor}\right) \tag{2}$$

2.3.2. System performance

The system performance score ($PS_{SYS,j}$) evaluates the system performance given by the strategy adopting a specific event threshold, compared to the most satisfactory system performance given by the benchmark strategy. The system performance is evaluated by several system performance indicators, including IEQ indicators to be maintained and energy use of concerned HVAC systems. In this study, a time-driven multi-agent based distributed optimal control strategy with a small time interval is adopted as the benchmark strategy. The system performance score ($PS_{SYS,j}$) is calculated using Equation (3). $I_{j,th}$ is a system performance indicator given by the strategy adopting a specific event threshold. $I_{j,B}$ is a system performance indicator given by the benchmark strategy.

$$PS_{SYS,j} = |I_{j,th} - I_{j,B}|/I_{j,B} \tag{3}$$

2.3.3. Sensor energy consumption

The sensor energy score (PS_{sensor}) evaluates sensor energy consumption under the strategy adopting a specific event threshold, compared to that under the benchmark strategy. Since the benchmark strategy adopts a small time interval, it requires the maximum sensor energy consumption. The sensor energy score (PS_{sensor}) is computed using Equation (4). $E_{sensor,th}$ is sensor energy consumption under the strategy adopting a specific event threshold. $E_{sensor,B}$ is sensor energy consumption under the benchmark strategy.

$$PS_{sensor} = E_{sensor,B}/(E_{sensor,B} - E_{sensor,th}) \quad (4)$$

Energy consumption of a sensor (E_{sensor}) is calculated by summing up the energy consumption for sensing (E_{sens}), message transmission (E_{tx}), message receiving (E_{rx}) and data processing (E_{pro}) [33], as shown in Equation (5).

$$E_{sensor} = E_{sens} + E_{tx} + E_{rx} + E_{pro} \quad (5)$$

E_{sens} is calculated using Equation (6) [7]. k is the length of a message. V_{dd} (=2.7 V [7]) is the supply voltage. I_{sens} (=25 mA [7]) is the total current required for sensing. T_{sens} (=0.5 ms [7]) is the time duration for sensing.

$$E_{sens} = k \cdot V_{dd} \cdot I_{sens} \cdot T_{sens} \quad (6)$$

E_{tx} and E_{rx} are calculated using the first order radio model, as shown in Equations (7) and (8) [8]. E_{elec} (=50 nJ/bit [8]) is the energy dissipated to transmit or receive a message. $\mathcal{E}_{amp}$ (=100 pJ/bit/m^2 [8]) is the energy dissipated by the transmit power amplifier. d is the transmission distance. γ is the path loss exponent relating to the transmission distance, which is set as 2 for a relatively short distance and 4 for a relatively long distance [34].

$$E_{tx} = E_{elec} \cdot k + \varepsilon_{amp} \cdot k \cdot d^{\gamma} \quad (7)$$

$$E_{rx} = E_{elec} \cdot k \quad (8)$$

E_{pro} is calculated using Equation (9) [35]. N is the number of clock cycles per task. C (=0.67nF [35]) is the average capacitance switched per cycle. I_o (=1.196 mA [7]) is the leakage current. n_p (=21.26 [7]) is a constant. V_T (=0.2 V [7]) is the thermal voltage. f is the sensor clock speed.

$$E_{pro} = NCV_{dd}^2 + V_{dd}\left(I_0 e^{\frac{V_{dd}}{nV_T}}\right)\left(\frac{N}{f}\right) \quad (9)$$

2.4. Event-driven distributed optimization scheme

The process to realize the distributed optimal control with the multi-agent system paradigm has been elaborated in detail in the previous work by this paper's authors [18]. As illustrated in section 2.1, the multi-objective optimization problem of the system concerning specific control objectives is mathematically formulated in a centralized form, i.e. Equation (1). According to the multi-agent system paradigm, Equation (1) with coupled constraints is decomposed into a number of optimization sub-problems to be processed in distributed agents using the decomposition theory, e.g. alternating direction method of multipliers (ADMM). There are multiple room agents with optimization sub-problems of maintaining IEQ indicators, the HVAC agent with an optimization sub-problem of reducing energy use and the central coordinating agent with simple rules for updating parameters. Using the exhaustive method, individual room agents conduct local optimization to determine their own set-points for maintaining IEQ indicators, and the HVAC agent conducts local optimization to determine its own set-point for reducing energy use. To guarantee the optimization accuracy, which means the optimal set-points in distributed optimal control are very close or equal to those in centralized optimal control, the iteration is conducted as shown in Figure 2. At each iteration *l*, room agents and the HVAC agent conducts local optimization in parallel by using the information of other agents updated in the last iteration. With this coordination process, local optimums converge to the global optimum iteratively.

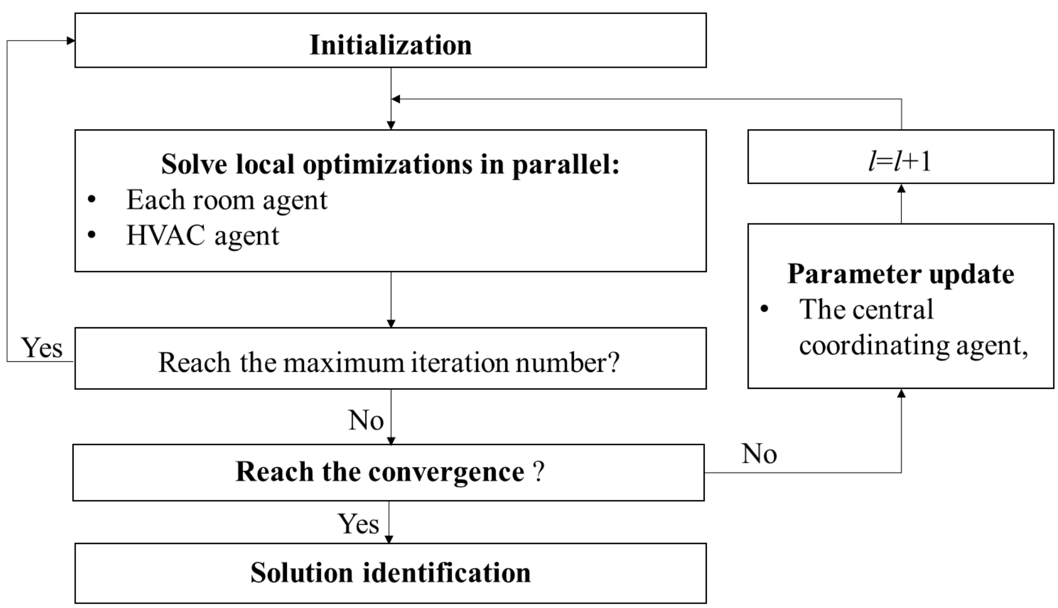


Figure 2. Flowchart of iteration for distributed optimization

3. Performance comparisons implementing existing centralized and different distributed strategies

Section 3.1 presents an outline of the comparison studies, including the HVAC system of concern and the configurations of IoT-based WSNs implementing the centralized and distributed optimal control architectures respectively. Section 3.2 presents the existing centralized and different distributed strategies to be compared. Section 3.3 presents the comparison of building system performance and sensor energy consumption using time-driven strategies adopting centralized and distributed optimal control architectures. Section 3.4 presents the comparison of building system performance and sensor energy consumption using distributed optimal control strategies adopting different event thresholds.

3.1. Outline of the comparison studies

3.1.1. Brief introduction of dedicated outdoor air systems (DOAS)

Dedicated outdoor air systems (DOAS), a popular type of HVAC system, are selected to conduct the comparison studies. The control objective of DOAS is to maintain indoor CO_2 concentration, an important indicator of IEQ, with minimized energy use of DOAS [36]. Therefore, the objective function of IEQ in room *i* ($Obj_{IEQ,i}$) and the objective function of energy use of HVAC system (Obj_{HVAC}) are shown in Equations (10) and (11). Where, $CO2_i$ is the steady-state CO_2 concentration of room *i*, $CO2_{Limit}$ is the CO_2 limit (i.e. 800 ppm [42]), $E_{Chiller}$ is the equivalent chiller energy use and E_{Fan} is fan energy use. The set-points of DOAS to be optimized are the outdoor air of individual rooms and the primary air-handling unit (PAU).

$$Obj_{IEQ,i} = \max\{0, CO2_i - CO2_{Limit}\}^2 \tag{10}$$

$$Obj_{HVAC} = E_{Chiller} + E_{Fan} \tag{11}$$

In this study, the average CO_2, the maximum CO_2 and daily energy use of the DOAS are used to evaluate building system performance. They are also system performance indicators to calculate system performance score. Six rooms are served by one PAU. Thus there are six room agents, one PAU agent and one central coordinating agent. It is worthy noticing that the energy use in DOAS is mainly contributed by PAU, thus the HVAC agent in section 2.4 is directly renamed as the PAU agent. The occupancy profiles and outdoor weather in a typical workday in the comparison studies are shown in Figure 3. The comparison studies are conducted on a TRNSYS-MATLAB co-simulation testbed. In TRNSYS, indoor real-time CO_2 variation is simulated under varying weather, occupancy and PAU control. In MATLAB, the objective functions concerning specific optimization sub-problems of room and PAU agents and updating rules of the central coordinating agent are programmed.

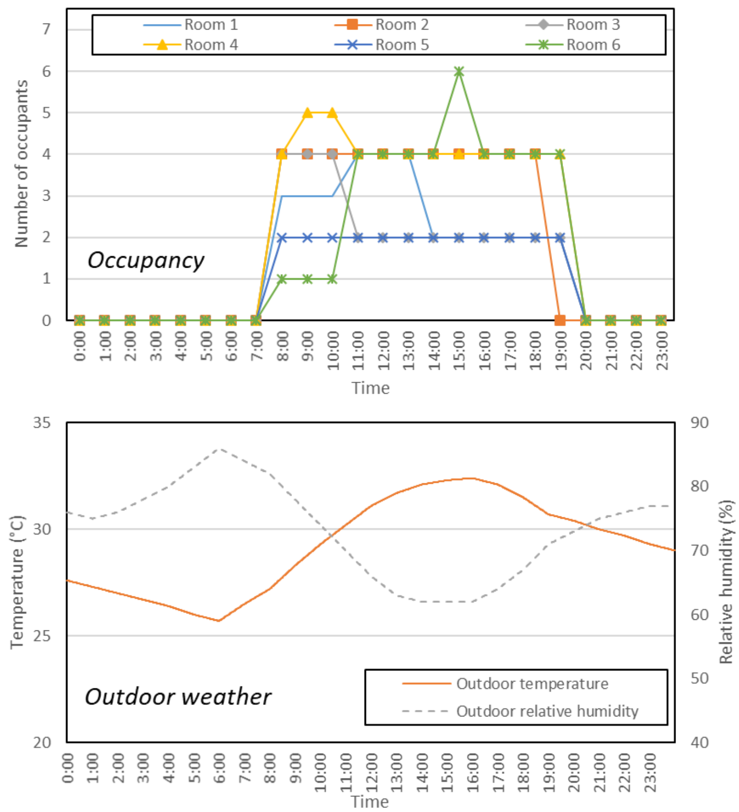


Figure 3. Occupancy profiles and outdoor weather in the comparison studies

3.1.2. The centralized optimal control architecture

The configuration of individual IoT sensors implementing the centralized optimal control architecture is shown in Figure 4. Under the centralized optimal control architecture, individual sensors transmit messages via a gateway to the central station for optimization decision-making [37,38]. IoT CO_2 sensors are installed in individual rooms (S_1 to S_6 in Room 1 to Room 6) and IoT airflow meter is installed on the PAU (S_{PAU}) respectively. The transmission distances between individual sensors and the gateway ($d_{1,c}$ - $d_{6,c}$ and $d_{PAU,c}$) are shown in Figure 4. The length of a message is assumed to be 800 bits [39-41].

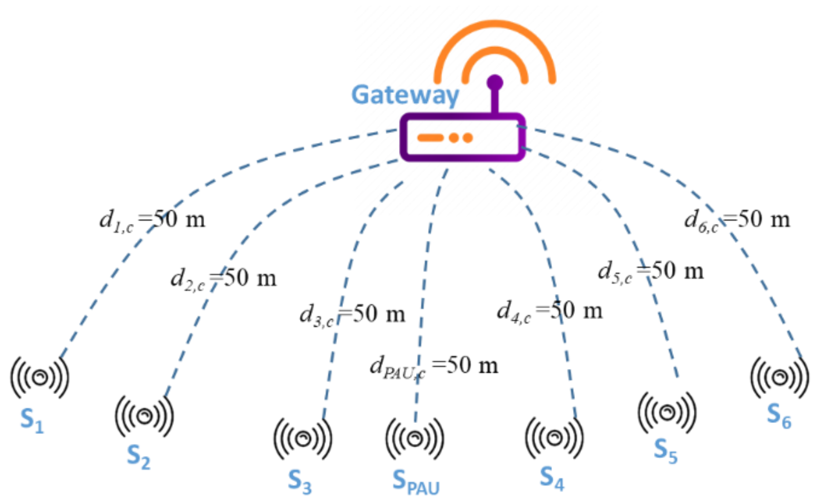


Figure 4. Configuration of individual IoT sensors implementing centralized optimal control architecture

3.1.3. The distributed optimal control architecture

The configuration and locations of individual IoT sensors implementing the distributed optimal control architecture are shown in Figure 5. Room agents and the PAU agent are implemented on IoT CO_2 sensors (S_1 - S_6) installed in individual rooms and the IoT airflow meter (S_{PAU}) installed on the PAU respectively. A coordinating agent facilitating the communication among other agents is implemented on a coordinator sensor (S_{Co}). Messages are transferred between room agents as well as the PAU agent and the coordinating agent, and distances between them ($d_{1,d}$ - $d_{6,d}$ and $d_{PAU,d}$) are shown in Figure 5.

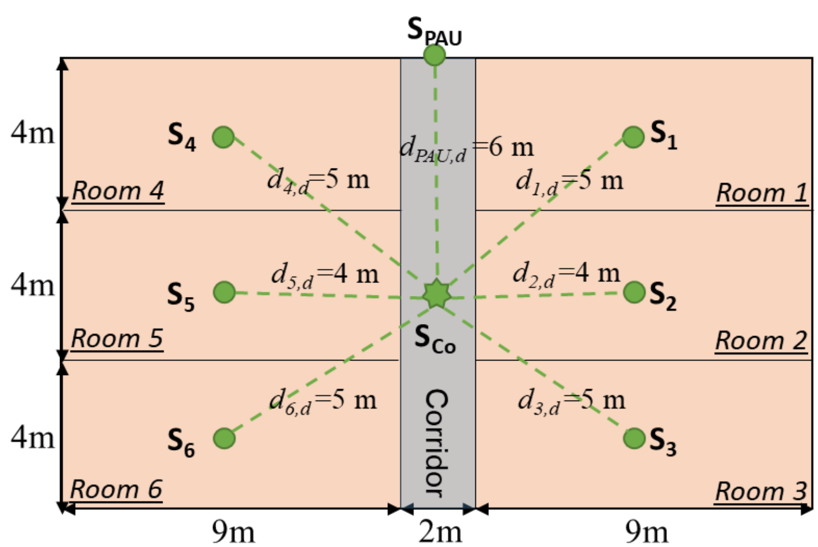


Figure 5. Configuration and locations of individual IoT sensors implementing distributed optimal control architecture

Besides message transmission/receiving, the room agents, PAU agent and the coordinating agent conduct advanced data processing. Room agents and the PAU agent adopt an exhaustive method for optimization. The central coordinating agent conducts simple arithmetic operations for parameter update. By referring to Equation (9), sensor energy consumption for data processing is proportional to the number of clock cycles per task, which depends on the performance of the central processing unit (CPU). In this study, simulation tests are performed on a personal computer (PC) with a CPU clock speed of 3.5 GHz. The CPU clock speed of typical IoT sensors is 191 MHz, much lower than that of a PC. The number of floating point operations (FLOPs) is used to assess the computation loads of the optimization tasks, which is independent from the CPU performance. The number of FLOPs is eventually used to calculate sensor energy consumption for data processing.

Since the distributed optimization method iterates a number of time before identifying the solutions to the optimization problems, the message and advanced data processing tasks are repeated. In this study, 15 iterations are assumed for each optimization step.

3.2. Existing centralized and distributed strategies used in comparison studies

Five existing optimal control strategies for multi-zone DOAS are tested and compared in the comparison studies. These strategies are described as listed in Table 1.

Table 1. Descriptions of centralized and distributed strategies used in comparison studies

Strategy	Description
C_T_1	The **c**entralized optimal control strategy with the **t**ime interval of **1** minute
D_T_1	The multi-agent based **d**istributed optimal control strategy with the **t**ime interval of **1** minute
D_E_5	The multi-agent based **d**istributed optimal control strategy with the **e**vent threshold of ΔCO_2 to be **5** ppm
D_E_3	The multi-agent based **d**istributed optimal control strategy with the **e**vent threshold of ΔCO_2 to be **3** ppm
D_E_2	The multi-agent based **d**istributed optimal control strategy with the **e**vent threshold of ΔCO_2 to be **2** ppm

- ***Strategy C_T_1*** is a typical optimal control strategy, which is widely investigated and implemented for multi-zone DOAS in the literature. The optimization is realized by centralized optimization algorithms in a central station. The optimization is conducted with the time interval of 1 minute.
- ***Strategy D_T_1*** is a relatively new optimal control strategy for multi-zone DOAS, as proposed in the previous work of this paper's authors [19]. The optimization is achieved using distributed optimization algorithms in IoT sensors of limited data processing capacity in battery-powered WSNs. The optimization is also conducted with the time interval of 1 minute. Such a high optimization frequency assures that variable operating conditions are handled timely. Thus, the system performance given by *Strategy D_T_1* is considered to be the best. It is therefore used as the benchmark strategy in this study.
- ***Strategy D_E_5*** is a multi-agent based distributed optimal control strategy only adopting the event-driven distributed optimization scheme. Optimization is conducted whenever the deviation in indoor CO_2 between the previous and current sampling times (ΔCO_2) is larger than 5 ppm.
- ***Strategy D_E_3*** is similar to *Strategy D_E_5*, except the event threshold (ΔCO_2) is changed to 3 ppm.
- ***Strategy D_E_2*** is similar to *Strategy D_E_5*, except the event threshold (ΔCO_2) is changed to 2 ppm. It is worthy noticing that the resolution of the CO_2 sensor, defined as the smallest detectable incremental change of input parameter that can be detected in the output signal, is generally smaller than 2 ppm. Thus ΔCO_2 to be 2, 3 and 5 ppm are applicable to be the event thresholds and the events are detectable.

3.3. Comparison of time-driven strategies adopting centralized and distributed optimal control architectures

Table 2 presents a comparison of the sensor operation mode and the corresponding energy consumption when adopting the centralized and distributed optimal control architectures. The test results of both centralized and distributed optimal control strategies with the time interval of 1 minute (i.e. *Strategy C_T_1* and *Strategy D_T_1*) are presented and compared.

The centralized optimal control strategy, *Strategy C_T_1*, completes optimization and obtains the optimal solution at each operation state in a central station using the centralized optimization method in a one-time effort. Individual sensors transmit the collected data to the central station via the gateway. No advanced data processing needs to be performed in these sensors. In each optimization interval (i.e. 1 minute), both sensing and message transmission are conducted once. As shown in Table 2, sensors consumed energy of 38.88 J/day for sensing, and 0.40 J/day for message transmission. A total energy of 39.28 J/day was consumed. This calculated value conformed to the actual energy consumption of typical IoT CO_2 sensors currently used in real cases.

The distributed optimal control strategy, *Strategy D_T_1*, needs several iterations (15 in this study) to complete optimization at each operation state using the distributed optimization method. The room sensors and the PAU sensor collect the data and transmit/receive messages to/from the coordinating sensor. The local optimization task, i.e. an advanced data processing task, is conducted on individual room sensors and the PAU sensor. The arithmetic operations for parameter update, i.e. another advanced data processing task, is conducted on the coordinating sensor. In each optimization interval (i.e. 1 minute), the sensing is conducted once by the room and the PAU sensors, and no sensing is conducted by the coordinating sensor. Meanwhile, the above mentioned message exchange and advanced data processing are repeated for about 15 rounds (i.e. 15 iterations). As shown in Table 2, each of the room and PAU sensors consumed 38.88 J of energy per day for sensing. Each of the room and PAU sensors consumed 3.92 J of energy per day for message exchange, while the coordinating sensor consumed 29.00 J/day. Each of the room and PAU sensors consumed 1438.29 J of energy per day for advanced data processing, while the coordinating sensor consuming 0.03 J/day.

It can be concluded that, under the centralized optimal control architecture, energy of sensors was mainly consumed for sensing and message transmission. Under the distributed optimal control architecture, energy of room and PAU sensors was mainly consumed for advanced data processing. The energy of the coordinating sensor was mainly consumed for message exchange.

Table 2. Comparisons of sensor energy consumption implementing the centralized and distributed optimal control architectures

		Optimal control architecture	Centralized	Distributed	
				Room and PAU sensors	Coordinating Sensor
Mode	Sensing	*Round per optimization interval*	1	1	-
	Message transmission /receiving	*Devices involved*	Sensors ↔The gateway	Room and PAU sensors ↔ Coordinating Sensor	
		Round per optimization interval	1	15	
	Advanced data processing	*Task type*	-	Exhaustive search for optimization	Arithmetic operations for parameter update
		Round per optimization interval	0	15	
	Sensing		38.88	38.88	0

Energy consumption (J/day)	Message transmission/receiving	0.40	3.92	29.00
	Advanced data processing	0	1438.29	0.03

Table 3 presents a comparison of the building system performance and sensor energy consumption (i.e. percentages of their battery capacities) when adopting the centralized strategy (i.e. *Strategy C_T_1*) and distributed strategy (i.e. *Strategy D_T_1*) with the time interval of 1 minute. The building system performance regarding the average CO_2, the maximum CO_2 and the daily energy use of the DOAS were close under the two strategies. This matches the conclusions of previous work by this paper's authors [18]. Concerning the sensor energy consumption, an AA size alkaline battery of 1500 mAh was employed in each sensor. On average, a sensor consumed about 0.48% of its battery capacity per day when implementing the centralized optimal control architecture. It was estimated that the battery of a sensor could last for about 208.33 days, i.e. nearly 7 months. On the other hand, a sensor consumed about 16.04% of its battery capacity per day when implementing the distributed optimal control architecture. It was estimated that the battery of a sensor would be exhausted in about 6.23 days. Such a short replacement interval is neither practical nor acceptable in application.

Table 3. Performance comparisons of different strategies in the comparison study

Strategy	Optimization method	Driven method	Time interval or event threshold	System performance			Total energy consumption of individual sensors (% of capacity per day)	Performance score
				Average CO_2 (ppm)	Maximum CO_2 (ppm)	Energy use of DOAS (kWh/Day)		
C_T_1	Centralized	Time-driven	Δt=1 min	627	840	39.63	0.48	-
D_T_1	Distributed			625	836	39.96	16.04	-
D_E_5		Event-driven	ΔCO_2=5 ppm	637	949	42.02	0.59	0.31
D_E_3			ΔCO_2=3 ppm	624	859	41.54	1.19	0.29
D_E_2			ΔCO_2=2 ppm	627	839	40.60	2.30	0.30

3.4. Comparison of distributed optimal control strategies adopting different event thresholds

Figure 6 shows the optimization frequencies of distributed optimal control strategies adopting different event thresholds (i.e. *Strategy D_E_5*, *Strategy D_E_3* and *Strategy D_E_2*). Table 3 presents a comparison of the building system performance and sensor energy consumption of these strategies. It can be found that the event threshold has a significant impact on building system performance and sensor energy consumption (and sensor battery replacement interval), elaborated in more detail below.

- ***Strategy D_E_2*** adopts the lowest event threshold. The optimization frequency was the highest. Individual room agents conducted local optimization tasks about one to six times at each optimization interval. This means that the event was not always activated in all room agents at the same time. The building system performance using *Strategy D_E_2* was closest to the "best" building system performance under the benchmark strategy (i.e. *Strategy D_T_1*). Specifically, when adopting *Strategy D_T_1* and *Strategy D_E_2*, the average CO_2 were 625 and 627 ppm, the maximum CO_2 were 836 and 839 ppm and the daily energy uses of the DOAS were 39.63 and 40.60 kWh respectively. Concerning the sensor energy consumption, it was the highest. The average daily energy consumption of each sensor was about 2.30% of its battery capacity, and the battery replacement interval was estimated to be about 43.48 days.
- ***Strategy D_E_5*** adopts the largest event threshold. The optimization frequency was the lowest. Individual room agents conducted local optimization tasks about one to four times at each optimization interval. The system performance using *Strategy D_E_3* was the worst. It gave the highest average CO_2, maximum CO_2 and daily energy use of DOAS. Concerning the sensor energy consumption, it was the lowest. The average daily energy consumption of each sensor was about 0.59% of its battery capacity, and the battery replacement interval was estimated to be about 169.49 days.
- ***Strategy D_E_3*** adopts the event threshold between those of *Strategy D_E_5* and *Strategy D_E_2*. The optimization frequency was also in between them. Individual room agents conducted local optimization tasks about one to five times at each optimization interval. The system performance and sensor energy consumption using *Strategy D_E_3* lied between those using *Strategy D_E_5* and *Strategy D_E_2*. Specifically, the average CO_2 was 624 ppm, the maximum CO_2 was 859 ppm and the daily energy use of DOAS was 41.54 kWh. The average daily energy consumption of each sensor was about 1.19% of its battery capacity, and the battery replacement interval was estimated to be about 84.03 days.

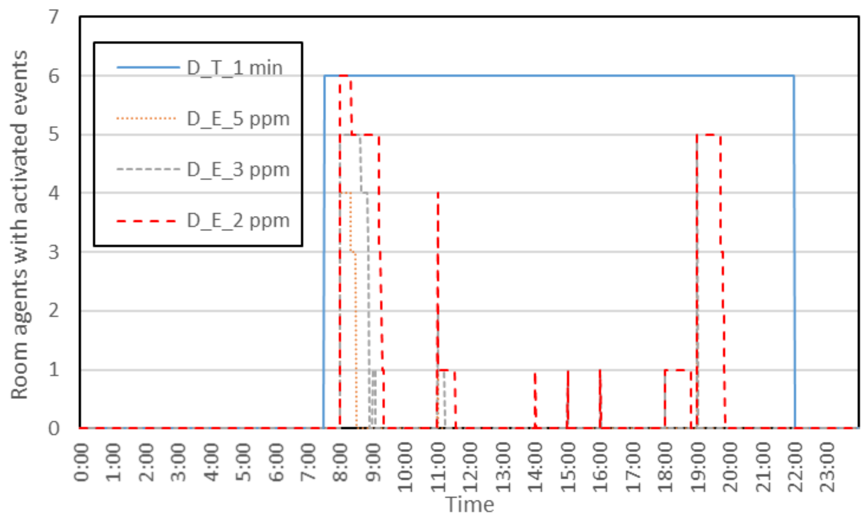


Figure 6. Optimization frequencies using different strategies

The performance scores of different strategies concerned are summarized in Table 3. The average CO_2, maximum CO_2, daily energy use of DOAS and the sensor energy consumption were comprehensively considered. It can be found that *Strategy D_E_3* offered the smallest (i.e. 0.29) performance score among the strategies. The best threshold (ΔCO_2) eventually identified was 3 ppm.

4. Case study and performance validation of the proposed strategy

As elaborated in Section 2, an event-driven multi-agent based distributed optimal control strategy is proposed to maintain the satisfied system performance while reducing sensor energy consumption in battery-powered WSNs. To test and validate this strategy, a case study was conducted. The performance of the proposed strategy is assessed by comparing with the benchmark strategy in this case study.

4.1. Outline of the case study

The same DOAS was used for the case study. The occupancy profiles and outdoor weather in another typical workday are shown in Figure 7. Using the most proper event threshold (ΔCO_2=3 ppm) identified, the proposed event-driven multi-agent based distributed optimal control strategy, i.e. *Strategy D_E_3*, is validated by comparing it with the benchmark strategy, i.e. *Strategy D_T_1* (the multi-agent based distributed optimal control strategy with the time interval of 1 minute).

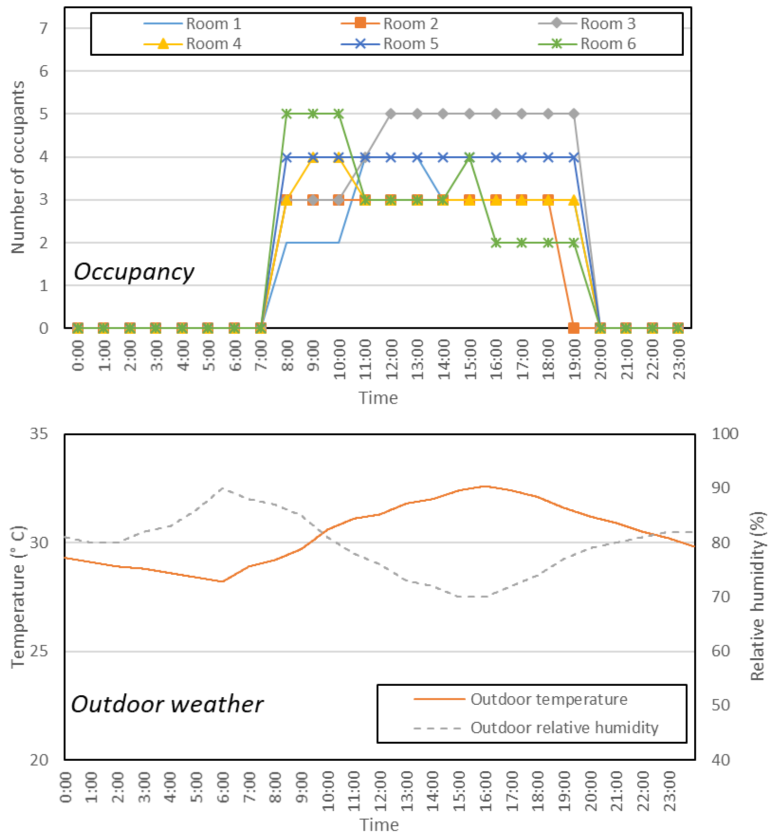
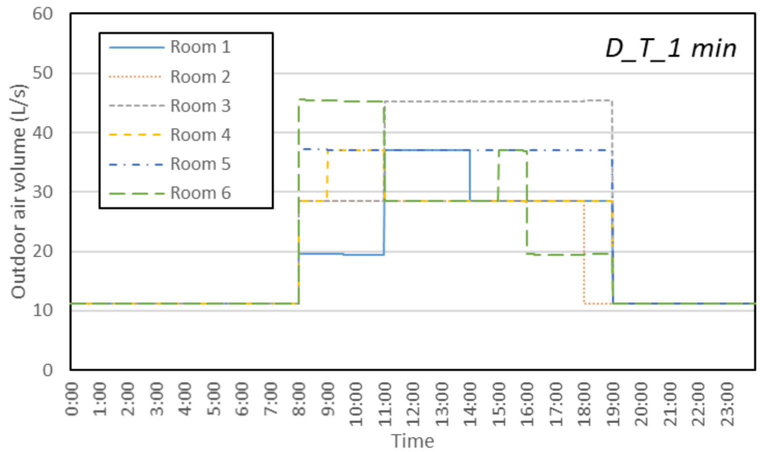


Figure 7. Occupancy profiles and outdoor weather in the case study

4.2. Building system performance

Figure 8 shows the optimized outdoor air volume of individual rooms in the case study using *Strategy D_T_1* and *Strategy D_E_3* respectively. Figure 9 shows the indoor CO_2 concentration of individual rooms. The building system performance using these two strategies regarding the average CO_2, maximum CO_2 and daily energy use of the DOAS are summarized in Table 4.

The building system performance given by *Strategy D_E_3* was not as good as the "best" building system performance given by the benchmark strategy (i.e. *Strategy D_T_1*), but was close to it. The average CO_2 was 626 ppm and the maximum CO_2 was 860 ppm using *Strategy D_E_3*, whereas the average CO_2 was 636 ppm and the maximum CO_2 was 849 ppm using *Strategy D_T_1*. In practice, the indoor CO_2 is prescribed as being at an excellent level when it is lower than 800 ppm and at a good level when it is between 800 and 1000 ppm [42]. The daily energy use of DOAS using *Strategy D_E_3* was 59.60 kWh, which was slightly higher than that using *Strategy D_T_1* (i.e. 57.05 kWh).



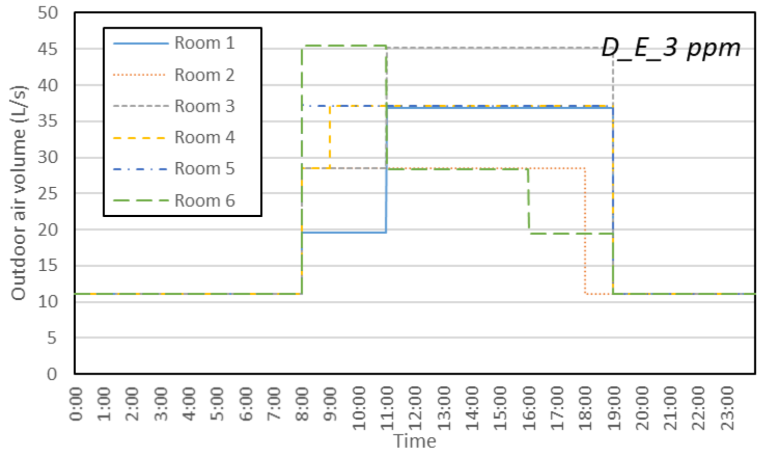


Figure 8. Optimized outdoor air volume of individual rooms in the case study using *Strategy D_T_1* and *Strategy D_E_3*

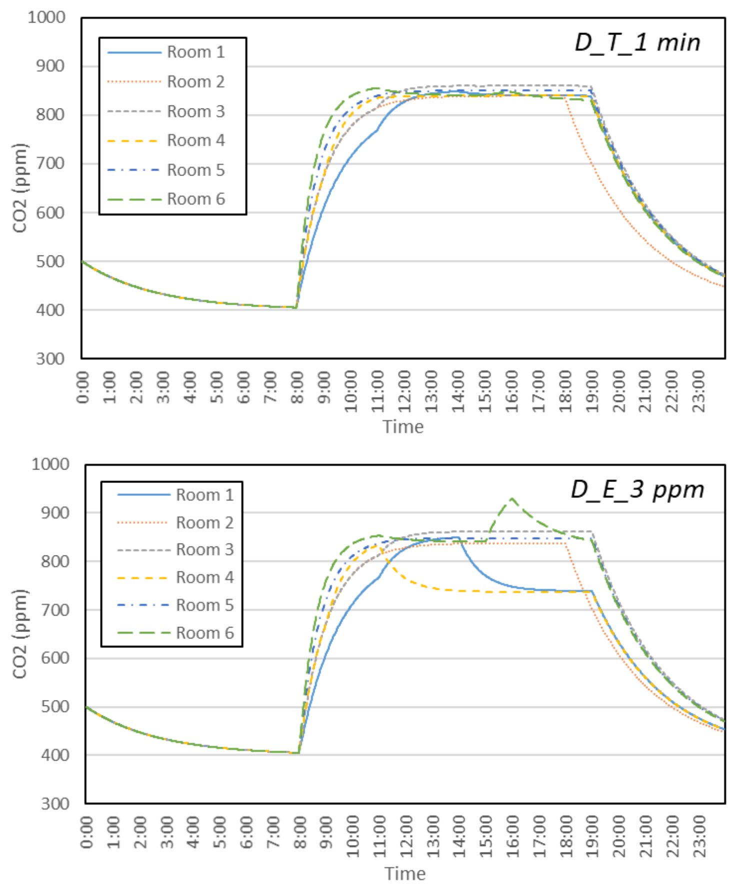


Figure 9. Indoor CO_2 concentration of individual rooms in the case study using *Strategy D_T_1* and *Strategy D_E_3*

Table 4. Comparison of *Strategy D_E_3* and *Strategy D_T_1*

Strategy	Driven method	Building system performance			Sensor energy consumption	
		Average CO_2 (ppm)	Maximum CO_2 (ppm)	Energy use of DOAS (kWh/day)	Average sensor energy consumption (% of capacity per day)	Maximum battery replacement interval (day)
D_T_1	Time-driven	636	849	57.05	16.13	6.20
D_E_3	Event-driven	626	860	59.60	1.08	92.59

4.3. Total energy consumption of individual sensors

Figure 10 shows the optimization frequencies using *Strategy D_T_1* and *Strategy D_E_3*. The optimization frequency was significantly reduced by adopting the event threshold (ΔCO_2=3 ppm) compared with the case using the fixed time interval (Δt=1 minute). The reduced optimization frequency results in a reduction of sensor energy consumption. As shown in Table 4, on average, each sensor consumed about 1.08% of its battery capacity per day under *Strategy D_E_3*, which was significantly smaller than the value of 16.13% when using *Strategy D_T_1*. The battery replacement interval was estimated to be about 92.59 days under *Strategy D_E_3*, significantly greater than under *Strategy D_T_1* (i.e. 6.20 days).

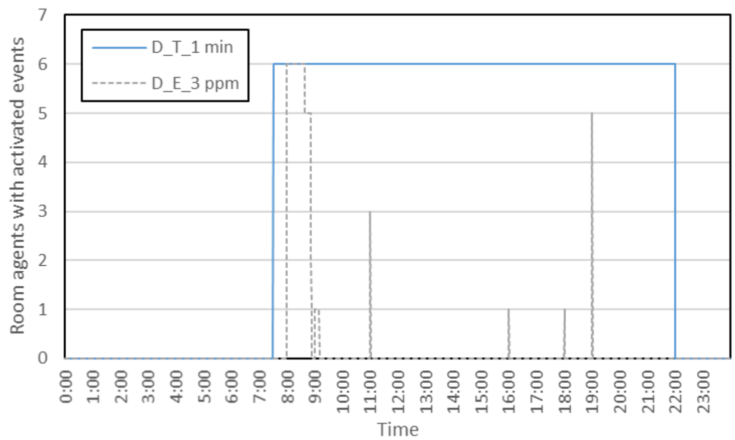


Figure 10. Optimization frequencies using *Strategy D_T_1* and *Strategy D_E_3*

5. Conclusions

An event-driven multi-agent based distributed optimal control strategy for HVAC systems to be implemented in IoT-based battery-powered WSNs is proposed. It consists of two novel schemes, the event determination scheme and the event-driven distributed optimization scheme. The event determination scheme determines the event threshold by properly trading-off system performance and sensor energy consumption in IoT-based battery-powered WSNs implementing the distributed optimal control architecture. The event-driven distributed optimization scheme solves the optimization problems using distributed optimization algorithms deployed in IoT sensors of limited data processing capacity only when events occur. The sensor energy consumption when implementing centralized and distributed optimal control architectures are compared. The impacts of adopting different event thresholds in distributed optimal control strategies are investigated. The case study is conducted to test and validate the performance of the proposed strategy. Based on the experiences and results of the comparison and case studies, the conclusions can be summarized as follows:

- Under the centralized optimal control architecture, the energy of sensors was mainly consumed for sensing (i.e. 38.88 J/day) and message transmission (i.e. 0.40 J/day). Under the distributed optimal control architecture, the energy of the room and PAU sensors was mainly consumed for advanced data processing (i.e. 1,438.29 J/day), while the energy of the coordinating sensor was mainly consumed for message exchange (i.e. 29.00 J/day).

- It is crucial to consider sensor energy consumption in a battery-powered WSN when developing distributed optimal control strategies. Sensor energy consumption implementing the distributed optimal control architecture is significantly higher than if implementing the centralized optimal control architecture (increasing from 0.48% to 16.04% of its battery capacity per day). Thus the battery replacement interval under a distributed optimal control architecture (i.e. 6.23 days) is too short to be practical or acceptable in application.
- The proposed event determination scheme can effectively determine a proper event threshold. The performance score of the distributed optimal control strategy when adopting an event threshold of 3 ppm was the smallest (i.e. 0.29). The building system performance was acceptable (i.e. average CO_2 level: 624 ppm, maximum CO_2 level: 859 ppm and DOAS daily energy use: 41.54 kWh). Meanwhile, the average sensor energy consumption was moderate (1.19% of its battery capacity per day) and had an acceptable battery replacement interval in practice (84.03 days).
- The proposed event-driven multi-agent based distributed optimal control strategy can assure both satisfactory system performance and reduced average sensor energy consumption. In the case study, when compared with the benchmark strategy, the proposed strategy could offer a slightly lower but still acceptable building system performance (i.e. average CO_2 level: 626 ppm, maximum CO_2 level: 860 ppm and DOAS daily energy use: 59.60 kWh). However, this strategy significantly reduced the average sensor energy consumption from 15.62 % to 1.08% of its battery capacity per day, and extended the battery replacement interval from 6.20 days to 92.59 days.

6. Acknowledgements

The research is financially supported by a collaborative research fund (C5018-20G) of the Research Grant Council (RGC) of the Hong Kong SAR.

References

[1] A. Čolaković, M. Hadžialić, Internet of Things (IoT): A review of enabling technologies, challenges, and open research issues, Computer Networks 144 (2018), pp. 17-39, https://doi.org/10.1016/j.comnet.2018.07.017.

[2] M. Jia, A. Komeily, Y. Wang, R.S. Srinivasan, Adopting Internet of Things for the development of smart buildings: A review of enabling technologies and applications, Automation in Construction 101 (2019), pp. 111-126, https://doi.org/10.1016/j.autcon.2019.01.023.

[3] V. Tanasiev, G.C. Pătru, D. Rosner, G. Sava, H. Necula, A. Badea, Enhancing environmental and energy monitoring of residential buildings through IoT, Automation in Construction 126 (2021), pp. 103662-103675, https://doi.org/10.1016/j.autcon.2021.103662.

[4] W. Li, C. Koo, S.H. Cha, T. Hong, J. Oh, A novel real-time method for HVAC system operation to improve indoor environmental quality in meeting rooms, Building and Environment 144 (2018), pp. 365-385, https://doi.org/10.1016/j.buildenv.2018.08.046.

[5] W. Li, C. Koo, T. Hong, J. Oh, S.H. Cha, S. Wang, A novel operation approach for the energy efficiency improvement of the HVAC system in office spaces through real-time big data analytics, Renewable and Sustainable Energy Reviews 127 (2020), pp. 109885-109900, https://doi.org/10.1016/j.rser.2020.109885.

[6] C. Miller, Z. Nagy, A. Schlueter, A review of unsupervised statistical learning and visual analytics techniques applied to performance analysis of non-residential buildings, Renewable and Sustainable Energy Reviews 81 (2018), pp. 1365-1377, https://doi.org/10.1016/j.rser.2017.05.124.

[7] M.N. Halgamuge, M. Zukerman, K. Ramamohanarao, H.L. Vu, An estimation of sensor energy consumption, Progress in Electromagnetics Research 12 (2009), pp. 259-295, 10.2528/PIERB08122303.

[8] W.R. Heinzelman, A. Chandrakasan, H. Balakrishnan, Energy-efficient communication protocol for wireless microsensor networks, Proceedings of The 33rd Annual Hawaii International Conference on System Sciences, Vol. 2, IEEE, 2000, p. 10, 10.1109/HICSS.2000.926982.

[9] M. Elhoseny, X. Yuan, H.K. El-Minir, A. Riad, Extending self-organizing network availability using genetic algorithm, Fifth International Conference on Computing, Communications and Networking Technologies (ICCCNT), IEEE, 2014, pp. 1-6, 10.1109/ICCCNT.2014.6963059.

[10] S.J. Roundy, Energy scavenging for wireless sensor nodes with a focus on vibration to electricity conversion, University of California, Berkeley Berkeley, CA, 2003, https://www.proquest.com/docview/305340201?pq-origsite=gscholar&fromopenview=true, August 3, 2021.

[11] V. Raghunathan, A. Kansal, J. Hsu, J. Friedman, M. Srivastava, Design considerations for solar energy harvesting wireless embedded systems, IPSN 2005. Fourth International Symposium on Information Processing in Sensor Networks, 2005., IEEE, 2005, pp. 457-462, 10.1109/IPSN.2005.1440973.

[12] D. Rivera, L. Cruz-Piris, G. Lopez-Civera, E. de la Hoz, I. Marsa-Maestre, Applying an unified access control for iot-based intelligent agent systems, 2015 IEEE 8th International Conference on Service-Oriented Computing and Applications (SOCA), IEEE, 2015, pp. 247-251, 10.1109/SOCA.2015.40.

[13] R.V. Barenji, A.V. Barenji, M. Hashemipour, A multi-agent RFID-enabled distributed control system for a flexible manufacturing shop, The International Journal of Advanced Manufacturing Technology 71 (9-12) (2014), pp. 1773-1791, 10.1007/s00170-013-5597-2.

[14] S. Xu, J. Bao, Distributed control of plantwide chemical processes, Journal of Process Control 19 (10) (2009), pp. 1671-1687, https://doi.org/10.1016/j.jprocont.2009.07.007.

[15] L. Klein, J.-y. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, P. Varakantham, M. Tambe, Coordinating occupant behavior for building energy and comfort management using multi-agent systems, Automation in Construction 22 (2012), pp. 525-536, https://doi.org/10.1016/j.autcon.2011.11.012.

[16] J. Cai, D. Kim, R. Jaramillo, J.E. Braun, J. Hu, A general multi-agent control approach for building energy system optimization, Energy and Buildings 127 (2016), pp. 337-351, https://doi.org/10.1016/j.enbuild.2016.05.040.

[17] B. Su, S. Wang, An agent-based distributed real-time optimal control strategy for building HVAC systems for applications in the context of future IoT-based smart sensor networks, Applied Energy 274 (2020), pp. 115322-115335, https://doi.org/10.1016/j.apenergy.2020.115322.

[18] W. Li, S. Wang, A multi-agent based distributed approach for optimal control of multi-zone ventilation systems considering indoor air quality and energy use, Applied Energy 275 (2020), pp. 115371-115384, https://doi.org/10.1016/j.apenergy.2020.115371.

[19] A. Yousefpour, C. Fung, T. Nguyen, K. Kadiyala, F. Jalali, A. Niakanlahiji, J. Kong, J.P. Jue, All one needs to know about fog computing and related edge computing paradigms: A complete survey, Journal of Systems Architecture 98 (2019), pp. 289-330, https://doi.org/10.1016/j.sysarc.2019.02.009.

[20] H.S. Asad, R.K.K. Yuen, G. Huang, Multiplexed real-time optimization of HVAC systems with enhanced control stability, Applied Energy 187 (2017), pp. 640-651, https://doi.org/10.1016/j.apenergy.2016.11.081.

[21] Z. Xu, G. Hu, C.J. Spanos, S. Schiavon, PMV-based event-triggered mechanism for building energy management under uncertainties, Energy and Buildings 152 (2017), pp. 73-85, https://doi.org/10.1016/j.enbuild.2017.07.008.

[22] J. Braun, S. Klein, W. Beckman, J. Mitchell, Methodologies for optimal control of chilled water systems without storage, ASHRAE transactions, Vol. 95, 1989, pp. 652-662, http://pascal-francis.inist.fr/vibad/index.php?action=getRecordDetail&idt=6935347, August 3, 2021.

[23] J. Wang, G. Huang, Y. Sun, X. Liu, Event-driven optimization of complex HVAC systems, Energy and Buildings 133 (2016), pp. 79-87, https://doi.org/10.1016/j.enbuild.2016.09.049.

[24] Q. Liu, Z. Wang, X. He, D. Zhou, A survey of event-based strategies on control and estimation, Systems Science & Control Engineering: An Open Access Journal 2 (1) (2014), pp. 90-97, https://doi.org/10.1080/21642583.2014.880387.

[25] K.J. Åström, B. Bernhardsson, Comparison of periodic and event based sampling for first-order stochastic systems, IFAC Proceedings Volumes 32 (2) (1999), pp. 5006-5011, https://doi.org/10.1016/S1474-6670(17)56852-4.

[26] M. Xia, V. Gupta, P.J. Antsaklis, Networked state estimation over a shared communication medium, IEEE Transactions on Automatic Control 62 (4) (2016), pp. 1729-1741, 10.1109/TAC.2016.2593645.

[27] X.-R. Cao, Stochastic learning and optimization-a sensitivity-based approach, IFAC Proceedings Volumes 41 (2) (2008), pp. 3480-3492, https://doi.org/10.3182/20080706-5-KR-1001.00589.

[28] Q. Jia, Y. Yang, L. Xia, X. Guan, A tutorial on event-based optimization with application in energy Internet, Control Theory and Applications 35 (1) (2018), pp. 32-40, 10.7641/CTA.2018.70064.

[29] J. Wang, S. Lou, P. Zhou, G. Huang, A design approach for event-driven optimization in complex air conditioning systems, 2017 13th IEEE Conference on Automation Science and Engineering (CASE), IEEE, 2017, pp. 912-917, 10.1109/COASE.2017.8256219.

[30] J. Wang, P. Zhou, G. Huang, W. Wang, A Data Mining Approach to Discover Critical Events for Event-Driven Optimization in Building Air Conditioning Systems, Energy Procedia 143 (2017), pp. 251-257, https://doi.org/10.1016/j.egypro.2017.12.680.

[31] J. HOU, G. HUANG, Event definition method for the event-driven optimal control strategy of air-conditioning systems, 2019, https://scholars.cityu.edu.hk/en/publications/publication(cd2ff9a4-8ffe-48b6-9ff8-024112636026).html, August 3, 2021.

[32] S. Saeidi, C. Chokwitthaya, Y. Zhu, M. Sun, Spatial-temporal event-driven modeling for occupant behavior studies using immersive virtual environments, Automation in Construction 94 (2018), pp. 371-382, https://doi.org/10.1016/j.autcon.2018.07.019.

[33] J. Zhu, S. Papavassiliou, On the energy-efficient organization and the lifetime of multi-hop sensor networks, IEEE Communications letters 7 (11) (2003), pp. 537-539, 10.1109/LCOMM.2003.820097.

[34] X. Min, S. Wei-Ren, J. Chang-Jiang, Z. Ying, Energy efficient clustering algorithm for maximizing lifetime of wireless sensor networks, AEU-International Journal of Electronics and Communications 64 (4) (2010), pp. 289-298, https://doi.org/10.1016/j.aeue.2009.01.004.

[35] A. Wang, A. Chandrakasan, Energy-efficient DSPs for wireless sensor networks, IEEE Signal Processing Magazine 19 (4) (2002), pp. 68-78, 10.1109/MSP.2002.1012351.

[36] I. Škrjanc, B. Šubic, Control of indoor CO2 concentration based on a process model, Automation in Construction 42 (2014), pp. 122-126, https://doi.org/10.1016/j.autcon.2014.02.012.

[37] M. Kintner-Meyer, M.R. Brambley, T.A. Carlon, N.N. Bauman, Wireless sensors: technology and cost-savings for commercial buildings, Teaming for Efficiency: Proceedings of the 2002 ACEEE Summer Study on Energy Efficiency in Buildings, Vol. 7, 2002, pp. 121-134, https://www.eceee.org/static/media/uploads/site-

2/library/conference_proceedings/ACEEE_buildings/2002/Panel_7/p7_10/paper.pdf, August 3, 2021.

[38] M. Frei, C. Deb, R. Stadler, Z. Nagy, A. Schlueter, Wireless sensor network for estimating building performance, Automation in Construction 111 (2020), pp. 103043-103060, https://doi.org/10.1016/j.autcon.2019.103043.

[39] C. Tamboli, C.N. Manikopoulos, Determination of the optimum packet length and buffer sizes for the industrial building automation and control networks, 1995 Proceedings of the IEEE International Symposium on Industrial Electronics, Vol. 2, IEEE, 1995, pp. 831-836, 10.1109/ISIE.1995.497294.

[40] W.P. Butler, J.P. Garozzo, Control system protocol for an hvac system, Google Patents, 2009https://patents.google.com/patent/US20090261174A1/en, August 3, 2021.

[41] Y. Ma, D. Wobschall, A sensor network for buildings based on the DALI bus, 2007 IEEE Sensors Applications Symposium, IEEE, 2007, pp. 1-3, 10.1109/SAS.2007.374376.

[42] W. Li, S. Wang, C. Koo, A real-time optimal control strategy for multi-zone VAV air-conditioning systems adopting a multi-agent based distributed optimization method, Applied Energy 287 (2021), pp. 116605-116619, https://doi.org/10.1016/j.apenergy.2021.116605.