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Collaborative Optimization Method for Solving the Diffusion and Allocation Issues in Complex Variable Flow Rate HVAC Systems

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Abstract

The complexity of current optimization methods for HVAC systems is increasing, resulting in relatively lower computational efficiency, particularly in more complex systems. This difficulty makes real-time optimization and control challenging in practice. Therefore, there is an urgent need to simultaneously improve both system energy efficiency and computational efficiency to enhance system robustness. Present optimization methods predominantly emphasize enhancing system energy efficiency, often overlooking computational efficiency. Consequently, these methods become infeasible or unstable when implemented in practical systems. In our research, a multi-agent-based collaborative optimization method is proposed to solve the global optimization problem of complex HVAC systems. Under the multi-agent framework, the global optimization problem is decomposed into multiple sub-optimization problems considering the interaction characteristics among components, thus reducing the complexity of the global optimization problem in HVAC systems. The proposed AH-AFSA algorithm supports the solution of optimization problems containing hybrid decision variables (continuous and discrete variables) and can directly search for optimal discrete variables in the binary space. This feature is suitable for searching the optimal ON/OFF sequence and setpoints simultaneously during the global optimization process. The results demonstrate that the proposed method can save 18.9% of electricity consumption with an average computing time of 12.2 seconds for each operating condition, saving about 54% of the time cost compared to centralized methods. The methodology used in our research holds significant theoretical and practical value for enhancing the computational efficiency and productivity of optimization methods in complex HVAC systems.

Keywords: HVAC systems; Collaborative optimization; Computational efficiency; Energy efficiency trade-off; Multi-agent system

Nomenclature

$a_0 \sim a_2$	coefficients of PLR correction factor in chiller model
$b_0 \sim b_5$	coefficients of temperature correction factor in chiller model
$c_0 \sim c_3$	coefficients of power consumption in cooling water pump model
$c_{p,w}$	water specific heat at constant pressure
C	constraints
$d_{i,j}$	distance between fish i and j
$d_0 \sim d_3$	coefficients of power consumption in cooling tower model
$e_1 \sim e_3$	coefficients of spatial coupling characteristics
F	global fitness
$g_1 \sim g_3$	coefficients of spatial coupling characteristics
g_c	constant
H	pump head (fan pressure)
$J_{\text{Diffu}} / J_{\text{Alloca}}$	objective function of diffusion / allocation problem
l	boundary for each dimension of individual
L	boundaries collection of optimization variable, space of feasible solution
m	flow rate
M	population size
n	dimension of artificial fish
n_f	number of companions
N	number of operational units
N_{try}	maximum try number
P	power consumption
PLR	part load ratio
Q	cooling load
R	action reward
$step$	moving step size of artificial fish
S	the collection of operating parameters for each unit
T	temperature
$visual$	searching visual of artificial fish
X, X_i, X_{best}	collection of optimization variables, the i^{th} individual, the best individual
Y	fitness
Z	information set from adjacent agents
η	efficiency
λ	defined threshold
δ	crowding factor

Subscripts

ahu	air handling unit
b / b	the b^{th} unit / the best
c	center of fish school
ch	chiller
chw / chwp	chilled water / chilled water pump
comp	component type

ct	cooling tower
cw / cwp	cooling water / cooling water pump
C	condenser
con	continuous fragment of artificial fish
d	discrete type
d	the d^{th} dimension
dis	discrete fragment of artificial fish
E	evaporator
h	the h^{th} chiller
i	the i^{th} artificial fish
i, o	inlet, outlet
j	the j^{th} artificial fish
k	the k^{th} AHU
l	the l^{th} room
m	the m^{th} cooling water pump
ma	mixed air
n	the n^{th} cooling tower
r	operating units
r	random action
R	rated value
sa	supply air of AHU
sys	the whole system
u	the u^{th} chilled water pump
Superscript	
*	optimal value
(t)	the t^{th} movement

1. Introduction

The heating, ventilation, and air conditioning (HVAC) system plays a vital role in regulating the indoor thermal environment of public buildings, which consists of a number of electromechanical equipment with nonlinear characteristics [1–3]. Typically, the HVAC systems are designed to handle the maximum cooling load of buildings, and the energy consumption accounts for over 50% of total building energy consumption [4,5]. Therefore, there exists significant potential for energy conservation when the HVAC systems operate under partial load conditions. However, due to the nonlinear and coupling characteristics inherent in HVAC systems, achieving optimal energy efficiency in practice poses significant challenges.

1.1. Diffusion and allocation optimization problems in HVAC systems

The main electromechanical components in a typical HVAC system include chiller (CHs), chilled water pump (CHWP), cooling water pump (CWP), cooling tower (CT) and air handling unit (AHU). As shown in Fig. 1, there are two configurations with different complexity for the HVAC system. In which, subgraph (a) depicts the HVAC system with identical parallel units, which is a typical configuration in practical system.

While the system in subgraph (b) is configured to contain parallel units with different capacity, which can better adapt the variation of cooling demand under partial load conditions. The configuration flexibility of the system in subgraph (b) renders it is also a commonly existed configuration in current public buildings.

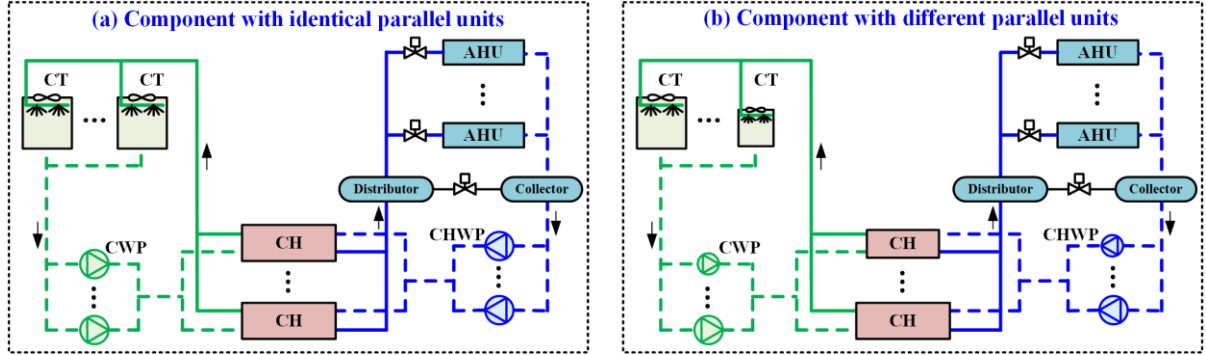


Fig. 1 Schematic diagram of the HVAC systems with different complexity

Given the strong nonlinear and coupled characteristics of its components, optimizing the HVAC system necessitates considering their interactions. Typically, the global optimization problem in HVAC systems involves optimizing the ON/OFF sequence of parallel units (allocation problem) and the setpoints of control loops (diffusion problem). The allocation optimization problem is a 0-1 integer programming problem with discrete decision variables, while the diffusion optimization problem involves continuous decision variables. Hence, the global optimization problem of the HVAC system is a hybrid optimization problem. To significantly enhance the global operational performance of HVAC systems containing parallel units, both the allocation and diffusion problems must be addressed during the optimization process. However, most research focuses solely on one of these two types of optimization problems and overlooks the hybrid problem.

The complexity of the optimization problem also differs for the two systems. In subgraph (a), the allocation problem simplifies to optimizing operating unit numbers without considering the ON/OFF sequence, denoted as N in complexity. Conversely, in subgraph (b), the allocation problem requires considering the ON/OFF sequence to obtain the optimal unit combination, resulting in a complexity of $2^N - 1$. And as the number of parallel units increases, the optimization problem complexity in subgraph (b) grows exponentially.

1.2. Literature review

In recent years, there has been a growing emphasis on improving the energy efficiency of HVAC systems by employing intelligent techniques, such as genetic algorithms (GA) [6–9], artificial neural networks [10,11], particle swarm optimization (PSO) [12–14], etc. These methods primarily aim to address the diffusion and allocation optimization problems in HVAC systems.

1.2.1. Diffusion optimization methods

He et al. [15] conducted a comparison of three computational intelligence algorithms, including PSO, evolutionary algorithms (EA), and harmony search (HS), for optimizing HVAC system setpoints. The results demonstrated that heuristic algorithms like PSO and HS offered rapid convergency speed and delivered

quality solutions for real-time optimization. Similarly, other heuristic algorithms such as the firefly algorithm (FA) [16], artificial bee colony algorithm [17], differential bat algorithm (DBA) [18] have been proven effective in solving diffusion optimization problems and enhancing the energy efficiency of HVAC system components. These studies have underscored the efficiency of heuristic search algorithms (e.g., GA, DE, PSO) in solving nonlinear optimization problems in HVAC systems, resulting in significant energy savings compared to conventional optimization methods like exhaustive search and the Lagrangian method. However, the performance of these advanced techniques relies on the accuracy of system models and the computational capabilities of the controller, posing challenges for practical implementation.

With the rapid advancement of artificial intelligence technology, the requirements for HVAC system control have become more intricate and diverse, necessitating increasingly complex optimization methods and control tasks. To address these diverse control demands, some researchers have proposed hybrid optimization methods. Nasruddin et al. [19] combined artificial neural networks (ANN) and multi-objective GA to optimize a two-chiller system, yielding superior performance in terms of thermal comfort and energy consumption compared to conventional designs. Li et al. [20] introduced a method integrating back-propagation neural networks and the grey wolf optimizer (GWO) algorithm to optimize the control effect and energy efficiency of HVAC systems. Compared to other hybrid methods such as ANN-GA [21] and ANN-PSO [22], the proposed method could rapidly achieve optimal thermal comfort and energy efficiency simultaneously. These hybrid methods integrate various techniques to offer superior performance in energy efficiency and control effectiveness compared to conventional single techniques. However, these studies overlook the complexity and computational efficiency of hybrid methods, making them impractical and challenging to implement in existing HVAC systems. Moreover, complex models and parameters may consume substantial computational resources of the central controller, thereby reducing its real-time computing performance and error tolerance.

1.2.2. Allocation optimization methods

To enhance the energy efficiency of HVAC systems with multiple chillers, Lee et al. [23] utilized the differential evolution (DE) algorithm to tackle the optimal chiller loading (OCL) optimization problem. Case studies revealed that DE with a scaling factor of 0.7 and crossover rate of 0.8 outperformed GA and PSO, overcoming divergence issues associated with the Lagrangian method at low cooling demand conditions. Similarly, Li et al. [24] introduced an improved sparrow search algorithm (TMSSA) to achieve optimal solutions, successfully avoiding local optimal traps. Comparative studies demonstrated that the algorithm converged within 10 iterations, achieving up to 24% higher relative energy savings compared to GA. These results showcased the improved algorithm's strengths in rapid convergence and energy-saving potential. Zheng et al. [25] proposed an enhanced artificial fish swarm algorithm (AFSA) with an adjustable search range to address the OCL problem. Simulation results illustrated that the improved AFSA exhibited better performance in terms of convergence rate and accuracy compared to PSO and evolutionary algorithms (EA). Other techniques like cuckoo search algorithm (CSA) [26] and invasive weed optimization (IWO) algorithm [27] have also been proven effective in solving allocation optimization problems.

To further enhance the expandability and universality of practical HVAC control systems, Yu [28]

proposed a distributed control framework for optimizing the flow rate allocation problem of parallel pumps, employing an evolutionary AFSA algorithm to solve the optimization problem. Simulation results demonstrated that the distributed AFSA offered superior computational efficiency while maintaining the same level of accuracy. Li et al. [29] introduced a multi-agent-based distributed method for resolving airflow allocation problems in ventilation systems. Simulation results indicated that the distributed method achieved comparable outputs to centralized methods and was more effective in addressing complex problems. Salsbury et al. [30] presented a smart distributed algorithm to optimize airflow allocation in multi-zone HVAC systems. Simulation results verified the algorithm's robustness and ease of implementation. Wang et al. [31] proposed a hierarchical framework with multiple layers to streamline the optimization process of HVAC systems. An improved Nesterov acceleration technique was adopted to enhance convergence rates. Simulation results demonstrated that the proposed distributed method could save 69.55% of computing time compared to conventional distributed methods. Despite the data-driven approaches using machine learning perform better in solving dynamic optimization problems, the heuristic search methods (such as AFSA) are also proven to be effective for optimizing HVAC system in multi-agent systems.

1.2.3. Researches on improving computational efficiency

In addition to energy conservation, computational efficiency is a crucial criterion for evaluating optimization methods in real systems. Therefore, simplifying optimization tasks and improving computational efficiency have become increasingly significant in today's HVAC systems. Jin et al. [32] proposed a simplified mechanical cooling tower model based on Merkel's theory and the effectiveness-NTU method to enhance the online computational efficiency of intelligent control methods for cooling water systems. Compared to conventional methods, this approach had simple coefficients, required no complex iterations, and significantly improved the online computational efficiency of system optimization. Similarly, Ma [33] introduced an online optimization method for cooling water systems based on a simplified heat transfer model, demonstrating its feasibility for online optimization and its potential to reduce energy consumption by 15.3%. Addressing the complex nonlinear characteristics of heat transfer at cooling coil units, Wang [34] proposed a simple model for better real-time control and optimization of HVAC systems. The model coefficients were easily obtained using linear or nonlinear least squares methods. Experimental comparisons with traditional methods demonstrated the model's robustness and superior real-time computing performance across all operating conditions. Considering the ease of obtaining temperature parameters in practical HVAC systems, Zhao [35] selected chilled and cooling water temperature as input variables and proposed an online predictive control method based on a multivariable linear regression model. Application results showed that the proposed method was easy to implement and replicable in practical systems, improving system global COP values by 5.35% and reducing energy consumption by 2.7%. Zhao [36] simplified models of cooling system components, including chillers, cooling water pumps, and cooling towers. The control method based on these simplified models was developed with easily obtained inputs and a programmable structure, achieving energy savings of 3.45% compared to traditional control methods. These studies aimed to enhance the computational efficiency of optimization methods by simplifying component models and system structures, enabling real-time implementation. However, they trade reduced model

accuracy for computational efficiency, indicating room for improvement in energy conservation. Moreover, while these simplifications targeted individual components (e.g., cooling tower, cooling coil units), their adaptability to entire HVAC system optimization was not thoroughly discussed, limiting their applicability in other systems.

In efforts to enhance computational efficiency without compromising control effectiveness, some scholars have proposed multi-agent-based optimization methods for HVAC systems, leveraging the advantages of distributed framework. In a multi-agent system, each agent functions as an autonomous entity capable of observing the environment, communicating with neighbors, and making decisions toward its goals [29]. And the cognitive and decision-making processes of agents can be described by the Belief-Desire-Intention (BDI) model [37]. This approach offers several strengths compared to centralized approaches. Firstly, it provides excellent extensibility, as agents possess plug-and-play characteristics, facilitating the easy addition or removal of zones or components [38]. Secondly, the central controller is replaced by multiple intelligent agents, improving the system's error tolerance. Thirdly, it offers good reconfigurability, as changing a component model requires local control reconfiguration only, without the need to modify the rest of the control system [39]. Considering these benefits, the multi-agent system has found applications in various aspects of building automatic control, such as optimizing indoor environment setpoints [40], user-centered control systems [41], building energy system optimization [42], and interactive demand-side management strategies [43]. Despite demonstrating effectiveness in building energy management, there remains a lack of an applicable multi-agent-based method for globally optimizing complex HVAC systems.

From these studies, it is evident that distributing the system's computational load across multiple computing nodes under a distributed framework improves computational efficiency compared to centralized framework. However, most research focuses on same-type parallel components or subsystems of the HVAC system, neglecting interactions among components or subsystems. Given that HVAC systems are complex systems comprising various components with nonlinear characteristics, it is crucial to consider interactions among components for better optimization and control.

1.3. Research gap

The literature review summary and comparison with our research are presented in Table 1. Most studies have focused on addressing either diffusion or allocation problems, where decision variables for these problems are continuous and discrete, respectively. There is a lack of research on solving the hybrid optimization problem from a global optimization perspective. HVAC systems are often configured with parallel units of varying capacities to better accommodate cooling demand fluctuations under partial load conditions, as illustrated in Fig. 1 (b) in current public buildings. However, existing research often fails to consider the feasibility and applicability of proposed optimization methods for solving the global optimization problem of such complex systems. Besides, the complexity of the hybrid optimization problem in the system depicted in Fig. 1 (b) is significantly high, leading to a heavy computational burden on the central controller and impacting its real-time performance. While some studies have aimed to enhance computational efficiency, they typically focus on subsystems or individual components, neglecting the need to balance trade-offs among components, making these methods unsuitable for system-wide optimization.

Therefore, there is an urgent need to identify a superior optimization approach to simplify the hybrid optimization problem, reduce computational load, and maintain the energy efficiency of the HVAC system.

Table 1 Literature review summary and comparison with our research

Literature	Year	Method	Research Object	Optimization Problem	Computational Efficiency	Applicable to Which System in Fig. 1
[6]	2020	GA	Whole system	Diffusion	Undiscussed	(a)
[7]	2019	GA	AHUs	Diffusion	Undiscussed	(a)
[9]	2014	GA	Chillers	Allocation	Undiscussed	(b)
[13]	2022	PSO	AHUs	Diffusion	Undiscussed	(a)
[15]	2015	PSO	AHUs	Diffusion	Undiscussed	(a)
[26]	2014	CSA	Chillers	Allocation	Undiscussed	(b)
[27]	2018	IWO	Chillers	Allocation	Undiscussed	(b)
[20]	2021	GWO	AHUs	Diffusion	Undiscussed	(a)
[24]	2023	TMSSA	Chillers	Allocation	Undiscussed	(b)
[25]	2019	AFSA	Chillers	Allocation	Undiscussed	(b)
[28]	2018	AFSA	Pumps	Allocation	Undiscussed	(b)
[29]	2020	Multi-agent	AHUs	Allocation	Undiscussed	Both (a) and (b)
[31]	2022	Multi-agent	Whole system	Both diffusion and allocation	Considered	(a)
[33]	2021	PSO	Cooling towers	Allocation	Undiscussed	(a)
[35]	2021	ES	Cooling system	Diffusion	Undiscussed	(a)
[42]	2016	Multi-agent	Whole system	Diffusion	Undiscussed	(a)
[44]	2024	DE	Whole system	Both diffusion and allocation	Considered	(a)
This work	/	Collaborative optimization	Whole system	Both diffusion and allocation	Considered	Both (a) and (b)

1.4. Motivation

To enhance both energy and computational efficiency in complex HVAC systems, we propose a collaborative global optimization approach that merges the strengths of multi-agent systems and heuristic algorithms. The complex hybrid optimization problem is decomposed into several simpler subproblems, with each subproblem addressed by different agents considering component interactions. To ensure that the agents collaboratively and simultaneously obtain optimal ON/OFF sequences and setpoints, we introduce an enhanced artificial fish swarm algorithm to address the global objective function.

This study is structured as follows: Firstly, we systematically formulate the optimization problems and models of the complex HVAC system within a multi-agent framework, considering interactions and nonlinear characteristics (Section 2.1). Next, we illustrate the mechanism of the collaborative method and introduce an adaptive hybrid artificial fish swarm algorithm (AH-AFSA) for agents to collaboratively determine optimal setpoints and ON/OFF sequences. The algorithm is designed to handle both continuous (setpoints) and discrete (ON/OFF sequence) parameters of the optimization problem (Section 2.2). Then, we provide details on the platform and operating conditions of the simulation tests and experiments in Section 3. Finally, we discuss the performance of the proposed method based on comparative results concerning energy-saving potential and computational efficiency (Section 4).

2. Methodologies

This section will first formulate the models of system components and coupling characteristics systematically. Then, the global optimization problem of the HVAC system under a multi-agent system will be illustrated, and the agents in this research will be defined. Next, the collaborative optimization method will be proposed for addressing the diffusion and allocation problems of the HVAC system. Finally, the distributed application and uniform convergence of the proposed method will be discussed.

2.1. System modeling

2.1.1. HVAC system models

Typically, the quantity of operational parallel units can be classified into two types: integer and 0-1 discrete types, denoted as $N_{r,comp}$ and $N_{d,comp}$, respectively. In the integer type, integers represent the number of operating units, while in the discrete type, a 0-1 vector indicates the ON/OFF state of each unit (ON = 1, OFF = 0), as shown in Eq. (1).

$$N_{d,comp} = (N_{d,comp,1}, \dots, N_{d,comp,b}, \dots, N_{d,comp,N_{comp}}), \quad comp \in \{ch, chwp, cwp, ct, ahu\} \quad (1)$$

$$N_{r,comp} = \sum_{b=1}^{N_{comp}} N_{d,comp,b} \quad (2)$$

The relationship between $N_{r,comp}$ and $N_{d,comp}$ can be expressed as Eq. (2), where $N_{d,comp,b}$ is a binary number representing the ON/OFF state, subscript b denotes the b^{th} unit of corresponding component, subscript $comp$ represents the component type, and N_{comp} is the total number of units.

The power consumption of parallel chillers can be expressed as Eq. (3) by referring to the Stoecker model [45]. Where, the subscript R represents the rated value, and $f_{PLR,ch,h}$ and $f_{T,ch,h}$ are correction factors for part load ratio and temperature, which can be calculated using Eqs. (4) and (5) respectively. Here, the subscripts E and C denote the evaporator and condenser, while the subscript o represents the outlet value. The coefficients $a_0 \sim a_2$ and $b_0 \sim b_5$ can be determined by fitting sample data.

$$P_{ch} = \sum_{h=1}^{N_{ch}} (P_{ch,R,h} \cdot f_{PLR,ch,h} \cdot f_{T,ch,h} \cdot N_{d,ch,h}) \quad (3)$$

$$f_{PLR,ch,h} = a_{0,h} + a_{1,h} \left(\frac{Q_{ch,h}}{Q_{ch,R,h}} \right) + a_{2,h} \left(\frac{Q_{ch,h}}{Q_{ch,R,h}} \right)^2 \quad (4)$$

$$f_{T,ch,h} = b_{0,h} + b_{1,h} T_{E,o} + b_{2,h} T_{E,o}^2 + b_{3,h} T_{C,o} + b_{4,h} T_{C,o}^2 + b_{5,h} T_{E,o} T_{C,o} \quad (5)$$

Based on the performance characteristics of pumps and fans, the power consumption of parallel chilled water pumps can be calculated using pump flow (m_{chw}) and head (H_{chw}) [46], as expressed in Eq. (6). Similarly, the power consumption of AHU fans can be calculated using fan flow (m_{sa}) and pressure (H_{sa}), as shown in Eq. (7).

$$P_{\text{chwp}} = \sum_{u=1}^{N_{\text{chwp}}} \left(\frac{m_{\text{chw},u} \cdot H_{\text{chw},u}}{g_c \cdot \eta_{\text{chw},u}} \cdot N_{\text{d,chwp},u} \right) \quad (6)$$

$$P_{\text{ahu}} = \sum_{k=1}^{N_{\text{ahu}}} \frac{m_{\text{sa},k} \cdot H_{\text{sa},k}}{g_c \cdot \eta_{\text{ahu},k}} \quad (7)$$

In the equations above, g_c represents a constant linked to the units of m and H . Assuming gravitational acceleration is 9.8 m/s^2 and P is measured in kW, if m and H are in m^3/h and mH_2O respectively, g_c equals 367.3. For units of m as kg/s and H as kPa , g_c becomes 134.9. η denotes pump and fan efficiency associated with m and H , determined through data fitting.

Regarding the power consumption of parallel cooling water pumps, its model deviates from that of chilled water pumps due to the open system nature of the cooling water loop [47], as shown in Eq. (8).

$$P_{\text{cwp}} = \sum_{m=1}^{N_{\text{cwp}}} P_{\text{cwp},R,m} N_{\text{d,cwp},m} \left[c_{0,m} + c_{1,m} PLR_{\text{cwp},m} + c_{2,m} (PLR_{\text{cwp},m})^2 + c_{3,m} (PLR_{\text{cwp},m})^3 \right] \quad (8)$$

where c_0 to c_3 represent the coefficients derived from data fitting, $PLR_{\text{cwp},m}$ denotes the part load ratio of the m^{th} cooling water pump, it is defined as the ratio of actual flow to rated flow, as depicted in Eq. (9).

$$PLR_{\text{cwp},m} = \frac{m_{\text{cw},m}}{m_{\text{cw},R,m}} \quad (9)$$

Similarly, the power consumption model of cooling tower fans can be expressed as Eq. (10), where $PLR_{\text{ct},n}$ represents the part load ratio of the fan and can be calculated using Eq. (11). The coefficients d_0 to d_3 can be determined through data fitting.

$$P_{\text{ct}} = \sum_{n=1}^{N_{\text{ct}}} P_{\text{ct},R,n} N_{\text{d,ct},n} \left[d_{0,n} + d_{1,n} PLR_{\text{ct},n} + d_{2,n} (PLR_{\text{ct},n})^2 + d_{3,n} (PLR_{\text{ct},n})^3 \right] \quad (10)$$

$$PLR_{\text{ct},n} = \frac{m_{a,n}}{m_{a,R,n}} \quad (11)$$

The air volume of the k^{th} AHU can be calculated using the air volume in each conditioned room, as shown in Eq. (12). The heat exchange between the air side and water side of the coil can be simply formulated as Eq. (13) [48]. Here, T_{ma} represents the temperature of the mixed air, m_{sa} denotes the coil water flow of the AHU, and e_1 to e_3 are model coefficients determined through data fitting.

$$m_{\text{sa},k} = \sum_{l=1}^{N_{\text{room}}} m_{\text{sa},k,l} \quad (12)$$

$$\sum_{l=1}^{N_{\text{room}}} Q_{k,l} = \frac{e_{1,k} \cdot m_{\text{sa},k}^{e_{3,k}} \cdot (T_{\text{ma},k} - T_{\text{E},o})}{1 + e_{2,k} \cdot (m_{\text{sa},k} / m_{\text{chw},k})^{e_{3,k}}} \quad (13)$$

Similar to the coil model, the heat exchange between the air and water sides of a cooling tower can be

expressed as Eq. (14) [36], where $T_{wb,od}$ is the outdoor wet bulb temperature, m_{cw} is the water flow of the cooling tower, m_a is the air volume of the cooling tower, and $g_1 \sim g_3$ are model coefficients that can be obtained through data fitting.

$$P_{ch} + \sum_{i=1}^{N_{ch}} Q_{ch,i} = \sum_{n=1}^{N_{ct}} \left(\frac{g_{1,n} \cdot m_{cw,n}^{g_{3,n}} \cdot (T_{C,i} - T_{wb,od})}{1 + g_{2,n} \cdot (m_{cw,n}/m_{a,n})^{g_{3,n}}} \right) \quad (14)$$

From the above models, it's inferred that each component's power consumption is solely determined by its own operating parameters. For example, P_{ch} is influenced only by Q_{ch} , $T_{E,o}$ and $T_{C,o}$, while P_{ct} is only related to m_a , etc. However, the operating parameters of different components interact in practical systems, leading to the existence of an energy efficiency trade-off issue among components.

2.1.2. Constraint conditions

In the diffusion optimization problem, the decision variables must be explored within a feasible solution space. Therefore, the constraint conditions for the diffusion problem are expressed as Eq. (15), where L denotes the boundary collection.

$$L_{min} \leq X^* \leq L_{max}, \quad X \in \{T_{E,o}, H_{chwp}, \Delta T_C, T_{C,i}, T_{sa}, H_{sa}\} \quad (15)$$

In allocation optimization problems, decision variables must meet the fundamental system requirement: each component type must have at least one operational unit. Therefore, constraints for allocation problems are defined in Eq. (16). Moreover, the allocated quantity for each unit should fall within a reasonable range. For instance, the water flow allocation for each chilled water pump should range between its minimum and maximum capacity. Hence, allocation constraints are expressed as Eq. (17), encompassing cooling capacity, chilled water flow, cooling water flow, cooling tower air volume, and AHU supply air volume.

$$N_{d,comp} \neq \{0\} \quad (16)$$

$$s_{comp,min} \leq s_{comp} \leq s_{comp,max}, \quad s_{comp} \in \{Q_{ch}, m_{chw}, m_{cw}, m_a, m_{sa}\} \quad (17)$$

To facilitate the search for optimal solutions using intelligent algorithms, the aforementioned constrained optimization problems need to be converted into unconstrained optimization problems. Constraints stated in Eq. (15) and (16) pertain to decision variables, which can be constrained within the feasible solution space of the algorithm. Concerning constraints in Eq. (17), the allocation optimization problems can be transformed into unconstrained problems by constructing penalty functions [8,9,44].

2.1.3. Global optimization problem in multi-agent system

The nonlinear characteristics of components result in energy efficiency trade-offs among them. In variable flow rate HVAC systems, two types of trade-off issues typically arise: diffusion problem and allocation problem. The diffusion problem primarily occurs among adjacent components (e.g., chiller, pump, and fan) and describes the energy efficiency trade-off among them. The allocation problem mainly exists among parallel units of the same type of component (e.g., chiller units) and concerns the energy efficiency trade-off among these parallel units. The schematic diagram of a typical HVAC system and the trade-off issues are illustrated in Fig. 2. The conventional optimization problem for such system can be formulated as

Eq. (18), and the decision variables are component ON/OFF sequence and control loop setpoints.

$$\begin{aligned} & (\{N_{d,comp}^*\}, T_{E,o}^*, H_{chwp}^*, \Delta T_{C^*}, T_{C,i}^*, T_{sa}^*, H_{sa}^*) \\ & = \arg \min f(\{N_{d,comp}\}, T_{E,o}, H_{chwp}, \Delta T_C, T_{C,i}, T_{sa}, H_{sa}) \end{aligned} \quad (18)$$

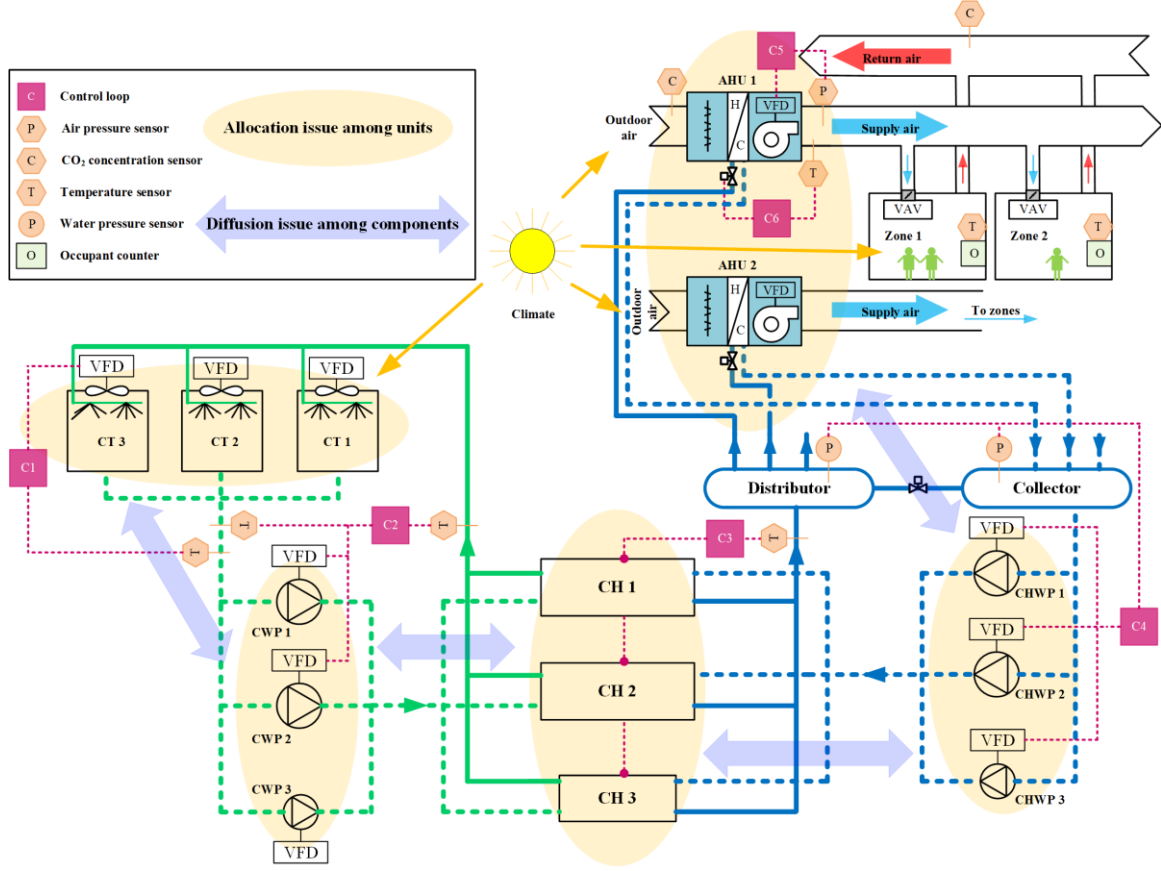


Fig. 2 Control schematic and trade-off issues of typical HVAC system

For the problem formulated in Eq. (18), which contains both discrete and continuous decision variables, and the complexity of the problem will be exponential increased as the paralleled component units increased. Managing such a complex system with various control loops and uncertainties presents a challenge for improving overall energy efficiency. Due to the existence of trade-off issues, components must cooperate with each other to achieve the global optimization. As illustrated in Fig. 2, the optimization problem for the system includes the diffusion optimization among different components and allocation optimization among parallel units. Thus, for a variable flow rate HVAC system with multiple parallel units, the original complex energy efficiency optimization formulated in Eq. (18) can be decomposed into several subproblems. These include one diffusion optimization problem formulated in Eq. (19) and five allocation optimization problems formulated in Eq. (20).

$$f_{\text{Diffu}} = \min P_{\text{sys}} = \min(P_{\text{ch}} + P_{\text{chwp}} + P_{\text{cwp}} + P_{\text{ct}} + P_{\text{ahu}}) \quad (19)$$

$$f_{\text{Alloca,comp}} = \min P_{\text{comp}}, \quad \text{comp} \in \{\text{ch, chwp, cwp, ct, ahu}\} \quad (20)$$

The diffusion optimization aims to address the coupling characteristics among components by determining the optimal setpoints of control loops under a certain unit ON/OFF status. Hence, the solution

to the diffusion optimization problem can be formulated as Eq. (21), where the six decision variables are the setpoints of the control loops (C1 ~ C6) illustrated in Fig. 2, and the superscript (*) represents the optimal value. The allocation optimization deals with coupling characteristics among parallel units by determining the optimal ON/OFF sequence under a certain setpoint. Therefore, the solution for the five allocation optimization problems can be expressed as Eq. (22), where the decision variable is the ON/OFF sequence of parallel units in discrete form.

$$(T_{E,o}^*, H_{chwp}^*, \Delta T_C^*, T_{C,i}^*, T_{sa}^*, H_{sa}^*) = \arg \min f_{\text{Diffu}}(T_{E,o}, H_{chwp}, \Delta T_C, T_{C,i}, T_{sa}, H_{sa}) \quad (21)$$

$$(N_{d,comp}^*) = \arg \min f_{\text{Alloca,comp}}(N_{d,comp}) \quad (22)$$

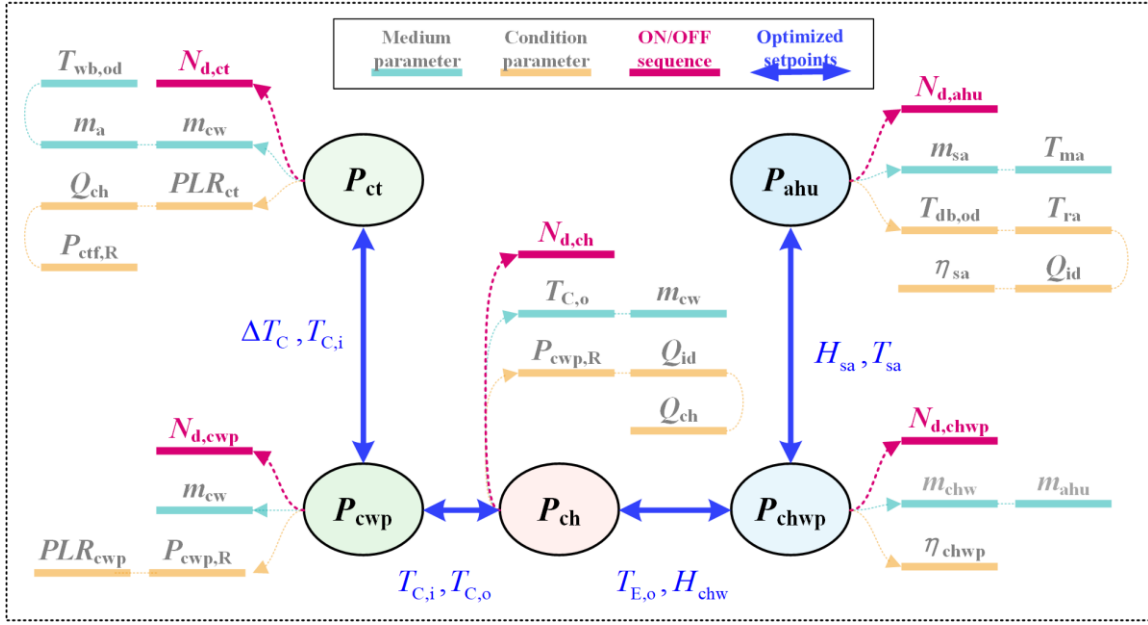


Fig. 3 Interactions and connections among different types of components

Based on the system models formulated in Section 2.1.1, the interactions and connections between different types of components can be illustrated in Fig. 3. In which, the optimized setpoints (highlighted with blue) and ON/OFF sequence (highlighted with red) are the decision variables for the diffusion problem and allocation problems, respectively. It can be learnt that these two kinds of decision variables are coupled each other. For example, the number of operating cooling tower ($N_{d,ct}$) influences and is influenced by the cooling water temperature ($T_{C,i}$). That demonstrates that the diffusion and allocation subproblems are interconnected each other under the multi-agent framework.

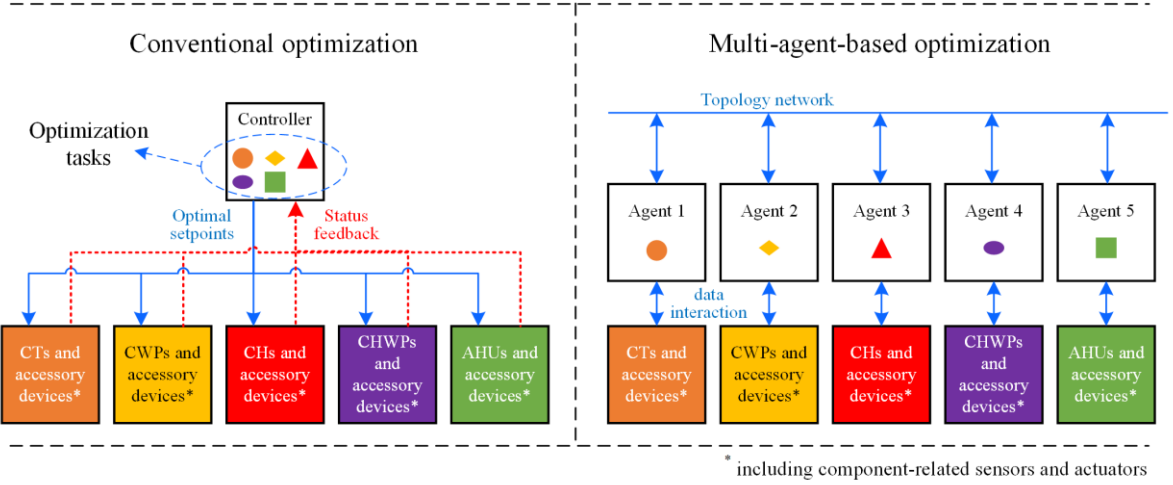


Fig. 4 The task allocation in HVAC system under different network framework

The problem description above indicates that diffusion and allocation subproblems are both independent and interconnected, requiring cooperative efforts to achieve system-wide optimization. By leveraging the distinct characteristics of these subproblems, they can be distributed among different agents in a multi-agent system to simplify the global optimization problem, as illustrated in Fig. 4. In this setup, allocation tasks can be handled locally by each agent, while the diffusion task can be addressed collaboratively among the agents.

2.2. AFSA-based collaborative optimization method

As detailed in Section 2.1.3, the global optimization problem for the HVAC system within a multi-agent framework can be decomposed as one diffusion optimization problem and five allocation optimization problems. The solutions for the diffusion problem are continuous variables, whereas for the allocation problems, they are discrete variables. Given this nonlinear hybrid optimization problem with multiple objective functions, conventional optimization algorithms are inadequate for finding optimal solutions. Hence, we propose an enhanced optimization algorithm rooted in the characteristics of the artificial fish swarm algorithm (AFSA) in this section.

In the AFSA algorithm, each individual of the population takes actions based on the information of adjacent individuals. This mode of interaction among individuals mirrors the interaction among multiple agents and HVAC components. Consequently, the AFSA algorithm is better suited for solving global optimization problems in multi-agent-based HVAC systems. The proposed enhanced AFSA algorithm is a hybrid algorithm that incorporates both continuous and discrete variables. It is tailored to address the global energy efficiency trade-off issue and the hybrid variables encountered by HVAC systems within a multi-agent framework. With this algorithm, each agent can explore its local optimal solutions using neighboring information and converge to the global optimal solution through iterations with adjacent agents.

2.2.1. The AFSA in continuous form (C-AFSA)

The AFSA is a heuristic random search algorithm initially proposed by Li [49,50] in 2002. In this algorithm, artificial fish typically swim independently or follow other fish towards areas with higher

concentrations of food (higher fitness). There are four steps throughout the entire search process of AFSA: initialization, prey, swarm, and follow. Below are detailed explanations of these steps, wherein the decision variables are in continuous form.

During the initial stage of C-AFSA, several parameters need to be initialized, including the fish population M , dimension n , feasible solution space L , *visual*, *step*, maximum try number N_{try} , maximum movement number T , and crowding factor δ . The initialization of the i^{th} individual can be expressed as Eqs. (23) and (24), where d represents the d^{th} dimension, and l is the feasible solution for each dimension.

$$X_i^{(0)} = (x_{i,1}^{(0)}, x_{i,2}^{(0)}, \dots, x_{i,d}^{(0)}, \dots, x_{i,n}^{(0)}) \quad (23)$$

$$x_{i,d}^{(0)} = l_{\min,d} + \text{rand}(0,1) \cdot (l_{\max,d} - l_{\min,d}) \quad (24)$$

After the initialization, the fitness of all individuals will be calculated, and the best individual and fitness will be recorded on the billboard. Referring to the Euclidean distance, the distance $d_{i,j}$ between fish i and j can be defined as Eq. (25).

$$d_{i,j} = \|X_i - X_j\| \quad (25)$$

During the prey stage, artificial fish i will randomly select a new position j as shown in Eq. (26) within the visual field ($d_{i,j} < \text{visual}$). If the fitness of X_j is better than X_i , then fish i would move one step towards position j , as expressed in Eq. (27). Here, t represents the t^{th} movement.

$$X_j = X_i + \text{visual} \cdot \text{rand}(-1,1) \quad (26)$$

$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_j - X_i^{(t)}}{d_{i,j}} \cdot \text{step} \cdot \text{rand}(0,1) \quad (27)$$

If fish i does not find a suitable prey target after N_{try} attempts, a random movement will be taken, as expressed in Eq. (28).

$$X_i^{(t+1)} = X_i^{(t)} + \text{step} \cdot \text{rand}(-1,1) \quad (28)$$

During the swarm stage, fish i will perceive the number of companions (n_f) and the center of fish school (c) within the visual field. If the fitness of X_c is better and the center is not crowded, then fish i will move one step towards the center, as expressed in Eq. (29). The precondition of the swarm action is expressed in Eq. (30). Here, X_c is defined as Eq. (31), and Y represents the fitness. If the condition is not met, then prey action is performed.

$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_c - X_i^{(t)}}{d_{i,c}} \cdot \text{step} \cdot \text{rand}(0,1) \quad (29)$$

$$\frac{n_f}{N} < \delta \quad \& \quad Y_c > Y_i \quad (30)$$

$$X_c = \frac{\sum_{j=1}^{n_f} X_j}{n_f} \quad (31)$$

During the follow stage, fish i will perceive the companion k with the best fitness in the field of visual. If the fitness of X_k is better and it is not crowded nearby, then fish i will move one step towards the companion

k , as expressed in Eqs. (32) and (33). If the condition of the follow action in Eq. (33) is not met, the prey action is performed.

$$X_i^{(t+1)} = X_i^{(t)} + \frac{X_k - X_i^{(t)}}{d_{i,k}} \cdot \text{step} \cdot \text{rand}(0,1) \quad (32)$$

$$\frac{n_f}{N} < \delta \quad \& \quad Y_k > Y_i \quad (33)$$

After each movement, artificial fish will compare its fitness with the fitness recorded on the billboard. If its fitness is better, then the billboard will be updated. The algorithm will terminate when the error of the optimal individual is within an acceptable range or when the fish reach the maximum movement number (T).

2.2.2. Definition of action reward and adaptive step

To further enhance the local search ability and convergence speed of C-AFSA, we defined the action reward and improved the fixed step to adaptive step. The action reward R is defined as the benefits for fish i moving to target o , as expressed in Eq. (34). The step for this action is defined as Eq. (35), where $\text{step}_{\min}$ and $\text{step}_{\max}$ are the boundaries of step .

$$R = \frac{Y_0 - Y_i}{Y_0} \quad (34)$$

$$\text{step} = \text{step}_{\min} + (\text{step}_{\max} - \text{step}_{\min}) \cdot R \quad (35)$$

Therefore, the step in the three actions (prey, swarm, and follow) expressed in Eqs. (27), (29) and (32) can be replaced with an adaptive step expressed in Eq. (35). For random movement, the action benefit is considered as 0, and the step is expressed as $\text{step}_{\max} \cdot \text{rand}(-1, 1)$.

The physical meaning of the adaptive step can be understood as follows: When the target fitness is much greater than the fitness of the fish itself, the action benefit for fish i is greater, and a larger step size will be taken, which is conducive to improving the convergence speed. When the target fitness is similar to the fitness of the fish itself, the action benefit is small, and a smaller step will be taken, which helps strengthen the local search ability.

2.2.3. Discretization improvement (D-AFSA)

As described in Section 2.1.3, the allocation problem is a 0-1 integer programming problem, and its decision variables are unit ON/OFF sequences, which are discrete variables. To solve such problems with discrete variables using AFSA, some discretization improvements for AFSA will be made in this section.

Firstly, the initialization of artificial fish is defined as Eq. (36), in which there are only two states (0 and 1) for each element. The distance $d_{i,j}$ between fish i and j can be expressed as Eq. (37).

$$X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,d}, \dots, x_{i,n}\}, \quad x_{i,d} \in \{0,1\}, d = 1, 2, \dots, n \quad (36)$$

$$d_{i,j} = \|X_i - X_j\| = \sqrt{\sum_{d=1}^n (x_{i,d} - x_{j,d})^2} \quad (37)$$

In D-AFSA, the visual is defined within the range of the dimension, herein set as $n/3$. The step is defined

as an integer within the range of the visual. During the prey stage, artificial fish i will move towards target j within the visual field based on Eq. (38), where $RAND(1, n, step)$ represents $step$ integers randomly generated between 1 and n . Eq. (38) indicates that $step$ elements in fish i (X_i) will move towards X_j . If no suitable prey target is found after N_{try} attempts, a random movement expressed in Eq. (39) will be taken.

$$x_{i,d}^{(t+1)} = \begin{cases} x_{j,d}, & x_{i,d}^{(t)} = x_{j,d} \\ \min(1, x_{j,d}), & x_{i,d}^{(t)} \neq x_{j,d} \end{cases}, d = RAND(1, n, step) \quad (38)$$

$$x_{i,d}^{(t+1)} = \begin{cases} 0, & x_{i,d}^{(t)} = 1 \\ 1, & x_{i,d}^{(t)} = 0 \end{cases}, d = RAND(1, n, step) \quad (39)$$

At the swarm stage, the swarm center can be expressed as Eq. (40), and fish i will move towards the center based on Eq. (41). This means that $step$ dimensions of X_i will move towards X_c .

$$x_{c,d} = \text{round} \left(\sum_{j=1}^{n_f} x_{j,d} / n_f \right) \quad (40)$$

$$x_{i,d}^{(t+1)} = \begin{cases} x_{c,d}, & x_{i,d}^{(t)} = x_{c,d} \\ \min(1, x_{c,d}), & x_{i,d}^{(t)} \neq x_{c,d} \end{cases}, d = RAND(1, n, step) \quad (41)$$

The follow action of D-AFSA is expressed as Eq. (42), which means step dimensions of fish i (X_i) will move towards the follow target (X_k).

$$x_{i,d}^{(t+1)} = \begin{cases} x_{k,d}, & x_{i,d}^{(t)} = x_{k,d} \\ \min(1, x_{k,d}), & x_{i,d}^{(t)} \neq x_{k,d} \end{cases}, d = RAND(1, n, step) \quad (42)$$

The discretization improvement for AFSA differs from conventional integer programming algorithms that obtain optimal solutions through SysConvert and rounding methods. D-AFSA can directly search for the optimal solution in a binary environment without SysConvert, making it more accurate and targeted for solving ON/OFF sequence problems. Moreover, with an increase in the number of parallel units (dimension), its advantages become more significant.

2.2.4. The adaptive hybrid AFSA (AH-AFSA)

To solve the hybrid optimization problem of HVAC systems, both continuous and discrete decision variables must be optimized together. Therefore, the adaptive hybrid AFSA (AH-AFSA) is proposed herein, inheriting the merits of both C-AFSA and D-AFSA. As illustrated in Sections 2.2.1 and 2.2.3, C-AFSA is more suitable for solving problems with continuous decision variables (e.g., the diffusion problem), while D-AFSA is for problems with discrete decision variables (e.g., the allocation problem).

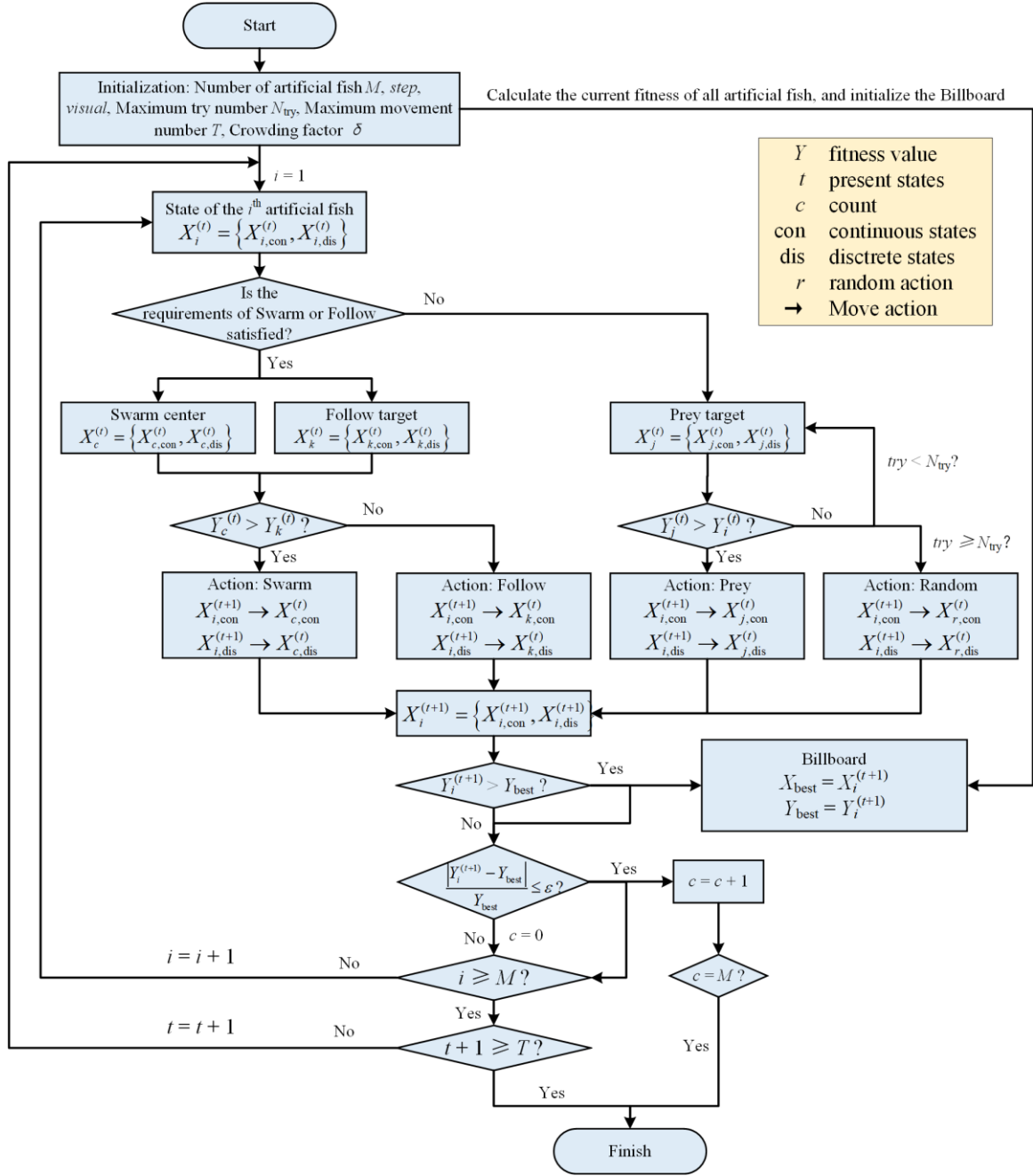


Fig. 5 Schematic diagram of AH-AFSA

The schematic of AH-AFSA is shown in Fig. 5. It also mainly contains four steps: initialization, prey, swarm, and follow. During the initialization process, each fish i (X_i) contains two types of fragments. One fragment is the continuous part ($X_{i,con}$), and the other is the discrete part ($X_{i,dis}$). Each fragment has its own dimension, and the sum of the dimensions of all fragments is the artificial fish dimension. For different fragments, except the visual and step, all other parameters are consistent. The visual and step for AH-AFSA can be expressed as $visual = \{visual_{con}, visual_{dis}\}$ and $step = \{step_{con}, step_{dis}\}$. The fragments and dimensions of artificial fish are determined according to the actual optimization problem.

During the prey, swarm, and follow stages, there are two ways to search for and move towards a target. For the fragment $X_{i,con}$, the algorithm will search for a target in the continuous fragments in the field of

$visual_{con}$, while for the fragment $X_{i,dis}$, the algorithm will search for a target in the discrete fragments in the field of $visual_{dis}$. After each search, the searched continuous and discrete fragments will be combined into a new state. If the fitness of the new state is better, then the new state will be determined as the action target (prey, swarm, or follow target). Then, each fragment will move towards the target with its own step ($step_{con}$ or $step_{dis}$).

2.3. Agent definition for the complex HVAC systems

2.3.1. Coordinating agent

Based on the optimization problems presented in Section 2.1.3, the compact form of the optimization problem can be described by Eq.(43).

$$\begin{cases} \min \left[f_{Diffu}(X_{con}) + \sum_{comp} f_{Alloca,comp}(X_{dis,comp}) \right] \\ \text{subject to } X \in \bigcap_{comp} C_{comp} \end{cases} \quad (43)$$

where X is the collection of decision variables, including the setpoints (X_{con}) and ON/OFF sequence (X_{dis}); f is the agent local objective function; C_{comp} is the local constraint condition.

In this research, the concept of coordinating agent [29] is introduced to ensure information synchronization among agents. The coordinating agent shares the same priority as other component agents and is primarily tasked with solving the diffusion optimization problem. Herein, the BDI model [37] is used to describe the cognitive and decision-making processes of agents. In which, belief represents the agent's perception of the environment and system state, desire represents the agent's local goals and preferences, and intention represents the specific action the agent makes based on beliefs and desires. For a coordinating agent, its beliefs can be understood as the coupling models among different components, and it updates its status according to environmental parameters received from neighboring agents. The desire of the coordinating agent is the local objective, which can be described by Eq. (44) based on the compact form of the global optimization problem, and is constrained by Eq. (15). The intention of the coordinating agent is defined as the action directed toward its goal, which can be formulated by Eq. (45).

$$\begin{cases} \min[f_{Diffu}(X_{con}) + P_f(X_{con})] \\ \text{subject to Eq.(15)} \end{cases} \quad (44)$$

$$X_{con}^{(t+1)} = \arg \min_{X_{con} \in C} \left[f_{Diffu} \left(X_{con}^{(t)} \mid Z_{con}^{(t)} \right) + P_f \left(X_{con}^{(t)} \mid Z_{con}^{(t)} \right) \right] \quad (45)$$

where f_{Diffu} is the local objective function of coordinating agent; P_f is the proxy term that penalizing unfeasible solution based on information from neighbors, and Z_{con} is the information set that constructed based on coupled variables from neighbors, which contains the updated solutions from neighbors.

It is important to note that the terms of Z_{con} change with each iteration of the algorithm, leading to updates in P_f and f_{Diffu} at each iteration. This term is essential for agent interactions and for updating their

decision variables. Herein, Z_{con} comprises the updated decision variables obtained from neighboring agents through communication, as expressed in Eq. (46).

$$Z_{\text{con}}^{(t)} = \{X_{\text{dis,ct}}^{*(t)}, X_{\text{dis,chw}}^{*(t)}, X_{\text{dis,ch}}^{*(t)}, \dots\} \quad (46)$$

At each iteration, the coordinating agent interacts with neighboring agents to obtain Z_{con} , which is then used to update its local state and evaluate its local fitness (Y_{con}) using the AH-AFSA algorithm. The local fitness is expressed in Eq. (47), where i represents the i^{th} artificial fish.

$$Y_{i,\text{con}}^{(t+1)} = \frac{1}{P_{\text{sys}}(X_{i,\text{con}}^{(t)} | Z_{\text{con}}^{(t)}) + P_{\text{f}}(X_{i,\text{con}}^{(t)} | Z_{\text{con}}^{(t)})} \quad (47)$$

To ensure solution optimality and consistency among agents, all agents must calculate both global and their local fitness. Firstly, each agent calculates its local fitness ($Y_{i,\text{con}}$ or $Y_{i,\text{dis,comp}}$) based on the current environment and broadcasts this information to its neighbors. Then, after receiving the local fitness values from neighboring agents, they calculate the global fitness according to Eq. (48). The local fitness helps the agent determine the optimal actions (such as swarming, following, preying, or random action) for each artificial fish. The global fitness allows the agent to select the best artificial fish, ensuring that all agents collectively move towards the global optimal solution.

$$F_i^{(t+1)} = Y_{i,\text{con}}^{(t+1)}(X_{i,\text{con}}^{(t+1)}) + \sum_{\text{comp}} Y_{i,\text{dis,comp}}^{(t+1)}(X_{i,\text{dis,comp}}^{(t+1)}) \quad (48)$$

All artificial fish will repeat the above process until either the maximum number of iterations is reached or the convergence condition is met, ultimately producing the optimal solution. During the iteration process, the convergence condition for the coordinating agent is defined by Eq. (49). Here, ε_{con} represents the threshold for the residuals, reflecting the maximum relative difference between two iterations. In this research, the value of ε_{con} is set to 0.01.

$$\left| \frac{Y_{i,\text{con}}^{(k+1)}(X_{i,\text{con}}^{(k+1)}) - Y_{i,\text{con}}^{(k)}(X_{i,\text{con}}^{(k)})}{Y_{i,\text{con}}^{(k)}(X_{i,\text{con}}^{(k)})} \right| \leq \varepsilon_{\text{con}}, \quad \forall i = 1, 2, \dots, M \quad (49)$$

Therefore, once the coordinating agent obtains the information set $Z_{\text{con}}^{(t)}$ from its neighbors, it updates its tentative solution $X_{\text{con}}^{*(t+1)}(Z_{\text{con}}^{(t)})$ using the AH-AFSA algorithm, incorporating the coupling models formulated in Section 2.1.1. And then, the coordinating agent will broadcast its tentative solution to its neighbors and receives their solutions for optimization in the next iteration. This process is similarly followed by the neighbors.

To prevent the algorithm from converging to local optimal solutions, the random movement described by Eq. (28) will be taken when the fitness of the artificial fish has not significantly improved over the previous g movements. The precondition for this is expressed as Eq. (50), with the threshold λ set at 5%.

$$\frac{|Y_i^{(t-g)} - Y_i^{(t)}|}{Y_i^{(t)}} < \lambda, \quad \forall i = 1, 2, \dots, M \quad (50)$$

2.3.2. Component agent

The component agents are responsible for solving the allocation problem for each type of component. The local problems of component agents 1 through 5 are described by Eq. (51), subject to the constraints given by Eqs. (16) and (17). Similarly, the action of the component agent at iteration $t + 1$ can be expressed by Eq. (52).

$$\begin{cases} \min[f_{\text{Alloca},comp}(X_{\text{dis},comp}) + P_{f,comp}(X_{\text{dis},comp})] \\ \text{subject to Eqs.(16)\&(17)} \end{cases} \quad (51)$$

$$X_{\text{dis},comp}^{(t+1)} = \arg \min_{X_{\text{dis},comp} \in C} [f_{\text{Alloca}}(X_{\text{dis},comp}^{(t)} | Z_{\text{dis},comp}^{(t)}) + P_{f,comp}(X_{\text{dis},comp}^{(t)} | Z_{\text{dis},comp}^{(t)})] \quad (52)$$

where subscript *comp* denotes the component type and belongs to the set {ch,chwp,cwp,ct,ahu}. Additionally, Z_{dis} represents the information set obtained from interactions with neighbors, which can be expressed by Eq. (53).

$$Z_{\text{dis},comp}^{(t)} = \{X_{\text{con}}^{*,(t)}\} \quad (53)$$

Similar to the iteration process of the coordinating agent, each component agent calculates its local fitness based on the received Z_{dis} to determine the actions of the artificial fish, as specified by Eq. (54). The agent then broadcasts its local fitness to neighboring agents. Subsequently, the component agent calculates the global fitness using Eq. (48) to identify the best artificial fish and move toward the global optimal solution.

$$Y_{i,\text{dis},comp}^{(t+1)} = \frac{1}{P_{comp}(X_{i,\text{dis},comp}^{(t)} | Z_{\text{dis},comp}^{(t)}) + P_{f,comp}(X_{i,\text{dis},comp}^{(t)} | Z_{\text{dis},comp}^{(t)})} \quad (54)$$

The convergence conditions for the component agents are defined by Eq. (55). Here, ε_{con} represents the residual thresholds for the component agents, reflecting the maximum relative difference between two iterations; the value is set to 0.01 in this research.

$$\left| \frac{Y_{i,\text{dis},comp}^{(k+1)}(X_{i,\text{dis},comp}^{(k+1)}) - Y_{i,\text{dis},comp}^{(k)}(X_{i,\text{dis},comp}^{(k)})}{Y_{i,\text{dis},comp}^{(k)}(X_{i,\text{dis},comp}^{(k)})} \right| \leq \varepsilon_{\text{dis}}, \quad \forall i = 1, 2, \dots, M \quad (55)$$

2.3.3. Application in the complex HVAC system

Based on the previous description, the optimization task of a conventional HVAC system can be assigned to six agents: the coordinating agent, the cooling tower agent, the cooling water pump agent, the chiller agent, the chilled water pump agent, and the AHU agent. The application principle of the AH-AFSA algorithm in the multi-agent HVAC system is depicted in Fig. 6, with six agents responsible for different optimization objectives. Among these, the optimization objective of the coordinating agent is the diffusion problem, involving determining the optimal setpoints $X_{\text{con}}^{(t+1)}$ based on the current operating conditions and ON/OFF sequence configuration. Agents 1 to 4 are responsible for allocation optimization problems related to the cooling tower, cooling water pump, chiller, and chilled water pump. Their tasks are to determine the

optimal ON/OFF sequence $X_{dis}^{(t+1)}$ based on the current operating conditions and setpoints. Agent 5 is tasked with the load allocation optimization problem for the AHUs, ensuring that the cooling capacity meets the demand of the conditioned rooms. In this research, we assume that the cooling capacity provided by AHUs can satisfy the cooling demand of conditioned rooms, and the setpoints of supply air temperature and static pressure will still be optimized on the premise of cooling demand. Each agent interacts with adjacent agents to update its local state, and search for its local optimal solution.

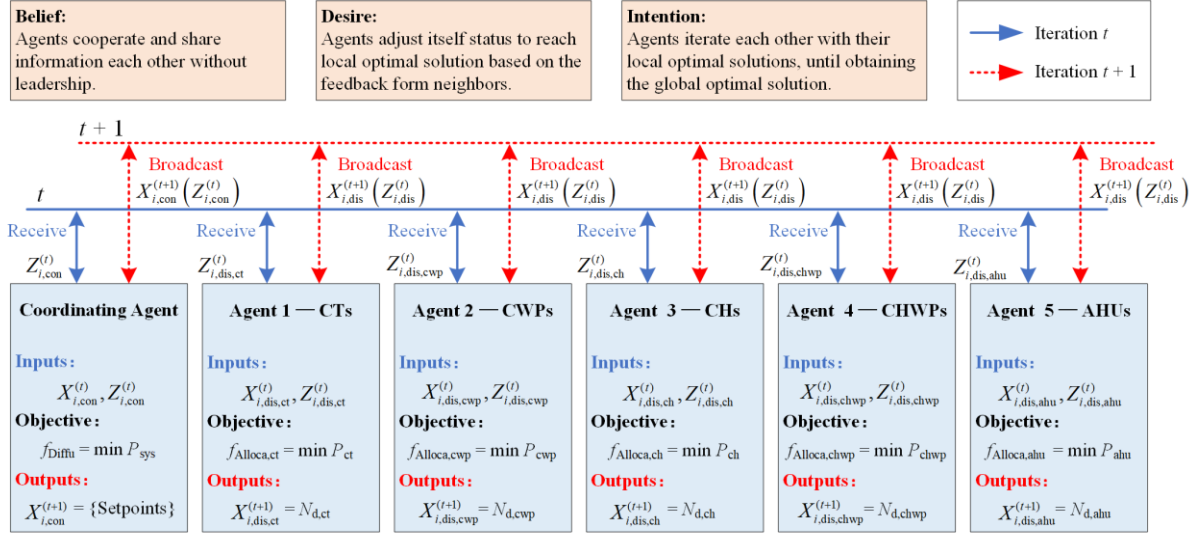


Fig. 6 Distributed application of AH-AFSA in BDI model based multi-agent system

As depicted in Fig. 2, the HVAC system can be divided into several subsystems based on the type of component. To achieve global optimization under a multi-agent framework, each subsystem is considered as an agent, containing only information relevant to its own system. For example, the input parameters of agent 1 (cooling tower agent) at iteration t are $X_{i,con,ct}^{(t)}$ and $Z_{i,dis,ct}^{(t)}$ from adjacent agents. With this information, m_a and m_{cw} of cooling tower at the current iteration can be calculated based on system models. All these parameters serve as the environment for the agent's local optimization problem, allowing it to determine the optimal action movement of each artificial fish. Similarly, its optimization result $X_{i,dis,ct}^{(t+1)}$ and corresponding fitness $Y_{i,dis,ct}^{(t+1)}$ will be broadcasted to adjacent agents. Then, it will calculate the global fitness based on Eq. (48) while receiving the fitness of other agents. All artificial fish will repeat this process until either the maximum number of actions is reached or the convergence conditions for both coordinating and component agents are satisfied, ultimately producing the optimal solution. This example illustrates the interaction process and optimal solution searching process for agent 1, and the same process applies to the other agents.

3. Experimental Research

3.1. System overview

The simulation system prototype is based on the HVAC system of a public building in Jiaxing City, China, covering a total area of 55,000 m² with an air conditioning area of 49,000 m². Fig. 7 shows the

schematic diagram of the system, which includes 3 chillers, 3 chilled water pumps (CHWPs), 3 cooling water pumps (CWP), 3 cooling towers (CTs), and 4 AHUs. These components are configured in two sizes (large and small), which is a common configuration in practical systems to accommodate varying cooling loads. The specifications of these components are provided in Table 2.

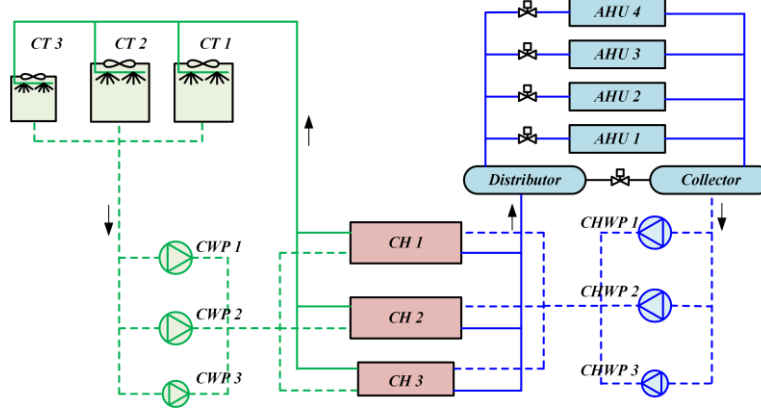


Fig. 7 Schematic diagram of the HVAC system

The proposed method's performance will be evaluated using a multi-agent-based experimental platform, as illustrated in Fig. 8. This platform integrates optimization-related packages and agent topology. Within this setup, agents 1 to 5 are equipped with models of components such as cooling towers, cooling water pumps, chillers, chilled water pumps, and air handling units, and are responsible for addressing allocation optimization problems. Meanwhile, the coordinating agent is equipped with interaction models among components and focuses on solving the diffusion optimization problem.

Table 2 Specifications of the main components of the HVAC system

Components	Amount	Specifications
Chiller (large)	2	rated power: 323.0 kW; cooling capacity: 1758 kW; COP: 5.44; model: DCLC500N
Chiller (small)	1	rated power: 125.3 kW; cooling capacity: 721 kW; COP: 5.75; model: WCFX30SRC
CHWP (large)	2	rated power: 37.0 kW; flow rate: 330 m ³ /h; lift: 18.5 m·H ₂ O; model: DFSG200-315
CHWP (small)	1	rated power: 15.0 kW; flow rate: 136 m ³ /h; lift: 22 m·H ₂ O; model: DFSG150-160A
CWP (large)	2	rated power: 37.0 kW; flow rate: 410 m ³ /h; lift: 23 m·H ₂ O; model: DFSG200-315
CWP (small)	1	rated power: 15.0 kW; flow rate: 160 m ³ /h; lift: 22 m·H ₂ O; model: DFSG150-160A
CT (large)	2	rated power: 15.0 kW; water flow rate: 450 m ³ /h; air volume: 522000 m ³ /h; model: CEF-450A
CT (small)	1	rated power: 7.5 kW; water flow rate: 250 m ³ /h; air volume: 260000 m ³ /h; model: CEF-250A
AHU	4	rated power: 59.8 kW; cooling capacity: 787 kW; air volume: 114000 m ³ /h; water flow rate: 90.4 m ³ /h; model: TBC3341CHW

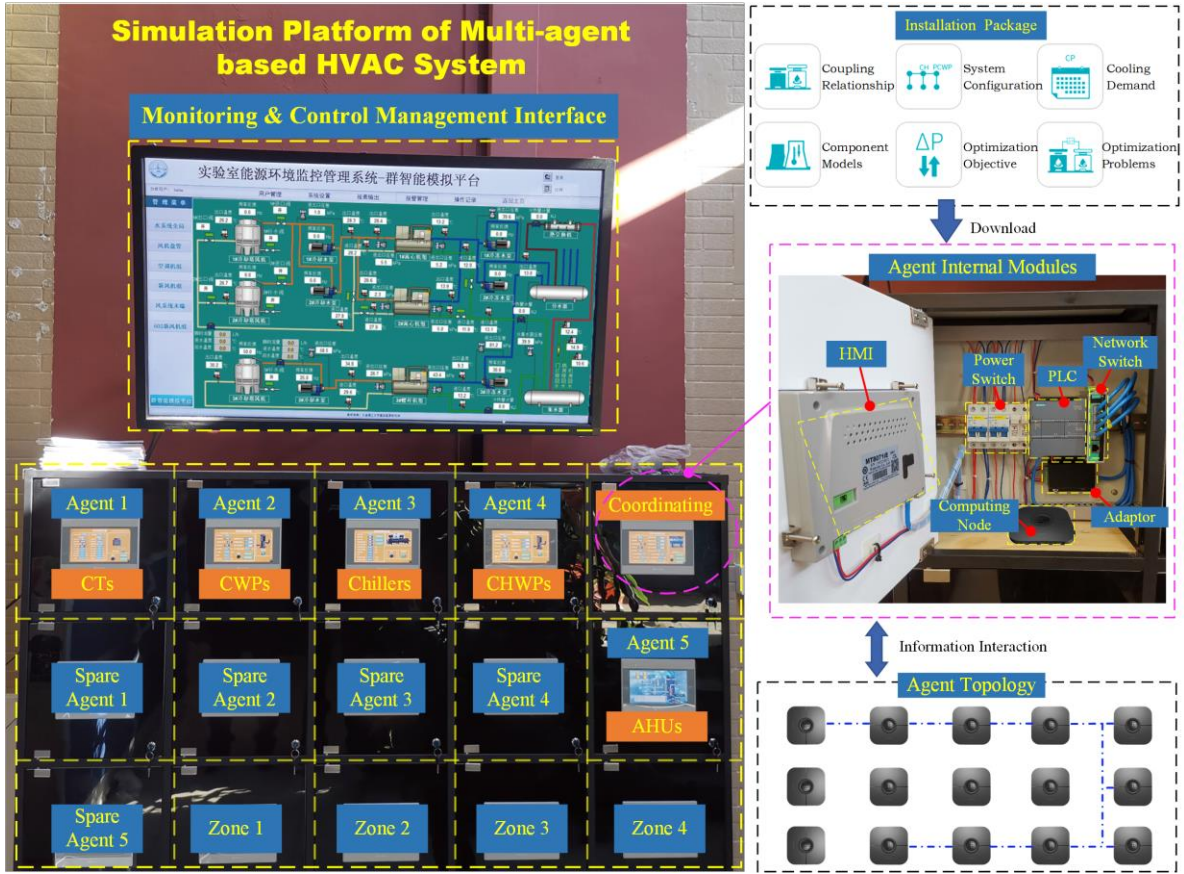


Fig. 8 Schematic of the multi-agent based experimental platform

3.2. Model identification

Based on the models established in Section 2.1, the model coefficients are determined using system historical operation data, with 70% allocated for identification and the remaining 30% for validation. The model identification results are presented in Table 3 and Table 4, corresponding to the large and small components, respectively.

Validation results are depicted in Fig. 9, where subgraphs (a) through (g) illustrate results for large components, and subgraphs (h) through (l) present results for small components. It is evident from Fig. 9 that the R^2 values of the models range from 0.902 to 0.984, indicating that the fitted models exhibit acceptable accuracy for further study.

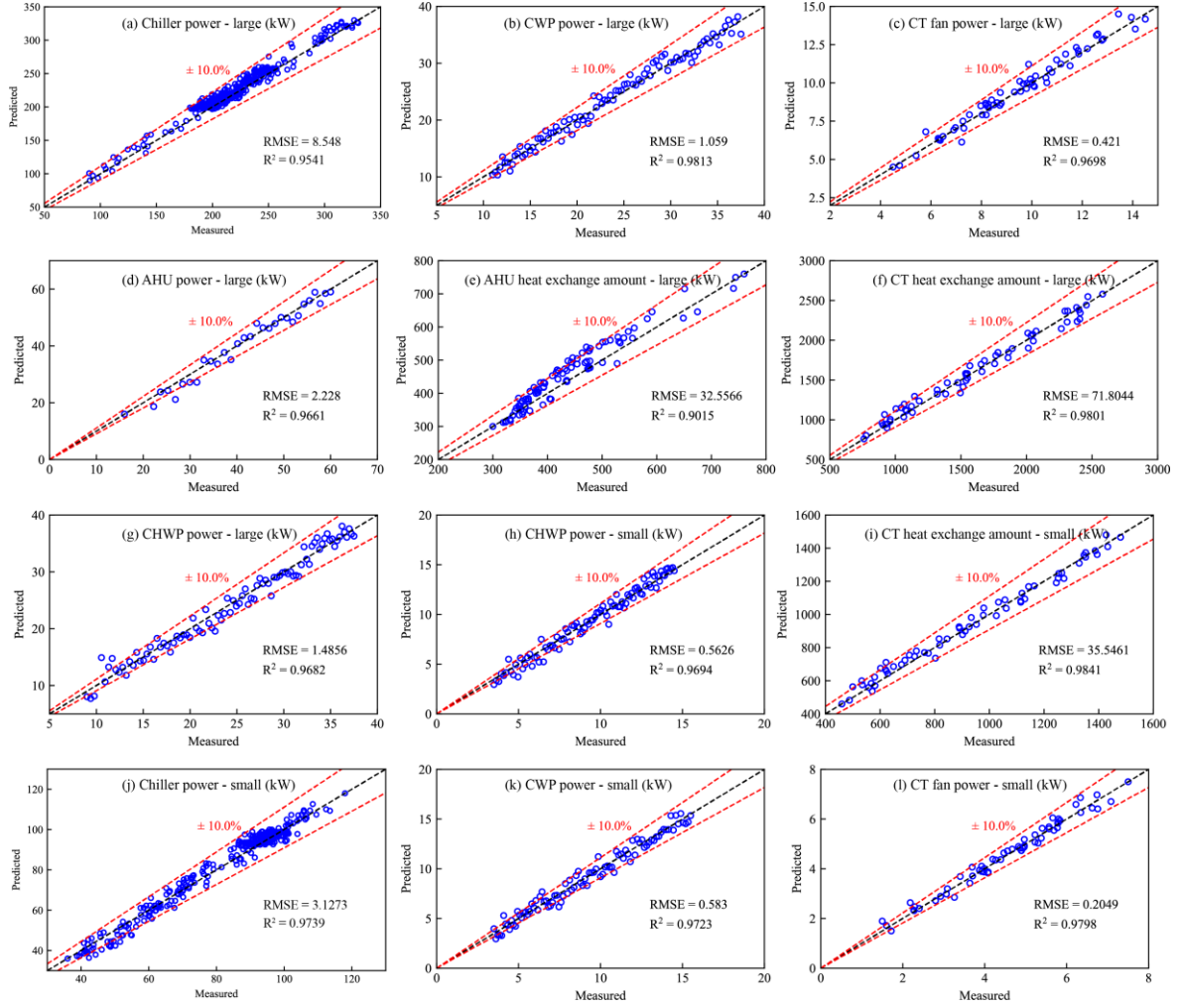


Fig. 9 Model validation results of the system

Table 3 Model identification results of the large components

	superscript 0	superscript 1	superscript 2	superscript 3	superscript 4	superscript 5
<i>a</i>	0.1632	0.3077	-0.1594	/	/	/
<i>b</i>	-0.8795	-0.1169	-0.0010	0.1410	-0.0018	0.0031
<i>c</i>	0.0573	0.0940	0.0052	8.09E-05	/	/
<i>d</i>	4.1528	7.1158	-0.5826	0.0053	/	/
<i>e</i>	/	5.60E-06	3.2895	5.7351	/	/
<i>g</i>	/	1.74E+05	1.03E+05	0.4610	/	/

Table 4 Model identification results of the small components

	superscript 0	superscript 1	superscript 2	superscript 3	superscript 4	superscript 5
<i>a</i>	0.3942	0.1756	0.0046	/	/	/
<i>b</i>	-0.8153	-0.1150	-0.0009	0.1425	-0.0017	0.0027
<i>c</i>	0.0919	0.4825	0.3619	-0.2833	/	/
<i>d</i>	3.0058	4.7342	-0.3982	0.0031	/	/
<i>e</i>	/	5.60E-06	3.2895	5.7351	/	/
<i>g</i>	/	1.16E+05	1.76E+05	0.8993	/	/

3.3. Optimization methods

To systematically evaluate the performance of the proposed method, comparison research will be conducted considering energy consumption and computing efficiency under varying operating conditions. The performance of the following four methods will be compared:

1. Method 1 (Constant): This is the conventional method that optimizes the system with constant setpoints. Under this method, setpoints for $x_5 \sim x_{10}$ are set as 7 °C, 22 m·H₂O, 5 °C, 30 °C, 18 °C and 900 Pa. If the cooling capacity of a single chiller unit exceeds its rated capacity, another unit (preferably the small component) should be loaded. Conversely, if the cooling capacity is below its rated capacity, one unit (preferably the small component) should be unloaded. The ON/OFF sequence of pumps and cooling towers corresponds to the chillers.

2. Method 2 (AHDE): An intelligent optimization method that optimizes setpoints using the differential evolution algorithm [44]. The crossover probability and scaling factor of the algorithm are adaptively adjusted during the search process, leading to superior performance in finding optimal results.

3. Method 3 (C-AFSA): An intelligent optimization method that optimizes setpoints using the algorithm introduced in Section 2.2.1.

4. Method 4 (AH-AFSA): The proposed intelligent optimization method introduced in Section 2.2.4.

Table 5 Parameter settings of the three heuristic algorithms

	framework	population N	maximum iteration T	crossover probability	scaling factor	$visual$	crowding factor δ	$step$
AHDE	centralized	20	100	[0.1, 0.6]	[0.1, 0.9]	/	/	/
C-AFSA	centralized	20	100	/		20	0.618	[3, 10]
AH-AFSA	multi- agent	20	100	/		20 / 1.5	0.618 / 0.618	[3, 10] / 1

In this research, Methods 1, 2, and 3 will be implemented on a centralized control framework, while Method 4 will be executed on a multi-agent control framework. The parameter settings for the three heuristic algorithms (Methods 2, 3, and 4) are outlined in Table 5. For C-AFSA (Method 3) and AH-AFSA (Method 4), the parameter settings are consistent except for the discrete part. In this research, the $visual_{dis}$ and $step_{dis}$ of AH-AFSA are set as 1.5 and 1, respectively. The feasible solution space of $x_5 \sim x_{10}$ for the three heuristic algorithms is as follows: 7 ~ 12 °C, 12 ~ 18 m·H₂O, 4 ~ 6 °C, 28 ~ 36 °C, 16 ~ 20 °C, and 700 ~ 1200 Pa, respectively.

3.4. Operating conditions

The building's annual cooling load and outdoor climate are simulated using the open-source simulation software EnergyPlus [51]. Upon importing the building model, configuring the parameters, and calibrating with available historical data, hourly results can be obtained, which include outdoor temperature, cooling load, and specific enthalpy of outdoor air, as depicted in Fig. 10. For this study, data from the 3624th hour (0:00 on June 1) to the 6551st hour (24:00 on September 30) are chosen as the cooling load data for the annual

cooling season, with a peak load of 3277.7 kW. This amounts to a total of 2928 hours of cooling load data, which will be used to evaluate the optimization methods.

Additionally, three days of cooling load data are selected as typical days for evaluating the daily performance of the optimization method from July, August, and September, respectively. The outdoor climate and cooling load of these three typical days are presented in Fig. 11.

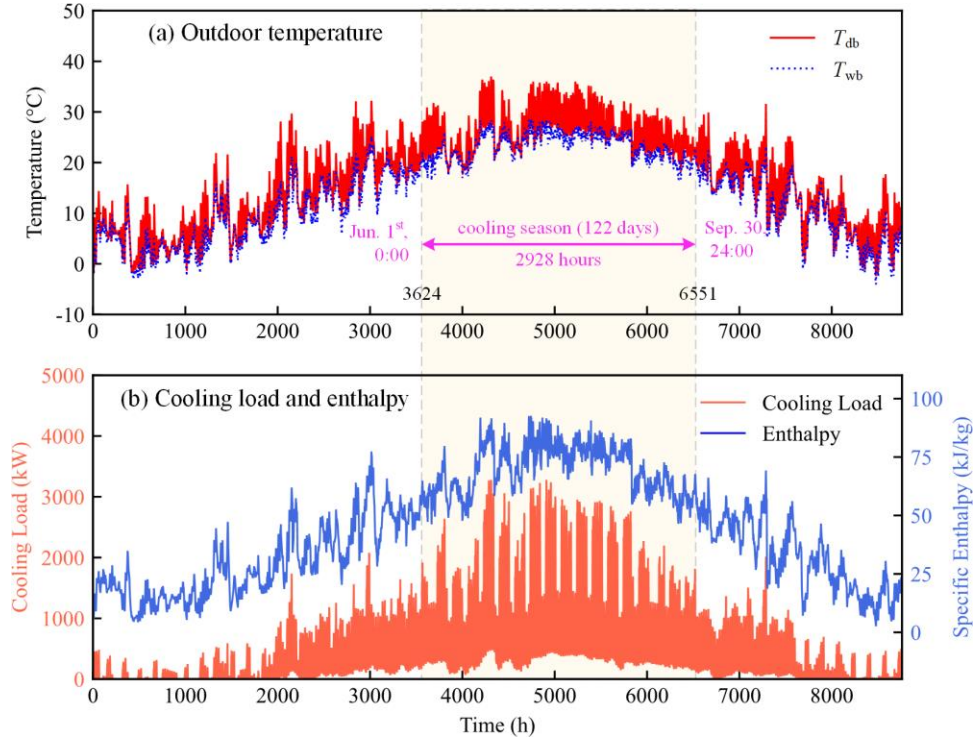


Fig. 10 Simulation results of the building annual cooling load and outdoor climate

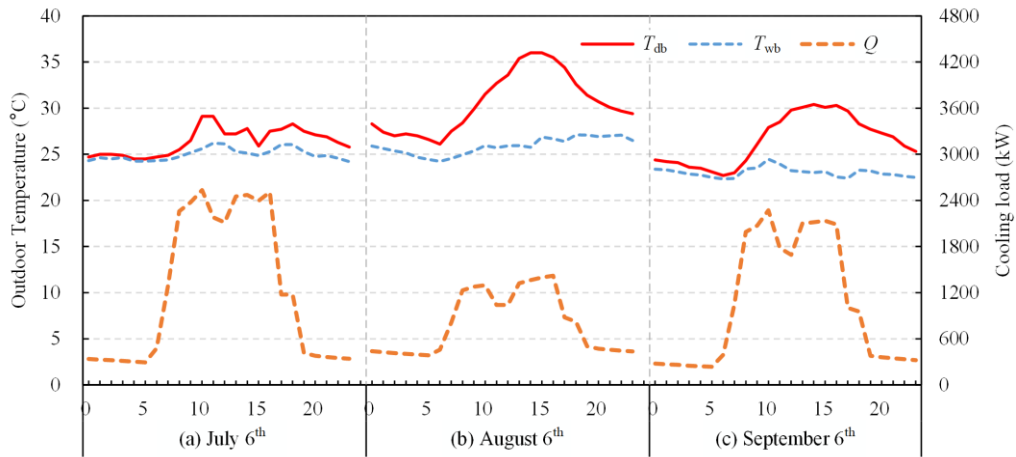


Fig. 11 Outdoor climate and cooling load in the three typical days

4. Results and Discussion

4.1. Daily performance

Fig. 12 illustrates the hourly power consumption of the system under four different optimization

methods during three typical days, with operating conditions based on those shown in Fig. 11. It is clear that the power consumption of the Constant method is notably higher than the other three intelligent methods, especially during periods of high cooling load (from 9:00 am to 14:00 pm). This emphasizes the superior performance of the variable setpoint optimization method in terms of energy conservation.

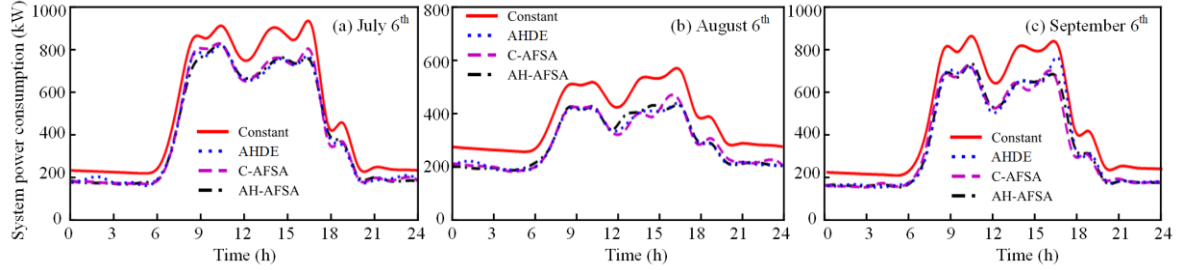


Fig. 12 Hourly total power of the HVAC system in the three typical days

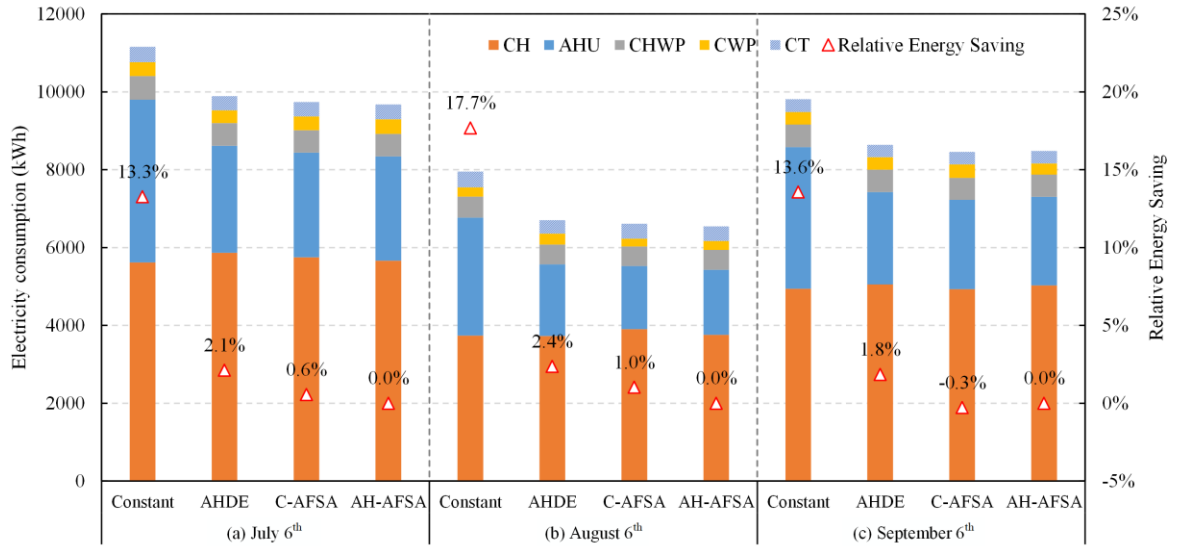


Fig. 13 Electricity consumption of the HVAC system in the three typical days

Fig. 13 illustrates the total electricity consumption of the system during three typical days, with the "relative energy savings" item presenting the energy savings of the proposed AH-AFSA method relative to the other methods. It can be observed that the AH-AFSA method achieves relative energy savings of 13.3% to 17.7% compared to the Constant method, while the maximum relative energy savings compared to the AHDE and C-AFSA methods are 2.4% and 1.0%, resulting in daily electricity reductions of 176.0 kWh and 33.2 kWh, respectively.

The results indicate that the total electricity consumptions of the HVAC system under the three intelligent methods are not significantly different, suggesting that the differences in solution accuracy among the three algorithms are minimal, and acceptable optimal solutions can be obtained within the maximum iterations for each operating condition. Additionally, the solution accuracy of the three intelligent methods can be mutually validated based on the results.

Moreover, the energy-saving potential of the AH-AFSA method is slightly higher than that of the AHDE and C-AFSA methods. These improvements can be attributed to the differences in handling the discrete decision variables among the three algorithms. As mentioned in Section 2.2.3, the AH-AFSA algorithm can directly search for optimal discrete decision variables in the binary space, ensuring search accuracy for discrete variables. In contrast, the C-AFSA and AHDE algorithms optimize discrete decision variables using SysConvert and rounding methods, leading to a loss of accuracy for discrete variables. This advantage of AH-AFSA would be more pronounced in a large-scale HVAC system with more parallel units.

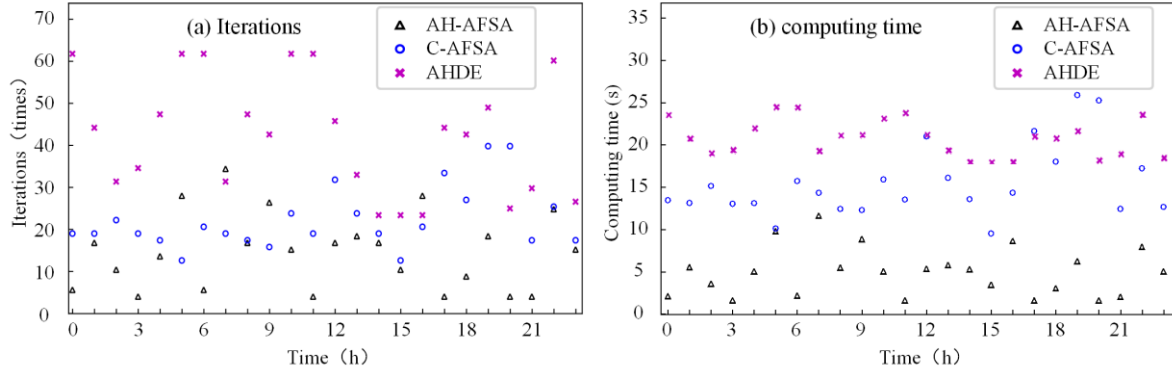


Fig. 14 Iterations and time cost of different methods in a typical day

The computational efficiency of three intelligent algorithms in a typical day is analyzed by comparing the iterations and computing time required to achieve convergence, as presented in Fig. 14 (a) and (b), respectively.

By comparing the iterations, it is evident that the AHDE method requires relatively more iterations compared to the other two methods during the optimization process, ranging from 20 to 70. Meanwhile, the difference in iterations between C-AFSA and AH-AFSA is relatively small, with both being kept within 40 iterations. Additionally, the iterations of AH-AFSA can be limited to within 10 iterations at some operating conditions, indicating that the search efficiency of AH-AFSA is slightly better than that of C-AFSA. This is because AH-AFSA can directly search the discrete decision variables in the binary discrete space, while C-AFSA first converts the binary discrete variables into integers and searches for the optimal solution in the continuous space, then rounds the optimal result and converts it into binary variables. In comparison, AH-AFSA does not involve an approximate rounding process, making it more efficient in solving the integer programming problem (ON/OFF sequence).

Comparing the computing time, it is observed that the AH-AFSA algorithm requires the shortest time to obtain the optimal solution. For the AHDE algorithm, the computation time for all operating points ranges from 18 to 25 seconds, with an average of 21 seconds per operating point. The iteration of AH-AFSA can be completed within 10 seconds at most operating conditions, while the computing time of C-AFSA ranges from 10 to 27 seconds. Although the difference in iterations between C-AFSA and AH-AFSA algorithms is not obvious, the computing time of the former is relatively longer, indicating that AH-AFSA has higher computational efficiency.

Although the basic parameter settings of the C-AFSA and AH-AFSA algorithms are consistent in this research, the application frameworks of these two algorithms are significantly different. Therefore, the results illustrated in Fig. 14 also indicate that algorithm computational efficiency can be effectively improved under the multi-agent framework, with relatively less time cost for each iteration.

4.2. Annual energy consumption

Fig. 15 illustrates the itemized annual electricity consumption of the HVAC system under different optimization methods, with percentages indicating the energy savings of AH-AFSA relative to the other methods for the same subitem. The annual electricity consumption of the three intelligent algorithms is relatively close, with the relative energy savings of the AH-AFSA method being 2.5% and 0.9% compared to the C-AFSA and AHDE methods, respectively, and as high as 18.9% compared to the conventional Constant method.

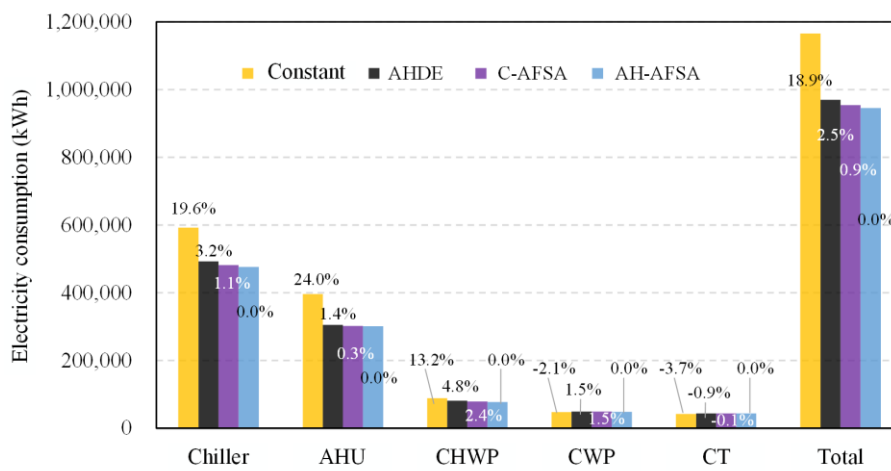


Fig. 15 The subitems of the system electricity consumption in the annual cooling season

Regarding the electricity consumption of the chillers, AHUs, and chilled water pumps, the relative energy savings of the AH-AFSA method compared to the conventional Constant method are 19.6%, 24.0%, and 13.2%, respectively. While the electricity consumption of AH-AFSA in terms of the cooling water pumps and cooling tower fans is slightly higher than that of the Constant method, this is not consistent with the common expectation that the energy consumption of all components would be reduced. This discrepancy arises because the optimization objective in our research is to search for optimal results for the entire HVAC system based on the trade-off characteristics among components. From the perspective of overall energy efficiency, it is more beneficial to appropriately increase the cooling water flow and cooling tower air flow to improve the overall energy efficiency of the HVAC system. The results also demonstrate that intelligent methods are capable of achieving global optimization by balancing energy efficiency between individual components and the whole system, even if it means sacrificing the energy efficiency of certain components such as cooling water pumps and cooling tower fans.

4.3. Computational efficiency

In Section 4.1, the computational efficiency of the three intelligent algorithms in daily performance has been compared and discussed. To further compare the differences in computational performance between centralized and distributed algorithms in solving the global optimization problem of HVAC systems, the performance of C-AFSA and AH-AFSA on computational efficiency is compared in detail.

The principles of these two algorithms are similar, and the basic parameter settings are identical. The main difference between these two algorithms is that C-AFSA is designed for centralized framework, while AH-AFSA is designed for multi-agent framework. Therefore, the computational performance of these two algorithms can represent the performance of algorithms under centralized and distributed frameworks, respectively.

Fig. 16 illustrates the iterations of the C-AFSA and AH-AFSA algorithms under annual cooling conditions, with corresponding statistical results presented in Table 6. Analysis of the data reveals that 60.3% of all operating condition points reach the optimal solution within 20 iterations for AH-AFSA, totaling 1765 instances. Additionally, 3.2% of operating conditions achieve the optimal solution within 60 to 80 iterations. In comparison, for C-AFSA, the respective proportions are 50.6% and 4.4%. Despite AH-AFSA demonstrating slightly superior performance in terms of iterations according to the statistical results, the overall difference between these two algorithms is not significant.

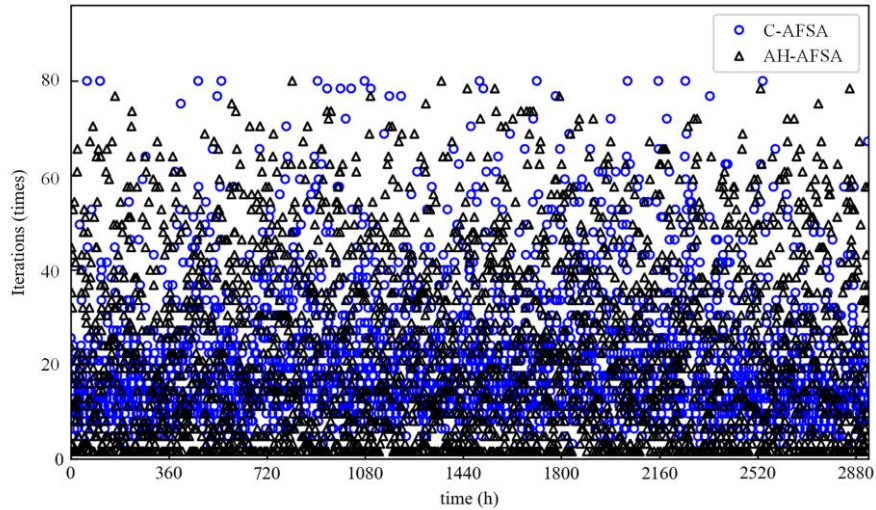


Fig. 16 Comparison results of iteration between the centralized and multi-agent methods

Table 6 Statistical results of iterations

Iteration (times)	0 ~ 20	20 ~ 40	40 ~ 60	60 ~ 80
C-AFSA	1482 (50.6%)	887 (30.3%)	428 (14.6%)	130 (4.4%)
AH-AFSA	1764 (60.3%)	878 (30.0%)	190 (6.5%)	95 (3.2%)

Fig. 17 displays the computing time required to solve the optimal solution using the two algorithms during the annual cooling season, with corresponding statistical results provided in Table 7. It's evident from the figure that AH-AFSA outperforms C-AFSA significantly in terms of computing time, with the vast

majority of operating conditions being completed within 15 seconds. Statistical analysis indicates that 89.0% of operating conditions can be optimized within 10 seconds using AH-AFSA, and all conditions can be completed within 20 seconds. In contrast, the computing time of the C-AFSA algorithm varies, occasionally reaching 40 to 60 seconds for certain conditions. Overall, AH-AFSA completes the annual optimization in 35399.9 seconds, with an average computing time of 12.2 seconds per operating condition, while C-AFSA requires 71905.2 seconds, averaging 26.5 seconds per condition. AH-AFSA achieves a 54.0% reduction in computing time compared to C-AFSA.

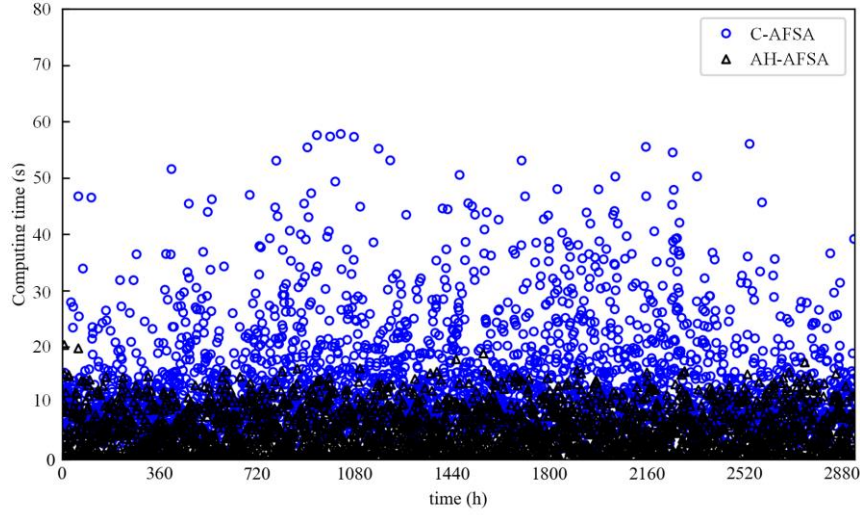


Fig. 17 Comparison results of computing time between the centralized and multi-agent methods

Table 7 Statistical results of the algorithm computing time

Computing time (s)	0 ~ 10	10 ~ 20	20 ~ 40	40 ~ 60
C-AFSA	1394 (47.6%)	1051 (35.9%)	390 (13.3%)	90 (3.1%)
AH-AFSA	2606 (89.0%)	321 (11.0%)	0 (0.0%)	0 (0.0%)

In summary, the analysis above demonstrates that AH-AFSA slightly surpasses the other two intelligent algorithms, C-AFSA and AHDE, in terms of accuracy and energy-saving potential. This superiority stems from AH-AFSA's ability to explore discrete decision variables in binary space, whereas the other algorithms derive optimal discrete variables using SysConvert and rounding methods. Despite minor differences in energy-saving potential among the three algorithms in the annual cooling season simulation, AH-AFSA exhibits significantly better computational efficiency. A comparison of AH-AFSA and C-AFSA, both based on AFSA but applied to different frameworks (multi-agent and centralized), reveals a 54.0% reduction in time cost for the multi-agent framework. This advantage arises from the multi-agent framework's ability to decompose complex optimization problems into sub-problems, facilitating collaborative optimization among agents and ultimately improving algorithm efficiency.

The benefits of the multi-agent framework extend beyond computational efficiency to enhance operating and debugging of HVAC systems. As system configurations become more complex and computational loads heavier, scalability and plug-and-play capability become crucial under centralized framework. In contrast,

the multi-agent framework offers layering and modularization characteristics, with methodologies that are generalizable and replicable. This framework also enhances fault tolerance and robustness during system operation and debugging, thereby boosting the productivity of intelligent methods in larger and more complex HVAC systems in the future. Recent research on agent-based optimization techniques is increasingly focusing on data-driven techniques due to their ability to learn from dynamic environments and improve over time. These techniques may have better accuracy on addressing complex dynamic optimization in HVAC system. However, for the parametric optimization problems in this research, the heuristic optimization methods still remain highly effective. Compared to the advanced data-driven techniques, such as reinforcement learning, the proposed heuristic algorithm offers critical advantages, including easy implementation, lower computational requirements, and no demand for extensive training data. These strengths are particularly valuable when applied in the controllers of practical HVAC systems.

5. Conclusions

This paper addresses the decrease in computational efficiency of optimization methods for HVAC systems under centralized framework due to increased system complexity. Based on the interacting characteristics among system components, a multi-agent-based collaborative optimization method is proposed to address the energy efficiency trade-off issues of complex HVAC systems containing parallel units with multiple capacities. The reliability of the proposed method is demonstrated through simulation research on a practical HVAC system, focusing on computational efficiency and energy savings potential. The following conclusions can be drawn:

(1) The proposed method decomposes complex optimization problems into several simpler subproblems and efficiently solves them. Additionally, it performs strong reconfigurability, enabling it to accommodate systems with varying complexities and optimization objectives.

(2) In terms of energy-saving potential, the proposed collaborative optimization method can save approximately 18.9% of electricity consumption compared to conventional methods. When compared to other intelligent methods based on C-AFSA and AHDE, its relative energy saving is only 2.5% and 0.9%, respectively.

(3) Regarding computational efficiency, the proposed multi-agent-based algorithm (AH-AFSA) significantly outperforms the centralized algorithm (C-AFSA) with an average computing time of 12.2 seconds for each operating condition, saving about 54% of the time cost compared to C-AFSA under centralized framework.

While the proposed collaborative optimization method has been validated on a real multi-agent system, its comparison research has been limited to the conventional and AFSA-based methods. Future research will explore superior methods within an agent-based framework, assessing their performance through practical system implementations. The agent-based framework will be implemented using Raspberry Pi or other suitable hardware to communicate with real HVAC components.

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