IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 17, 2019, accepted April 21, 2019, date of publication May 22, 2019, date of current version May 31, 2019.

*Digital Object Identifier 10.1109/ACCESS.2019.2913359*

# A Decentralized Swarm Intelligence Algorithm for Global Optimization of HVAC System

**SHIQIANG WANG[1], JIANCHUN XING[1], (Member, IEEE), ZIYAN JIANG[2], AND YUNCHUANG DAI[2]**

[1]College of Defense Engineering, Army Engineering University of PLA, Nanjing 210001, China
[2]Building Energy Research Center, Tsinghua University, Beijing 100000, China

Corresponding author: Jianchun Xing (xjc@893.com.cn)

This work was supported in part by the National Key Research and Development Program of China under Grant 2017YFC0704100.

**ABSTRACT** To solve the high labor and maintenance cost while save energy problems in actual engineering, a decentralized control structure and optimization method for the heating, ventilation, and air conditioning (HVAC) systems are proposed. In this decentralized HVAC control system, each updated smart equipment is connected according to the physical correlations and can communicate with adjacent nodes collaboratively. Furthermore, a novel fully distributed and self-organizing swarm intelligence optimization algorithm is presented. And the algorithm runs in each smart equipment to achieve the optimal operation and avoid the conflict among correlated equipment. Moreover, the convergence property of the novel method is analyzed theoretically. This method is confirmed effective for realizing the global optimal operation of HVAC system through simulation results and hardware tests on actual engineering.

**INDEX TERMS** HVAC system, global optimization, decentralized swarm intelligence, energy conversation.

## I. INTRODUCTION

The optimal operation of HVAC systems is critical due to their common application in building engineerings. An heating, ventilating, and air-conditioning (HVAC) system is a multi-variable, strongly coupled large scale system. Each system comprises a set of interconnected subsystems, including the heating and cooling plants, the ventilation system, and one or more zones served by the terminal units of the ventilation system. Each subsystem consists of several components, such as sensors, electrical and mechanical actuators, and controllers [1]. The energy consumption of air-conditioning systems accounts for a large proportion of the total energy consumption in buildings, thus it is important to improve the energy efficiency of such systems [2]. A small increase in system operating efficiency can result in substantial energy conversation. Much research has been done on HVAC control, including simulation and experiment. However, the deployment of advanced controls in buildings has been progressing very slowly [3].

Currently, in the practical HVAC system operation engineerings, the typical control variables (such as cooling and chilled water temperature, supply air temperature) are always set as constant. However the automatic control provisions and even the computerized building management systems have been mainly provided for full load settings, and not necessarily part load situations [1]. And the cooling load is always changing in the buildings, therefore HVAC system cannot operate in the optimal condition such that extra energy is consumed in most time. There have been many research works reported for improving either individual component efficiencies or partial system efficiencies, not considering the global optimization of total HVAC system [4]–[6]. Due to the multi-variable, large-scale and nonlinear characteristics of HVAC system optimization, the above methods either fix some control variables or overlook some control equipments to reduce the complexity. Obviously, the simplified methods cannot achieve the global optimization of HVAC system.

Several researchers have devoted to a global HVAC system optimization for minimizing the energy consumption. Lu *et al.* proposed a global optimization for overall HVAC systems in [7], [8]. Besides, a number of studies focused on the real-time optimization algorithm of HVAC systems such as classic linear/quadratic programming [9], or gradient-based iterative methods [10], mixed-integer linear programming (MILP) [11]. Recently, to address the complexity of large-scale HVAC systems, advanced optimization algorithms have also been developed, such as evolutionary algorithms [12], particle swarm optimization (PSO) algorithm [13], [14], radial basis function neural network (RBFNN) [15], expert control [16] and other computational intelligence techniques [17]. Besides, a modified genetic

The associate editor coordinating the review of this manuscript and approving it for publication was Jie Tang.

algorithm is devised for a mix-integer nonlinear constraint optimization problem to find optimal set points to minimize the overall system energy consumption [18].

Further, an event-driven optimization (EDO) method for HVAC system is proposed in [19]. And a multiple objective optimization model considering the energy consumption and indoor air quality(IAO) also is developed [20], [21]. Previous studies have shown that the global optimization of HVAC systems is able to exploit complex interactions between physical variables and their dynamics to achieve substantial energy savings (up to 10%) without sacrificing air quality and thermal comfort [22]–[25].

However, an HVAC system is highly complex and nonlinear, with a large-scale control system that is spatially and temporally distributed. The current centralized control architecture for HVAC systems has several deficiencies during construction and operation. In actual projects, the proprietor has to rely on a system integrator for HVAC control systems. In this case, network construction is a complex and time-consuming process because a considerable amount of secondary development, such as configuration and commissioning, is necessary onsite. Besides, a global HVAC system model needs to be established which is always difficult. In the key procedure, the control algorithm and model is written into the centralized controller, which needs to be reprogrammed from case to case because the system configuration or device type changes. Thus, the design and deployment of centralized control systems requires a tedious and time-consuming manual calibration procedure. Even in some cases, a central controller is unfeasible and exceedingly demanding [14].

During practical operations, a centralized method needs information transmission to the supervising computer for control and alarm processes, which can cause grievous link congestion and operational lag. The implementation of centralized methods also encounters difficulties when the scale of system increases. Once the central node breaks down, the entire system cannot continuously process the information and always develops chain breaks. To date, most HVAC control systems are not fully operational and only decorative.

In some senses, the conventional centralized structure has become a barrier in the HVAC control systems; hence the desired HVAC industry requires a new platform. This new platform should be open, flexible, and plug-and-play to enable easy installation with low configuration cost.

Recently, some distributed HVAC system control structure and optimization method is proposed [26]. But the distributed optimization method still needs a coordinator agent. And it is based on the multi-agent consensus algorithm, thus is only applicable to single cooling or chilled water circulating system [3]. But it is still not feasible for a global HVAC system. What's more, the above method didn't consider the non-convex characteristics of HVAC system. In addition, to reduce the computational burden of HVAC optimal control, [14] proposed a multiplexed real-time optimization method, but it usually introduces artificial disturbances.

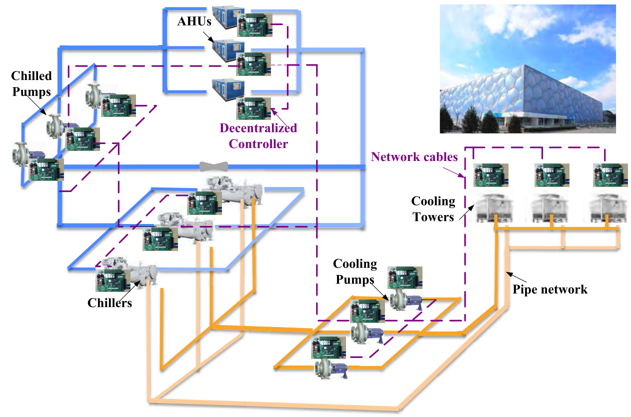


**FIGURE 1.** Decentralized HVAC control structure in the Water Cube.

Motivated by this observation, a novel decentralized control structure and optimal operation method in HVAC system is proposed to meet theoretical challenges and practical needs. The term decentralized in this study will denote a solution which is fully distributed without any form of central coordination, which evolves by local interaction. In this new network structure, each equipment is fitted with a microprocessor unit such that it becomes a smart agent. The field engineer would only need to configure the inter-agent connections and plug-and-play [27]. In the proposed decentralized optimal operation method, each smart equipment can communicate with adjacent nodes and operate collaboratively to complete optimal operation without monitoring host. The method provided good scalability and its energy savings were comparable with the traditional approaches.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

The following simplifications were made: (i) all equipments are insulated; (ii) there was no heat transfer between fans and pumps; (iii) the air state in the duct and each room was the same so that the system could be treated as a lumped parameter system; (iv) the kinetic and potential energies of air molecules were insignificant and neglected; (v) the influence of moisture in the air was ignored. The cooling load of each conditioned terminal $\mathrm{Q_L}$ can be calculated by measured data from the control system. And $Q_L$ can be measured and calculated and treated as constants for the optimization process during one sample period.

Taken the HVAC system in the Water Cube of Beijing, China as an example, the detailed system structure and its decentralized control system is illustrated in Fig. 1. In the HVAC system, three parallel chillers supply chilled water to air-handling units (AHUs) for critical zones A, B and C by three chilled pumps. Besides, there are three cooling pumps provide power for cooling water to flow to three cooling towers with double fans. And in the decentralized control structure, each equipment is updated as a smart agent by a microcontroller embedded in, and is connected through network cables corresponding to the pipe and duct network as illustrated in the purple dotted line in Fig.1. Then, these scattered equipment nodes can be correlated as an organic and flat network. As seen from Fig.1, the control network topology is closely mapped from the actual system physical layout. This makes the controller setup process more straightforward.

Besides, in this HVAC control structure, each smart equipment has its own performance (utility) function which is written into the corresponding decentralized controller chip before it leaves the factory.

### A. SYSTEM MODEL

Firstly, the specific cost functions of each equipment are described as follows.

#### 1) COST FUNCTION

##### a: CHILLER

Chiller is the key point which connects cooling water and chilled water systems. It transfers heat from the chilled water to the condensing water. And its energy consumption is affected by evaporating temperature, condensing temperature and cooling load [28]. The evaporating temperature is related with the supply chilled water temperature and the condensing temperature is related with the entering cooling water temperature. The coefficient of performance (COP) is usually used to describe a chiller's performance, which is defined as chiller's capacity over its power consumption. COP could be described as the quadratic polynomial shown as

$$\begin{aligned} COP = a_1 + a_2 \cdot PLR + a_3 \cdot T_e + a_4 \cdot T_c \\ + a_5 \cdot PLR^2 + a_6 \cdot T_e^2 + a_7 \cdot T_c^2 + a_8 \cdot PLR \cdot T_e \\ + a_9 \cdot PLR \cdot T_c + a_{10} \cdot T_e \cdot T_c \end{aligned} \quad (1)$$

where $PLR$ is the partial load ratio, $T_{CWS}$ is the entering cooling water temperature,°; $T_{CHWS}$ is the supply chilled water temperature,°; $a_0 \sim \mathrm{a}_{10}$ is the model fitting parameters. Based on the test data in the actual engineering, the fitting parameters can be determined and written in the chiller agent. During the operation, $T_{CWS}$ and $T_{CHWS}$ can be obtained by the temperature sensors. And the chilled and cooling water flow rate can be received from the chilled and cooling pump agent.

##### b: CHILLED PUMP

Pumps provide power for water to flow in water cycle system. There are two types of pumps–chilled water pump and cooling water pump. These two pumps have the same model but different coefficients based on the property of chilled and cooling water. The energy consumption of VSD (variable speed drive) chilled pumps can be formulated as [7]:

$$\begin{aligned} P_{CHWpump} &= \frac{\rho_w \cdot g \cdot m_{CHW} \cdot H_{CHW}}{\eta_{CHW}} \\ &= \frac{\rho_w \cdot g \cdot m_{CHW} \cdot H_{CHW}}{f_{CHW}(m_{CHW}, H_{CHW})} \end{aligned} \quad (2)$$

where $m_{CHW}$ is the supply chilled water flow rate, $m^3/h$. The speed ratio $w$ for each pump is described in (4) and $w_0$ is the lower limitation of the speed ratio.

$$w = n/n_0 (w_0 < w < 1) \quad (3)$$

where $n_0$ is the rated pump speed and $n$ is the pump speed under non-rated conditions.

For centrifugal pumps, the operation curves between the pump head $H_{CHW}$, flow rate $m_{CHW}$ and pumps efficiency $\eta_{CHW}$ at all working conditions can be expressed as

$$H_{CHW} = b_0 m_{CHW}^2 + b_1 w m_{CHW} + b_2 w^2 \quad (4)$$

and

$$\eta_{CHW} = c_0 \left(m_{CHW}/w\right)^2 + c_1 \left(m_{CHW}/w\right) + c_2 \quad (5)$$

Based on the test data in the actual engineering, the fitting parameters can also be determined and written in the chiller agent.

If the pressure difference $H_{CHW}$ is determined, the total chilled water flow rate $m_{CHW}$ can be obtained by equation (6). After that pump frequency $w$ can be calculated by equation (4).

$$H_{CHW} = S_{CHW} (\sum m_{CHW,i})^2 \quad (6)$$

where $S_{CHW}$ is the resistance of the current pipe net. Note that $S_{CHW}$ can be determined if the operating number of chillers and opening degree of each valve in AHU.

##### c: COOLING PUMP

The cooling pump is also equipped with VSD in the Water Cube HVAC systems. As the above analysis, the cost function of VSD cooling pump is

$$P_{CWpump} = \frac{\rho_w \cdot g \cdot m_{CW} \cdot H_{CW}}{\eta_{CW}} = \frac{\rho_w \cdot g \cdot m_{CW} \cdot H_{CW}}{f_{CW}(m_{CW}, H_{CW})}, \quad (7)$$

where $m_{CW}$ is the supply cooling water flow rate, $m^3/h$. And the operation curves between the pump head $H_{CW}$, flow rate $m_{CW}$ and pumps efficiency $\eta_{CW}$ at all working conditions can be expressed as

$$H_{CW} = d_0 m_{CW}^2 + d_1 w m_{CW} + d_2 w^2 \quad (8)$$

and

$$\eta_{CW} = e_0 m_{CW}^2 + e_1 m_{CW} + e_2 \quad (9)$$

The fitting parameters $d_0$, $d_1$,$d_2$ and $e_0$, $e_1$, $e_2$ can be determined and written in the cooling pump agent based on the test data in the actual engineering.

If the pressure difference $H_{CW}$ is determined, the control system will calculate the total water flow rate $m_{CW}$ can be obtained by equation (10). After that pump frequency $w$ can be calculated by equation(8).

$$H_{CW} = S_{CW} (\sum m_{CW,i})^2 \quad (10)$$

where $S_{CW}$ is the resistance of the current pipe net. Note that $S_{CW}$ can be determined if the operating number of chillers and cooling towers.

#### *d: AHU FAN*

AHU fan is the main energy consumption component in an AHU. For cooling coil fans equipped with VSD, the characteristics of performance are similar to those of chilled water pumps, and therefore, their models have almost the same format. And its cost function can be described as [7]

$$P_{AHU} = \frac{m_{SA} \cdot H_{SA}}{\eta_{SA}} = \frac{m_{SA} \cdot H_{SA}}{f_{SA}(m_{SA}, H_{SA})}, \tag{11}$$

where $m_{SA}$ is the AHU air flow rate, $m^3/h$. The speed ratio $u$ for each fan is described in (12) and $u_0$ is the lower limitation of the speed ratio.

$$u = m/m_0(u_0 < u < 1) \tag{12}$$

where $m_0$ is the rated fan speed and $m$ is the fan speed under non-rated conditions. And the operation curves between the fan head $H_{SA}$, flow rate $m_{SA}$ and fan efficiency $\eta_{SA}$ at all working conditions can be expressed as:

$$H_{SA} = j_0 m_{SA}^2 + j_1 u m_{SA} + j_2 u^2, \tag{13}$$

$$\eta_{SA} = g_0 m_{SA}^2 + g_1 \cdot m_{SA} \cdot u + g_2 \cdot u^2. \tag{14}$$

If the static pressure $H_{SA}$ is determined, the control system will calculate the total air flow rate $m_{SA}$ can be obtained by equation (15). After that fan frequency $w$can be calculated by equation(13).

$$H_{SA} = S_{SA}(\sum m_{SA,i})^2 \tag{15}$$

where $S_{SA}$ is the resistance of the current pipe net. Note that $S_{SA}$ can be determined if the opening degree of each air damp on VAV box.

#### *e: COOLING TOWER FAN*

The cooling tower is responsible for the heat exchange between water and outdoor air. The cooling water exchanges heat with outdoor air by fans such that the cooling water temperature is decreased. Thus, the cooling tower fan is the major energy consumption component. The power consumption of fan can be considered as a function of one independent variable, air flow rate. Thus, the energy consumption of cooling tower fan can be formulated in relatively simple format as [7]

$$P_{CT} = l_0 + l_1 m_a + l_2 m_a^2, \tag{16}$$

where $m_a$ is the cooling tower air flow rate, $m^3/h$;$l_0$, $l_1$, $l_2$ are the parameters can be approximated by polynomials, or any other curve fitting representations.

In addition, the duct and pipe networks are the important components in an HVAC system that connects different devices. And the pressure loss across each segment of the pipes and valves can be obtained by on-site testing data [28]. In addition, an alternative method is to use the available information at each end unit and to resolve the problem through artificial neural network [20].

The energy consumption of HVAC system is related with multiple variables. Any change of one of variable will influence the efficiency of the whole HVAC system, and they are constrained and correlated by the physical relationships. In general, there are two types of constraints: physical limitations of components and interaction between components [17] and are established as follows.

### 2) CONSTRAINTS ESTABLISHMENT

#### *a: BOUNDARY CONSTRAINTS*

*Supply chilled (cooling ) water temperature:*

$$\begin{aligned} T_{CHWS,\min} &\le T_{CHWS} \le T_{CHWS,\max} \\ T_{CWS,\min} &\le T_{CWS} \le T_{CWS,\max}, \end{aligned} \tag{17}$$

where $T_{CHWS,min}$ and $T_{CWS,min}$ are the low limit of supply chilled and cooling water temperature, and $T_{CHWS,max}$ and $T_{CWS,max}$ are the upper limit of supply chilled and cooling water temperature.

*Chilled and cooling water flow rate:*

$$\begin{aligned} m_{CHW,\min} &\le m_{CHW} \le m_{CHW,\max} \\ m_{CWS,\min} &\le m_{CW} \le m_{CW,\max}, \end{aligned} \tag{18}$$

where $m_{CHW,min}$ and $m_{CW,min}$ are the low limit of chilled and cooling water flow rate, and the $m_{CHW,max}$ and $m_{CWS,max}$ are the upper limit of chilled and cooling water flow rate.

*Air flow rate on AHU and cooling tower:*

$$\begin{aligned} m_{SA,\min} &\le m_{SA} \le m_{SA,\max} \\ m_{a,\min} &\le m_a \le m_{a,\max}, \end{aligned} \tag{19}$$

where $m_{SA,min}$ and $m_{a,min}$ are the low limit of AHU and cooling tower air flow rate, and the $m_{SA,max}$ and $m_{a,max}$ are the upper limit of AHU and cooling tower air flow rate.

#### *b: CORRELATED CONSTRAINTS*

The correlations among different devices are mainly embodied in the corresponding heat exchange models as follows.

1) The interaction between AHU and chilled pump can be described by the heat exchange model on the cooling coils. And, the heat transfer model of AHU cooling coils is [29]

$$Q_L = \frac{p_0 m_{SA}^q}{1 + p_1 \left(\frac{m_{SA}}{m_{CHW}}\right)^q} \left(T_{MA} - T_{CHWS}\right), \tag{20}$$

where $T_{MA}$ is the mixed air temperature. This model does not need iterative computations, which makes it suitable for real time implementation. In this model, no geometric data of coils are required and only three empirical parameters ($p_0$, $p_1$ and $r$) need to be identified from manufacture catalog data or experiment data.

2) The interaction between chillers and chilled pump is based on the mass and energy conservation equation as

$$Q_L = m_{CHW} \cdot c_{pw} \cdot (T_{CHWR} - T_{CHWS}). \tag{21}$$

where $Q_L$ is the cooling load, $kW$, $c_{pw}$ is the water specific heat capacity, which is 4.186 kJ/(kg·°),$m_{\mathrm{CHW}}$ is the water mass flow rate, kg/s, $\rho$ is the water density, which is 1000kg/m$^3$(4°), $v$ is the water flow rate, $m^3/h$, $T_{CHWR}$ is the return chilled water temperature.

3) The interaction between chillers and cooling pump is also based on the mass and energy conservation equation as

$$Q_L = m_{CW} \cdot c_{pw} \cdot (T_{CWR} - T_{CWS}), \tag{22}$$

where$T_{CWR}$ is the return cooling water temperature.

4) The interaction between cooling tower and cooling pump can be described by the heat exchange model as

$$Q_L = \frac{r_0 m_{CW}^t}{1 + r_1 \left(\frac{m_{CW}}{m_a}\right)^t} \left(T_{CWR} - T_{wb}\right), \tag{23}$$

where $T_{wb}$ is the wet bulb temperature outdoor. The parameters ($r_0$, $r_1$ and $t$) are identified from manufacture catalog data or experiment data.

As seen from formula (16), the energy consumption on cooling tower fan can be decreased by increasing the supply cooling water flow rate. But the cooling pump energy consumption would increase. Thus, the cooperation of cooling tower and cooling pump is also correlated with each other.

Further, in decentralized control framework, each equipment only knows the energy consumption itself and its correlated constraints. Thus, its formulation of optimal operation can be reconstructed as follows:

*Chiller agent optimization:*

For the HVAC system in the Water Cube, the chiller type is centrifugal and the rated cooling load $Q_L = 2813$kW, the rated power is $N = 535$kW. Its utility function can be formulated as

$$\begin{aligned}
&\min P_{chiller}(T_{CHWS}, T_{CWR}) = Q_L/COP \\
&s.t. Q_L = \frac{p_0 m_{SA}^q}{1 + p_1 \left(\frac{m_{SA}}{m_{CHW}}\right)^q} \left(T_{MA} - T_{CHWS}\right) \\
&\text{(Coolingcapacity on AHU cooling coil)} \\
&Q_L = \frac{r_0 m_{CW}^t}{1 + r_1 \left(\frac{m_{CW}}{m_a}\right)^t} \left(T_{CWR} - T_{wb}\right) \\
&\text{(Coolingcapacity on cooling tower cooling coil)}
\end{aligned} \tag{24}$$

where and $29 \leq T_{CWR} \leq 35$(°C), and the fitting parameters can be determ $4 \leq T_{CHWS} \leq 9$ ined as $a_1 = 14.43, a_2 = 9.58, a_3 = 0.40, a_4 = -0.54, a_5 = -12.02, a_6 = 0.02, a_7 = 0.01, a_8 = -0.09, a_9 = 0.22, a_{10} = -0.01$ based on the test data in the actual engineering and written in the cooling chiller agent.

*Chilled pump agent optimization:*

The chilled pump type is G360-40-55NY and the rated flow rate $W = 365m^3/h$, rated pressure difference $H = 36.5$m$H_2O$. Its utility function can be formulated as

$$\begin{aligned}
&\min P_{CHWpump}(H_{CHW}) \\
&s.t. Q_L = \frac{p_0 m_{SA}^q}{1 + p_1 \left(\frac{m_{SA}}{m_{CHW}}\right)^q} \left(T_{MA} - T_{CHWS}\right) \\
&\text{(Cooling capacity on AHU cooling coil)}
\end{aligned} \tag{25}$$

where $15 \leq H_{CHW} \leq 30(mH_2O)$ and the fitting parameters $b_0, b_1, b_2$ and $c_0, c_1, c_2$ can also be determined as $b_0 = -8e-5, b_1 = 0.0299, b_2 = 29.344, c_0 = -3e-6, c_1 = 0.0026, c_2 = 0.2015$ based on the test data in the actual engineering and are written in the chilled pump agent.

*Cooling pump agent optimization:*

The cooling pump type is G600-40-110NY and the rated flow rate $W = 637m^3/h$, rated pressure difference $H = 38.2$m$H_2O$. Its utility function can be formulated as

$$\begin{aligned}
&\min P_{CWpump}(H_{CW}) \\
&s.t. Q_L = \frac{r_0 m_{CW}^t}{1 + r_1 \left(\frac{m_{CW}}{m_a}\right)^t} \left(T_{CWR} - T_{wb}\right) \\
&\text{(Cooling capacity on cooling tower cooling coil)}
\end{aligned} \tag{26}$$

where $40 \leq P_{CP} \leq 60$(m$H_2O$) and the fitting parameters $d_0$, $d_1$,$d_2$ and $e_0$, $e_1$, $e_2$ can be determined as $d_0 = -7.5e-5, d_1 = 0.0316, d_2 = 32.524, e_0 = -2.3e-6, e_1 = 0.0032, e_2 = 0.5037$ based on the test data in the actual engineering and written in the cooling pump agent.

*AHU agent optimization:*

The heat recovery AHU's utility function can be formulated as

$$\begin{aligned}
&\min P_{AHU}(H_{SA}) \\
&s.t. Q_L = \frac{p_0 m_{SA}^q}{1 + p_1 \left(\frac{m_{SA}}{m_{CHW}}\right)^q} \left(T_{MA} - T_{CHWS}\right) \\
&\text{(Cooling capacity on AHU cooling coil)}
\end{aligned} \tag{27}$$

where $300 \leq P_{AHU} \leq 500$(Pa) and the fitting parameters $j_0, j_1, j_2$ and $g_0, g_1, g_2$ can be determined as $j_0 = -0.5, j_1 = 6.299, j_2 = 500.344, g_0 = -0.0025, g_1 = 0.0955, g_2 = 2.5e-3$ based on the test data in the actual engineering and written in the cooling AHU agent.

*Cooling tower agent optimization:*

The cooling tower type is CEF-700 and the rated cooling load $Q_L = 3375$kW. Its utility function can be formulated as

$$\begin{aligned}
&\min P_{CT}(m_a) \\
&s.t. Q_L = \frac{r_0 m_{CW}^t}{1 + r_1 \left(\frac{m_{CW}}{m_a}\right)^t} \left(T_{CWR} - T_{wb}\right) \\
&\text{(Cooling capacity on cooling tower cooling coil)}
\end{aligned} \tag{28}$$

where $1.2e5 \leq m_a \leq 1.5e5$($m^3$/h) and parameters $l_0, l_1, l_2$ are determined as $l_0 = 16.10, l_1 = 10.14, l_2 = 11.51$ based on the test data in the actual engineering. In the actual engineering, the air flow rate $m_a$ supplied by cooling tower fan which can be obtained by fan frequency indirectly is selected as the control variable.

Besides, the number of operating chillers, pumps and cooling towers can be determined by the total cooling load and the nominal cooling load of each equipment. The distribution of the total cooling load to each equipment is proportional to the nominal cooling load which can be solved in a distributed way as in [30]. After that, the key problem lies in how to achieve the optimal coordination among AHU fan, chilled pump, chiller, cooling pump and cooling tower.

It can be seen that different equipments performance function is correlated by the heat exchange equation on AHU and cooling tower cooling coils. For example, the cooling capacity in the cooling coils on an AHU involves the air flow rate and temperature supplied by the AHU fan, the chilled water flow rate by chilled pump and the supply chilled water temperature by chiller. In other words, different decision variables are coupled in the decentralized optimizations (24),(25) and (27).

Further, as seen from formula (24), the energy consumption of chillers can be decreased by increasing the supply chilled water temperature $T_{CHWS}$. But the chilled water flow rate supplied by chilled pump should be increased to provide the same cooling load $Q_L$. In such way, the pump energy consumption would increase according to the cost function (25) of the chilled pump. Thus, the cooperation of chillers and chilled pump can affect the total energy consumption of HVAC, and there exist an optimum between chillers and chilled pumps. And there exist an optimum between chillers and chilled pumps.

Similarly, the energy consumption on cooling tower fan can be decreased by increasing the supply cooling water flow rate as described in (28). But the cooling pump energy consumption (26) would increase. Thus, the cooperation of cooling tower and cooling pump is also correlated with each other.

When the cooling load $Q_L$ is given, the purpose of decentralized optimal operation is to minimize global electric power of the entire system (cost function) as

$$\min P_{total} = P_{chiller} + P_{CHWpump} + P_{CWpump} + P_{AHU} + P_{CT}, \tag{29}$$

by different agents optimal coordination and cooperation. Through the above analysis, HVAC optimization is a multi-variable and nonlinear problem which can be abstracted as

$$P_{total} = f(m_{SA}, m_{CHW}, T_{CHWS}, T_{CHWR} \times, m_{CW}, T_{CWR}, T_{CWS}, m_a, i, j, k) \tag{30}$$

Furthermore, if the chilled water flow rate, the supply chilled water temperature and cooling load are given, the return chilled water temperature can be determined by equation (21). And if the cooling water flow rate, cooling water temperature and cooling load are given, the return cooling water temperature can also be determined by equation (22). Thus, the supply chilled water temperature, chilled water flow rate, cooling water flow rate, air flow rate of cooling tower fan and air flow rate of AHU fan are selected as control variables (decision variables) in this study,. In other words, the energy consumption only involves 6 independent variables as:

$$P_{total} = f(m_{SA}, m_{CHW}, T_{CHWS}, m_{CW}, T_{CWS}, m_a, i, j, k). \tag{31}$$

### B. PROBLEM FORMULATION

From mathematical perspective, each equipment has its own utility and decision variable set. And it can be abstracted as (32)-(34). For agent$i(i = 1, 2, .., n)$,

$$\min_{\{x_i\}} f_i(x_i) \tag{32}$$

$$s.t. g_i(x_i|x_{ij,i}) \leq 0 \tag{33}$$

$$h_i(x_i|x_{ij,i}) = 0, j \in N_i \tag{34}$$

where convex or non-convex $f(x_i)$ is the cost function of agent $i$ and cannot be known or shared by other agents. Constraints (33)-(34) can denote the local physical constraints, such as energy, mass, and momentum conservation equation. And the notation $g_i(x_i|x_j)$, $h_i(x_i|x_j)$ represents the function of $x_i$ in which the neighborhood state $x_j$ is fixed. The local constraints in (33)-(34) only involve its neighborhood variables, *e.i.* the decentralized optimization problems are local coupling.

Note that problem (32)-(34) is different from the abstractions formulated by [31], because each agent has several local linear and nonlinear local coupling constraints. And the decision variable $x_i$ of agent $i$ only involves the local agents but not the whole system information. The new knowledge differentiates our work from previous work.

And (32)-(34) can be taken as the decentralized optimization with penalty function as

$$F_i(x_i, x_j) = f_i(x_i) + \sum_{j \in N_i} G_j(x_j, x_i), i \in \nu \tag{35}$$

where $G_j$ denotes the betray degree of population $x_i$ on constraint $j$ The utility function (35) not only includes each agent's cost function but also the penalty term involving $x_i$.

The purpose of this paper is to design an algorithm by only local interaction between (35) on each updated smart equipment but can obtain a global optimum point approaching to the centralized fashion as

$$\min_{\{x\}} \sum_{i \in \nu} f_i(x) \tag{36}$$

$$s.t. g_r(x) \leq 0, r = 1, 2, \ldots, p \tag{37}$$

$$h_t(x) = 0, t = 1, 2, \ldots, q, \tag{38}$$

where the centralized objective function is the summary of all the agents' cost functions. Problem (36)-(38) can also be formulated in penalty term as

$$F(x) = \min_{\{x\}} \sum_{i \in \nu} f_i(x_i) + \rho G(x) \tag{39}$$

where

$$G(x) = \sum_{j=1}^{s} G_j(x) \tag{40}$$

express the betray degree of $x$ on all the constraints, where $s$ denotes the constraints number.

Different decision variables are sparsely coupled in the decentralized optimizations (35), such that coordination is needed to schedule the optimization process. To make the parallel connected agents achieve global optimal operation and avoid the confliction of different agents, a feasible algorithm is necessary.

## III. ALGORITHM DESIGN

Decentralized optimization problem (35) on different updated smart equipment is always local coupled because decision variable on each updated smart equipment is always involved in the same local constraints as (33) or (34). This makes the purpose of achieving global optimization via local interaction with neighbors difficult. Thus, the key problem lies in designing an appropriate mechanism in the following paragraph.

There are two fundamentally different approaches for the design of the decentralized optimization as(35) including game learning algorithms and multi-agent consensus based methods currently. The learning algorithms in game theory for distributed optimization are a subset of potential games [32] However, such approaches are inclined to plunge into suboptimal Nash equilibrium solutions and cannot guarantee to obtain the global optimization [33]. And, the multi-agent consensus based method is mainly to optimize problems where multiple agents have different objective functions and are coupled by a common vector decision variable [31], [34]. But, for the problem (35), there exist couples of local constraints and the decision variable xi is different for all the nodes. So the current methods are not applicable for problem (35). The new knowledge in the decentralized optimization model for the HVAC decentralized optimization problem of this paper differentiates our work from previous work.

Thus, a fully decentralized optimization algorithm with penalty function that achieves the global optimality for problem (35) is sought in this paper. Due to the typical optimization problems of (24)-(28) are multi-variable, non-linear and non-convex, this feature makes swarm intelligence algorithm and genetic algorithms(GAs) be more adaptive to solve the optimal operation task of HVAC systems.

However, the parallelism of current swarm intelligence algorithms and GA lies in its large number of populations, that is all the chromosomes and individuals in these algorithms involve identical global variables [35]. Although the cooperative GA and swarm intelligence algorithm where each group represents only one dimension of the search space is proposed to solve the high dimensional problems in large-scale optimization, a coordinator is always required as described in part I [36]. Thus, these approaches cannot be applied to decentralized optimization system as (35) because they solve a problem in which the agents do not share common variables.

### A. ALGORITHM DESCRIPTION

Learning from the traditional GA and swarm intelligence algorithm, a decentralized swarm intelligence method is proposed for the novel control system of large-scale collaborative system illustrated in part II. In this so-called decentralized method, each updated smart device agent is viewed as an individual in the swarm intelligence can cooperate with adjacent individual. And, each agent has its own utility as (35) and a decentralized GA(DGA). Different from the traditional GA, except the mutation, crossover and selection operators, a local exchange operator is designed in the DGA. And the local exchange operator is described as: each individual can intersect with adjacent nodes on coupling variables, and product new chromosomes as shown in Fig. 3.

As seen from Fig.2, DGA is different from traditional evolutionary algorithms, where the populations of each smart agent only cover its own variable. And this process is being done simultaneously at each decision maker.

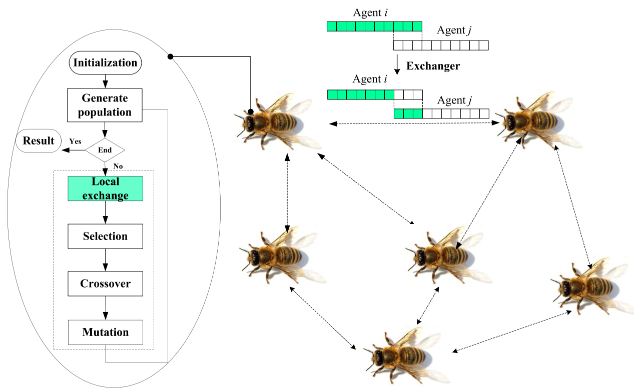


**FIGURE 2.** Flow chart of DGA.

### B. CONVERGENCE PROOF

The proof of the DGA converging to the centralized optimality by GA is illustrated in the following paragraph and presented in proposition 1.

*Proposition 1: $[x_1, \ldots, x_i, \ldots, x_n]$ generated by DGA can converge to the optimal Nash equilibrium of the decentralized optimization problem (4) with a probability of 1, and can be equivalent to the solution of centralized optimization method (8).*

*Proof:*

Assume the global solution space is defined as $\Omega = \Omega_1 \cap \Omega_2 \cap \ldots \cap \Omega_N$, where $\Omega_i$,$i = 1, 2, \ldots, n$, is the space of the *i-th* agent and its corresponding variable $x_i$.

The maintaining optimum SGAS (MOSGAS) is used in the presented algorithm. This operator favors the $g$ elites of a population by giving them a chance to be passed on directly the next generation. Thus, the new population consists of $(L - g)$ new chromosomes, with $g < L$.

Firstly, the optimality convergence of each agent $i(i = 1, 2, \ldots, n)$ is discussed. The present study assumes that the search space $\Omega_i$ of problem (35) is a closed and bounded region. The objective function is taken as the fitness function $J_i(x_i)$, and the optimal solution set is expressed as

$$D_0 = \left\{x_i \in \Omega_i \middle| |J_i(x_i) - J_i^*| < \varepsilon\right\} \tag{41}$$

where $J_i^* = \min \{J_i(x_i) \colon x_i \in \Omega_i\}$.

For agent $i$ ($i = 1, 2, \ldots, n$), the $L$ chromosomes of GA may contain the following two cases:

(I) At least one chromosome belongs to $D_0$, which is written as $S_0$;

(II) All $L$ chromosomes belong to $D_1$, which is written as $S_1$, where

$$D_1 = \Omega \backslash D_0. \tag{42}$$

And if $q_{ij}(i, j = 0, 1)$ represents the probability that the $(k+1)$-*th* generation $x_i(k+1)$ transfers to $S_j$ when the $k$-*th* generation $x_i(k)$ keeps the state of $S_i$, then the following conditions hold:

*$x_i$ $(k)$ at $S_0$ and $q_{00}$ =1:*

Condition (I) is obviously valid because the elite-preserving operator is used in this paper.

*$x_i$ $(k)$ at $S_1$ and $q_{11} \le c$, where $c \in (0,1)$:*

Conditions (II) is analyzed as follows: For any $\varepsilon > 0$, if $x_{i0} \in \{x_i \in \Omega_i || J_i(x_i) - J_i^*| < \varepsilon/2\}$, there exists $r > 0$ satisfying

$$|J_i(x_i) - J_i(x_{i0})| < \varepsilon/2 \tag{43}$$

when

$$||x_i - x_{i0}||_\infty = \max |x_i - x_{i0}| \le r. \tag{44}$$

Define

$$Q_{x_{i0},r} = \{x_i \in \Omega_i ||| x_i - x_{i0}||_\infty \le r\}, \tag{45}$$

so that

$$Q_{x_{i0},r} \subset D_0 \tag{46}$$

due to

$$\begin{aligned}|J_i(x_i) - J_i^*| &\le |J_i(x_i) - J_i(x_{i0})| + |J_i(x_{i0}) - J_i^*| \\ &< \frac{\varepsilon}{2} + \frac{\varepsilon}{2} = \varepsilon\end{aligned} \tag{47}$$

The probability that $x_i$ transfers to $S_0$ can be defined by

$$P\{x_{i+} \in Q_{x_{i0},r}\} = P\{|x_{i+} - x_{i0}| \le r\} \tag{48}$$

where $x_{i+}$ is the chromosome of a new generation, and $i = 1, 2, \ldots, n$. Given that the evolutionary computation of GA is based on probability, each element of the chromosome generates a series of the probability function$g(x_i)$, with $i = 1, 2, \ldots, n$.

For $x_{i+}$,

$$x_{i+} \sim g(x_i) \tag{49}$$

and thus

$$P\{x_{i+} \in Q_{x_{i0},r}\} = \int_{x_{i0}-r}^{x_{i0}+r} g(x_i)dx_i \tag{50}$$

For simplicity,$P\{x_{i+} \in Q_{xi0r}\}$can be denoted by

$$P_1(x_{i+}) = P\{x_{i+} \in Q_{x_{i0},r}\} \tag{51}$$

then clearly

$$0 < P_1(x_{i+}) < 1 \tag{52}$$

Define

$$P_1(y_{i0}) = \min P_1(x_{i+}), \tag{53}$$

so that

$$P_1(y_{i0}) \le P_1(x_{i+}) \le q_{10}. \tag{54}$$

As

$$q_{11} + q_{10} = 1, \tag{55}$$

the following result can be achieved:

$$q_{11} = 1 - q_{10} \le c(0 < c < 1), \tag{56}$$

where the constant $c$ is

$$c = 1 - P_1(y_{i0}). \tag{57}$$

Further, for any $\varepsilon$>0, set

$$p_k = P\{|J_i(x_i^*(k)) - J_i^*| \ge \varepsilon\} \tag{58}$$

And

$$p_k = \begin{cases} 0 & \exists T \in \{0, 1, 2, \ldots, k\}, x_i^*(T) \in D_0 \\ \overline{p_k}, & x_i^*(m) \notin D_0 m = 0, 1, 2, \ldots, k \end{cases} \tag{59}$$

thus, the following equation is obtained:

$$\overline{p_k} = P\{x_i^*(m) \notin D_0, m = 0, 1, 2, \ldots, k\} = q_{11}^k \le c^k, \tag{60}$$

so that

$$\sum_{k=1}^{\infty} \overline{p_k} \le \sum_{k=1}^{\infty} c^k = \frac{c}{1-c} < \infty \tag{61}$$

Then the following theorem is introduced to complete the proof process.

*Theorem 1(Borel-Cantelli theorem):The present study assumes that $A_1$, $A_2$,..., is the event sequence based on probability and defines $p_k = P\{A_k\}$. If*

$$\sum_{k=1}^{\infty} p_k < \infty \tag{62}$$

*then*

$$P\left\{\bigcap_{m=1}^{\infty} \bigcup_{k \ge m} A_k\right\} = 0 \tag{63}$$

*If*

$$\sum_{k=1}^{\infty} p_k = \infty \tag{64}$$

*and $A_k$ are independent of one another, then*

$$P\left\{\bigcap_{m=1}^{\infty} \bigcup_{k \ge m} A_k\right\} = 1 \tag{65}$$

According to theorem 1,

$$P\left\{\bigcap_{m=1}^{\infty} \bigcup_{k \ge m} [|J_i(x_i^*(k)) - J_i^*| \ge \varepsilon]\right\} = 0 \tag{66}$$


**FIGURE 3.** Distributed nodes network.

is true. Therefore, $x_i^t(m)$, where $t = 1, 2, \ldots, L$ is the population of the$m$-$th$ generation of GA for agent $i$ $(i = 1, 2, \ldots, n)$, which consists of $L$ chromosomes. If the fitness function $J_i(x_i)$ is continuous on the bounded region $\Omega_i$, the optimal solution $x_i^*(m)$ converges to the optimum for agent $i$ with a probability of 1, and

$$x_i^*(m) = \arg\min_{1 \le t \le L} J_i(x_i^t(m)) \tag{67}$$

Then the validity of the global optimization is deduced in the subsequent paragraphs.

According to the above analysis, the solution $x_i$ can converge to the optimum $x_i^*$ for agent$i$with a probability of 1. Define the probability as $p_i$, that is,

$$x_i \xrightarrow{p_i} x_i^* \tag{68}$$

And

$$p_i = P\left\{\bigcap_{m=1}^{\infty}\bigcup_{k\ge m}[|J(x_i(k)) - J_i^*| < \varepsilon]\right\} = 1 \tag{69}$$

Thus, the probability of a single variable can be obtained by marginal probability $p_i$ $(i = 1, 2, \ldots, n)$. Furthermore, the global combined probability function can be described as

$$P = \prod_{i=1}^{N} p_i = 1 \tag{70}$$

where $pi$ can be multiplied directly according to the definition of probability. For the coupled variables,

$$P = \left(\prod_{i=1}^{N} p_i\right)/p_{ij} = 1 \tag{71}$$

Then, the present study directly obtains

$$[x_1, \ldots, x_i, \ldots, x_n] \xrightarrow{P} [x_1^*, \ldots, x_i^*, \ldots, x_n^*] \tag{72}$$

where $[x_1^*, \ldots, x_i^*, \ldots, x_n^*]$ is an optimal Nash equilibrium of problem (35). In conclusion, $[x_1, \ldots, x_i, \ldots, x_n]$ converges to an optimal solution of the centralized optimization problem with a probability of 1 as the iteration step $m \to \infty$. Then, proposition 1 can be obtained.

In order to demonstrate the performance of the proposed decentralized swarm intelligence method, an illustrative numerical case is conducted. Consider a simple multi-nodes network as in Fig. 3. The network consists of $n = 4$ nodes, which are sequentially identified as 1 to 4.

Further, the decentralized optimization on each node $i$ $(i = 1, 2, 3, 4)$is formulated as

$$\begin{aligned} &\min f(x_i) = x_i^2 \\ &s.t. x_i + x_j = 10, j \in N_i \\ &\quad 0 < x_i < 10. \end{aligned} \tag{73}$$

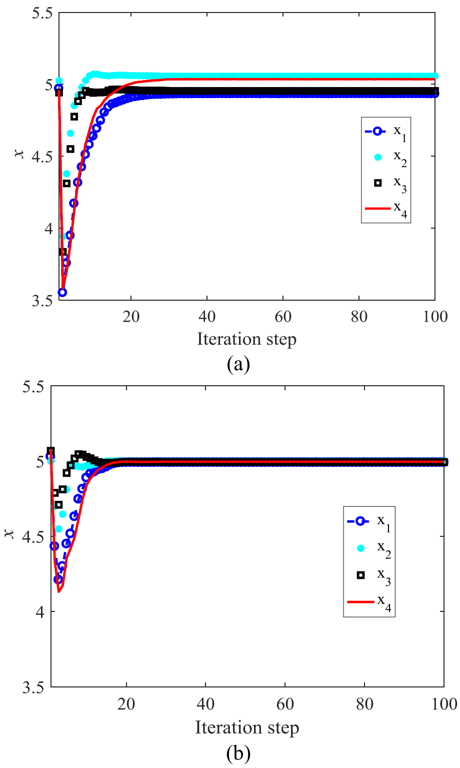


**FIGURE 4.** Iterative process of distributed nodes network: (a) Dentralized method. (b) Centralized method.

Then, assisted by the proposed decentralized swarm intelligence algorithm, the evolutionary process of each node is obtained and shown in Fig.4. For comparison, the centralized method is also executed and illustrated in the same figure. As seen from figure 4, the global minimum of [5, 5, 5, 5] can be obtained in both centralized and decentralized swarm intelligence algorithm.

## IV. APPLICATION

To investigate the performance of the proposed decentralized swarm intelligence optimization strategy, it is applied to the optimal control of actual HVAC system in the Water Cube as in Fig.1.

### A. EXPERIMENTAL CONDITION

The average cooling demand profile of the HVAC system from 9:00 to 18:00 is calculated by DEST($T_{wb} = 24°$), and is shown in Fig.5. As can be seen, the cooling load varies between 1800 kW to 6900 kW.

### B. SIMULATION RESULT

Firstly, the current centralized GA under a selected working condition is validated and illustrated for comparison. Assume the cooling load is 4000 kW(Zone A and Zone B) on one sample period. The centralized GA method is coded in the software of MATLAB (R2016b) and executed in the laptop (Intel Core i5 P8600@2.4GHz).

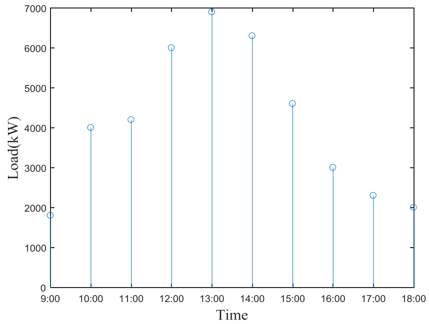


**FIGURE 5.** Load profile of the Water Cube between 9:00 to 18:00.

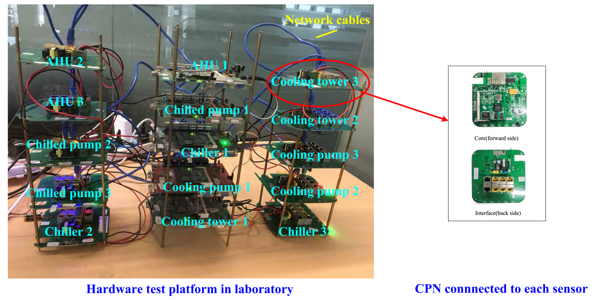


**FIGURE 6.** Hardware test platform.

Moreover, a decentralized test platform is developed in the present study which consists of a series of computing nodes (CPNs) as shown in Fig.6. Each CPN acts as an equipment-Agent which the equipment model and decentralized algorithm can be written into. In practical engineering, each CPN belongs to corresponding equipment and is connected through a network cable (e.g. RJ45 jacks) or wireless communication according to Fig.1. The whole

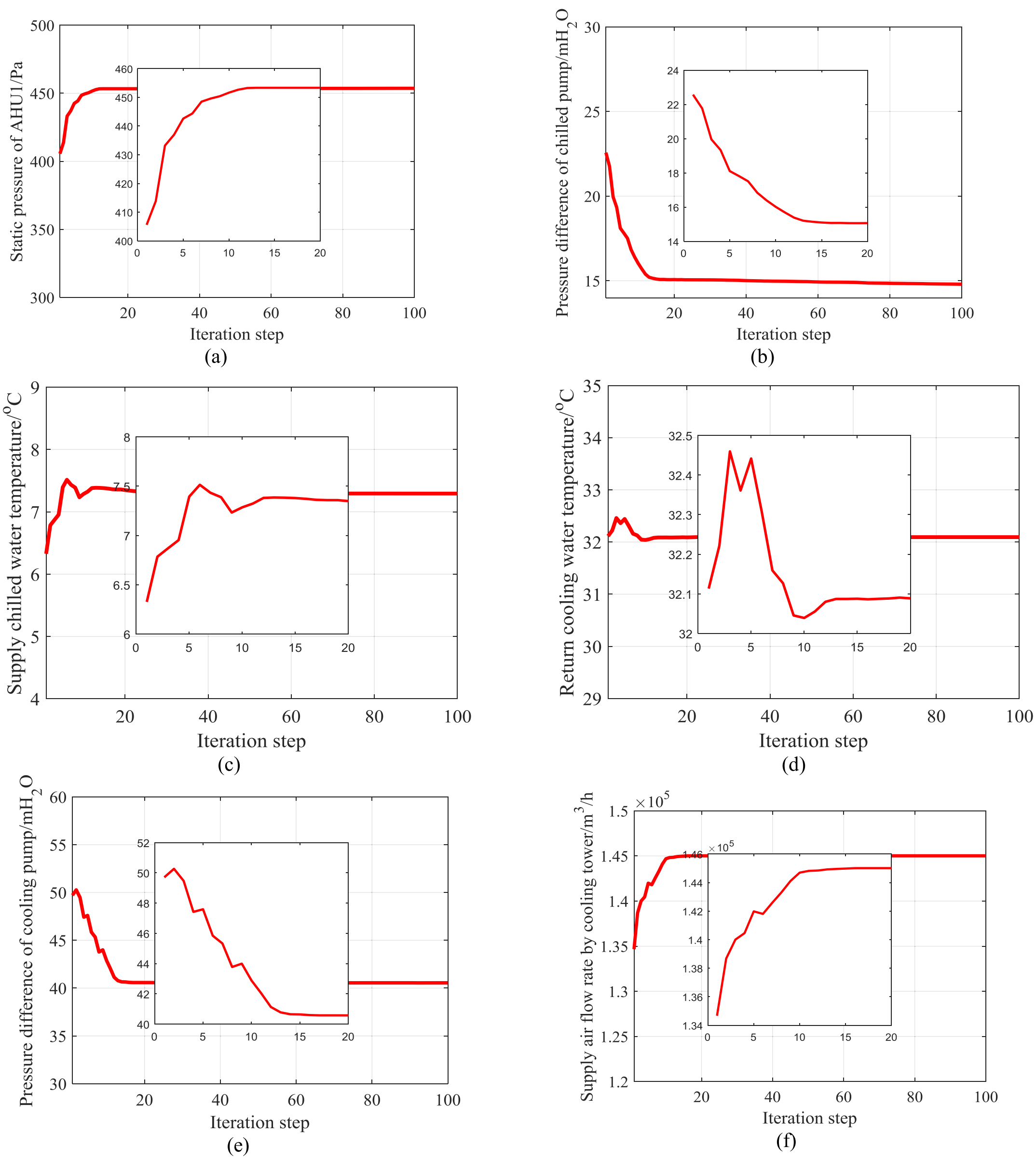


**FIGURE 7.** Iterative process of decision variable.

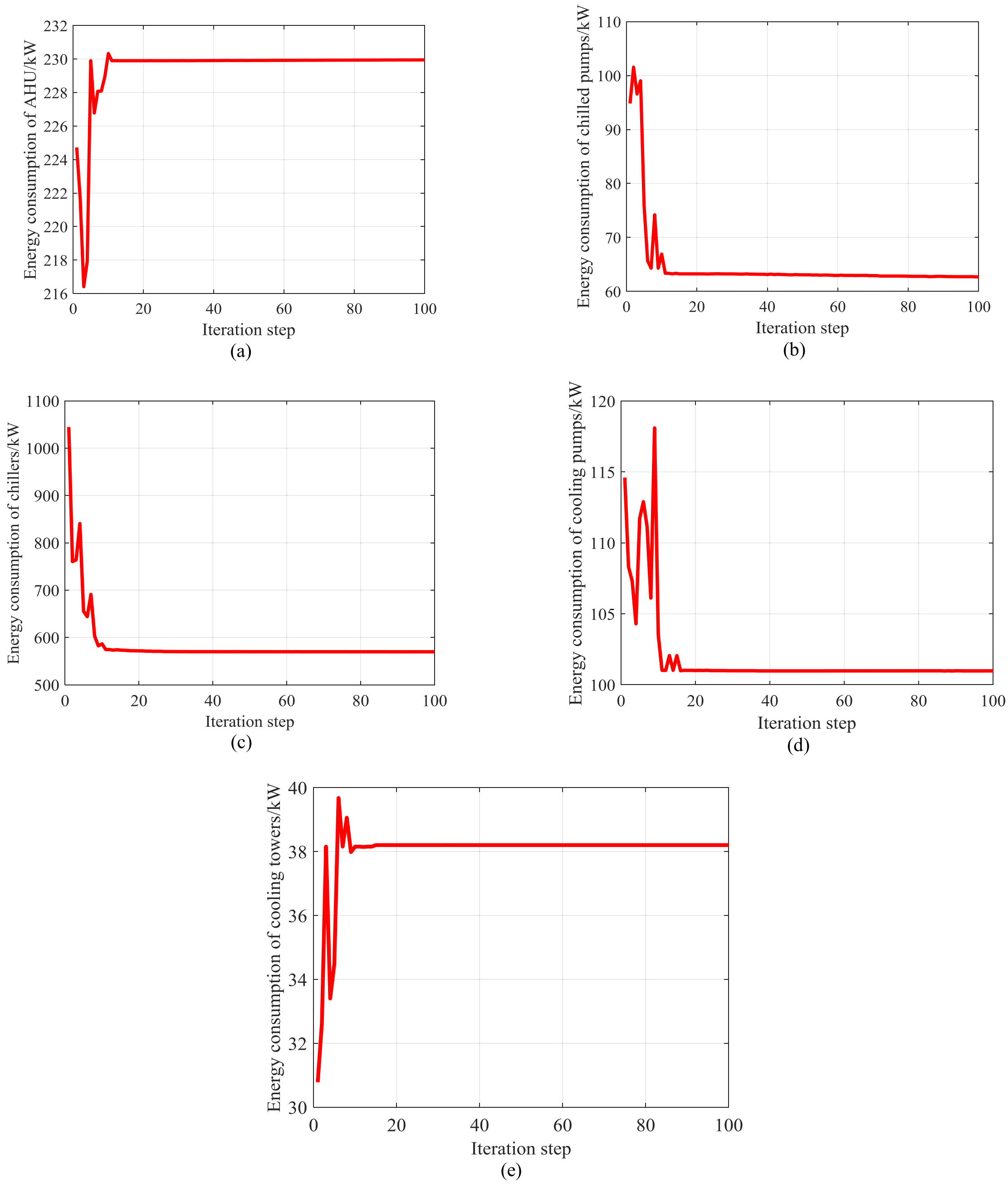


**FIGURE 8.** **Iterative process of energy consumption on each equipment in decentralized method.**

process is plug-and-play without complex secondary development work onsite. The communication protocol between CPN has been designed. Then, the CPN can collaborate with each other to realize the collaborative task in a self-organizing way.

Then the proposed decentralized optimization algorithm is written into the CPN in each smart equipment. Then each smart equipment can cooperate and coordinate with adjacent smart equipment nodes to find an optimal operating point at a given cooling load.

The evolutionary optimization results of each equipment in the proposed algorithm on CPN network platform are described in Fig.7. As seen from Fig.7, the decision variables of each agent fluctuates initially, and finally reaches a stable equilibrium point both in centralized and decentralized method. Then, the convergence of the proposed algorithm can be validated.

Further, to analyze the optimality of the proposed algorithm, the optimization results of energy consumption on each equipment in the proposed method is described in Fig.8. In addition, the optimization results of total energy cost and load meeting degree in centralized and decentralized method are illustrated in Fig.9. By comparing Fig.8 and Fig.9, although not all the cost of five equipments decrease, the total

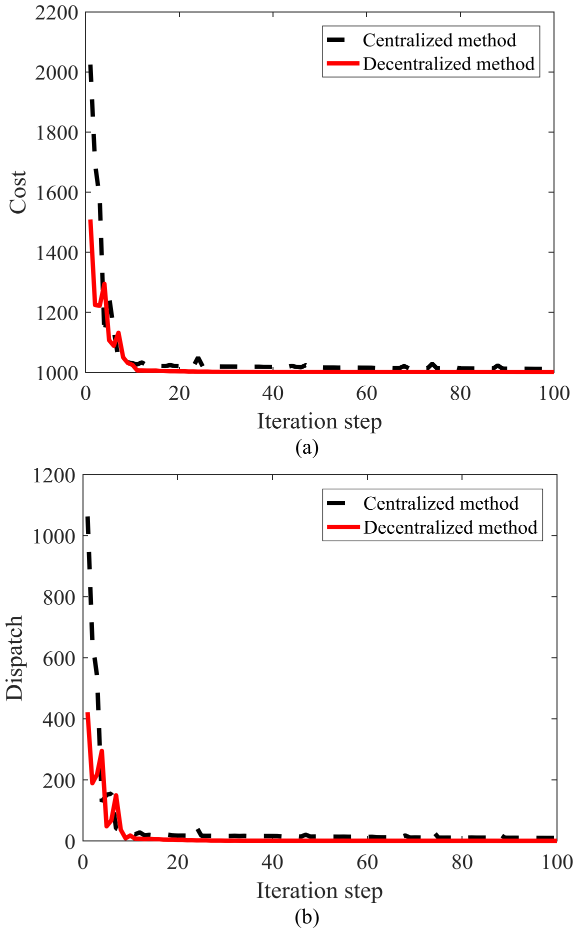


**FIGURE 9.** Iterative process of in decentralized method and centralized method: (a) Energy consumption (b) Load meeting degree.

cost is decrease during the iterative process. And as seen from Fig.9, the proposed decentralized method can achieve the same energy cost performance as in a centralized manner by mutual negotiation and adjustment of smart equipments. Therefore, it can be included that the presented decentralized swarm intelligence algorithm could achieve a global optimum operation of the HVAC system effectively.

Note that the simulation is implemented on the Matlab (2016a) of centralized optimization method takes 2 hours approximately. But, the average consuming time of CPN hardware test is only about 10 s, which is much shorter than the simulation on computer. Besides, in the decentralized method, these smart device agent can be plug-and-play on condition that the field engineer knows the inter-agent physical connections. Considering the above advantages, decentralized optimization method is more promising than the current control method in practical application.

Once the optimization process is completed, the optimal set points can be downloaded to each local PID control unit for this sampling period. And HVAC system can run in an optimal operation.

Further, a discrete simulation under 10 working conditions among 9:00-18:00 is executed in the following paragraph as shown in Fig.10 and Fig. 11. Besides, to validate the energy conversation capability of proposed method, traditional method that fixed $T_{\mathrm{CHWS}}$ and $T_{\mathrm{CWS}}$ control is also presented. And the supply chilled water temperature is set as 7° and the return cooling water temperature is 32° in the comparison.

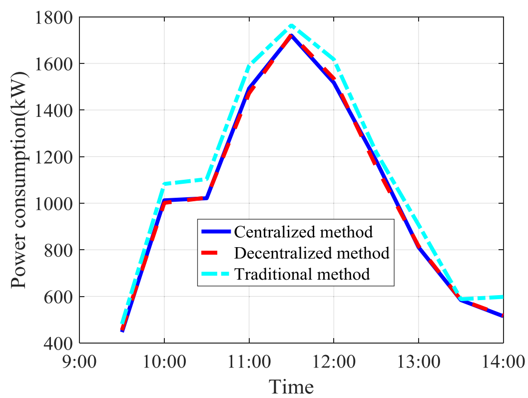


**FIGURE 10.** Iterative process of energy consumption under the 10 working conditions.

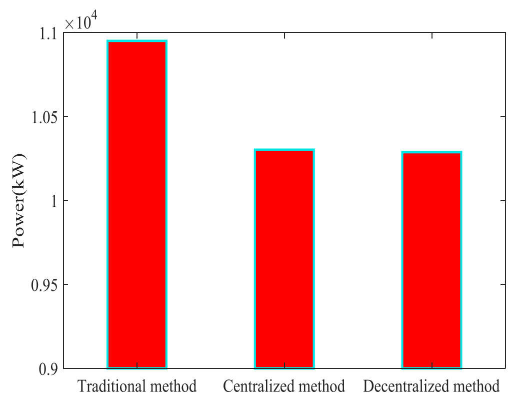


**FIGURE 11.** Energy consumption during 10 working conditions in different methods (kW).

As shown in Fig.10 and Fig.11, the power cost in centralized and decentralized method is almost the same as each other. For one experiment, the energy consumption in the proposed algorithm may a little better or worse than the centralized GA, this originates from the random characteristic. In general, the power cost can be reduced by approximately 6% comparing to the traditional method.

## V. CONCLUSION

This paper proposed a decentralized swarm intelligence method for optimizing the HVAC system operation to solve the actual engineering problems. With the rapid development of the electronic industry, smart hardware has been widely employed in different fields. According to the vision of decentralized method, traditional devices can be upgraded and transformed into smart devices through the incorporation of a decentralized control chip. The accurate model and decentralized algorithm can be written into this chip by the manufacturer who knows the equipment's performance as it leaves the factory.

The smart equipments will communicate with their neighboring nodes and work collaboratively to realize the optimal operation in the proposed decentralized swarm intelligence algorithm. In this case, the complicated onsite modeling, configuration, commissioning, and other secondary developing works can be simplified to the wring of communication connection among smart equipments, which can then be self-organized and plug-and-play. The convergence property of the novel method is also analyzed theoretically. Simulation results and hardware test indicate that the proposed method can perform HVAC global optimization.

## REFERENCES

[1] K. F. Fong, V. I. Hanby, and T. T. Chow, "HVAC system optimization for energy management by evolutionary programming," *Energy Buildings*, vol. 38, no. 3, pp. 220–231, 2006.
[2] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," *Energy Buildings*, vol. 40, no. 3, pp. 394–398, 2008.
[3] J. Cai, D. Kim, R. Jaramillo, J. E. Braun, and J. Hu, "A general multi-agent control approach for building energy system optimization," *Energy Buildings*, vol. 127, pp. 337–351, Sep. 2016.
[4] D. Marini, "Optimization of HVAC systems for distributed generation as a function of different types of heat sources and climatic conditions," *Appl. Energy*, vol. 102, pp. 813–826, Feb. 2013.
[5] S. Wang and J. Burnett, "Online adaptive control for optimizing variable-speed pumps of indirect water-cooled chilling systems," *Appl. Thermal Eng.*, vol. 21, no. 11, pp. 1083–1103, 2001.
[6] B. Fan, X. Jin, and Z. Du, "Optimal control strategies for multi-chiller system based on probability density distribution of cooling load ratio," *Energy Buildings*, vol. 43, no. 10, pp. 2813–2821, Oct. 2011.
[7] L. Lu, W. Cai, Y. S. Chai, and L. Xie, "Global optimization for overall HVAC systems—Part I problem formulation and analysis," *Energy Convers. Manage.*, vol. 46, nos. 7–8, pp. 999–1014, May 2005.
[8] L. Lu, W. Cai, Y. S. Chai, and L. Xie, "Global optimization for overall HVAC systems—Part II problem solution and simulations," *Energy Convers. Manage.*, vol. 46, nos. 7–8, pp. 1015–1028, May 2005.
[9] J. Sun and T. A. Reddy, "Optimal control of building HVAC&R systems using complete simulation-based sequential quadratic programming (CSB-SQP)," *Building Environ.*, vol. 40, no. 5, pp. 657–669, May 2005.
[10] B. C. Ahn and J. W. Mitchell, "Optimal control development for chilled water plants using a quadratic representation," *Energy Buildings*, vol. 33, no. 4, pp. 371–378, 2001.
[11] C. Dullinger, W. Struckl, and M. Kozek, "A general approach for mixed-integer predictive control of HVAC systems using MILP," *Appl. Thermal Eng.*, vol. 128, pp. 1646–1659, Jan. 2017.
[12] J. Seo, R. Ooka, J. T. Kim, and Y. Nam, "Optimization of the HVAC system design to minimize primary energy demand," *Energy Buildings*, vol. 76, pp. 102–108, Jun. 2014.
[13] A. Kusiak, M. Li, and F. Tang, "Modeling and optimization of HVAC energy consumption," *Appl. Energy*, vol. 87, no. 10, pp. 3092–3102, 2010.
[14] X. He, Z. Zhang, and A. Kusiak, "Performance optimization of HVAC systems with computational intelligence algorithms," *Energy Buildings*, vol. 81, pp. 371–380, Oct. 2014.
[15] S. M. Attaran, R. Yusof, and H. Selamat, "A novel optimization algorithm based on epsilon constraint-RBF neural network for tuning PID controller in decoupled HVAC system," *Appl. Thermal Eng.*, vol. 99, pp. 613–624, Apr. 2016.
[16] K. V. Ling and A. L. Dexter, "Expert control of air-conditioning plant," *Automatica*, vol. 30, no. 5, pp. 761–773, 1994.
[17] M. W. Ahmad, M. Mourshed, B. Yuce, and Y. Rezgui, "Computational intelligence techniques for HVAC systems: A review," *Building Simul.*, vol. 9, no. 4, pp. 359–398, 2016.
[18] L. Lu, W. Cai, L. Xie, S. Li, and Y. C. Soh, "HVAC system optimization—In-building section," *Energy Buildings*, vol. 37, no. 1, pp. 11–22, 2005.
[19] J. Wang, G. Huang, Y. Sun, and X. Liu, "Event-driven optimization of complex HVAC systems," *Energy Buildings*, vol. 133, pp. 79–87, Dec. 2016.
[20] X. Wei, A. Kusiak, M. Li, F. Tang, and Y. Zeng, "Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance," *Energy*, vol. 83, pp. 294–306, Apr. 2015.
[21] A. Kusiak, F. Tang, and G. Xu, "Multi-objective optimization of HVAC system with an evolutionary computation algorithm," *Energy*, vol. 36, no. 5, pp. 2440–2449, 2011.
[22] H. S. Asad, R. K. K. Yuen, and G. Huang, "Multiplexed real-time optimization of HVAC systems with enhanced control stability," *Appl. Energy*, vol. 187, pp. 640–651, Feb. 2017.
[23] A. Kusiak, G. Xu, and Z. Zhang, "Minimization of energy consumption in HVAC systems with data-driven models and an interior-point method," *Energy Convers. Manage.*, vol. 85, pp. 146–153, Sep. 2014.
[24] I. Ursu, N. Ilinca, C. Sorin, I. Andreea, and T. Adrian, "Intelligent control of HVAC systems. Part I: Modeling and synthesis," *Incas Bull.*, vol. 5, no. 1, pp. 103–118, 2013.
[25] I. Ursu, N. Ilinca, C. Sorin, I. Andreea, and T. Adrian,, "Intelligent control of HVAC systems. Part II: Perceptron performance analysis," *Incas Bull.*, vol. 5, no. 3, pp. 127–135, 2013.
[26] I. T. Michailidis *et al.*, "Energy-efficient HVAC management using cooperative, self-trained, control agents: A real-life German building case study," *Appl. Energy*, vol. 211, pp. 113–125, Feb. 2018.
[27] S. Baldi, I. Michailidis, C. Ravanis, and E. B. Kosmatopoulos, "Model-based and model-free 'Plug-and-Play' building energy efficient control," *Appl. Energy*, vol. 154, pp. 829–841, Sep. 2015.
[28] H. Chen, W. Cai, and C. Chen, "Model-based method for testing, adjusting and balancing of HVAC duct system," *Energy Buildings*, vol. 126, pp. 498–507, Aug. 2016.
[29] Y.-W. Wang, W.-J. Cai, Y.-C. Soh, S.-J. Li, L. Lu, and L. Xie, "A simplified modeling of cooling coils for control and optimization of HVAC systems," *Energy Convers. Manage.*, vol. 45, nos. 18–19, pp. 2915–2930, 2004.
[30] I. Kouveliotis-Lysikatos and N. Hatziargyriou, "Fully distributed economic dispatch of distributed generators in active distribution networks considering losses," *IET Gener. Transmiss. Distrib.*, vol. 11, no. 3, pp. 627–636, Feb. 2017.
[31] Z. J. Towfic and A. H. Sayed, "Adaptive penalty-based distributed stochastic convex optimization," *IEEE Trans. Signal Process.*, vol. 62, no. 15, pp. 3924–3938, Aug. 2014.
[32] H. Tuy *et al.*, *Pareto Optimality, Game Theory and Equilibria*. New York, NY, USA: Springer, 2008.
[33] N. Li and J. R. Marden, "Designing games for distributed optimization," *IEEE J. Sel. Topics Signal Process.*, vol. 7, no. 2, pp. 230–242, Apr. 2013.
[34] M. Zhu and S. Martinez, "On distributed convex optimization under inequality and equality constraints," *IEEE Trans. Autom. Control*, vol. 57, no. 1, pp. 151–164, Jan. 2012.
[35] A. Slowik and H. Kwasnicka, "Nature inspired methods and their industry applications—Swarm intelligence algorithms," *IEEE Trans. Ind. Inform.*, vol. 14, no. 3, pp. 1004–1015, Mar. 2018.
[36] M. N. Omidvar, X. Li, Y. Mei, and X. Yao, "Cooperative co-evolution with differential grouping for large scale optimization," *IEEE Trans. Evol. Comput.*, vol. 18, no. 3, pp. 378–393, Jun. 2014.

**SHIQIANG WANG** received the B.S. degree in electrical engineering and automation from Hunan University, and the M.S. degree in power system and automation from the PLA University of Science and Technology, Nanjing, China. He is currently pursuing the Ph.D. degree with PLA Army Engineering University. His research interests include multi-agent control systems, distributed optimization, and software engineering.

**JIANCHUN XING** (M'91) received the B.Sc. and M.Sc. degrees in electric system and automation from the Engineering Institute of Engineering Corps, China, and the Ph.D. degree in information system engineering from the PLA University of Science and Technology, China. He is currently a Professor with PLA Army Engineering University. His research interests include intelligent control, artificial intelligence, workflow management, and software engineering. He is a member of the CCF.

**ZIYAN JIANG** received the Ph.D. degree from Tsinghua University, where he is currently an Associate Professor. His research interests include buildings swarm intelligence control systems, the Internet of Things, and cyber-physical energy systems.

**YUNCHUANG DAI** received the Ph.D. degree from Tsinghua University, where he currently holds a postdoctoral position. His research interests include buildings swarm intelligence control systems and building energy systems.