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Optimal chiller loading of dual temperature chilled water plants for energy saving

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Abstract

The chiller plant is one of the major sectors of building energy consumption. The Optimal Chiller Loading (OCL) in single-temperature chiller plants has been a hot topic to reduce the energy consumption of buildings, which has shown significant energy-saving potentials. A dual temperature chilled water plant commonly applied in systems that required low humidity, such as Make-up Air Units (MAUs) in Temperature and Humidity Independent Control (THIC) air conditioning system. A dual temperature chilled water plant has shown better energy efficiency than the single-temperature chiller plant for both cooling and dehumidification. In this paper, an optimal chiller loading strategy for dual temperature chilled water plants has been proposed, and the mathematical description of this optimization problem was defined first, including decision variables, objective function, and constraints. A meta-heuristic algorithm inspired by the dynamic mass balance principle, Equilibrium Optimizer (EO), was applied to solve the optimal control problem. Then, the performance of the proposed optimal control strategy was analyzed and compared with the conventional equal load control strategy on a dual temperature chilled water plant in a semiconductor fab. The results show that chillers with higher energy efficiency were assigned with a higher part-load ratio rather than an equal value to achieve lower energy consumption of the entire chiller plant. Using the optimal control strategy could reduce the chiller plant's power consumption ranging from 79.8 kW to 310.5 kW and achieve 3.3% to 13.1% energy savings than the average loading control strategy under different cooling load conditions.

Introduction

Buildings' energy consumption accounts for almost 40% of the total energy consumption of our society (Yang et al., 2014; IEA, 2019), and therefore, reducing building energy consumption has become a global topic for sustainable development (Clift, 2007; Li et al., 2013). In buildings, A large proportion of the energy consumption was consumed by the Heating Ventilation and Air Conditioning (HVAC) system (Pérez-Lombard et al., 2008; Ali et al., 2013). The central cooling system was a major section of the HVAC system for buildings' space cooling, especially in medium and large size buildings. In these buildings, 25-50% of the building's energy budget was due to the central cooling system and more than 50% of energy was consumed by chillers (Wang, 2010). Multiple-chillers with identical or distinct capacities were commonly employed in a central cooling system, which could provide the standby capacity, low-disruption maintenance, and high energy efficiency under different partial load conditions (Wang, 2010). The control and operation of chillers have a significant impact on the plant's energy consumption while satisfying the cooling demand of end-users. The control of chillers includes sequencing and processing control. The sequencing control of the chiller is to determine proper thresholds for switching on and off chillers to provide enough chilled water efficiently. Different chiller sequencing control strategies have been reported in the literature, using a direct or an indirect system cooling load indicator. According to the indicator used in the control loop, they were divided into five classes, namely, cooling load-based (Q-based), chilled water return temperature-based (T-based), bypass flow rate-based (F-based), chiller electric current/power-based sequencing control (I/P-based) and hybrid sequencing control (Wang and Ma, 2008; Liao et al., 2014; Shan et al., 2016). The widely used method is the Q-based sequencing control method. The process control of chillers is to determine the part load ratio of each chiller in operation. Chillers with identical design capacity, an equal load ratio for each chiller according to the ratio of the total load demand to chillers' design capacity is a simple chiller loading strategy. Similarly, for chillers with different capacities, they could be controlled with an equal partial derivative of individual energy consumption (ASHRAE, 2011). However, this loading control method could not guarantee the minimum power consumption since this method does not consider the individual character of chillers (ASHRAE, 2011; Abou-Ziyan and Alajmi, 2014). Moreover, a near-optimal performance map-based chiller loading strategy has been proposed to enhance the energy performance of the multi-chillers. In this method, the upper boundary of the performance map was taken as the near-optimal performance line and the cooling load was dispatched under the guidance of the near-optimal performance line (Wang et al., 2019). In recent two decades, optimal chiller loading has been a hot topic to reduce the energy consumption of chiller plants since chillers consume a large portion of building energy budget. Researchers have employed various optimization algorithms in optimal single-temperature chiller plant loading to reduce energy consumption and improve the energy efficiency of chillers. Chang et al. have used different optimization algorithms to optimize the chiller loading for energy saving, including Lagrangian Method (LM) (Chang and Tu, 2002; Chang, 2004; Chang et al., 2005), Genetic Algorithm (GA) (Chang, 2005), Branch and Bound (B&B) (Chang et al., 2005), Simulated Annealing (SA) (Chang, 2006), and Evolution Strategy (ES) (Chang, 2007; Chang et al., 2009). In the following years, many other new optimization algorithms have been tested on two generally used cases first proposed by Chang et al (2005a; 2005b). Lee et al. (2009; 2011) optimized the chiller loading using Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms and the performance of different algorithms was compared based on the test cases. The results showed that a better energy-saving rate than the GA algorithm was obtained by both algorithm and the DE outperform in low part-load ratio conditions. Geem (2011) has further improved the quality of solutions by using a hybrid optimization algorithm, the mixed PSO, and the Generalized Reduced Gradient (GRG) method. A modification of the basic Firefly Algorithm (FA) proposed by Coelho and Mariani (2013) has been applied in two generally used optimal chiller loading cases. In recent years, many new optimization algorithms and their variants, such as Differential Cuckoo Search Approach (DCSA) (Coelho et al., 2014), Enhanced Invasive Weed Optimization (EIWO) (Zheng and Li, 2018), Exchange Market Algorithm (EMA) (Sohrabi et al., 2018), Two-stage Differential Evolution (T-DE) (Lin et al., 2019), Improved Artificial Fish Swarm (IAFS) and Augment Group Search Optimization (AGSO) (Teimourzadeh et al., 2019), have been proposed to further improve the quality of the solution, the computation efficiency and the stability of the solution.

In the literature, the optimal chiller loading is mainly conducted on the single-temperature chiller plant. However, the study on optimal control for dual temperature chilled water plants was lack. A dual temperature chilled water plant is typically used for systems that required deep dehumidification, such as the Temperature and Humidity Independent Control (THIC) air conditioning system. In THIC systems, dehumidification coils are usually designed to remove all the humidity load from the fresh air and internal wet source and required cold enough chilled water to process air to a drier state, normally lower than the indoor air dew-point temperature. While a lower chilled water supply temperature decreases the efficiency of chillers. In this situation, a dual temperature chilled water plant is normally used to improve the energy efficiency of the whole system. In a typical THIC system, a dual temperature chilled water plant providing chilled water for the primary and secondary cooling coils in Make-up Air Unit (MAU) could reduce 8.2% power consumption than a single-temperature chiller plant (Tsao et al., 2008). For a dual temperature chilled water plant, the control and operation of the chiller plant were much more complicated due to the decoupled feature of two chiller groups. The cooling load distribution both among chillers in the group with identical chilled water temperature and between different groups has significant impacts on the power consumption of the whole chiller plant. Therefore, it is crucial to optimize the chiller loading of a dual temperature chilled water plant and improve the chiller plant's energy efficiency. In optimal control, optimization algorithms are generally used to seek the optimum control parameters. The Equilibrium Optimizer (EO) inspired by a well-mixed dynamic mass balance on a control volume has been proposed by Faramarzi recently, and it has been proved to outperform most of the well-known metaheuristic algorithms, such as PSO and GA (Faramarzi et al., 2020).

This paper has proposed an optimal chiller loading strategy for dual temperature chilled water plants. The EO, a metaheuristic optimization algorithm was applied to seek the optimum control parameters and minimize the total energy consumption of chillers. Then, the energy performance of the proposed optimal control strategy was evaluated and compared with the conventional average loading control strategy on a dual temperature chilled water system in a semiconductor factory.

Methodology

Mathematical optimization is the selection of input values from an allowed set to achieve the minimum of the objective function. The fundamental elements of the optimization problem are the decision variables, objective function, and constraints.

Decision variables

In optimal chiller loading, the part load ratio of each chiller ($\mathrm{PLR_i}$) and the state of chillers (S_i) are two types of decision variables. PLR_i are continuous variables and S_i are binary variables. Therefore, the optimal chiller loading problem is a typical mixed variable type (continue/binary) optimization problem.

Objective function

The objective of the optimal chiller loading is to minimize the energy consumption of chillers by optimizing chillers' cooling load and numbers of chiller running reasonably, while no operating constraints are violated. The objective function for the optimal control of a dual temperature chilled water plant could be defined as the total energy consumption of med-temperature chillers and low-temperature chillers, as shown in Equation (1),

$$J = \sum_{i=1}^{N} S_i \times P_i + \sum_{j=1}^{M} S_j \times P_j \tag{1}$$

where, S_i is the on/off state of ith chiller, which was a binary variable. 0 and 1 indicate that the chiller was staged off and on, respectively. P_i and P_j are the power consumption of the ith med-temperature chiller and the jth low-temperature chiller (kW), respectively. N and M is the total number of med-temperature chillers and low-temperature chillers, respectively.

The power consumption of chillers is impacted by the cooling load, the chilled water supply temperature, and cooling water supply temperature. For a given cooling load and weather condition, chiller's power consumption is a second-order polynomial its partial load ratio (PLR_i), as shown in Equation (2),

$$P_i = a_i + b_i PLR_i + c_i {PLR_i}^2 \tag{2}$$

Where a_i, b_i and c_i are coefficients of the ith chiller. PLR_i is the partial load ratio of ith chiller.

Constraints

The primary task of chillers was to supply enough chilled water for terminal cooling coils. In a dual temperature chilled water plant serving MAUs with two-stage cooling coils, the total cooling load of MAUs was supplied by two groups of chillers, med-temperature chiller group, and low-temperature chiller group. Therefore, the operation of chillers was constrained to satisfy the cooling demand by two groups of chillers together and then to maintain the supply air dew point temperature of 8.5 °C, as defined in Equation (3). Due to the limitation of chilled water temperature, the cooling supply of the med-temperature chillers has been limited by the maximum cooling capacity of primary cooling coils. The maximum cooling capacity can be estimated by the lowest achievable outlet air enthalpy of the cooling coil. It was an inequality constraint defined as Equations (4) to (5).

$$\sum_{i=1}^{N} PLR_i \times Q_{rate,i} + \sum_{j=1}^{M} PLR_j \times Q_{rate,j} = CL \tag{3}$$

$$\sum_{i=1}^{N} PLR_i \times Q_{rate,i} \leq Q_{pri,max} \tag{4}$$

$$Q_{pri,max} = m_a \times \left(h_w - h_{pri,min}\right) \tag{5}$$

where, $Q_{rate,i}$ and $Q_{rate,j}$ is the rated cooling capacity of ith med-temperature chiller and jth low-temperature chiller, respectively (RT). CL is the total cooling demand for MAUs (RT). $Q_{pri,max}$ represents the maximum cooling capacity of primary cooling coils (RT). m_a is the air mass flow rate processed by MAUs (kg/s). h_w is the inlet air (normally outdoor air) enthalpy of MAUs (kJ/kg). $h_{pri,min}$ is the minimum enthalpy that the air could achieve after the primary cooling coil (kJ/kg).

According to the recommendation of the manufacture, the part load ratio of chillers should be higher than 0.5, when a chiller is in operation. When the chiller is staged off, the PLR_i is 0. This physical constraint on both med-temperature chillers and low-temperature chillers was defined as Equation (6),

$$\begin{cases} 0.5 \leq PLR_i \leq 1 & if\ S_i = 1 \\ PLR_i = 0 & if\ S_i = 0 \end{cases} \tag{6}$$

Optimization algorithm

The optimal control aims to find the optimum PLR_i of the chillers in operation, which helps to achieve the lowest energy consumption of all chillers, while providing enough chilled water for end-users. It was a multi-variable, nonlinear, constrained, complex optimization problem. Metaheuristic algorithms are considered to show better performance in finding the global optimal solution than the traditional gradient-based optimization algorithms in these complex optimization problems. The Equilibrium Optimizer (EO) (Faramarzi et al., 2020), a metaheuristic algorithm inspired by a simple well-mixed dynamic mass balance on a control volume, has shown high effectiveness in obtaining optimal solutions with typically higher efficiency (i.e., less computational time or fewer iterations) than the well-known metaheuristic algorithms, such as GA and PSO (Faramarzi et al., 2020). Therefore, in this study, the EO has been adopted to solve the optimization problem defined above.

The EO is inspired by a simple well-mixed dynamic mass balance on a control volume. Based on the underlying mass balance theory, the concentration of the control volume (potential solution of the optimization) could be formulated as Equations (7) – (8),

$$C = C_{eq} + \left(C_0 - C_{eq}\right)F + \frac{G}{\lambda V}(1 - F) \tag{7}$$

$$F = exp\left(-\lambda(t - t_0)\right) \tag{8}$$

where C is the concentration of the substance inside the control volume. C_{eq} is the concentration of the equilibrium state. C_0 is the concentration of the control volume at the initial time t_0. In the optimization process, C_0 was randomly initialized with a uniform distribution between the lower and upper bound to cover the entire searching space. The G is the generation rate of the substance source in the control volume. λ is the flow change rate. V is the volume of the control volume, which can be considered as unit volume ($V = 1$).

The exponential term, F, contributes to the main concentration updating rule. In exponential term F, λ is assumed to be a random vector in the interval of [0, 1]. The time, t, is defined as a function of iteration ($Iter$) and thus decreases with the number of iterations (Equation (9)).

$$t = (1 - \frac{Iter}{Max_{iter}})^{\left(a_2 \frac{Iter}{Max_{iter}}\right)} \tag{9}$$

where $Iter$ and Max_{iter} are current and the maximum number of iterations, respectively. a_2 is a hyperparameter used to manage the ability of exploitation. It determines the magnitude of exploitation by mining around the best solution. In this paper, the maximum number of iterations is set to 1000. According to empirical testing, the a_2 equals 1.5 showing good searching ability.

The exponential term (F) was carefully designed. Finally, it was defined as in Equation (10). More detailed information on the establishment of the F could be found in (Faramarzi et al., 2020).

$$F = a_1 sig(r - 0.5)\left[e^{-\lambda t} - 1\right] \quad (10)$$

where a_1 is a constant value that controls the exploration quantity of the EO algorithm. A higher value of a_1 indicates a higher exploration ability. However, when a_1 greater than three, the ability was degraded significantly. In this paper, a_1 is set to 2 which is selected by empirical testing of the objective function. $sign(r - 0.5)$ controls the exploitation direction. r is a random number evenly distributed between 0 and 1.

The generation rate, G, was described as a first-order exponential decay process, as defined in Equations (11) to (13),

$$G = G_0 F \quad (11)$$

$$G_0 = GCP\left(C_{eq} - \lambda C\right) \quad (12)$$

$$GCP = \begin{cases} 0.5 r_1 & r_2 \geq GP \\ 0 & r_2 > GP \end{cases} \quad (13)$$

where r_1 and r_2 are random numbers in [0, 1] with uniform distribution. GP specifies how many particles use generation term to update their states. A good balance between exploration and exploitation is achieved with $GP = 0.5$.

Results and Discussion

System description

This study focused on a dual temperature chilled water plant with dedicated chillers in a semiconductor fab located in Tianjin, China. The dual temperature chilled water plant is composed of two chiller groups, med-temperature, and low-temperature chiller group, as shown in Figure 1. It was used to provide med-temperature chilled water for the primary coil and low-temperature chilled water for the secondary cooling coil in MAUs. MAUs are typically used in cleanroom HVAC systems, which provides dry and cool fresh air for cleanrooms to maintain the cleanroom temperature and humidity in its allowing range (24 ± 1 ℃, 45 ± 5%). There are 11 MAUs with the design airflow rate of 80000 m^3/h. Three chillers with the cooling capacity of 1300 RT were designed to provide the med-temperature chilled water at 5.5 ℃. Three chillers with the cooling capacity of 650 RT were employed to provide low-temperature glycol water mixture at 0.0 ℃, and two chillers for working and one standby. The power consumption of chillers is normally affected by the cooling load, chilled water temperature, and cooling water temperature. The chilled water temperature of chillers is set to a constant value. For a given operating condition, the cooling water temperature was known. Thus, the energy consumption of chillers can be defined as a second-order polynomial of the partial load ratios, as defined in Equation (2). In this dual temperature chilled water plant, the most frequent cooling water temperature setpoint is 24 ℃, and thus, the power consumption of chillers under different partial load ratios was shown in Figure 2 with a cooling water temperature of 24 ℃. The coefficients of chillers' performance curves were listed in Table 1.

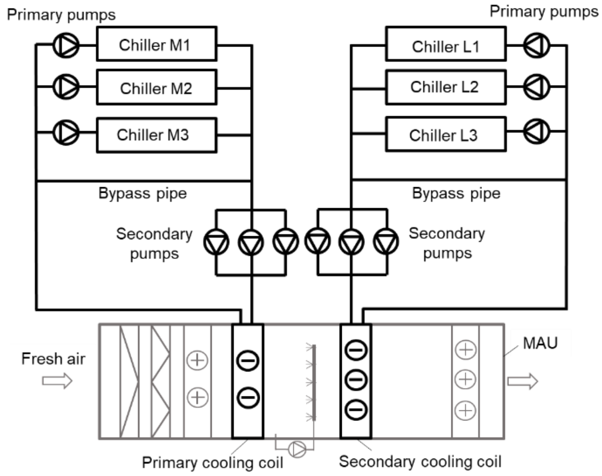

Figure 1. The dual temperature chilled water plant with dedicated chillers

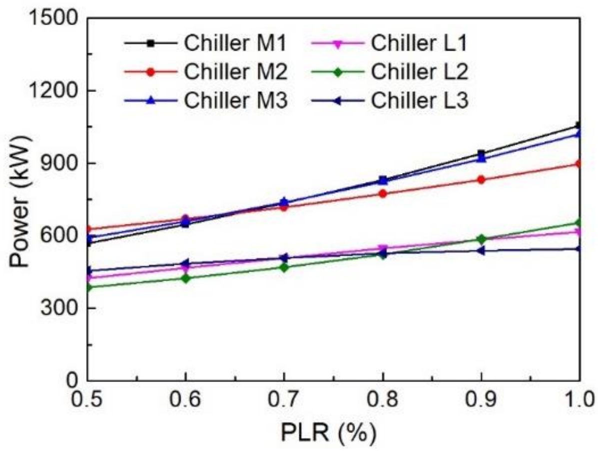

Figure 2. Chillers' performance curve with the cooling water temperature at 24 ℃

Table 1. Coefficients of chillers' performance curves

Chillers	a_i	b_i	c_i	Capacities (RT)
M1	322.15	250.02	484.00	1300
M2	488.18	144.44	262.70	1300
M3	381.45	204.94	432.70	1300
L1	167.35	576.47	-127.20	650
L2	303.81	-21.62	370.80	650
L3	219.24	618.90	-293.26	650

Control strategies

In this paper, an optimal chiller loading control strategy was proposed to minimize the energy consumption of dual temperature chilled water plants. The energy performance of the proposed optimal control strategy was evaluated under different cooling load conditions on a dual temperature chilled water plant and it was compared with the conventional control strategy. Both control strategies are described as follows.

For the conventional control strategy, the control of different chiller groups of a dual temperature chilled water plant with dedicated chillers was relatively independent. The numbers of the chiller in operation and the partial load ratio of med-temperature chillers are regulated to maintain the setpoint of air dry-bulb temperature after the primary cooling coil. The approach temperature of the primary cooling coil was 9.5 ℃ at the design condition, and thus, the dry bulb temperature of the air after the cooling coil was set to 15 ℃. Similarly, the cooling supply of low-temperature chillers is adjusted to ensure that the outlet air dewpoint temperature of the secondary coil is around 9.5 ℃ and further to maintain the indoor air humidity in its allowing range (22 ± 1 ℃, 45 ± 5%). Chillers in each group are controlled with an equal part load ratio. This conventional control strategy, defined as Average Loading (AVL), was taken as the baseline of the energy performance comparison.

An optimal control strategy for chiller loading of dual temperature chilled water plants was introduced in this Section. In a dual temperature chilled water plant, the cooling demand of MAUs is satisfied by the primary cooling coil and secondary cooling coils together. Both the cooling load distribution among different chillers and between two chiller groups impact the energy performance of the whole chiller plant. Therefore, an optimal control strategy was proposed. In this strategy, the number of chillers running, and the partial load ratio of chillers were optimized to achieve the lowest energy consumption of chillers. The optimum control parameters were determined by solving the optimization problem defined in the Section of Methodology using the EO algorithm. This strategy redistributes the cooling load both among different chillers in each group and between different chiller groups to minimizes the total energy consumption of all chillers while providing enough chilled water to satisfy the cooling demand and then to maintain the dewpoint temperature of the MAUs' outlet air at 9.5 ℃.

Energy performance comparison

To evaluate the proposed optimal control strategy, the conventional and the proposed optimal control strategies were applied on a dual temperature chilled water plant and their energy consumption was estimated and compared with the cooling load varying from 1400 RT to 4600 RT with an interval of 400 RT, which covers the most operating conditions of the system.

The primary task of chillers was to provide enough chilled water to coils for cooling and dehumidification. Chillers' load distribution under different conditions was shown in Figure 3. From this figure, it can be seen that the cooling load distribution of these two control strategies is different and both strategies can satisfy the cooling demand of end-users. Using the optimal chiller loading strategy, chillers with higher energy efficiency were assigned with a larger load ratio rather than an equal load ratio to maximize the whole chiller plant efficiency. Moreover, the optimal control strategy not only optimizes the cooling load distribution among different chillers in each chiller group but also redistributes the cooling load between two chiller groups.

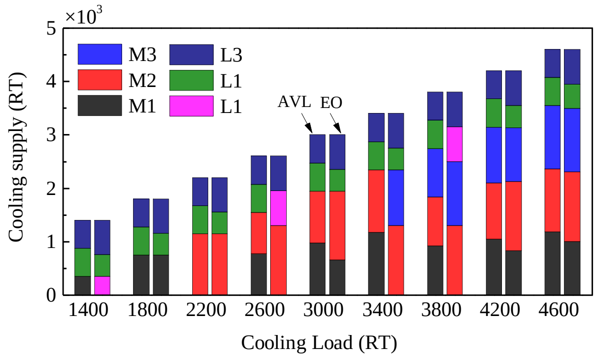

Figure 3. The cooling load distribution under different conditions

The energy consumption of the conventional control strategy (AVL) and optimal control strategy (EO) under different load conditions was shown in Figure 4. Compared with the conventional control strategy, the optimal control strategy consumes less energy in all the tested load conditions. The optimal chiller loading strategy could save 79.5 kW to 310.5 kW power consumption under different cooling load conditions, as listed in Table 2.

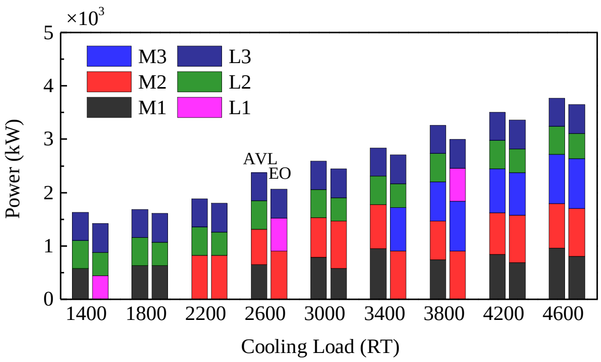

Figure 4. The power consumption with different control strategies

Based on the data listed in Table 2, the energy-saving rate of the proposed optimal control strategy under different operation conditions could be obtained easily. Taking the power consumption of the average loading strategy as the baseline, the optimal chiller loading in a dual temperature chilled water plant could reduce 3.3% to 13.1% power consumption under different cooling load conditions.

Table 2. The energy consumption of chillers under different control strategies.

Load (RT)	AVL (A)	EO (B)	A-B
	Power (kW)	Power (kW)	Power (kW)
4600	3769.8	3646.9	122.9
4200	3500.8	3359.0	141.8
3800	3256.7	2996.1	260.6
3400	2832.2	2700.2	132.0
3000	2582.1	2440.5	141.6
2600	2367.3	2056.8	310.5
2200	1878.1	1798.6	79.5
1800	1683.2	1603.6	79.6
1400	1627.5	1416.7	210.8

Conclusions

A dual temperature chilled water plant is typically used for systems that required deep dehumidification and low chilled water temperature, such as THIC systems. The dual temperature chilled water plant has shown significant energy-saving potentials than the single-temperature chiller plant for dehumidification coils, which maximizes the efficiency of chillers with higher chilled water supply temperature.

In this paper, an optimal chiller loading strategy has been proposed and applied on a dual temperature chilled water plant serving for cleanrooms in a semiconductor fab. The mathematical description of optimal control for dual temperature chilled water plant was established first, including decision variables, objective function, and constraints. Considering the complexity of the optimization problem, the EO algorithm, a metaheuristic optimization algorithm inspired by the mass balance law, was employed to seek the optimum control parameters. To evaluate the energy performance of the optimal control strategy, 9 operation conditions were selected with the cooling load of the MAUs varying from 1400 RT to 4600 RT with an interval of 400 RT, which covers the most operating conditions of the system. Then, the energy performance of the optimal control strategy was compared with the conventional control strategy under different conditions. Using the optimal control strategy, chillers with higher energy efficiency were assigned with a higher load ratio rather than an equal load ratio to achieve lower energy consumption of the entire chiller plant. Compared with the average loading control strategy, the optimal control strategy in a dual temperature chilled water plant could reduce 79.8 kW to 310.5 kW power consumption and achieve 3.3% to 13.1% energy savings under the tested cooling load conditions.

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