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Amelioration of the Cooling Load based Chiller Sequencing Control

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Abstract:

Cooling Load based Control (CLC) for the chiller sequencing is a commonly used control strategy for multiple-chiller plants. To improve the energy efficiency of these chiller plants, researchers proposed various CLC optimization approaches, which can be divided into two groups: studies to optimize the load distribution and studies to identify the optimal number of operating chillers. However, both groups have their own deficiencies and do not consider the impact of each other. This paper aims to improve the CLC by proposing three new approaches. The first optimizes the load distribution by adjusting the critical points for the chiller staging, which is easier to be implemented than the existing approaches. In addition, by considering the impact of the load distribution on the cooling tower energy consumption and the pump energy consumption, this approach can achieve a better energy saving. The second optimizes the number of the operating chillers by modulating the critical points and the condenser water set point in order to achieve the minimal energy consumption of the entire chiller plant that may not be guaranteed by existing approaches. The third combines the first two approaches to provide a holistic solution. The proposed three approaches were evaluated via a case study. The results show that the total energy consumption saving for the studied chiller plant is 0.5%, 5.3% and 5.6% by the three approaches, respectively. An energy saving of 4.9% to 11.8% can be achieved for the chillers at the cost of more energy consumption by the cooling towers (increases of 5.8% to 43.8%). The pumps' energy saving varies from -8.6% to 2.0%, depending on the approaches.

Keywords: Multiple-chiller Plant; Chiller Sequencing Control; Model-based Optimization

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1. Introduction

1.1 Background

In the United States, commercial building cooling equipment consumed around 77.4 GWh primary energy in 2010 [1]. Chiller plants are widely used to provide cooling for large buildings, data centers and district cooling systems. As major components of the chiller plants, chillers alone represented about 35% of the energy consumption by the commercial building cooling [2]. Due to their significant energy consumption, optimal control of the chiller plants is of great interest to the nation. To enhance the operational efficiency of the chiller plants, many researchers have devoted efforts to achieve the optimal control of the plants. As a result, many approaches have been proposed [3-43].

Among various configurations of chiller plants, the multiple-chiller plants are the most widely used. For those plants, it is recommended to operate chillers sequentially rather than simultaneously [44]. To operate chillers in sequence, one uses a chiller sequencing control, usually based on the cooling load, to bring chillers online or offline. Depending on the approach to indicate the cooling load, the chiller sequencing control can be categorized as: the return chilled water temperature based control, the bypass flow based control, the direct power based control, and the Cooling Load based Control (CLC) [45]. Among them, the CLC is considered to be the most promising because other approaches employ the use of indirect indicators of the cooling load (e.g. the return chilled water temperature, the volume flow rate at bypass of secondary loop, and the chiller power), which may not be proportional to the cooling load [21]. The CLC directly calculates the cooling load using the chilled water flow rate and the difference between the chilled water supply temperature and return temperature [9].

In the CLC, one chiller will not be brought online/offline unless the cooling load is larger/smaller than the total available cooling capacity of the operating chillers. The total available cooling capacity of i operating chillers can be referred as a Critical Point (*CP*):

$$CP_i = \sum_{j=1}^{i} CC_{act,j}, \tag{1}$$

where $CC_{act,j}$ is the actual cooling capacity of the jth chiller. In the real world implementation, the nominal capacity of the chiller, $CC_{nom,j}$, is conventionally used to represent $CC_{act,j}$. Thus, equation (1) can be converted into:

$$CP_i = \eta \sum_{j=1}^{i} CC_{nom,j}, \tag{2}$$

where η is the safety factor (e.g., 90%) to mitigate the risk of insufficient cooling supply during the chiller start-up period. Besides, a state machine [46] can also be used to facilitate the implementation of the CLC. To avoid a chiller short circling, a waiting time t_{wait} and a dead band CP_{db} are usually employed. For instance, Figure 1 shows a conventional CLC for a chiller plant with three identical chillers. The transition between states indicates adding or reducing the number of the operating chillers.

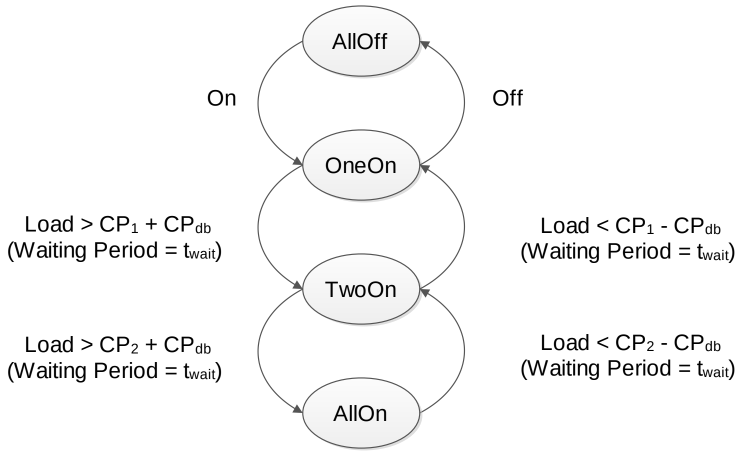

Figure 1 The state machine of a conventional CLC for a chiller plant with three identical chillers

1.2 CLC Optimization

Although widely used, the conventional CLC has limitations and can't guarantee the minimal energy consumption by the chiller plants. To improve the energy efficiency of the chiller plants, researchers proposed various CLC optimization approaches [5-7, 9, 20-33, 40-43]. Generally speaking, those approaches can be divided into two groups: studies to optimize the load distribution and studies to identify the optimal number of operating chillers. We will discuss the concept and the limitations of each group as follows.

The first group aims to optimize the load distribution among the chillers. The conventional CLC turns on an additional chiller only when the cooling loading approaches the total nominal cooling capacity of the operating chillers. This means that chillers will work at the highest Partial Load Ratio (*PLR*). The *PLR* is the ratio of the cooling load handled by one chiller to its nominal cooling capacity. However, the ASHRAE Handbook [44] points out that a higher chiller *PLR* does not necessarily mean a higher operational efficiency. The chiller's operational efficiency is usually measured by the coefficient of performance (*COP*), which is the ratio of the cooling energy provided by the chiller to its power consumption. Figure 2 shows that the highest *COPs* may occur at relatively low *PLRs* for three different chillers.

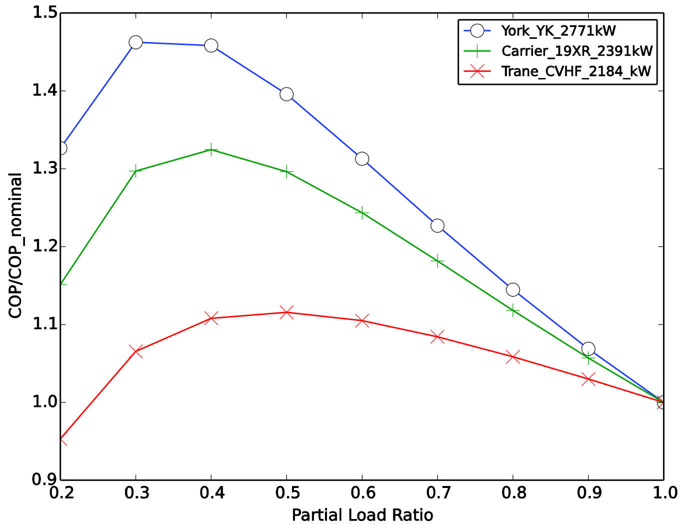

Figure 2 The relationship between PLRs and the relative COPs for three different chillers calculated according to the chiller dataset provided by EnergyPlus [47]

To achieve the optimal load distribution, researchers developed model based optimization approaches to adjust the *PLR* of each chiller individually according to a given cooling load [5, 7, 22-33]. Some studies aimed to maximize a summation of the operating chillers' *COP* as follows [5, 22, 24, 33]:

$$J = \max\left(\sum_{i=1}^{M} COP_i\right), \quad s.t. \tag{3}$$

$$\sum_{i=1}^{M} PLR_i CC_{nom,i} = \dot{Q}, \tag{4}$$

where COP_i and PLR_i are the *COP* and *PLR* of the ith chiller, respectively. The M is the number of the chillers in the chiller plant and $\dot{Q}$ is the cooling load. They utilized a regressed *PLR-COP* curve in equation (5) to calculate the COP_i under the PLR_i:

$$COP_i = \sum_{j=0}^{m} a_j PLR_i{}^j, \tag{5}$$

where a_j is the jth constant coefficient and m is the number of the constant coefficients.

Other approaches tried to minimize the sum of the chillers' power as follows [7, 23, 25-32]:

$$J = \min\left(\sum_{i=1}^{M} P_{ch,i}\right), \quad s.t. \tag{6}$$

$$\sum_{i=1}^{M} PLR_i CC_{nom,i} = \dot{Q}, \tag{7}$$

where $P_{ch,i}$ is the power of the ith chiller. The regressed Power-*PLR* curve in equation (8) was employed to calculate $P_{ch,i}$.

$$P_{ch,i} = \sum_{j=0}^{n} b_j PLR_i{}^j, \tag{8}$$

where b_j is the jth constant coefficient and n is the number of the constant coefficients.

Both the above approaches used the PLRs as the independent variables to directly/indirectly reduce the total power of the chillers. However, it is difficult to implement the PLR control in the real world application since the PLR can only be indirectly controlled. Some scholars improved the above approaches by replacing the $PLRs$ with other relevant controllable parameters, such as the chilled water flow rates through each chiller [6, 40], the temperature set points of the chilled water leaving each chiller [41, 42], and the combination of the previous two parameters [43]. However, these approaches still have some limitations. For instance, the approaches of adjusting the chilled water flow rate through chillers can only be applied to the chiller plant equipped with chillers and pumps that can handle variable chilled water flow rates. In addition, these approaches only consider the impact of the load distribution on the chiller power. However, for plants with dedicated pumps and dedicated cooling tower for each chiller, the load distribution also impacts the pump power and the cooling tower power. Without considering the impacts on the pump power and the cooling tower power, these approaches can't guarantee the minimal energy consumption for the entire chiller plant.

The second group is associated with the optimization on the number of the operating chillers. As mentioned above, the conventional CLC uses the chillers' nominal cooling capacities to represent the chillers' actual cooling capacities. However, the actual cooling capacity of a chiller varies by its operating conditions [9, 21]. As shown in Figure 3, a chiller's capacity increases up to 110% of its nominal capacity when the temperature of the condenser water entering the chiller ($T_{cw,ent}$) decreases from 23.89°C (nominal condition) to 18.89°C. Therefore, it is possible that a chiller's actual cooling capacity is larger than its nominal capacity and so does the entire multi-chiller plant. In this case, the chiller plant can meet a higher cooling load without turning on an additional chiller. Since we usually have a dedicated primary chilled water pump and a dedicated condenser water pump for each chiller, reducing the number of the operating chillers can save energy from the dedicated pumps [44].

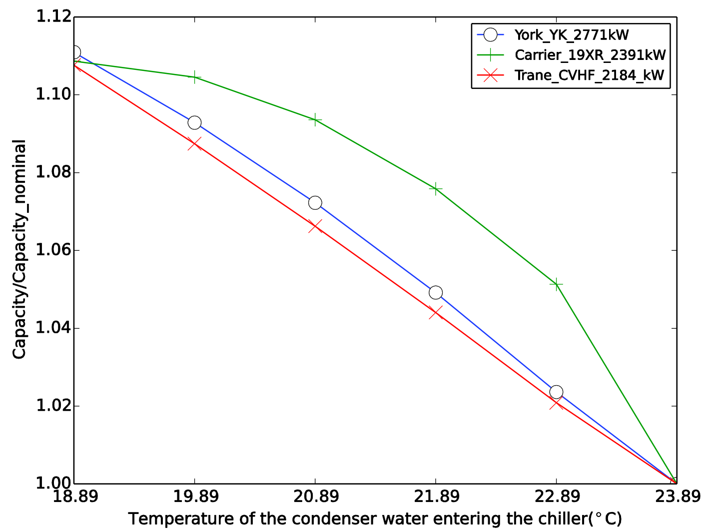

Figure 3 The relationship between the temperature of the condenser water entering the chiller and the relative cooling capacity for three different chillers calculated according to the chiller dataset provided by EnergyPlus [47]

To identify the optimal number of the operating chillers, some researchers proposed to reset the *CP*s based on the estimation of the actual cooling capacity [9, 20, 21]. They calculated $CC_{act,i}$ using the operating parameters of the chiller (such as the pressure in the evaporator, compressibility factor and so on) at a given operating condition. Although these approaches may reduce the pump energy consumption, they can't guarantee the minimal energy consumption of the entire chiller plant including chillers, cooling towers and pumps. For instance, by increasing the *CP*s according to the calculated cooling capacities, it is possible to reduce the number of the operating chillers. In that case, the *PLR* of each operating chiller has to increase to meet the same cooling load with fewer chillers. As we mentioned above, the increased *PLR*s may lead to lower *COP*s.

To summarize, there are deficiencies in the existing CLC optimization approaches. In addition, although the optimization of the load distribution and the optimization of the number of the operating chillers interact with each other, they were only studied separately in previous studies. In response to these issues, we propose three new CLC optimization approaches. The first approach is to optimize the load distribution by adjusting the *CP*s. The second approach is to optimize the number of the operating chillers by modulating the *CP*s and the condenser water set point. The third approach combines the first two approaches aiming to achieve more energy savings with a holistic solution.

This paper makes contributions to the literature in a number of ways: first, we developed a new approach for the optimal load distribution. This approach is easier to be implemented than existing approaches in literature and can achieve a better energy performance for the entire chiller plant. Second, we proposed a new approach to optimize the number of the operating chillers. This approach considers the impact of the *CP*s reset on the energy performance of the chillers, the cooling towers and the pumps, which is not considered in the existing approaches. Third, we provided a holistic solution to address the optimal load distribution problem and the optimal number of the operating chillers problem simultaneously, which has not been reported in the literature yet to our knowledge.

The paper is organized as follows: after the introduction, we introduce the three new approaches for the CLC optimization. We then elaborate the implementation of these approaches. Finally, we evaluate the performances of these approaches via a case study.

2. New Approaches for the CLC optimization

2.1 General Assumptions

In this paper, we consider a water-cooled chiller plant with M chillers and N cooling towers. Each chiller has a dedicated constant speed chilled water pump and a dedicated constant speed condenser water pump. The towers have variable cooling tower fans controlled by the same set point for the temperature of the condenser water leaving the towers, which is called condenser water set point, $T_{cw,set}$. The other control parameters except the *CP*s and $T_{cw,set}$, such as set points for the temperature of the chilled water leaving the chillers, $T_{chw,set}$, are constant. Thus, the total power of chillers, pumps, and cooling towers, P_{tot}, at time t can be described as follows:

$$\begin{aligned} P_{tot}(t) &= \sum_{i}^{M}(P_{ch,i}(t) + P_{pu,i}(t)) + \sum_{j}^{N} P_{tw,j}(t) \\ &= f_1\big(T_{cw,set}(t), CP_1(t),\ \dots, CP_{M-1}(t), \dot{Q}(t), T_{wb}(t), \vec{S}(t)\big), \end{aligned} \tag{9}$$

where $P_{pu,i}$ and $P_{tw,j}$ is the power of the dedicated chilled water pump and the dedicated condenser water pump for the ith chiller and the jth cooling tower, respectively. The T_{wb} is the wet bulb temperature and $\vec{S}$ is the state vector of the system (e.g. equipment operating status, water temperature in the condenser and the evaporator of the chiller). Then the energy consumption of the chiller plant for a period from t_0 to $t_0 + \Delta t$, $E_{tot}|_{t_0}^{t_0+\Delta t}$, is

$$E_{tot}|_{t_0}^{t_0+\Delta t} = \int_{t_0}^{t_0+\Delta t} P_{tot}(t)dt = \int_{t_0}^{t_0+\Delta t} f_1\big(T_{cw,set}(t), CP_1(t), \dots, CP_{M-1}(t), \dot{Q}(t), T_{wb}(t), \vec{S}(t)\big)dt. \quad (10)$$

The wet bulb temperature and the cooling load during the period of $[\mathrm{t}_0, \mathrm{t}_0 + \Delta \mathrm{t}]$ can be obtained from the weather forecast and by using regression models, respectively. Then we can use the predicted cooling load, $\dot{Q}^P$, and the predicted wet bulb temperature, ${T_{wb}}^P$, to represent $\dot{Q}$ and T_{wb} in the optimization:

$$\dot{Q}(t) = \dot{Q}^P(t), \quad (11)$$

$$T_{wb}(t) = {T_{wb}}^P(t). \quad (12)$$

We assumed $CP_i(t)$ and $T_{cw,set}(t)$ were constant during the period of $[t_0, t_0 + \Delta t]$:

$$T_{cw,set}(t) = T_{cw,set}(t_0), \quad (13)$$

$$CP_i(t) = CP_i(t_0). \quad (14)$$

In addition, since $\vec{S}(t)$ is a function of $\vec{S}(t_0)$, equation (10) can be converted into:

$$E_{tot}|_{t_0}^{t_0+\Delta t} = \int_{t_0}^{t_0+\Delta t} f_2\big(T_{cw,set}(t_0), CP_1(t_0), \dots, CP_{M-1}(t_0), \dot{Q}^P(t), {T_{wb}}^P(t), \vec{S}(t_0)\big)dt. \quad (15)$$

2.2 The New Approaches

2.2.1 Approach 1: Optimal Load Distribution

For the load distribution optimization, we assumed $T_{cw,set}$ is constant, thus equation (15) can be changed to:

$$E_{tot}|_{t_0}^{t_0+\Delta t} = \int_{t_0}^{t_0+\Delta t} f_3\big(CP_1(t_0), \dots, CP_{M-1}(t_0), \dot{Q}^P(t), {T_{wb}}^P(t), \vec{S}(t_0)\big)dt. \quad (16)$$

We used the *CP*s to replace *PLR*s as the independent variables to minimize $E_{tot}|_{t_0}^{t_0+\Delta t}$. Based on equation (16), the optimization problem can be defined as

$$J = \min\Big(E_{tot}|_{t_0}^{t_0+\Delta t}\Big) = \min\Big(\int_{t_0}^{t_0+\Delta t} f_3\big(CP_1(t_0), \dots, CP_{M-1}(t_0), \dot{Q}^P(t), {T_{wb}}^P(t), \vec{S}(t_0)\big)dt\Big), \quad (17)$$

s.t.

$$CP_1^{min} < CP_1(t_0) \le \eta \sum_{j=1}^{1} CC_{nom,j}, \quad (18)$$

$$CP_{i-1}(t_0) < CP_i(t_0) \le \eta \sum_{j=1}^{i} CC_{nom,j} \ \ (i > 1), \quad (19)$$

where CP_1^{min} is the low bound for $CP_1(t_0)$. The $\dot{Q}^P(t)$, ${T_{wb}}^P(t)$ and $\vec{S}(t_0)$ are the input variables while $CP_1(t_0), \dots, CP_{M-1}(t_0)$ are the independent variables in the optimization. Approach 1 does not consider the change of chiller cooling capacities by the operating conditions, thus the high bounds for *CP*s are determined as $\eta \sum_{j=1}^{i} CC_{nom,j}$.

Compared to the existing optimal load distribution approaches [5, 7, 22-33], Approach 1 has the following advantages: first, it is easier for implementation since *CP*s can be directly adjusted; second, the impact of the load distribution on the energy consumption by the cooling towers and the pumps is considered in the objective function. Thus, Approach 1 can lead to a better energy saving for the entire chiller plant.

2.2.2 Approach 2: Optimal Number of the Operating Chillers

For the cooling capacity based *CP*s reset, we changed the reset into an optimization problem based on equation (15) to minimize $E_{tot}|_{t_0}^{t_0+\Delta t}$:

$$J = \min\left(E_{tot}|_{t_0}^{t_0+\Delta t}\right) =$$

$$\min\left(\int_{t_0}^{t_0+\Delta t} f_2\left(T_{cw,set}(t_0), CP_1(t_0), \ldots, CP_{M-1}(t_0), \dot{Q}^P(t), T_{wb}{}^P(t), \vec{S}(t_0)\right)dt\right), \quad (20)$$

s.t.

$$T_{cw,set,L} \leq T_{cw,set}(t_0) \leq T_{cw,set,H}, \quad (21)$$

$$\eta \sum_{j=1}^{i} CC_{nom,j} \leq CP_i(t_0) \leq CP_i^{max}, \quad (22)$$

where $T_{cw,set,L}$ and $T_{cw,set,H}$ is the low bound and the high bound for $T_{cw,set}(t_0)$, CP_i^{max} is the high bound for CP_i. The $\dot{Q}^P(t)$, $T_{wb}{}^P(t)$ and $\vec{S}(t_0)$ are the input variables. The $T_{cw,set}$ is selected as an independent variable because $T_{cw,set}$ can be used to regulate $T_{cw,ent}$ which in turn affects the actual cooling capacity of the chillers. The *CP*s can directly impact the number of the operating chillers and the associated pumps. To reduce the number of the operating chillers and the operating pumps, we used $\eta \sum_{j=1}^{i} CC_{nom,j}$ as the low bound for *CP*s and allowed *CP*s to be higher values up to CP_i^{max}.

Because the chiller cooling capacities vary by operating conditions, it is possible that we may not be able to provide sufficient cooling if the estimated CP_i^{max} is larger than the actual maximum capacity. In that case, we may save energy by reducing the number of the operating chillers and the associated pumps, but the thermal comfort in the demand side would be sacrificed since provided cooling is insufficient. We used the deviation of temperature of chilled water leaving the chiller, $T_{chw,lea}$, from $T_{chw,set}$ as an indicator to determine if sufficient cooling is supplied. The deviation, $D_{chw,lea,}$ is calculated by

$$D_{chw,lea} = \int_{t_0}^{t_0+\Delta t} \left| T_{chw,lea}(t) - T_{chw,set} \right| dt \tag{23}$$

Ideally, $D_{chw,set}$ should be equal to 0. However, the deviation may also be caused by the waiting time in the CLC which is inevitable. With that in mind, we designed the following constraint:

$$D_{chw,lea} \leq D_{chw,lea,base}, \tag{24}$$

where $D_{chw,set,base}$ is $D_{chw,set}$ at the baseline in which no optimization occurs.

To summarize, the optimization can be described as:

$$J = \min\left(E_{tot}|_{t_0}^{t_0+\Delta t}\right) = \min\left(\int_{t_0}^{t_0+\Delta t} f_2\left(T_{cw,set}(t_0), CP_1(t_0), \ldots, CP_{M-1}(t_0), \dot{Q}^P(t), T_{wb}{}^P(t), \vec{S}(t_0)\right)dt\right), \tag{25}$$

s.t.

$$T_{cw,set,L} \leq T_{cw,set}(t_0) \leq T_{cw,set,H}, \tag{26}$$

$$\eta \sum_{j=1}^{i} CC_{nom,j} \leq CP_i(t_0) \leq CP_i^{max}, \tag{27}$$

$$D_{chw,lea} \leq D_{chw,lea,base}. \tag{28}$$

Approach 2 considers the impact of the *CP*s reset on the energy performance of the chillers, the cooling towers and the pumps. Thus it can guarantee the minimal energy consumption for the entire chiller plant, which may not be achieved by the existing *CP*s reset approaches [9, 20, 21].

2.2.3 Approach 3: A Holistic Solution for the CLC

It is possible to save more energy by combining Approach 1 and Approach 2. In this holistic approach, the CLC optimization problem can be defined as:

$$J = \min\left(E_{tot}|_{t_0}^{t_0+\Delta t}\right) = \min\left(\int_{t_0}^{t_0+\Delta t} f_2\left(T_{cw,set}(t_0), CP_1(t_0), \ldots, CP_{M-1}(t_0), \dot{Q}^P(t), T_{wb}{}^P(t), \vec{S}(t_0)\right)dt\right), \tag{29}$$

s.t.

$$T_{cw,set,L} \leq T_{cw,set}(t_0) \leq T_{cw,set,H}, \tag{30}$$

$$CP_1^{min} < CP_1(t_0) \leq CP_1^{max}, \tag{31}$$

$$CP_{i-1}(t_0) < CP_i(t_0) \leq CP_i^{max} \ (i > 1), \tag{32}$$

$$D_{chw,lea} \leq D_{chw,lea,base}. \tag{33}$$

The $\dot{Q}^P(t)$, $T_{wb}{}^P(t)$ and $\vec{S}(t_0)$ are the input variables while $T_{cw,set}(t_0)$, $CP_1(t_0), \ldots, CP_{M-1}(t_0)$ are the independent variables.

2.3 Implementation

2.3.1 Constraints Setting

The CLC optimizations described in Approach 1, Approach 2 and Approach 3 are all constrained optimization problems. The commonly used technologies for solving the constrained optimization problems include the barrier function method and the penalty function method [48]. On one hand, the barrier function method imposes a punishment on the value of the objective function if the value of the objective function approaches the feasible region boundary. On the other hand, the penalty function method adds a term to the objective function and the added term generates a negative impact on the objective function when constrains are violated. In our CLC optimization, $T_{cw,set}(t_0)$ and/or $CP_i(t_0)$, which make $D_{chw,lea} = D_{chw,lea,base}$, can be optimal values, which is not allowed in the barrier function method. Thus, we adopted the penalty function method. For example, the optimization problem in Approach 3 can be converted into:

$$J^* = \min(\int_{t_0}^{t_0+\Delta t} f_2\big(T_{cw,set}(t_0), CP_1(t_0), \dots, CP_{M-1}(t_0), \dot{Q}^P(t), {T_{wb}}^P(t), \vec{S}(t_0)\big)dt + k \cdot \max(0, D_{chw,lea} - D_{chw,lea,base})), \tag{34}$$

s.t.

$$T_{cw,set,L} \le T_{cw,set}(t_0) \le T_{cw,set,H}, \tag{35}$$

$$CP_1^{min} < CP_1(t_0) \le CP_1^{max}, \tag{36}$$

$$CP_{i-1}(t_0) < CP_i(t_0) \le CP_i^{max}\ (i > 1), \tag{37}$$

where k is the iteration index of one optimization and $\max(0, D_{chw,lea} - D_{chw,lea,base})$ is the term for the penalty function method.

2.3.2 Optimization Framework

To enable the CLC optimization described in Section 2.2, we developed an optimization framework (Figure 4). The $\dot{Q}^P(t)$, ${T_{wb}}^P(t)$ and $\vec{S}(t_0)$ are used as input variables. Then the generated optimal $CP_i(t_0)$ and/or $T_{cw,set}(t_0)$ will then be used to obtain $\vec{S}(t_0 + \Delta t)$ as initial values for the next optimization period starting from $t_0 + \Delta t$.

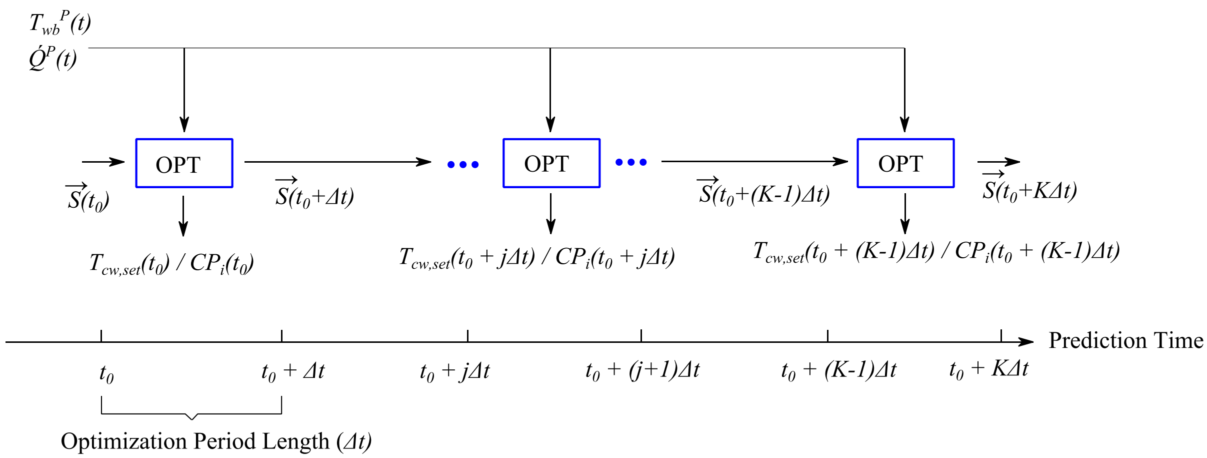

Figure 4 The optimization framework

3. Case Study

3.1 Case Description

3.1.1 Configuration of the Chiller Plant

We studied a chiller plant with three identical chillers, three identical chilled water pumps, three identical condenser water pumps, and three identical cooling towers (show in Figure 5). Each chiller has one dedicated chilled water pump, one dedicated condenser water pump and one dedicated cooling tower. The model of the chiller is a York_YK2771kW, which has the nominal cooling capacity as 2,771 kW (788 ton). For the cooling tower, the nominal fan power is 37 kW (50 HP) and was assumed to be proportional to the cubic of the fan speed ratio. The nominal wet bulb temperature and the nominal approach temperature is 23.89°C (75.00°F) and 0.89°C (1.60°F), respectively. The chilled water and the condenser water pumps are constant speed pumps and their powers are 34 kW and 47 kW, respectively. In the condenser water loop, a three-way valve is employed to modulate the condenser flow rates through the cooling towers so that the temperature of the condenser water entering the chiller, $T_{cw,ent}$ will not be less than 12.78°C (55.00°F), which is the lowest $T_{cw,ent}$ can be accepted by the chillers.

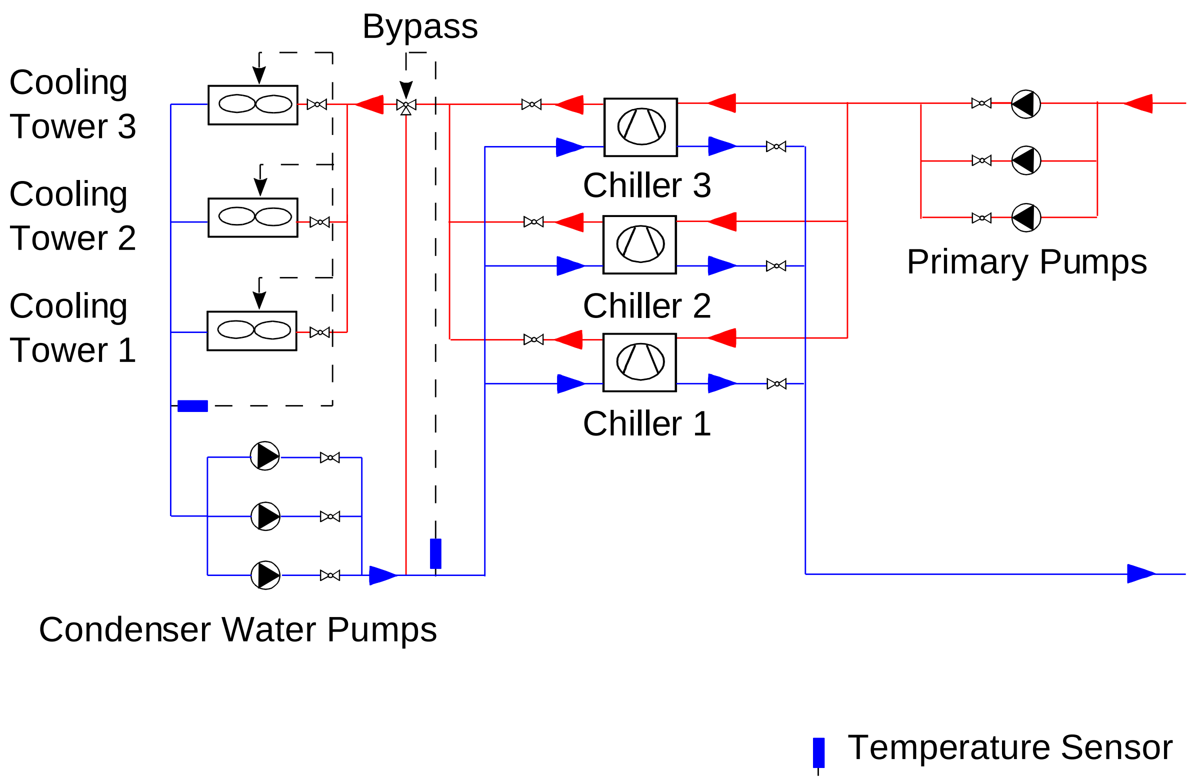

Figure 5 The schmatic of the studied chiller plant

A supervisor controller is used to control the chiller operation status according to the measured cooling load. The control sequence is described as Figure 1 with CP_1 and CP_2 fixed as 709 ton and 1,418 ton, respectively. The dead band (50 ton) and a waiting period (900 s) are also applied.

3.1.2 System Model

In this study, we used Modelica, which is an equation-based object-orient modeling language, to establish the system model. Modelica is very suitable for modeling the multi-domain systems [13, 49-51] such as the chiller plants that contain not only the physical system but also the control system.

In this study, the Modelica *Buildings* library [49] and the *Modelica_StateGraph2* library [52] were used to model the chiller plant system. In this model, $\dot{Q}$ and T_{wb} data is read externally. The performance curve of York_YK2771kW from the chiller dataset provided by EnergyPlus [47] was adapted in the chiller model. The detail of the system model can referred to [53].

3.1.3 Optimization Setting

In this study, we used the Hooke Jeeves algorithm [54] in the GenOpt [55] optimization engine to perform the searching of the optimal *CP*s and the optimal condenser water set point. The optimization was set to be performed every day. We set the safety factor $\eta = 90\%$ for all proposed approaches. For Approaches 2 and 3, we set the lowest allowable condenser water set point to be 13.89°C and CP_i^{max} to be $1.1CC_{nom}$. The intervals for $T_{cw,set}$, CP_1 and CP_2 are 1°C, 78.8 ton and 78.8 ton, respectively. Table 1 summaries the settings used in the baseline and proposed approaches.

Table 1 Settings for each CLC optimization approach

CLC Optimization Approaches	$T_{cw,set}$ [°C]	CP_1 [ton]	CP_2 [ton]
Baseline	Fixed as 23.89	709	1418
Approach 1		[0, 709]	[CP_1, 1,418]
Approach 2	[13.89, 23.89]	[709, 867]	[1,418, 1,734]
Approach 3		[0, 867]	[CP_1, 1,734]

We used real historic data for $\dot{Q}$ and T_{wb} from an actual chiller plant in Washington D.C. as the input variables for the optimization. The $\dot{Q}$ is from on-site measurement and T_{wb} is from a nearby weather station [56]. Since both $\dot{Q}$ and T_{wb} are hourly data, they were linearly interpolated during one hour for provide the inputs for the dynamic simulation. This is equivalent to have perfect prediction models that can provide reference inputs to evaluate the optimization approaches with less impact factors. In real world implementation, one can obtain the predicted cooling load by using regression models and the wet bulb temperature from weather forecast.

3.2 Results

3.2.1 Annual Simulation

Figure 6 shows the annual energy saving of the three CLC optimization approaches compared to the baseline. Approach 1 could reduce the annual chiller energy consumption by 4.9%. However, the energy consumption of the cooling towers and the pumps were increased (-5.8% and -8.6% in saving, respectively). Thus, the total energy saving ratio was only 0.5%. Approach 2 achieved a total energy saving around 5.3%. The energy use of the chillers and the pumps was reduced by 8.6% and 2.0%, respectively. Meanwhile, the cooling tower energy use was significantly increased (-41.8% in saving). As expected, Approach 3 provided the highest annual total energy saving (around 5.6%). The chiller energy saving ratio was the highest as 11.8% with the cost of the highest cooling tower energy consumption (-43.8% in saving). In addition, the pump energy also rose slightly (-3.7% in saving).

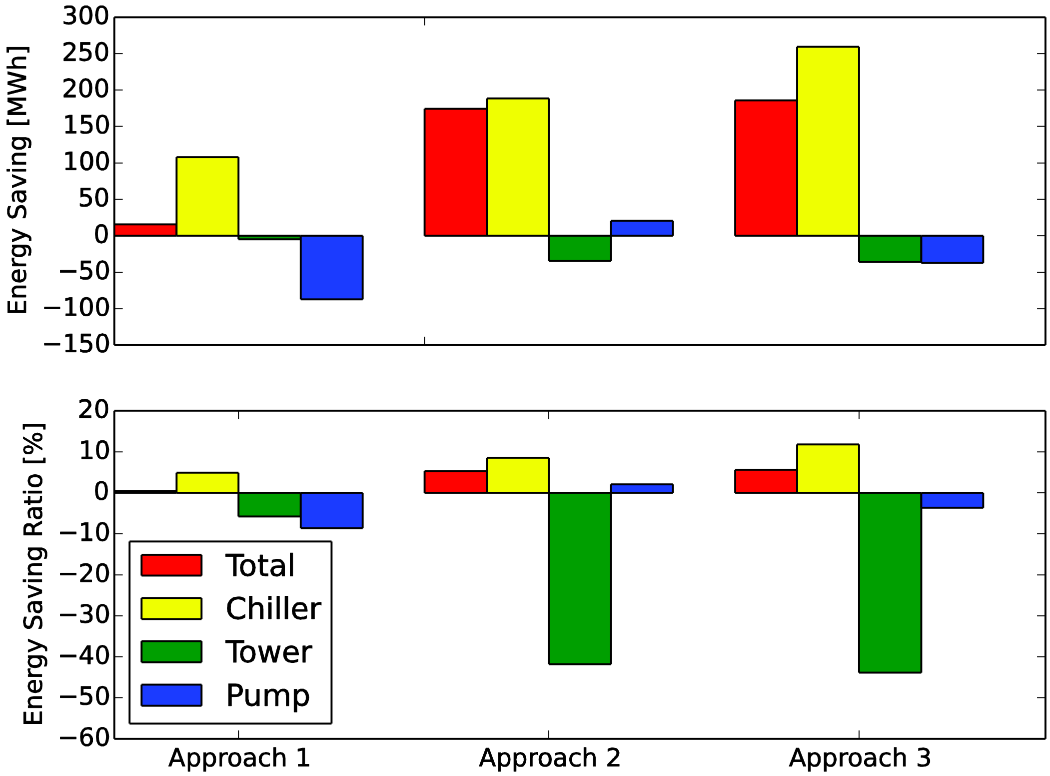

Figure 6 Comparison of the energy savings by different approaches

To understand when the energy saving occurred, we show the detailed analysis. As shown in Figure 7, the chiller energy consumption was saved mainly in the summer (May to September) for Approach 1. The cooling tower energy consumption was sometimes decreased and sometimes increased. The pump energy consumption was increased in the summer, which indicates that the number of the operating chillers was mainly increased to achieve an optimal load distribution. The total energy consumption was decreased mainly in the summer. However, at a very few days, the total energy consumption was even increased. The explanation is that the initial values of the state vectors (such as the chiller operating status) were different from that in the baseline at these days. Thus, it is possible that Approach 1 may generate higher total energy consumption. For example, in October 27, there were two chillers operating at the beginning for Approach 1 while there was only one for the baseline. The total energy consumption increased for Approach 1 compared with the baseline is around 0.2%.

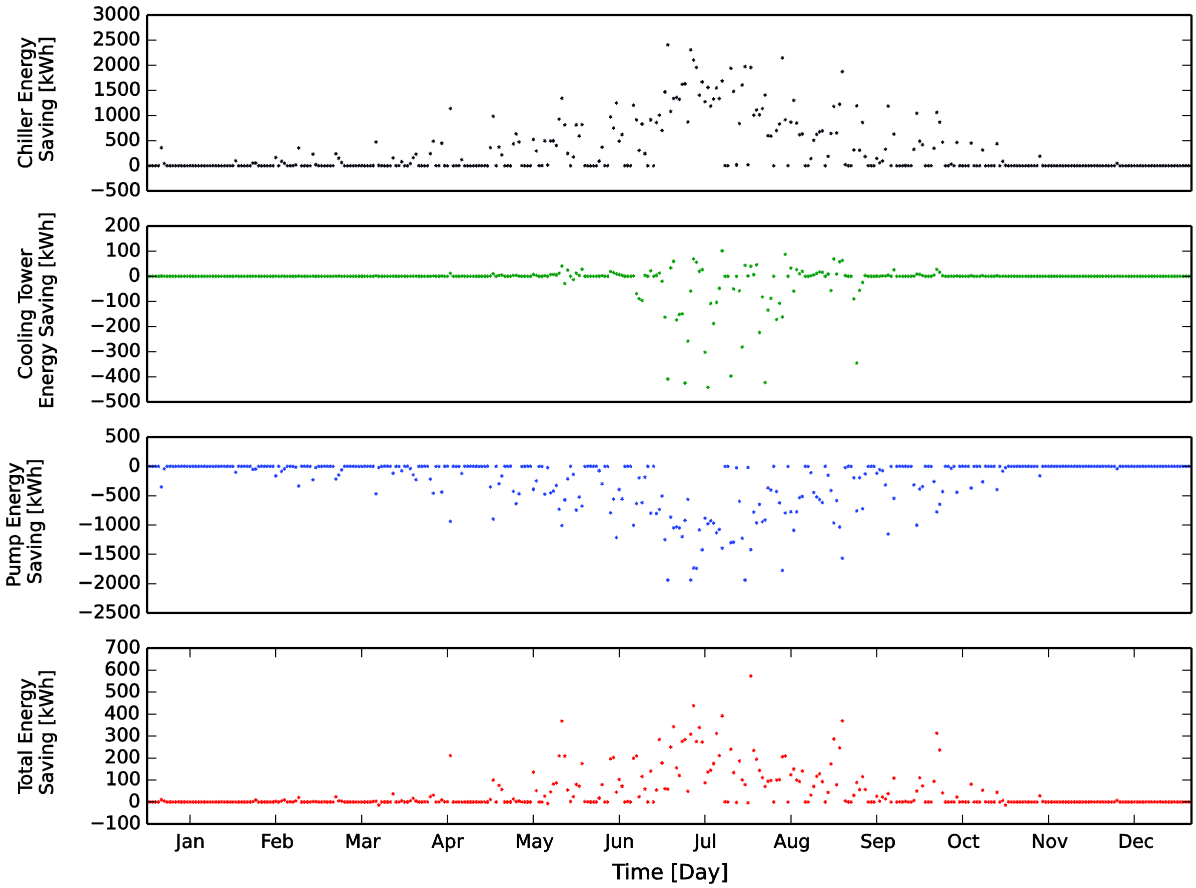

Figure 7 Daily energy saving by Approach 1

For Approach 2, the chiller energy consumption was saved mainly in the non-summer season (Figure 8). The cooling tower energy consumption was increased in the non-summer season due to the lower $T_{cw,set}$. The pump energy consumption was also saved in the non-summer season, which implies that the number of the operating chillers was mainly decreased. Since the studied chillers have higher efficiency at the part loads thus the energy saving from the chiller should be mainly due to the lower $T_{cw,ent}$.

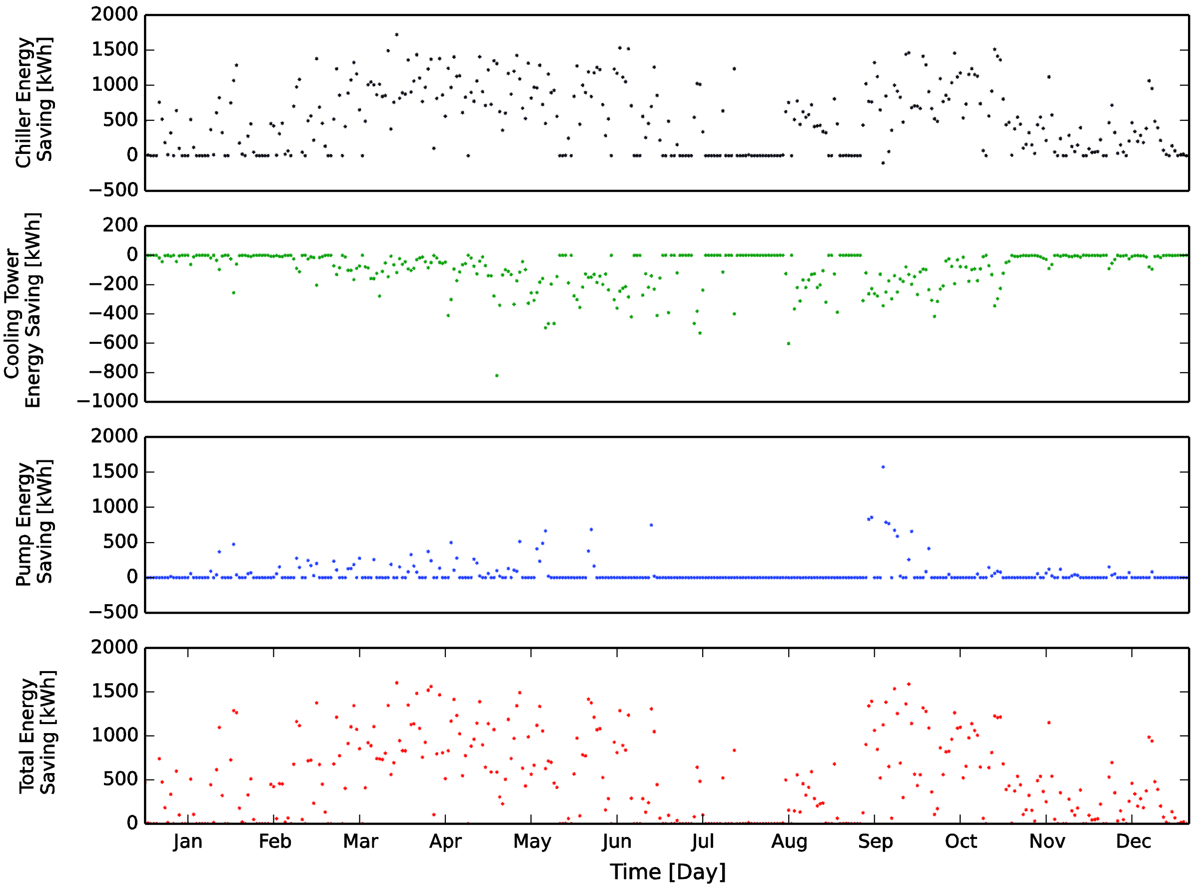

Figure 8 Daily energy saving by Approach 2

As shown in Figure 9, the chiller energy consumption was saved for the most of time in the studied year for Approach 3, which could be attributed to both the optimal load distribution and the lower $T_{cw,ent}$. The cooling tower energy consumption was mostly increased. It is also interesting to see that cooling tower energy consumption was reduced sometimes in the summer. The pump energy consumption was increased or reduced around the year. In the summer, the pump energy consumption was usually increased which indicates that more chillers were operating compared with the baseline. In the rest time, the pump energy consumption was reduced which means the cooling load was met with less chillers.

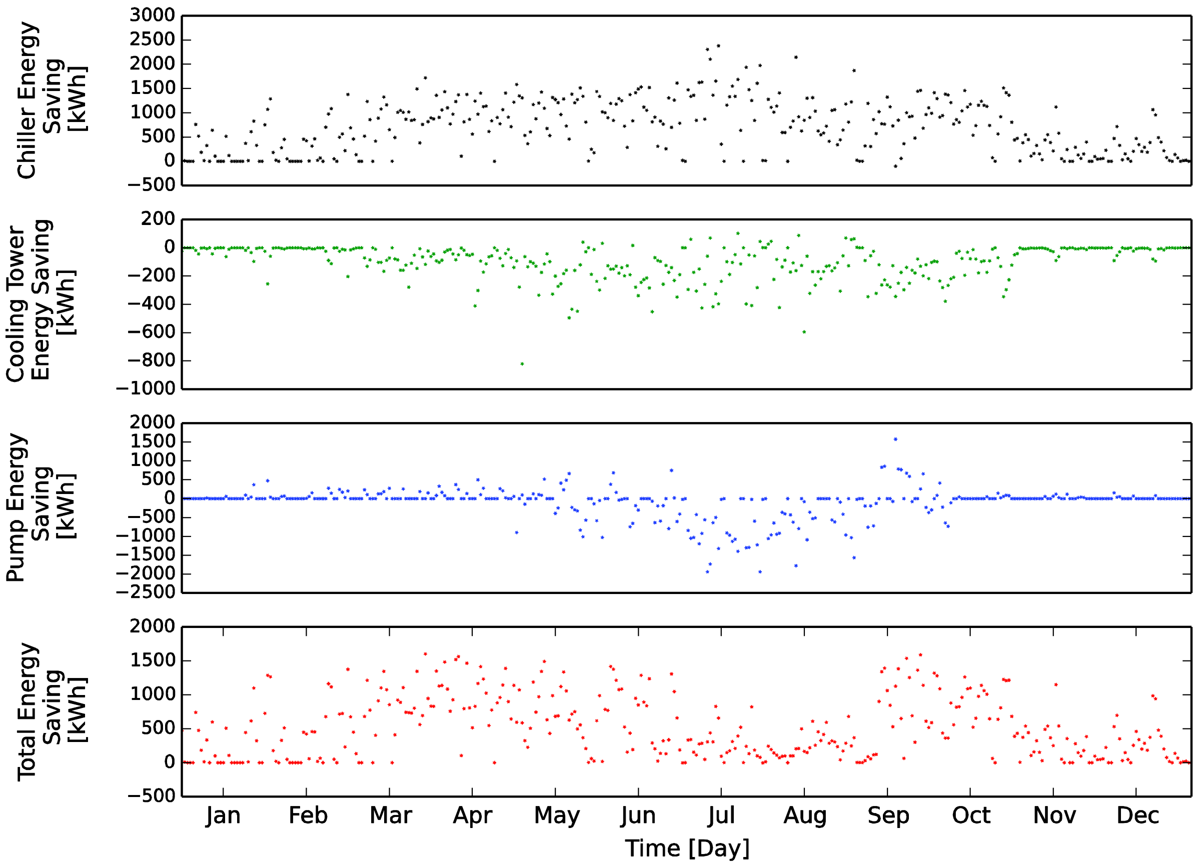

Figure 9 Daily energy saving by Approach 3

Based on the above analysis, we could find that:

- Approach 1's energy savings from chillers was mostly offset by the increased energy used by the pumps. This means that the optimal load distribution approach should be performed on chiller plants with high efficiency condenser water pumps and high efficiency chilled water pumps.

- Approach 2 can save the pump energy for about 2.0% and the chiller energy use for about 8.6%. The pump energy use decreased because of the reducing number of the operating chillers while the chiller energy use saving was mainly due to the lower temperature of the condenser water entering the chiller.

- Approach 3 can increase the energy saving by combining the previous two approaches, but the total energy saving is less than the summation of their savings. Approach 3 can save the energy used by the chillers, the cooling towers as well as the pumps. In the summer, it increased the number of the operating chillers to save energy for the chillers and the cooling towers. In the non-summer season, it reduced the operating chiller number so that the pump energy saving can be obtained.

3.2.1 Typical Days

In order to further identify how energy saving for different components was achieve at different seasons, we analyzed the performance of Approach 3 for one non-summer day and one summer day. As shown in Figure 10, the cooling load in the non-summer day (April 9) ranged from around 400 ton to 800 ton and the wet bulb temperature was within the range from around 5ºC to 10ºC. The optimal CP_1 and CP_2 predicted by Approach 3 were 867 ton and 1,418 ton while the optimal $T_{cw,set}$ was 13.89ºC. Since the cooling load was always lower than 817 ton, there was only one chiller operating for Approach 3. However, for the baseline, since the cooling load was larger than 759 ton at around 13:00, the number of the operating chillers increased to 2 accordingly and then decreased to 1 around 17:00 when the cooling load was less than 659 ton. There was almost no deviation of $T_{chw,lea}$ from $T_{chw,set}$ for both Approach 3 and the baseline.

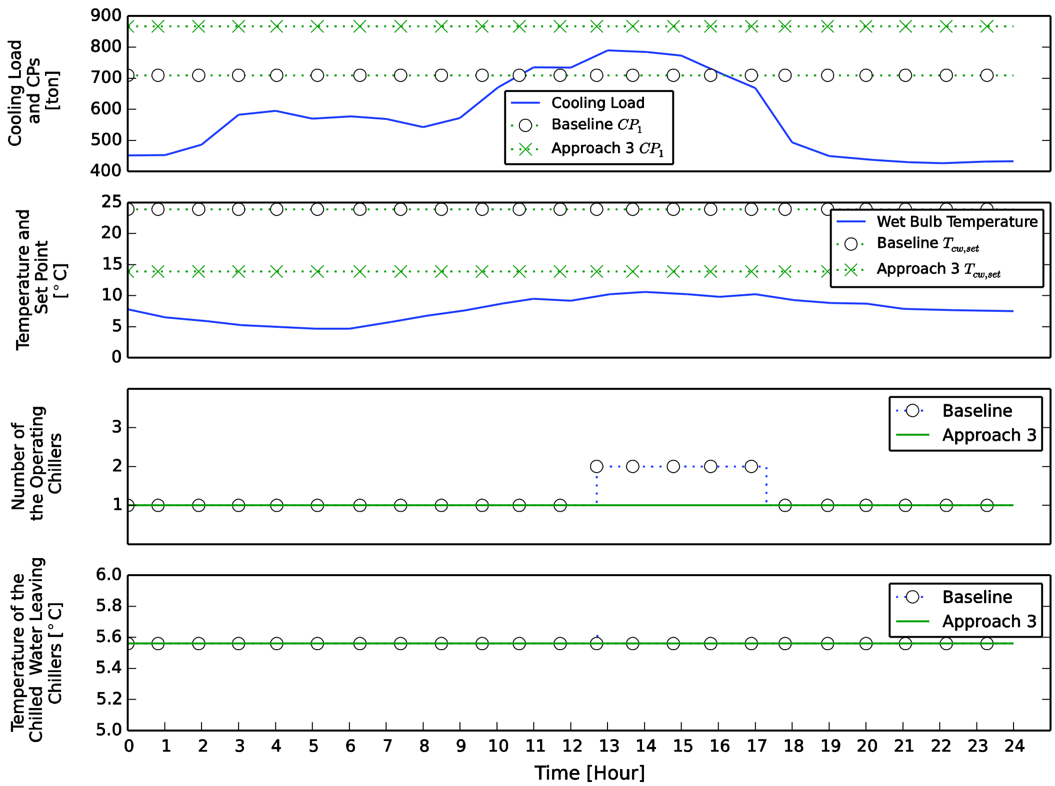

Figure 10 Simulated system statuses for a non-summer day

As shown in Figure 11, the hourly chiller energy consumption by Approach 3 is significantly less than the baseline over the day since the chiller is more efficient with a cooler condenser water achieved by lowering the $T_{cw,set}$. However, having a lower $T_{cw,set}$ significantly increased the cooling tower energy consumption. The pump energy was the same for Approach 3 as that for the baseline except the period when there was two operating chillers for the baseline. Since the chiller energy consumption and the pump energy consumption dominate the chiller plant energy consumption, Approach 3 always required less energy consumption than the baseline.

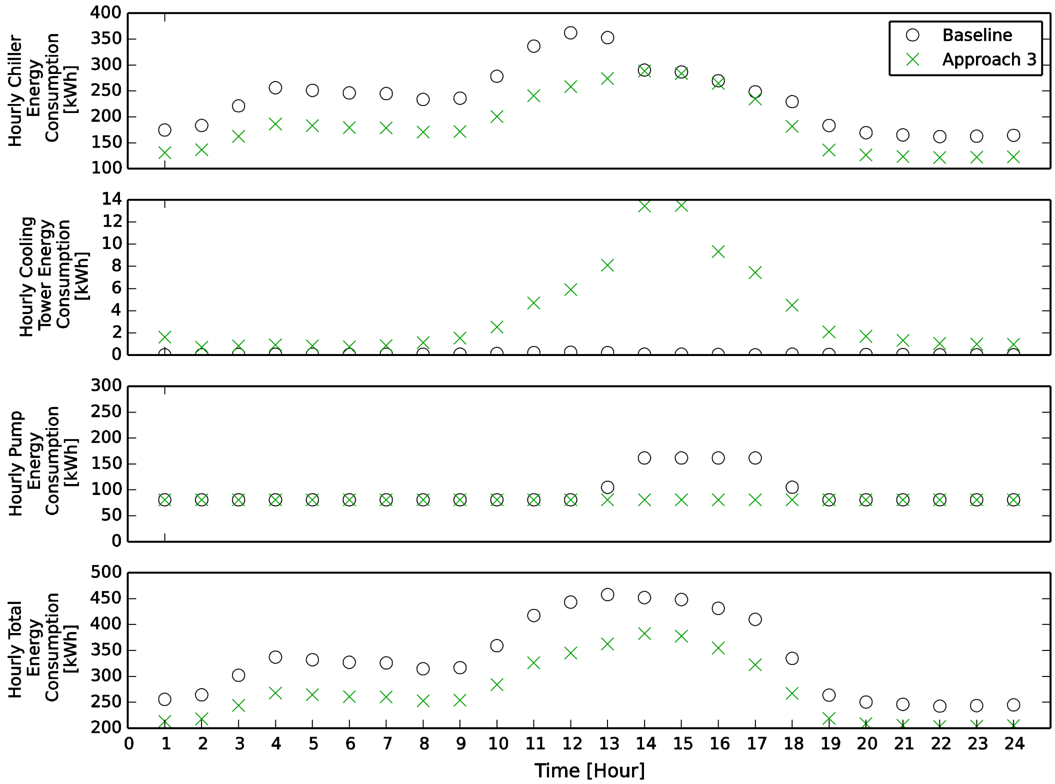

Figure 11 Simulated energy consumptions for a non-summer day

As shown in Figure 12, the cooling load in the summer day (July 20) ranged from around 1,000 ton to 1,500 ton and the wet bulb temperature was within the range from around 20 to 25ºC. The optimal CP_1 and CP_2 predicted by Approach 3 were 709 ton and 1,182 ton compared to the baseline value of 709 ton and 1,418 ton. The optimal $T_{cw,set}$ predicted by Approach 3 was 23.89ºC which was the same as the baseline. At the beginning, there were three chillers operating for Approach 3. The cooling load decreased to be less than 1,132 ton at around 19:00 and one of the operating chillers was turned off. For the baseline, the number of the operating chillers was two at the beginning and then turned to three at around 14:00. At around 15:30, it turned back to two. No significant deviation of $T_{chw,lea}$ from $T_{chw,set}$ for both Approach 3 and the baseline was observed.

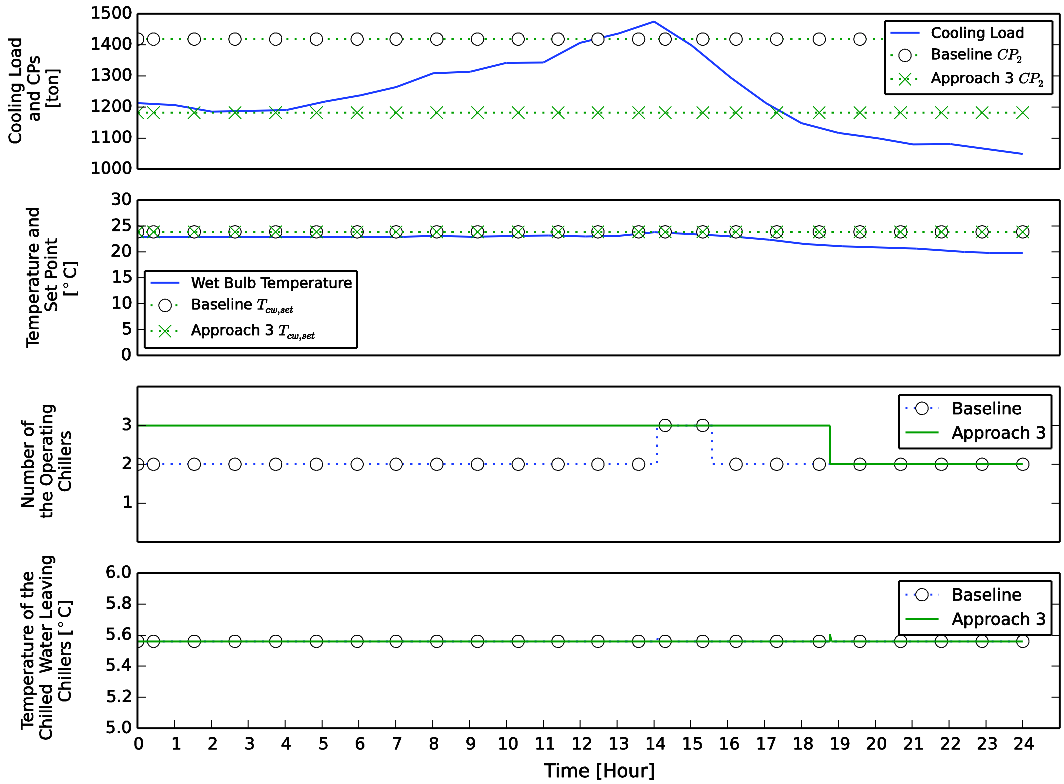

Figure 12 Simulated system statuses for a summer day

As shown in Figure 13, the hourly chiller consumption for Approach 3 was significantly less than that for the baseline mostly because the chillers are more efficient at lower *PLR*s enabled by an additional chiller. When the number of the operating chillers was the same (e.g. 20:00-24:00), the chiller energy were the same for both Approach 3 and the baseline.

The cooling tower energy consumption was smaller for Approach 3 than that for the baseline for most of the day since running three towers at lower speed is more energy efficient than running two towers at a higher speed. However, in the period from 14:00 to 16:00, the cooling tower energy consumption for the baseline was smaller. The reason is that at this period, the wet bulb temperature was relatively higher and the cooling towers were not able to maintain $T_{cw,ent}$ as the set point. In that case, adding the number of the operating cooling towers would not affect the load ratio of each cooling tower (always be full load) and thus the cooling tower energy consumption was increased as a result.

The pump energy was mostly higher for Approach 3 than that for the baseline because additional pumps was running for the additional chiller. However, the total energy consumption for Approach 3 was smaller than that in the baseline for the most time of the day because the energy saving from the chillers and the cooling towers can offset the additional energy consumption by the pumps.

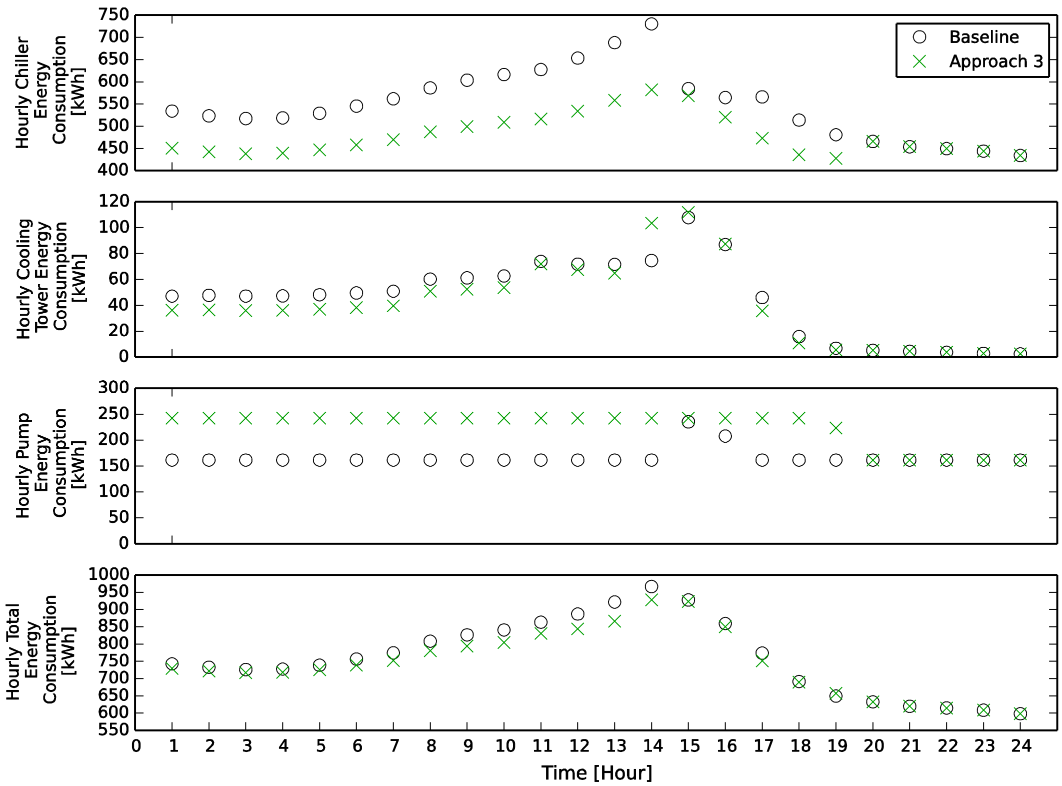

Figure 13 Simulated energy consumptions for a summer day

4. Conclusion

In this study, we proposed three new CLC optimization approaches to enhance the CLC. Approach 1 is to optimize the load distribution by adjusting the *CP*s. Approach 2 is to optimize the number of the operating chillers by modulating the *CP*s and the condenser water set point. Approach 3 is the combination of the first two approaches. The results suggest that the three approaches for optimizing the chiller sequencing control can all result in energy savings with little risk. The results also suggest that one needs to look at both the energy savings in the chillers as well as the increased energy used of other components of the chiller plant in the chiller sequencing control optimization. Among the three approaches, Approach 3 achieved the highest energy saving because it considered the trade-off among the energy consumption by the chillers, the cooling towers and the pumps. In the summer, we can make more chillers operating to achieve higher energy efficiency for the chillers and the cooling towers. In the non-summer season, we can reduce the number of the operating chillers to save the pump energy consumption.

The new CLC optimization approaches can be directly implemented in the real chiller plant for resetting the *CP*s and/or the condenser water set point. They can also be used as references to help the operators manually adjust the chiller sequencing control.

It should be noted that the evaluation of the three approaches was limited to the application in the chiller plants with a constant primary chilled water flow rate and identical chillers in this study. In future study, we can assess the performance of three approaches for chiller plants with variable primary chilled water flow rates and non-identical chillers.

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