A NEW METHOD FOR THE OPTIMAL CHILLER SEQUENCING CONTROL

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ABSTRACT

Cooling Load based chiller sequencing Control (CLC) significantly affects the energy performance of multiple-chiller plants. The conventional CLC method has two limitations: first, it cannot guarantee the optimal load distribution; second, it may result in an inappropriate number of operating chillers. Previous research tended to address the two limitations separately. In this paper, we proposed a new CLC method that overcame the two limitations at the same time. The optimization objective is to minimize the total energy consumption of the chiller plant including chillers, cooling towers and pumps. The independent variables are the thresholds for chiller staging and the condenser water set point. We implemented this method in a Model Predictive Control (MPC) framework so that the optimization can be continuously performed according to the predicted cooling load and wet bulb temperature. To compare the performance, we also implemented two existing CLC optimization methods (the optimal load distribution method and the cooling capacity based critical points reset method) in the same MPC framework. Simulation results showed that the proposed CLC method could provide about 5.6% annual energy saving for the studied chiller plant compared to the conventional CLC. The performance of our method is also better than the other two existing CLC optimization methods.

INTRODUCTION

In the United States, commercial building cooling equipment consumed around 2.64 quadrillion BTU (77.4 GWh) primary energy in 2010, which accounted for about 2.7% of the nation's total primary energy usage (U.S. Department of Energy). Westphalen, et al. (2001) reported that chiller plants represented about 35% of the commercial building cooling energy consumption. Due to their significant energy consumption, optimal control of the chiller plants is of great interests to this nation.

Among various configurations of chiller plants, a multiple-chiller plant is one of the most widely used types. For the multiple-chiller plant, it is recommended to operate chillers sequentially than simultaneously (ASHRAE 2011). To operate chillers in sequence, we need a Chiller Sequencing Control (CSC) to define the conditions under which the chillers should be brought online or offline according to the cooling load, which is represented by some indicators. Depending on the methods to indicate the cooling load, the CSC can be categorized as: return chilled water temperature based CSC, bypass flow based CSC, direct power based CSC, and Cooling Load based CSC (CLC) (Honeywell 1997). Among them, the CLC is considered to be the best because other methods employ the indirect indicators of the cooling load, which may not be proportional to the cooling load (Sun, et al. 2013). In the CLC, the cooling load is calculated using the chilled water flow rate and the difference between the chilled water supply temperature and return temperature (Li, et al. 2014). Then the calculated cooling load would be combined with a state machine (Kent, et al. 1991) to determine when and which chiller should be brought online or offline. For instance, Figure 1 shows the CLC for the chiller plant with three identical chillers. The transition between states indicates adding or reducing the number of operating chillers. When one or more chillers is operating, another chiller should not be brought online/off unless the measured load is larger/smaller than a certain Critical Point (CP). The CP is determined as follows

$$CP_i = \eta \sum_{j=1}^{i} CC_j, \tag{1}$$

where CP_i is the CP to bring the $(i+1)th$ chiller online, CC_j is the cooling capacity of the jth chiller, and η is the safety factor (e.g., 90%). To avoid chiller short circling, a waiting time t_{wait} and a dead band CP_{db} are usually employed.

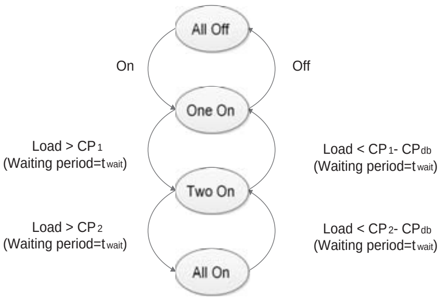

Figure 1 The State machine diagram for CLC

There are two directions in current research to enhance the CLC. One is to optimize the load distribution between the operating chillers and the other is to reset the CPs according to the estimation of the chiller capacity. We will discuss the concepts and the limitations of both methods in the following sessions.

Optimal Load Distribution

According to the ASHRAE Handbook (2011), the load distribution for the multiple-chiller plant is to operate chillers at as the highest Partial Load Ratio (PLR, the ratio of the cooling load handled by the chiller to its nominal cooling capacity) as possible. However, the ASHRAE Handbook also points out higher chiller PLR does not necessarily mean better operational efficiency. To describe chiller operational efficiency, we use a coefficient of performance (COP), which is the ratio of the cooling energy the chiller provides to its power consumption. Figure 2 shows that the highest COPs may occur at relatively low PLRs for the three different chillers.

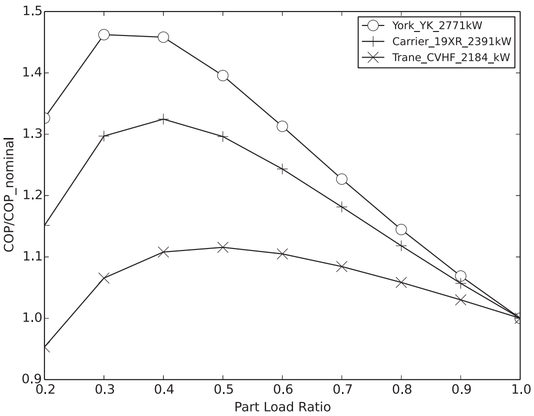

Figure 2 The relationship between PLRs and relative COPs for three chillers in the chiller dataset provided by EnergyPlus (Crawley, et al. 2001)

In order to achieve higher operational efficiency, some researchers developed model based optimization methods to adjust the PLR of each chiller individually according to a given cooling load (Chang 2004, Chang, et al. 2005, Chang 2006, Chang 2007, Ardakani, et al. 2008, Chang, et al. 2009, Lee, et al. 2009, Fan, et al. 2011, Geem 2011, Coelho, et al. 2013, Chen, et al. 2014, Coelho, et al. 2014). However, the PLR cannot be directly controlled, so it is not possible to implement these methods directly in real-world applications. Some scholars revised the above methods by replacing the PLR with other controllable parameters, such as the chilled water flow rate through each chiller (Yu, et al. 2007, Yu, et al. 2008), the temperature set points of the chilled water leaving each chiller (Chang, et al. 2006, Chang, et al. 2008), and the combination of the previous two parameters (Lu, et al. 2011). However, these methods still have some limitations. For instance, the methods 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.

Cooling Capacity based CPs Reset

The conventional CLC method assumes that the chiller cooling capacity at any operating conditions is equal to the chiller's nominal capacity, which is a capacity measured at the nominal operating condition. However, the actual cooling capacity of a chiller varies with its operating conditions (Sun, et al. 2013, Li, et al. 2014). As shown in Figure 3, the 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 ^{o}C (nominal condition) to 18.89 ^{o}C. Therefore, it is possible that the actual cooling capacity of the operating chillers in a chiller plant is larger than the summation of their nominal capacities. That means that the chiller plant can meet 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 to each chiller, reducing the number of the operating chillers can save energy for their dedicated pumps (ASHRAE 2011). To address this issue, some researchers proposed model based cooling capacity estimation methods to reset the CPs according to the chiller operating conditions (Sun, et al. 2009, Sun, et al. 2013, Li, et al. 2014). However, as we mentioned above, adjusting the number of the operating chillers would affect the efficiency of the chiller plant since it will also change the PLR of each chiller. Because these CPs reset methods did not consider the side effect on the chiller efficiency, they may not lead to the optimal chiller operation.

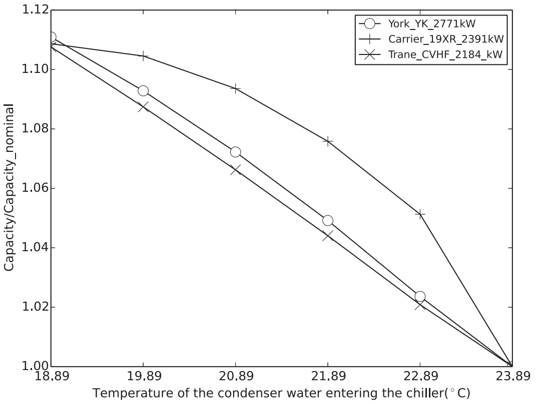

Figure 3 The relationship between the temperature of the condenser water entering the chiller and relative cooling capacity for three chillers calculated in the chiller dataset provided by EnergyPlus

To sum up, although the load distribution control and CPs reset may interact with each other, they were only studied separately in previous studies. In response to this, we proposed a new method to consider both of them in the CLC optimization simultaneously. To demonstrate the usage of the proposed method, we built a Model Predictive Control (MPC) framework and implemented the proposed CLC method in the framework. We also implemented the optimal load distribution and the cooling capacity based CPs reset methods in the MPC framework and evaluated the performance of the three methods in a case study.

METHODOLOGY

To implement the proposed CLC, we built a MPC framework to find the optimal CPs and the optimal condenser water set point according to the operating condition (cooling load and wet bulb temperature). To enable the MPC, it is indispensable to have a model that can realistically represent both the physical and the control system of the chiller plant. However, conventional building modelling tools, such as EnergyPlus, are not suitable for this purpose since they tend to highly idealize the control process (Piette, et al. 2012). Thus, we selected Modelica that is an equation-based object-orient modelling language for dynamic systems (Modelica Association 2000).

Optimization Formulation

Here we consider a 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 tower, $T_{cw,set}$. Assuming that the set points for the temperature of the chilled water leaving the chillers, $T_{chw,set}$, are constant, the total power of chillers, pumps, and cooling towers, P_{tot}, at time t can be described as follows:

$$P_{tot}(t) = \sum_i^M (P_{ch,i}(t) + P_{pu,i}(t)) + \sum_j^N P_{tw,j}(t) = f\big(T_{cw,set}(t), CP_1(t), .., CP_{M-1}(t), \dot{Q}(t), T_{wb}(t), S(t)\big), \quad (2)$$

where $P_{ch,i}(t)$, $P_{pu,i}(t)$ $P_{tw,j}(t)$ are the powers of the ith chiller, the dedicated chilled water pump and condenser water pump for the ith chiller, and the jth cooling tower, respectively. $\dot{Q}(t)$ is the cooling load, $T_{wb}(t)$ is the wet bulb temperature, and $S(t)$ is the state vector of the system, including the operating status of chillers (On/Off) as well as temperatures of chillers and cooling towers.

Then the energy consumption of the chiller plant for a period from t_0 to $t_0 + \Delta t$ is

$$E_{tot}|_{t_0}^{t_0+\Delta t} = \int_{t_0}^{t_0+\Delta t} P_{tot}(t)\, dt. \quad (3)$$

The operating status and PLR of each chiller are modulated for energy saving by adjusting $CP_1, .., CP_{M-1}$. In addition, the $T_{cw,ent}$ is controlled by changing $T_{cw,set}(t)$ so that the cooling capacity of the chillers can also be regulated. We used $T_{cw,set}(t)$ and $CP_i(t)$ as the independent variables and assumed they were constant during the period $[t_0, t_0 + \Delta t]$:

$$T_{cw,set}(t) = T_{cw,set}(t_0), t \in [t_0, t_0 + \vartriangle t], \quad (4)$$

$$CP_i(t) = CP_i(t_0), t \in [t_0, t_0 + \Delta t] \quad (5)$$

The objective function is to minimize the total energy consumption under the constraints of physical plants. The optimization problem can be defined as:

$$J = \min\big(E_{tot}|_{t_0}^{t_0+\Delta t}\big), t \in [t_0, t_0 + \Delta t] \quad (6)$$

subject to:

$$T_{cw,set,L} \le T_{cw,set}(t_0) \le T_{cw,set,H}, \quad (7)$$

$$CP_1^{min} \le CP_1(t_0) \le CP_1^{max}, \quad (8)$$

$$CP_{i-1}(t_0) < CP_i(t_0) \le CP_i^{max}\ (i > 1), \quad (9)$$

where $T_{cw,set,L}$ and $T_{cw,set,H}$ are the low and the high bounds for $T_{cw,set}(t_0)$, CP_1^{min} and CP_1^{max} are the low and the high bounds for $CP_1(t_0)$, CP_i^{max} is the high bound for $CP_i(t)$. There are also other constrains such as that the temperature of the temperature of the chilled water leaving chillers, $T_{chw,\text{lea}}$ should be equal to $T_{chw,set}$ and these constrains were considered in the system model.

Model Predictive Control

Figure 4 shows the configuration of our MPC. $T_{wb}(t)$ and $\dot{Q}(t)$ for a future period (termed as prediction horizon) are given by prediction models and the prediction horizon would be divided into K steps (termed as control horizon). For the control horizon starting from t_0, $T_{wb}(t)$, $\dot{Q}(t)$ and $S(t_0)$ are used as input variables to perform the optimization, then the generated optimum $T_{cw,set}(t_0)$ and $CP_i(t_0)$ would be used to obtain $S(t_0 + \Delta t)$ which would be used in the optimization at next control horizon.

CASE STUDY

To compare the performance of proposed CLC method with the optimal load distribution method and the cooling capacity based CPs reset method, the following case study was performed.

Case Description

As shown in Figure 5, we studied a chiller plant with three identical chillers and three identical cooling towers. Each chiller has one dedicated chilled water pump, one dedicated condenser water pump and one dedicated cooling tower. The model of the chiller is York_YK2771kW, which has the nominal cooling capacity (CC_{nom}) as 2771 kW. The corresponding chiller performance curves from the chiller dataset provided by EnergyPlus are adopted in this study. For the cooling tower, the nominal fan power is 37.285 kW (50 HP). The fan power is assumed to be proportional to the cubic of the fan speed ratio. The nominal wet bulb temperature and approach

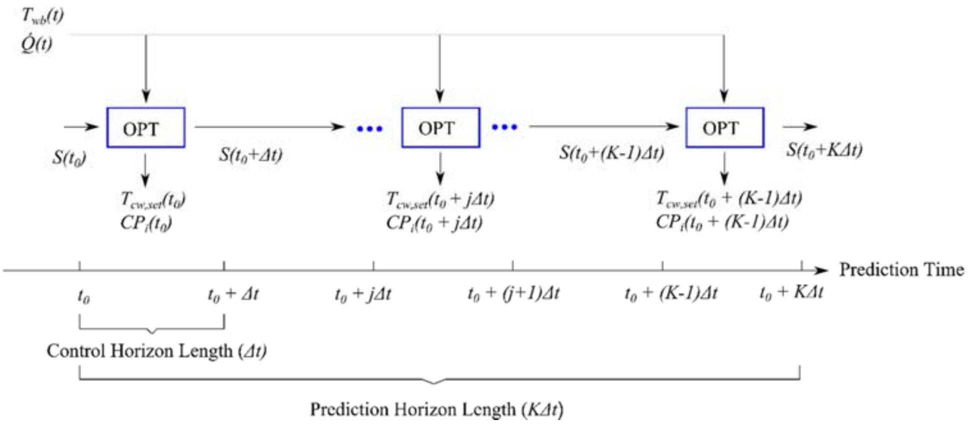

Figure 4 MPC configuration

temperature is 23.89 ºC (75 ºF) and 0.89 ºC (1.6 ºF), respectively. The chilled and condenser water pumps are constant speed pumps and their powers are 34 kW and 47 kW, respectively.

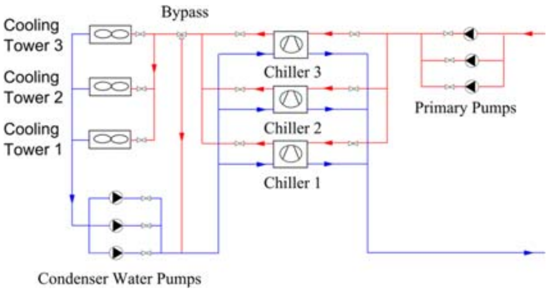

Figure 5 The schematic drawing of the studied chiller plant

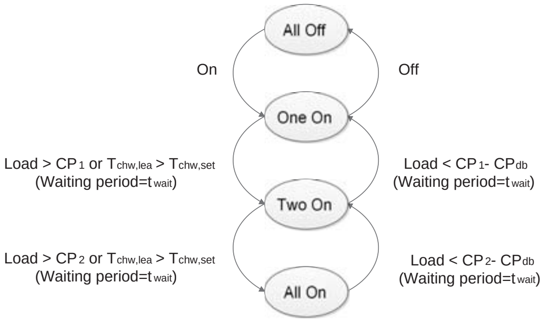

Figure 6 The CLC

The operation of chillers is managed by the CLC (η= 90%,t_{wait} = 900s,CP_{db} = 50 ton). We modified the conventional CLC by adding $T_{chw,lea}$ as another indicator so that $T_{chw,\mathrm{lea}}$ would not exceed $T_{chw,\mathrm{set}}$ (shown in Figure 6). In the condenser water loop, a three-way valve is employed to modulate the flow rate through the cooling towers to avoid overcooling. The condenser water is considered to be overcooled if the temperature of the condenser water leaving the cooling tower is less than 12.78 ºC (55 ºF).

We used Dymola 2005 FD01 (http://www.3ds.com/) as the Modelica simulation platform. Figure 7 shows the Modelica model in the system level. The sub-systems, e.g. chillers, were packaged in sub-system models and shown as an icon in the system model. The chillers and cooling towers were modelled using ElectricEIR and YorkCalc models, both from Modelica *Buildings* library (Wetter, et al. 2014). We used *Modelica_StateGraph2* library (Otter, et al. 2009) to model the CLC prescribed in Figure 6 and the implementation is shown as Figure 8.

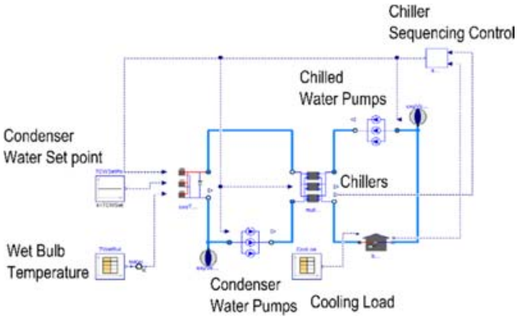

Figure 7 The diagram of the Modelica model in the system level for the chilled water plant

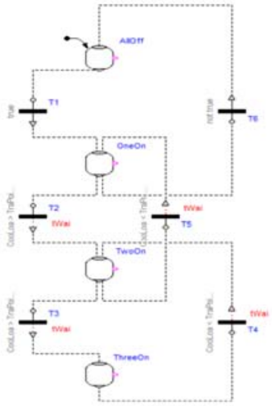

Figure 8 The implementation of the CLC in Modelica

We used the historic data of weather and cooling load measured from a district cooling system in Washington DC as the input variables. This is equivalent to have a perfect prediction model. Figure 9 shows the on-site measurement of hourly cooling load data in 2012 while Figure 10 shows the hourly wet bulb temperature on the same year from a dataset called Quality Controlled Local Climatological Data (National Climatic Data Center). A linear interpolation was applied to obtain the data between the sampling points.

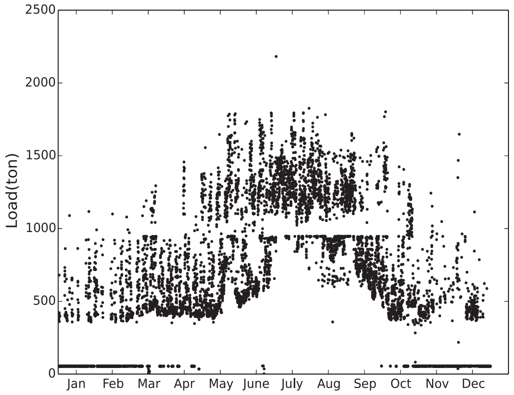

Figure 9 The annual hourly cooling load

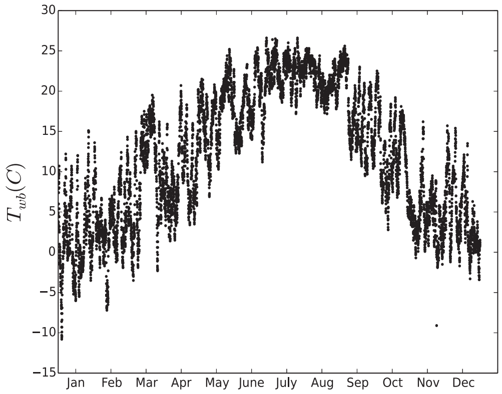

Figure 10 The annual hourly wet bulb temperature

MPC Setting

In this study, we used GenOpt (Wetter 2001) as the optimization engine and Hooke Jeeves method (Hooke, et al. 1961) as the optimization algorithm. The optimization settings for three methods are listed in the Table 1.

Table 1 Optimization settings for different scenarios

Method	CP_1 [ton]	CP_2 [ton]	$T_{cw,set}$ [°C]
Opt 1	[0,1] ηCC_{nom}	$[CP_1, 2\eta CC_{nom}]$	Fixed as 23.89
Opt 2	[1,1.2] ηCC_{nom}	[2,2.4] ηCC_{nom}	
Opt 3	[0,1.2] ηCC_{nom}	$[CP_1, 2.4\eta CC_{nom}]$	[13.89,23.89]

(The intervals for CP and $T_{cw,set}$ are 0.1 ηCC_{nom} and 1 °C, respectively)

Method Opt 1 was designed to assess the energy saving from the optimal load distribution only. It did not consider the possible capacity increase due to the decreased $T_{cw,ent}$. Thus, CP_1 and CP_2 should not be larger than the nominal values. In addition, the capacities of the chillers were not regulated intentionally. Therefore, $T_{cw,set}$ was fixed as the nominal value.

Method Opt 2 was designed to evaluate the potential energy saving from the cooling capacity based CPs reset which aims to reduce the number of operating chillers. To realize the objective, CP_1 and CP_2 could be larger than the nominal values. We would not adjust the chiller capacity. Thus, $T_{cw,set}$ was fixed as the nominal value.

Method Opt 3 was our proposed method, which attempted to consider both energy saving methods mentioned above. Therefore, the ranges of CP_1 and CP_2 were the combination of those in the Opt 1 and 2. Besides, we also modulated the capacities of the chiller by adjusting $T_{cw,set}$.

For comparison, we also designed a baseline case to represent the conventional CLC. For the baseline case, CP_1 , CP_2 and $T_{cw,set}$ were all fixed as the nominal values: ηCC_{nom} , $2\eta CC_{nom}$ and 23.89 °C.

Result

Figure 11 shows the energy saving of Opt 1, 2 and 3 compared to the baseline. For Opt 1, the energy savings from chillers was mostly offset by the increasing energy used of the pumps. Thus, the total system energy saving for Opt 1 was only around 0.3% although it saved about 4% chiller energy. For Opt 2, there was almost no energy saving can be obtained, which means it is difficult to save energy by reducing the number of operating chillers when the capacities of the chillers were not regulated. For Opt 3, the energy saving was more significant than that in Opt 1 and 2. The annual total energy saving was around 5.6%. The chiller energy saving ratio in Opt 3 was 11% while the cooling tower energy increased by 41%. In addition, the pump energy rose by 1.7%.

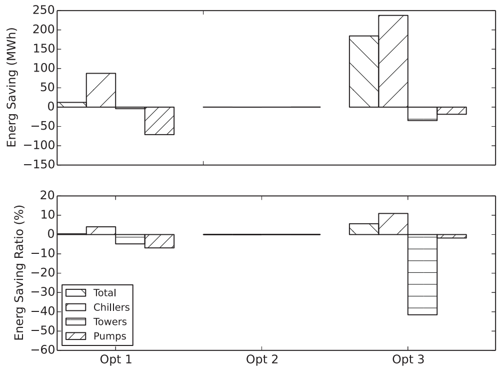

Figure 11 Annual simulation result

The comparison of simulation results for the three CLC optimization methods shows that if we combine the optimal load distribution and the cooling capacity

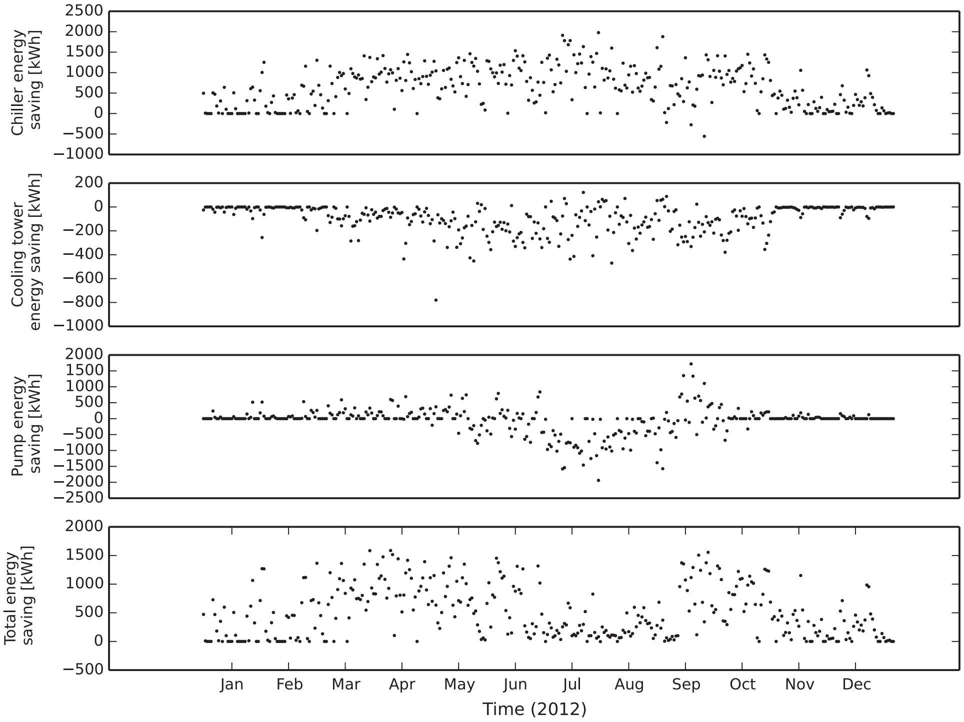

Figure 12 Daily energy saving in Opt 3

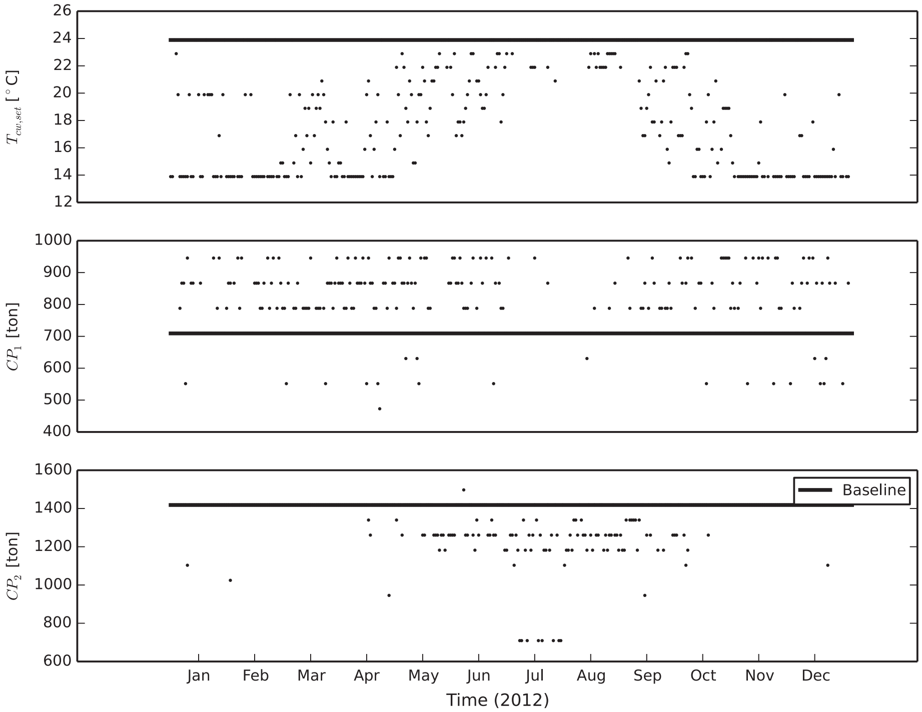

Figure 13 Annual distribution of the optimal $T_{cw,set}$, CP_1 and CP_2 in Opt 3

based CPs reset, the energy saving from the CLC optimization can be significantly increase as shown in the results of Opt 3. To understand the result, we provide some detail analysis as follows.

As shown in Figure 12, the chiller energy consumption was saved for the most of time in the studied year, which could be attributed to both the optimal load distribution and lower $T_{cw,ent}$. Sometimes, the chiller energy consumption may increase, such as a few hours in September. In those cases, the number of operating chillers decreased to reduce the energy use by dedicated pumps, although the PLR for each operating chiller raised and the total chiller energy increased.

The cooling tower energy consumption mostly increased because the system cooled the condenser water to a lower set point with the aim of reducing chiller energy. It is also interesting to see that cooling tower energy consumption reduced sometimes in the summer (May to September). This happened when the number of operating cooling towers increased and the cooling load handled by each towers decreased. The cooling tower energy consumption dropped because the variable speed cooling tower fans worked more effectively at partial speeds rather than the full speed.

The pump energy consumption was increased or reduced around the year depending on the number of operating chillers. In the summer, the pump energy consumption usually increased which indicates that more chillers were operating in Opt 3 compared with the baseline. In the rest time, the pump energy consumption was reduced which means the cooling load was met with less chillers.

Based on Figure 13, we can see that the optimal $T_{cw,set}$ was mostly different from that the constant set point of 23.89 °C in the baseline. In general, the value of optimal $T_{cw,set}$ was high in summer and low at the other season. The optimal CP_1 was larger than that in the baseline for most of time, which indicates that we could delay the start of the second chiller to save energy. In addition, the optimal CP_1 is sometimes less than that used in the baseline (reduced by up to 33%). This means that we could also save energy by increasing the running time of the second chiller. On the other side, the optimal CP_2 was usually small than that in the baseline (dropped by up to 50%), which means we could enhance the energy efficiency by making the third chiller operate more frequently.

CONCLUSION

In this study, we proposed a new CLC method for multi-chiller plants by combining the optimal load distribution method and the cooling capacity based CPs reset method. The new method was implemented using a MPC framework. Our case study showed that the new method could provide a higher energy saving for the whole chiller plant compared with the optimal load distribution method and the cooling capacity based CPs reset method alone.

In this study, the evaluation of this proposed method was limited to the application in the chiller plant with identical chillers. In future study, we could assess the performance of this method for chiller plants with non-identical chillers.

NOMENCLATURE

T = Temperature
$\dot{Q}$ = Cooling load
E = Energy consumption
P = Power
PLR = Partial load ratio
S = State vector
CP = Critical point for chiller staging control
η = Safety factor
CC = Cooling capacity
tot = Cooling towers ,chillers and Pumps
wb = Wet bulb temperature
cw = Condenser water
chw = Chilled water
ch = Chiller
tw = Cooling tower
pu = Pump
set = Set point
t = Instantaneous time
t_0 = Start time for a period
L = Lower limit
H = Higher limit
ent = Entering the chiller
lea = Leaving the chiller
db = Dead band
$wait$ = Waiting time

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