A robust chiller sequencing control method for enhancing cooling supply reliability and energy efficiency

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Abstract. Control of heating, ventilation and air-conditioning systems (HVAC) has become an active area of research due to the significant energy expenditures and maintenance cost. Among the various controls of HVAC systems, chiller sequencing control is of great importance for multi-chiller plant to keep cooling reliability, system stability and energy efficiency. However, conventional chiller sequencing control usually lacks consideration of system stability and the accessional cost caused by the sequencing actions. Especially, those short-time or unnecessary sequencing actions become the main reason for operators to shut down automatic control. To enhance the reliability of chiller sequencing control, a robust hybrid predictive control is developed. This control is developed based on the typical total cooling load-based control and use an ARX prediction model to double check necessity of the sequencing actions. Case studies were carried out on a TRNSYS dynamic simulation with the configuration data from a real secondary school. Results showed that the switch number can be reduced more than 20\% and operation cost can be reduced up to 4.25\% without scarified in thermal comfort and energy efficiency.

1. Introduction

Heating, ventilating and air-conditioning (HVAC) system is the largest energy end-user in model complex buildings. In subtropical zone, its energy consumption can up to 40\% of the total building energy use [1]. To facilitate a high energy efficiency of HVAC system, reliable automatic control is significant [2]. Given that the HVAC systems are constructed by multiple systems, sub-systems are interplayed and the switch-on or -off of core equipment (such as chillers) may lead to a large fluctuation in other sub-systems. A retrofitting case shows that unstable chiller sequencing control caused the chilled water systems to be tuning in cycles, and the supply air temperature to fluctuate from 12~18\degree C (with the setpoint of 12.5\degree C) all the morning time, influencing indoor thermal comfort [3]. From the thermal comfort and maintenance perspectives, it is expected to keep the system operation in a relative stable condition.

In HVAC systems, chiller plants are the cooling source and largest energy end-users, taking up more than 60\% of the system whole energy consumption [4]. For saving energy, chiller plants are normally configured with multiple chillers and sequenced by chiller sequencing controller, viz. decide online chiller number and staging time based on the cooling load conditions. Since chiller plants are the core component of HVAC systems, the switching actions will lead the sub-systems (chilled water system and condenser water system) as well as the associate equipment (e.g. cooling tower, pumps and water valves) to adjust correspondingly. If chillers are sequenced frequently, the sub-systems would also be tuned frequently. The whole system will be under fluctuation. This condition will not only lead to unstable indoor environment control but also reducing service life of equipment, as well as the maintenance cost.
For system steady purpose, designer and operator normally use a time constraint (e.g. 20mins~30mins) to keep the steady state of chiller plant, viz. a chiller should not be switched on (or off) before the load increasing (or decreasing) condition is last for more than 20~30mins [5]. Without constraint, a small or short-time cooling load variation may be detected by controller and a chiller would be switched on or off. The chiller will be switched off or on again since this load variation is eliminated. In engineering, many operators may prefer to sequence chillers manually to avoid the unnecessary sequence caused by nonsignificant variation of cooling load. Although time constraint can remove some unnecessary sequence, it also leads to a delay in the rationale controls [6]. Manual control fully depends on the experience of operators, it neither sequences chillers properly to the real time load variation for energy efficiency nor keep the indoor thermal well.

If we can predict the cooling load variation tendency in advance, we will be able to double-check the necessity of current sequencing command given by basic control logic. If the variation is in a small range or just happen in a short time, we may not switch a chiller on or off. Actually, both buildings and HVAC systems have thermal hysteresis characteristics, the small variation may be absorbed by buildings and would not lead to a room temperature increase or the small temperature increment may not be sensed by occupants [7]. Therefore, in this work, a hybrid predictive control is proposed for chiller sequencing control so as to enhance the operation stability of HVAC system. This method sequences chillers with a typical total cooling load-based control strategy and integrates an ARX model-based cooling load prediction strategy [8] to double check the necessity of sequencing actions. Case studies will be carried out to show the effectiveness of the proposed control.

2. Hybrid predictive chiller sequencing control

2.1. Chiller sequencing control

The purpose of chiller sequencing control is to provide sufficient cooling for maintaining building indoor thermal comfort and meanwhile keep a high energy efficiency of chiller plant. The principle of chiller sequencing control can be illustrated as Figure 1, where the x-axis is the building instantaneous cooling load, which is calculated by:

\[ Q = c_w m_p (T_{rm} - T_{sup}) \]  \hspace{1cm} (1)

The thresholds, denoted by \( Q_{z-1}^{th} \) and \( Q_{z}^{th} \), are the intersection points of the total power curves of online chillers with a dead-band \( d \) to prevent frequent switching. When the load is smaller than the threshold \( Q_{z}^{th} \), the use of \( z-1 \) chillers is better than \( z \) chillers in terms of energy efficiency. Thus, the controller will switch off one of the online chillers. Vice versa.

\[ \text{Figure 1. Basic principle of chiller sequencing control} \]

2.2. Hybrid predictive control

The basic idea of the hybrid predictive control is to optimal the chiller sequencing control at the perspective of reducing operation cost by using the cooling load prediction as a sequencing corrective measure. Structure of the hybrid predictive control consists of two parts: the basic sequencing control part and the load prediction part, as shown in Fig.2. For sequencing control, the total cooling load-based control is selected since it is the most direct control strategy according to the principle of chiller sequencing control. For cooling load prediction, a autoregressive with exogenous (ARX) model with format shown in Eqns.(2) ~ (4) is selected.
\[ Q_k = w_1 T_k + w_2 R H_k + w_3 R a d_k + w_4 W i n d_k + w_5 Q_{k-1} + w_6 Q_{k-2} + w_0 \]  
\[ W = \begin{bmatrix} w_1 & w_2 & \cdots & w_7 & w_0 \end{bmatrix} \]  
\[ A_k = [T_k \ R H_k \ R a d_k \ W i n d_k \ Q_{k-1} \ Q_{k-2} \ 1] \]  

Where \( w_0, w_2, \ldots, w_7 \) are the coefficients associated with the input variables. \( Q_k, T_k, RH_k, Rad_k \) and \( Wind_k \) are the predicted load, dry-bulb temperature, relative humidity, direct irradiation and wind speed at time step “\( k \)”, respectively. \( Q_{k-1} \) and \( Q_{k-2} \) are the measured load at time step ‘\( k-1 \)’ and ‘\( k-2 \)’. \( W \) is the coefficient matrix and \( A_k \) is the vector of input variables at time step \( k \).

For starting prediction, historical measured building cooling load and associated weather data are firstly used to generate the weight coefficient matrix \( W_0 \) with a least square method, i.e. minimizing the square of the load prediction errors using Eqn.(5)–(7). \( A \) is the parameter matrix and will be kept update by replacing the last set of data with the newest measured parameters, so that update the weight coefficient matrix is updated. Future cooling loads are predicted by the ARX model using the updated coefficients as well as the necessary weather and cooling load data [9].

\[ W = (A^T \cdot A)^{-1} \cdot A^T \cdot B \]  
\[ A = \begin{bmatrix} A_1 & A_2 & A_3 & \cdots & A_k \end{bmatrix} \]  
\[ B = \begin{bmatrix} Q_1 & Q_2 & Q_3 & \cdots & Q_k \end{bmatrix} \]  

The measured cooling load is firstly compared with the pre-set thresholds \( Q_{\text{on}} \) and \( Q_{\text{off}} \) to decide whether a sequencing action is needed. Then this action will be re-judged by the predicted load \( \Delta Q_{p,k} \). If \( \Delta Q_{p,k} \) is larger than a user-defined threshold \( \theta \), it means the building cooling load will keep increase and thus the switch-on action is needed. An idling chiller will be switch-on. Otherwise, this action will be cancelled. Similarly, if a switch-off action is triggered, and \( \Delta Q_{p,k} \) is smaller than a user-defined threshold \( \theta \), meaning the cooling load will keep decrease, an online chiller will be switched off. Noted that \( \Delta Q_{p,k} \) is calculated by prediction loads at different instants of time using Eqn.(8). \( \theta \) is a minimum value indicating the cooling load variation speed, e.g. 1% of online chiller capacity.

\[ \Delta Q_{p,k} = Q_{k+\tau_2} - Q_{k+\tau_1}, (\tau_2 > \tau_1) \]  

**Figure 2.** Structure of the hybrid predictive control.

### 2.3. Performance indices

Three performance indices are defined for evaluate the control performance. The **total chiller switch number** (\( N_s \)), indicating the chiller plant stability, is increased by 1 whenever one chiller is switched on or off. The **under-cooling percentage** (\( P_{UC} \)), indicating the risk probability of cooling supply insufficiency, and **accumulated air temperature errors** (\( \Delta T_{air} \)), indicating the severity of temperature rise, is calculated by Eqn.(9)–(10). According to ASHRAE 55-2010, when the room temperature is within thermal comfort region, 0–+0.5°C temperature increment may not be sensed by occupants. We
can infer that if the cooling load increase would not lead to a temperature increment larger than 0.5°C, we may

\[ P_{UC} = \frac{1}{\varepsilon} \sum_k \xi_k \Delta t \quad \text{with} \quad \xi_k = \begin{cases} 1, & \text{if } T_r > T_{sp} + \varepsilon \\ 0, & \text{otherwise} \end{cases} \]

(9)

The operation cost, represented by Eqn.(11), is the sum cost of the chiller plant energy consumption in a whole period, the start-up costs and the maintenance costs of devices. Start-up costs are the energy cost incurred at the warm-up period for chillers [10]. Maintenance costs are the converted costs of equipment depreciation and reversals of valves/actuators caused by the on/off control of chillers. The sequencing of chillers will Valve/actuator life is commonly characterized by the number cycles that they are expected to withstand during their lifetime. Increasing the number of reversals experienced by a valve/actuator will reduce equipment life and increase the potential for premature failure and replacement, i.e. maintenance cost.

\[ f_c = \{ \sum_{k=1}^{K} \left( P_{chwp}(k) + P_{cwp}(k) + P_{tf}(k) + P_{chi}(k) \right) \times \Delta t \times f_e \} + \frac{1}{2} \left( N_e \times f_e + N_e \times f_m \right) \]

(11)

Where \( k \) denotes a sub-period within \( \Delta t \) time interval. \( K \) is the whole step number. \( f_e \) is the electricity fee. \( P_{chwp}(k), P_{cwp}(k), P_{tf}(k), P_{chi}(k) \) are the power consumption of chilled water pumps, cooling water pumps, fans of towers and chillers, respectively. \( f_c \) is the start-up cost from the beginning till reaching a steady operation. \( f_m \) is the maintenance cost during a switch-on/off cycle.

3. Case studies

3.1. Simulation platform

For case studies, we constructed a decoupled multiple-chiller system serving a secondary school of buildings by using TRNBuild models on TRNSYS with detail building information from a real school in Hong Kong. Nine functional zone (Administration room, classroom, activity room et al) were served by nine VAV air-conditioning (AC) system with 18 variable speed fans. The fan speeds were controlled by PI controllers based on the zone temperature and its setpoint. For simplifying calculations, all zones temperature setpoints were set to be 25°C. Typical weather data of Hong Kong is used for cooling load prediction and case studies. The chilled water system is a typical decoupled system with structure shown in Fig.3. Two loops: the primary chilled-water production loop and the secondary chilled-water distribution loop, are decoupled by a bypass line. The primary loop consists of 4 screw chillers with rated capacity of 500kW and 4 constant-speed pumps with a rated flow rate 23.86L/s. The associate COP of the chillers is shown in Eqn.(12) with the highest COP equal to 5.02 at PLR= 85%. The mixed chiller water from primary loop chillers is delivered to the variable-speed pump with a rated flow rate 95.44L/s in secondary loop, and distributed to the cooling coils. The setpoint of supply air temperature is 16°C and controlled by a PI controller with varying the opening degree of the cooling coil valve based on the drop pressure (DP) of the critical loop.

\[ COP = -9.12 \cdot PLR^2 + 15.77 \cdot PLR - 1.45 \]

(12)

3.2. Parameter setup

The conventional cooling load-based control with time constraints and the proposed predictive control are simulated. The thresholds are the same for each control, viz. thresholds equal to the 90% of the rated capacity of online chillers. The time constraints \( t_i \) for switch on or off are 20 mins, i.e. a switch happens only when a condition lasts for 20 minutes. Accordingly, time span for the proposed control prediction is set to be \( \tau_1=10 \) mins and \( \tau_2=20 \) mins, so that the load variation in future 20 mins can be predicted. The electricity cost \( f_e \) is 0.05$/kWh, start-up cost \( f_c \) and maintenance-cost \( f_m \) are set as 5$ per cycle when a chiller is sequenced on and off, respectively.
Figure 3. Structure of the decoupled chilled water system and chiller sequencing control.

4. Results analysis

4.1. Typical weekly data analysis

Figure 4 presents the building cooling load and the predicted load at the left axis. The black line is the real time load and the blue line is the predicted load. The predicted one had very consistent variation tendency with the real time load. The right axis of Figure 4 presents the switch actions of the conventional control and the hybrid predictive control. At the beginning of days, chiller plant needed to remove the cooling load accumulated during the night time and the inherent heat of the air conditioning system, leading to a huge load met by chillers. However, this condition only happened in a short time, e.g. less than 20 mins at the first Thursday. When the conventional control was used, an idling chiller was switched on to cover this extra load and then shut down again. When using the hybrid predictive control, the short-time actions were reduced. With the two weeks, more than 7 times of short-time switch-on actions were eliminated. Figure 4 also showed the phenomenon of switching-on caused by handful load increment, indicating by “unnecessary actions”. According to the definition of chiller sequencing control, the chillers should be switched on/off at the highest energy efficient point, which is normally smaller than 100%. This is reasonable for chiller energy efficiency when the cooling load was changing obviously. However, if the cooling load variation is small and can be covered by the maximum capacity of chillers, these switch-on actions do not lead to energy saving but increase the warm-up cost and system fluctuation. Using hybrid predictive control, 4 times of unnecessary switch-on actions were reduced and the total switch number was reduced by 31.91% due these two weeks.

Figure 4. Control actions and performance of two typical weeks.

4.2. Monthly data analysis

To evaluate the comprehensive improved performance of the hybrid predictive control in chiller sequencing, simulations were conducted for three air-conditioning months (July, August and September). Performance comparison with the conventional total cooling-load control were presented in Table 3 with performance indices for indoor thermal comfort, operation stability, energy efficiency and operation cost. Firstly, it can be seen that the total switch number was reduced 20.4%, 22.22% and 19.57% in July, August and September, respectively. The energy consumption was also reduced slightly in July and September, but increased 0.71% in August. This is because the elimination of some switching actions might cause the online chiller to operate under lower COP. However, we can see that the
operation cost was reduced 4.06%, 3.46% and 4.25% in total. The little energy increase was offset by the chiller warm-up energy and other cost.

When regarding indoor thermal comfort, the undercooling time and accumulate errors were increased in all three months by using the hybridize predictive control. These results demonstrated that the temperature control was slightly sacrificed to achieve a better stability of HVAC system as we expected. However, from the absolute data we can found the increment of undercooling time in July was 4 mins, compared with the total sampling time 12960 mins, the undercooling percentage was only 0.03%, it is neglectable. It means both the energy and indoor environment were kept in a good level.

| Month | Control strategy | T_{up} (mins) | AccT_{up} (°C) | N_l | E_a (kWh) | C_{op} ($) |
|-------|------------------|---------------|----------------|-----|-----------|------------|
| July  | Q-based          | 488           | 248            | 196 | 85943     | 5277       |
|       | Hybrid control   | 492           | 252            | 156 | 85656     | 5063       |
|       | Increment (%)    | 0.82          | 1.37           | -20.41 | -0.33     | -4.06      |
| Aug   | Q-based          | 498           | 250            | 180 | 81011     | 4951       |
|       | Hybrid control   | 522           | 260            | 140 | 81586     | 4779       |
|       | Increment (%)    | 4.82          | 4.65           | -22.22 | 0.71     | -3.46      |
| Sept  | Q-based          | 2224          | 1524           | 184 | 77552     | 4798       |
|       | Hybrid control   | 2260          | 1546           | 148 | 77075     | 4594       |
|       | Increment (%)    | 1.62          | 1.37           | -19.57 | -0.62     | -4.25      |

5. Conclusions
In this paper, a robust hybrid predictive control has been developed for the sequencing control of multiple-chiller plant. Performance comparisons with the conventional total cooling load-based control showed that the hybrid predictive control can improve the control performance in perspective of system stability, energy efficiency and operation cost. When the cooling load variation was in a short-time or smaller in amount, the shot-time and unnecessary switching actions were reduced, making the total switch number decreased more than 20%. Meanwhile, the operation cost was reduced about 4% in each air-conditioning month. Although the overcooling and undercooling time were increase a bit, the amount of the accumulated temperature were very small, meaning that the indoor thermal comfort were well controlled. Moreover, the proposed control just used a simple prediction model to double check the cooling load variation trend, without using it as a solid constraint for control, the accuracy of prediction was not highly required. It means the proposed control is practical for real applications.

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