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Development and Validation of An Effective and Robust Chiller Sequence Control Strategy Using Data Driven Models

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Abstract:

Chiller sequence control significantly affects the efficiency and operation stability of plants with multiple chillers. However, in real practice, the energy efficiency is commonly sacrificed to avoid uncertainties. Also, the strategies found in literature may be too complicated to be used practically. An effective and robust strategy for centrifugal chiller plants is therefore developed. The strategy innovatively utilizes chillers inlet guide vane openings as the load, and more particularly the energy efficiency indicator. A validation of the use of such an indicator is conducted using the in-situ measurements from the chiller plant in a high-rise building. The strategy is compared with two other commonly used strategies through tests. In the ideal condition (no measurement errors), the proposed strategy saves 3% energy comparing to the original strategy. When systematic errors exist in the cooling load measurements, energy performance of the plant is not affected when controlled by the proposed strategy.

Keywords:

Chiller sequence control; optimal chiller loading; robust control; measurement error; centrifugal chiller; data driven models.

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1. Introduction

1.1 Background

As the largest energy consumers in central air-conditioning systems, chillers consume about 40% of the energy consumed by air-conditioning systems, and there is a strong potential to reduce the energy consumption of air-conditioning systems by enhancing the efficiency of chillers [1].

Optimal chiller sequence control, also known as optimal chiller loading, plays an important role in enhancing the chiller efficiency. In a well-designed large central air-conditioning system, multiple chillers are commonly used to fulfill the cooling load demand. The control of these chillers becomes important as they affect the cooling supply and the overall efficiency of chillers.

If the chillers are not well sequenced, they may either operate at low efficiency or fail to fulfill the demanded cooling load. In practical operations, chillers usually operate with low coefficients of performance (COP) due to the use of over-conservative control strategies. Those strategies force extra chillers to operate, resulting in a low Partial Load Ratio (PLR) of all operating chillers. They also increase the operation time of water pumps which further increases the energy consumption of the chiller plants.

Various advanced strategies are developed by researchers to solve the problem. For instance, data fusion technology [2] is used for chiller sequence control, which is validated using online data [3]. This technology takes the advantages of two cooling load calculation methods. Although the two methods suffer from measurement noises or model/systematic errors, the fused cooling load could have better accuracy [2]. Other available strategies include particle swarm optimization [4], Lagrangian method [5], genetic algorithm [6], differential evolution algorithm [7], and stochastic control method [8].

However, these technologies involve complicated operations and large storage capacity and cannot be implemented easily in common building management systems (BMS). BMS engineers and operators also find them to be difficult to understand because they are less logically deductive than the control strategies in practice and are uncertain of their reliability. Consequently, these complicated control strategies are not widely implemented in real air-conditioning systems.

To address these issues, the fault tolerant control method can be used [9]. In this paper, a chiller sequence control method that is tolerant to sensor errors is developed based on typical strategies using basic principles.

1.2 Typical chiller sequence control strategies

Different methods need different measurements to control chillers. Typical measurements used for chiller sequence controls are marked in Fig. 1.

Fig.1. Parameters required by different types of chiller sequence control strategies

Chilled water temperature based sequence control: The method determines chiller ON/OFF based on the return chilled water temperature [10][11]. If the return chilled water temperature is higher than a predefined maximum, an idling chiller will be staged on. If it becomes lower than a predefined minimum, a running chiller will be staged off. This method highly relies on the control of secondary chilled water pumps to ensure that the return chilled water temperature is a good indicator of the cooling demand. However, this method is not precise nor reliable due to its complexity in practice.

By-pass water flow based sequence control: This strategy utilizes the water flow and the flow direction in the bypass line [10][11]. If the bypass water flow exceeds the design flow of a chiller plant, a running chiller will be staged off. If the flow is reversed, an idling chiller will be staged on. This strategy is also not precise or reliable in practice because the bypass water flow also depends on proper control of secondary chilled water pumps.

Chillers current or power based sequence control [10]: Chillers' current or power consumption can be a reliable indicator of chiller cooling load. This strategy stages on an extra chiller if its current or power consumption is near their rated values, and it stages off a running chiller if its current or power consumption is low. This method is not accurate because chiller COP and cooling capacity vary significantly with its operating conditions.

Total cooling load based sequence control: This strategy determines the number of operating chillers by comparing the maximum capacity of chillers with the cooling load [10]. It estimates the chiller cooling load by the chilled water flow and the difference between supply and return chilled water temperatures as demonstrated in Eq. (1). Although this strategy is considered as the best strategy in principle [10], its precision is vulnerable to measurement errors and uncertainties [3][10].

$$Q = c_p \cdot M_w \cdot \left(T_{ev,in} - T_{ev,out}\right) \qquad (1)$$

where Q is the cooling load, c_p is the water specific heat, M_w is chilled water flow, $T_{ev,in}$ and $T_{ev,out}$ are return (evaporator inlet) and supply (evaporator outlet) chilled water temperatures, respectively.

1.3 The proposed strategy and its innovation

This paper proposes an effective and robust chiller sequence control strategy to overcome the limitations of current control methods. The strategy eliminates the effects of the measurement errors on the control decisions and provides a method simpler to execute than the strategies in literature. This is mainly achieved by its use of inlet guide vane as a main and reliable indicator of the chiller efficiency. Although it is normally available in centralized multiple centrifugal chiller plants, its use in chiller sequence control is rare in both literature and practice.

The rest of the paper is organized in 6 sections. Section 2 presents the proposed effective and robust chiller sequence control strategy. Section 3 provides an in-situ validation of the reliability of using chiller vane opening as chiller efficiency and load indicator. Section 4 describes the building and its air-conditioning system used for test and validation, the test platform built for evaluating the studied strategies, as well as the two reference strategies used for comparison. Section 5 presents the performance and limitations of a reference strategy in real application. The validation of the test platform is also conducted using in-situ chiller operation data. Section 6 illustrates the comparison and discussion on the online test results, followed by the conclusion section.

2. The proposed effective and robust chiller sequence control strategy

Fig. 2 describes the logic of the proposed control strategy developed for a chiller plant in a high-rise building. Whether to stage on a chiller depends on the electric currents of operating chillers, vane openings, and supply chilled water temperatures. Specifically, a chiller is about to be staged on when the currents of all operating chillers have been near the full load current for a certain time threshold. This avoids frequent chiller on-off actions. The full load conditions of the operating chillers are further confirmed by monitoring their vane openings. By monitoring the temperature of supply chilled water to all individual zones, the strategy guarantees a sufficient cooling supply. If the chillers cannot satisfy the cooling demand, the supply chilled water temperature will be higher than its set-point.

Whether to stage off a chiller is determined based on the chiller vane opening and the measured cooling load. The logic for staging off a chiller is activated only when one of the operating chillers has its vane opening less than 60%. This saves computational resources and may avoid staging off chillers unnecessarily. The control strategy then predicts the maximum cooling capacity of the chillers with one less operating chiller by a data-driven model in Eq. (2). Eq. (2) uses the multi-linear regression method [12], which is a type of machine learning algorithm, due to its simplicity and effectiveness. This model uses the evaporating and condensing pressures to predict the maximum cooling capacity and is trained using chiller full load operation data with a vane opening higher than 90%. Noticeably, even for identical chillers, they may have different coefficients in their corresponding models.

$$Q_{\max,i} \sim lm\left(p_{ev,i}, p_{cd,i}\right) \tag{2}$$

where $Q_{\max,i}$ is predicted maximum cooling capacity of i^{th} chiller, $p_{ev,i}$ and $p_{cd,i}$ are the evaporating and condensing pressure of the i^{th} chiller respectively, and $lm(\cdot)$ represents the multi-linear regression model.

Fig.2. Logic of the proposed chiller sequence control strategy

3. Chiller vane opening *vs* energy efficiency and load – An in-situ validation

This section presents the evaluation on the key parameters that are used as simple and reliable chiller efficiency indicators based on analyzing in-situ operation data. Two parameters (i.e. PLR and chiller vane opening) are assessed.

Partial Load Ratio

PLR is defined as the ratio of the actual refrigeration (or cooling) load of a chiller to its full load capacity. It is well understood that high overall COP can be achieved by controlling a chiller to operate at its optimum PLR as they have strong correlation. Fig. 3 demonstrates such correlation between these two variables of a chiller in the studied building by using in-situ operation data and manufacturer's catalog data obtained from test according to the ARI standard 550/590-1998 [13]. The COP of real operation data is lower than that in manufacturer's catalog due to difference in operation conditions. Since the bend at the peak of manufacturer's catalog data curve is not clear in real operation data. Considering measurement errors, it may not be practical or necessary to control chiller sequence through optimizing PLR at its optimal range specified in manufacturer's catalog data.

Fig. 3. The correlation between COP and PLR

Chiller vane opening

A constant speed centrifugal chiller maintains its supply chilled water temperature at the set-point by adjusting its refrigerant inlet guide vane opening and hence its capacity. This means that the vane opening should indicate chillers' operating capacities and efficiencies. Fig. 4 shows the correlation between chiller COP and its vane opening using in-situ operation data. Obviously, chiller COP is maintained at a high level when the vane opening is higher than 40%. In other words, the chiller is operating at its highest efficiency if its vane is widely open. The curve shape in Fig.

4 is very suitable for optimal control since COP is not sensitive to the vane opening in the high efficiency range.

Fig. 4. The correlation between COP and vane opening using in-situ operation data

4. Building air conditioning system and arrangement of online validation test

4.1 The building and its air-conditioning system

The proposed strategy is validated by an air-conditioning system in the tallest high-rise building in Hong Kong. The building has a height of 490 m and consists of 108 floors. It is divided into three parts: a car park (24,000 m^2) on the ground floor; shopping arcades (67,000 m^2) which are located between the ground floor and the fifth floor; the building tower (230,000 m^2) which consists of commercial offices and a six-star hotel on the top floors.

A large and complex air-conditioning system serves all floors of this building except the hotel on the floors above the 100th floor. Fig. 5 demonstrates the chilled water production and delivery system. Table 1 shows specifications of main equipment in the system. The six high voltage centrifugal chillers (3 phase, 11,000 volt) are designed to supply the building with chilled water at 5.5 °C. Each chiller is associated with a chilled water pump and a cooling water pump. Both of them are constant speed pumps, and their on/off are interlocked with chillers.

Eleven cooling towers of two types (types A, B) are used to cool the condensers of the chillers. They are equipped with variable speed fans. The six type A cooling towers are controlled by one Variable Speed Drive (VSD) system, while the other five type B cooling towers are controlled by another VSD. Their fan speeds are modulated by local controllers to achieve the cooling water temperature set-point.

Chilled water is supplied to three sectors containing four zones as marked with A, B and C in dashed rectangles in Fig. 5. Heat exchangers are used to isolate chilled water for individual zones in order to avoid high pressure in water pipes caused by the weight of water in riser pipes and on higher floors.

Fig. 5. The chilled water production and delivery system

Table 1. Specifications of main equipment in the system

4.2 Dynamic platform for online test and validation of sequence control strategies

A dynamic platform was built to evaluate the online performance of the developed strategy by using TRNSYS [14]. Fig. 6 demonstrates the framework of the platform. Since the test was conducted based on the operation history data of the studied air-conditioning system, cooling load and condenser entering water temperature ($T_{cd,in}$) in the test came directly from recorded history data. A heat balance model (Eq. (3)) was used to calculate return chilled water temperature using cooling load and supply chilled water temperature. Water flows through condenser and evaporator were assumed to be constant because they are provided by constant speed pumps.

$$T_{ev,in} = \frac{Q}{c_p \cdot M_w} - T_{ev,out} \tag{3}$$

where Q is the cooling load, c_p is water specific heat, M_w is chilled water flow, $T_{ev,in}$ and $T_{ev,out}$ are return (evaporator inlet) and supply (evaporator outlet) chilled water temperatures, respectively.

Fig. 6 Framework of the test platform

A chiller model in Wang et al [15] was used to simulate the chiller dynamic performance under various working conditions. The model is based on impeller tip speed, impeller exhaust area, impeller blades angle and other 13 coefficients/parameters. The compression process in the compressor, and the heat transfer process in the evaporator and the condenser are simulated. The compressor model is based on the Euler turbo-machine equation (Eq. (4)), mass conversion equation, and energy balance equation. Eqs. (5–6) describe the energy balances in the compressor control volume and the impeller control volume. Flow friction losses, inlet losses and incidence losses are considered in the two control volumes. Eqs. (7–8) show such hydrodynamic losses ($H_{hyd,com}$ and $H_{hyd,imp}$).

$$H_{th} = u_2\left[u_2 - \left(\frac{\pi^2}{8}\right)^2 c_{r2}\left(ctg\beta + B\frac{\upsilon_{in}}{\upsilon_{ext}}tg\gamma\right)\right] \quad (4)$$

$$H_{th} = H_{pol,com} + H_{hyd,com} \quad (5)$$

$$H_{th} = H_{pol,imp} + H_{hyd,imp} + \frac{c_{imp,ext}^2}{2} \quad (6)$$

$$H_{hyd,com} = \varsigma\left[1 + \psi_1\left(\frac{\upsilon_{in}}{\upsilon_{ext}}\frac{1}{\cos\gamma}\right)^2 + \psi_2\left(\frac{\upsilon_{in}}{\upsilon_{ext}}tg\gamma\right)^2\right]c_{r2}^2 \quad (7)$$

$$H_{hyd,imp} = \varsigma\left[\chi + \psi_1\left(\frac{\upsilon_{in}}{\upsilon_{ext}}\frac{1}{\cos\gamma}\right)^2 + \psi_2\left(\frac{\upsilon_{in}}{\upsilon_{ext}}tg\gamma\right)^2\right]c_{r2}^2 \quad (8)$$

where H_{th} is the compressor theoretical head, H_{hyd} is the hydrodynamic losses, H_{pol} is the polytropical compression work, u_2 is the impeller tip speed, c_{r2} is impeller exit radial velocity, β is the vane angle, γ is the pre-rotation vane angle, B is the ratio of the impeller channel depth at the intake to that at exhaust, υ_{in} and υ_{ext} are the specific volumes at the impeller intake and exhaust, respectively, $c_{imp,ext}$ is the vapor velocity at the impeller exhaust, and ς, ψ_1, ψ_2, χ are the introduced constants. Subscripts *com* and *imp* indicate compressor and impeller, respectively.

The chiller power is calculated using Eq. (9), which is based on the internal compression power (W_{inter}) and a constant leakage ratio [15]. First part of the equation ($c\cdot W_{inter}$) represents the driving power and variable part of power loss with a coefficient c, while the second part (W_{loss}) represents constant part of power losses.

$$W = c\cdot W_{inter} + W_{loss} \tag{9}$$

The classical heat exchanger efficiency method is used to simulate the heat transfer processes in the evaporator and the condenser. Two thermal storage units are used to represent the dynamic responses of the chiller to the changes of inlet temperatures. Eqs. (10–11) show the first-order differential models of the two heat exchangers.

$$CAP_{flow,ev}\frac{dT'_{ev,in}}{d\tau} = c_p M_{w,ev}\left(T_{ev,in} - T'_{ev,in}\right) \tag{10}$$

$$CAP_{flow,cd}\frac{dT'_{cd,in}}{d\tau} = c_p M_{w,cd}\left(T_{cd,in} - T'_{cd,in}\right) \tag{11}$$

where CAP_{flow} is the capacity flow rate, T is the temperature, T' is the temperature after introducing dynamic effects, c_p is the specific heat of water, subscript “*ev*” indicates evaporator, subscript “*cd*” indicates condenser and subscript “*in*” indicates inlet.

The dynamic test platform was validated by using the chillers in-situ operation data. Fig. 7 shows the comparison between the real and predicted cooling load and power consumption at different chiller vane openings. The mean relative difference between the simulated and real capacity is

10.8%, and the mean relative difference between the simulated and real power is 6.0%. That accuracy level should be enough for the simulation test.

Fig. 7. Validation of the dynamic test platform

4.3 Comparison of sequence control strategies

The proposed control strategy (namely Strategy S_N) was evaluated by comparing its performance with the following two strategies.

Reference Strategy S_R1 - Strategy based on total cooling load

Fig. 8 demonstrates the principle of the reference strategy S_R1, which is based on the measured cooling load. The vertical axis shows total electric power consumption of multiple chillers. For a certain cooling load, the option which has minimum electric power consumption is the optimal number of chillers for chiller sequence control. A dead band is used to avoid frequent switching on and off of chillers in case cooling load varies within a small range near the switching points. Eq. (12) defines the cooling load threshold for staging on/off a chiller. Based on that, the optimal number of operating chillers could be determined by Eq.(13).

$$\begin{aligned} Q_{on} &= (N-1)\cdot\left[C_{rated}\cdot(1-d)\right] \\ Q_{off} &= N\cdot\left[C_{rated}\cdot(1+d)\right] \end{aligned} \quad (12)$$

$$N_{next} = \begin{cases} N+1, Q > Q_{on} \\ N-1, Q < Q_{off} \end{cases} \quad (13)$$

where Q_{on} and Q_{off} are the cooling load thresholds for staging on and off of a chiller respectively, N is the current number of operating chillers, C_{rated} is the rated cooling capacity of individual chillers, d is a user defined dead band ranging from 0 to 100% and is determined to be 5% in this study, Q is the current cooling demand and N_{next} is the determined number of chillers.

Fig. 8 Strategy S_R1: The strategy solely based on total cooling load

Reference Strategy S_R2 - Strategy based on chiller electrical current and cooling load

Strategy S_R2 was developed by the BMS provider and the consultants of the building to control the chillers. It utilizes measured chiller electrical current and cooling load to determine the number of chillers to be used. Table 2 shows the logic for staging on/off of a chiller during operation. Whether to stage on a chiller is determined by the currents of all operating chillers. Specifically, an idling chiller will be staged on when the currents of all operating chillers remain near their full load currents for a predefined time period. By monitoring the supply chilled water temperature to the building, the strategy guarantees a sufficient cooling supply.

A chiller will be staged off if the measured cooling load is less than the corresponding thresholds as tabulated in Table 2. These thresholds are empirically determined based on the rated chiller full load capacity.

Table 2. Staging rules of strategy based on chillers electrical current and cooling load (Strategy S_R2)

5. In-situ operation performance and limitation of the reference strategy S_R2

To understand the chiller performance before the implementation of the new strategy, the performance and limitations of the design control strategy S_R2 is assessed. The analysis is based on the in-situ operation data collected at a 1-minute interval throughout 2014.

The measured cooling loads of individual chillers are summarized and presented in Fig. 9. The histograms are used to roughly assess the probability distribution of individual chiller load in the year. The figure presents all the data when there is more than one chiller in operation, and data with unavoidably low PLR are excluded in the analysis. Comparing the distribution of the cooling load in the histograms with the rated chiller capacity 7230 kW, it can be observed from Fig. 9 that all the six chillers operated at low PLR rather frequently.

Fig.9 also shows that the maximum capacity of chiller 4 (CH4) was significantly higher than the other chillers though all chillers are identical. That is because of the use of directly measured cooling load (Eq.(1)) in the analysis, and the significant systematic errors in the measured cooling load of CH4.

Fig.9. Cooling load distributions of individual chillers except only one chiller in operation

Fig. 10 shows the chiller operation statuses in the year. The horizontal axis represents the sum of the direct measured cooling loads of all operating chillers, and the vertical axis represents the sum of the currents of all running chillers that are heavily correlated with the total power consumption. They are categorized into four groups according to the number of operating chillers. Although chiller power consumption should be the lowest when number of operating chillers is the smallest, there are significant overlaps among different groups in Fig. 10. Hence there is a high potential to use better sequence control strategies to reduce the chiller power consumption.

The vertical dotted lines in Fig. 10 separate the operation points into different regions according to the rated total cooling capacity of different number of chillers and are the staging set-points of strategy S_R1. If the strategy S_R1 is used, the results could be better since the overlaps among different groups are far beyond its defined dead band (+/- 5%). It is also noticeable that maximum cooling capacities in each group are much higher than their total rated cooling capacity.

Fig. 10.Chiller total current *vs* total cooling load when strategy S_R2 is used

6. Online operation performance and validation of proposed sequence strategy

Simulation tests are conducted to evaluate the online performance of the proposed sequence control strategy by comparing its performance with that of the two reference strategies. In the tests, cooling load data were directly obtained from the operation of tested building in a week in July 2014, as shown in Fig. 11.

Fig.11. Cooling load used in the test

The strategies are first evaluated in ideal conditions, i.e. the measurements are accurate without errors. Then, measurement errors of cooling loads are considered to simulate real conditions. In this study, only systematic errors are considered since the random error could be removed by filters such as the exponentially weighted moving average filter.

6.1 Test results when there is no measurement error in cooling load

The chiller energy consumption of the strategies S_N, S_R1 and S_R2 in the observed week were 369,408 kWh, 364,955 kWh, and 380,664 kWh respectively, and strategy S_R1 is the best strategy because its energy consumption was the smallest. This is not surprising because cooling load is the best indicator of building cooling requirement if the system contains no uncertainties. Strategy S_N consumed 1.2% more energy than S_R1, while Strategy S_R2 consumed 4.3% more energy than S_R1. The proposed strategy therefore saved 3% energy compared with the case using the strategy S_R2.

Fig. 12 shows the comparison of the number of operating chillers among the three strategies. Compared to the strategy S_R1, both S_R2 and S_N required more chillers occasionally, especially on the second day. Strategy S_N staged a chiller off earlier than S_R2, and the strategies S_N and S_R1 staged chillers off around the same time. Since S_R1 is in theory the best strategy, it can be concluded that the strategy S_N staged chillers off at the right time [10].

Fig. 12. Comparison on the numbers of operating chillers when using the three strategies

Fig. 13 shows the comparison of power consumptions among the three control strategies. When S_R2 and S_N staged on two chillers and S_R1 staged on one chiller only, S_R2 and S_N required higher power consumption than S_R1. However, their power consumption difference was not significant on day two when S_R2 and S_N used four chillers and S_R1 used three chillers. This is because the increase of PLR with the number of operating chillers becomes smaller as the number of operating chillers increases.

Fig. 13. Comparison on the power consumption of using the three strategies

6.2 Test results when cooling load measurements contain systematic errors

As aforementioned, cooling load measurements contain errors inevitably, and errors could be as high as over 30% [10]. Performance of the three strategies were further studied by altering the cooling loads with systematic errors ranging from -10% to 20%. Fig. 14 shows the chiller energy consumption in the week.

Fig. 14. Chiller energy consumptions when using three different strategies

Strategy S_R1 was robust when the systematic errors were between -5% and 5% since the dead band in strategy S_R1 was set to be 5%. However, when the systematic errors were higher than 5%, the strategy staged off a chiller later than it should and resulted in higher chiller energy consumption. When the systematic errors were lower than -5%, the strategy failed to provide sufficient cooling because it staged off a chiller too early. Therefore, S_R1 is not suitable for real practice.

As the systematic errors varied from -10% to 20%, the chiller energy consumption of S_R2 increased gradually. Positive systematic errors in the cooling load measurements made strategy S_R2 stage off a chiller later than it should. On the contrary, negative systematic errors in cooling load measurements forced the strategy to stage off a chiller earlier than it should. Since strategy S_R2 intrinsically staged a chiller off later than the ideal condition, negative systematic errors can reduce the total energy consumption. However, a very negative systematic error may cause the strategy to stage off a chiller too early. There would not be sufficient cooling to meet the cooling demand, just as strategy S_R1 did when the systematic errors were lower than -5%.

Strategy S_N was the most robust strategy because its performance was not affected by systematic errors in the cooling load measurements as shown in Fig.14. The stage-on point was not affected by systematic errors in the cooling load measurements since it was determined according to chiller currents. The stage-off point was also not affected because it depends on the predicted maximum chiller capacity model in Eq.(2) rather than the measured cooling load. In each of the test cases, the maximum chiller capacity model was trained based on data with systematic errors in cooling load measurements, and hence strategy S_N considered the systematic errors in the cooling load measurements. For instance, in the case where cooling load measurements contain +10% systematic errors, the predicted maximum chiller capacity was 10% higher than its real maximum capacity. The strategy decided to stage off a chiller based on the measured cooling load and the predicted maximum cooling capacity. The comparison result would be the same as the result without the systematic errors if both the measured cooling load and the predicted maximum cooling capacity contained the systematic errors of the same magnitude. Strategy S_N is therefore immune to systematic errors in cooling load measurements. However, if the systematic error in cooling load measurement changed significantly after the training of the maximum cooling capacity model, the strategy would not be robust to the new cooling load measurement errors. To maintain the robustness of the strategy, the maximum cooling capacity models should be periodically trained and updated using the most recent operation data.

7. Conclusion

This paper proposed an effective and robust chiller sequence control strategy that is suitable for centrifugal chiller plants. In the control strategy, the chiller inlet guide vane is used as an indicator of chiller efficiency and cooling load. The energy performance and robustness of the developed strategy are evaluated with in-situ data in a large building and compared with an ideal control strategy and the original chiller control strategy in the building.

Analysis on the chiller in-situ operation data in a large building indicates that the chillers are operating at a high efficiency when the vane opening is higher than 40%. The COP is not sensitive to the vane opening once it exceeds 40%. As a result, the vane opening could be an excellent and reliable indicator of chiller efficiency.

The proposed control strategy was compared with two reference strategies through performance tests based on measured data in a summer week in the same real building. In the case when there were no systematic errors in cooling load measurements, the proposed strategy saved 3% energy compared with the original strategy applied in the building. When there were systematic errors in cooling load measurements, the proposed strategy was the most robust one compared with the two reference strategies. Its energy consumption remained the same regardless of variations in the magnitude of systematic errors. Both reference strategies wasted extra energy when the cooling load measurement contained positive systematic errors. When negative systematic errors were included in cooling load measurements, the reference strategy solely based on cooling load had a risk of failing to fulfill the demanded cooling load.

Since the proposed method is not commonly seen in real application, further efforts should be conducted to provide sufficient data for practical reference. As a first step, the original strategy S_R2 in the building has already been replaced by the proposed strategy S_N for its daily operation, and the future research will focus on refining the maximum chiller capacity model for wider practical adaptation.

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Figures

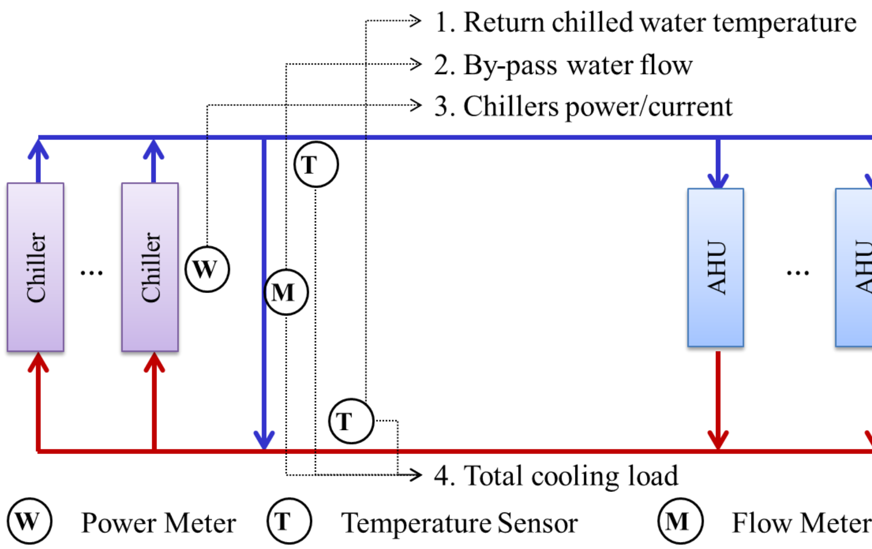


Fig.1. Parameters required by different types of chiller sequence control strategies

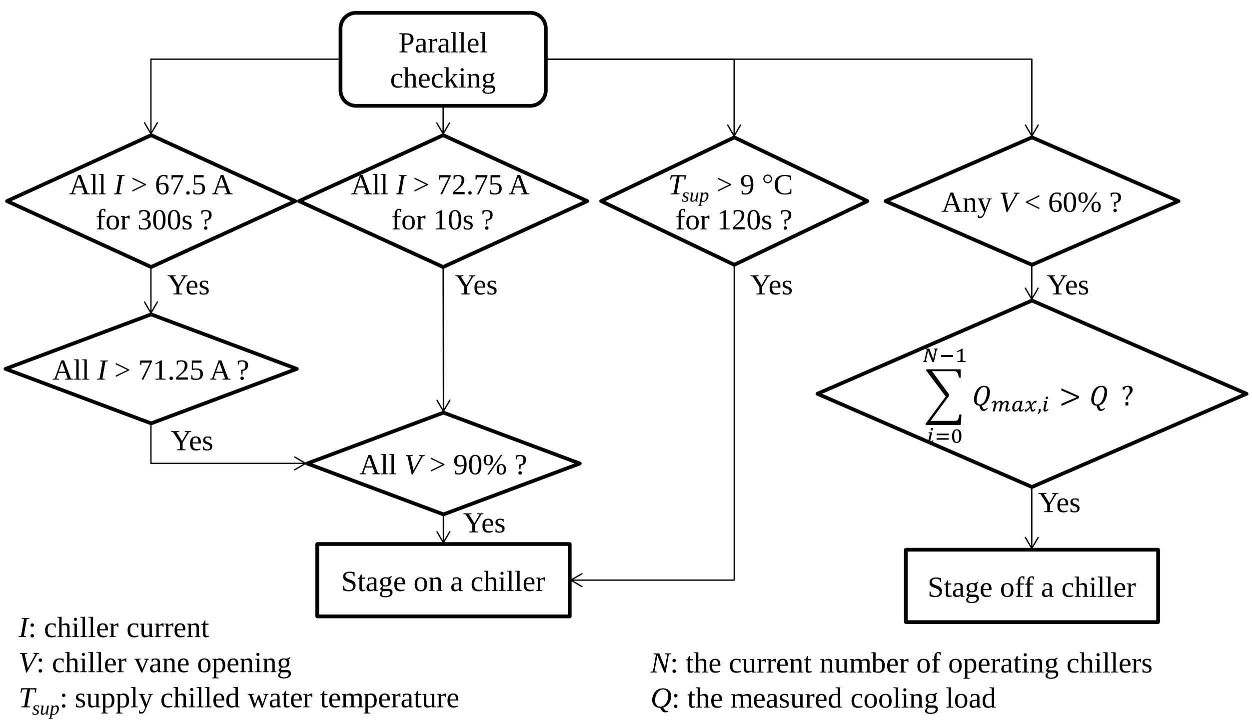
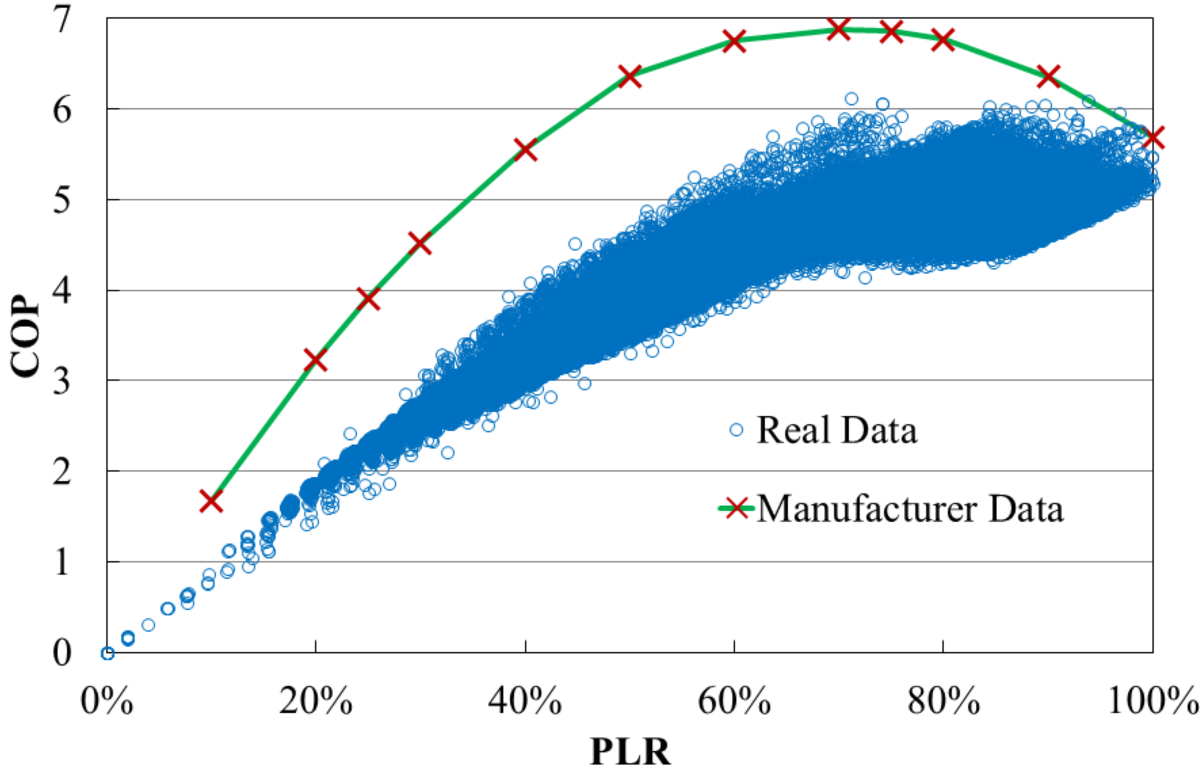


Fig.2. Logic of the proposed chiller sequence control strategy



424 Fig. 3. The correlation between COP and PLR

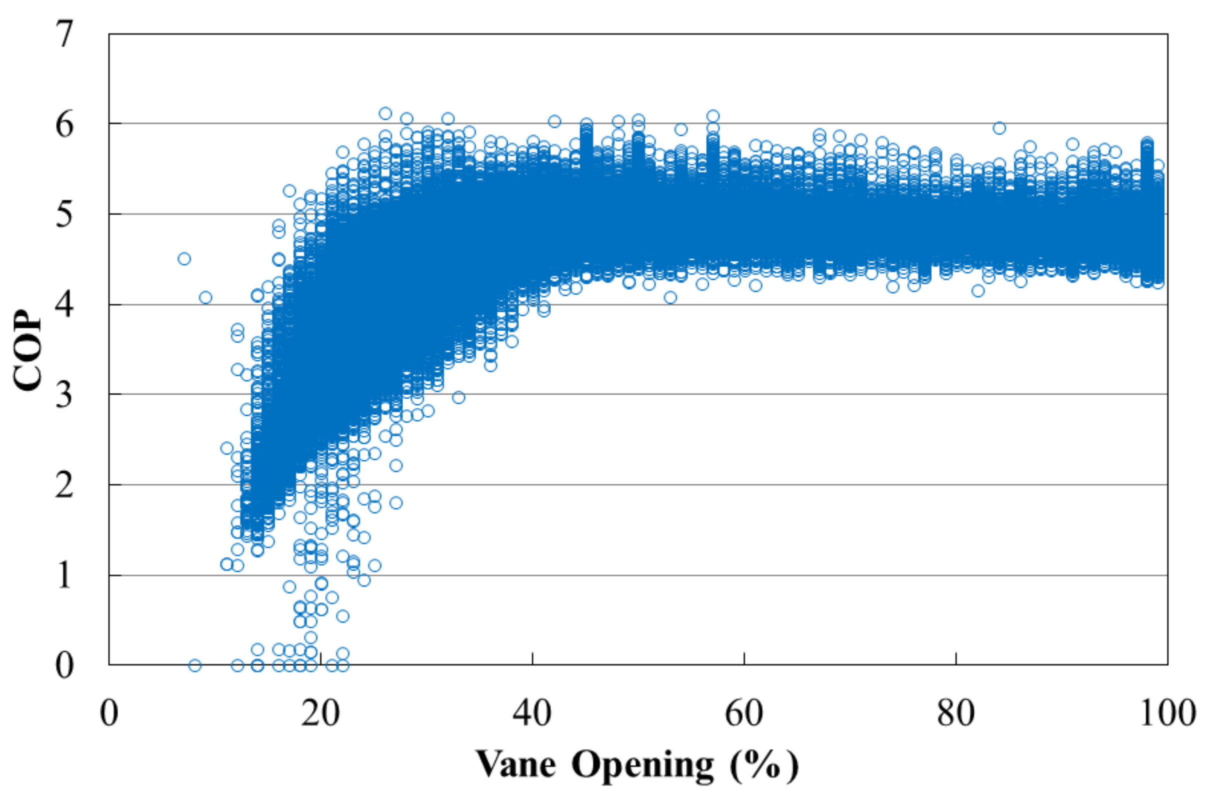


Fig. 4. The correlation between COP and vane opening using in-situ operation data

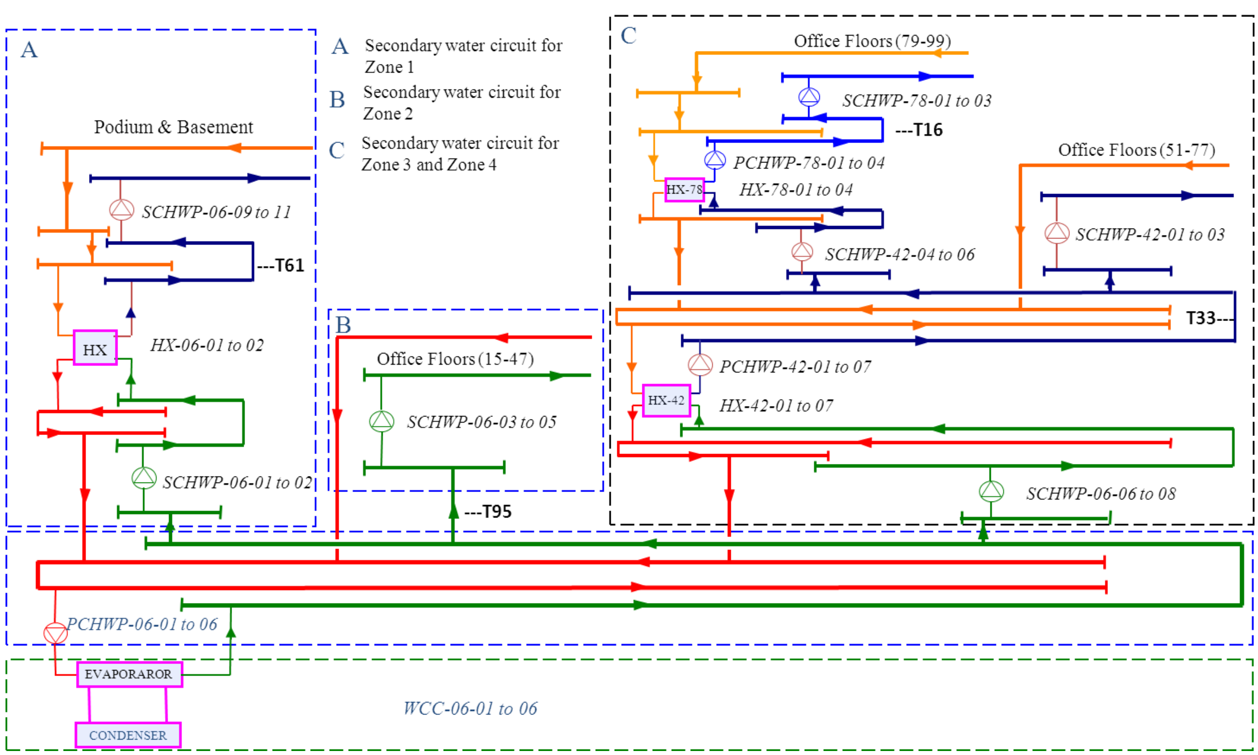


Fig. 5. The chilled water production and delivery system

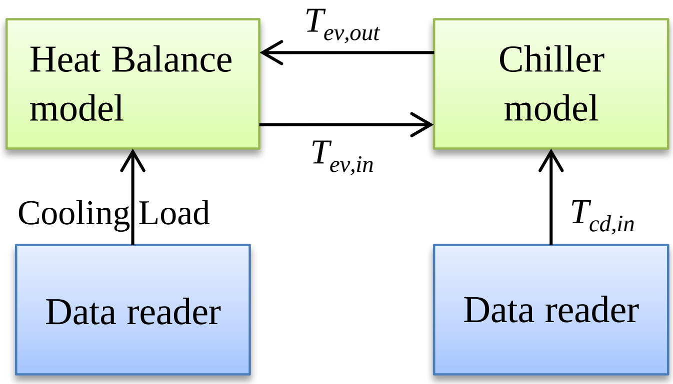


Fig. 6 Framework of the test platform

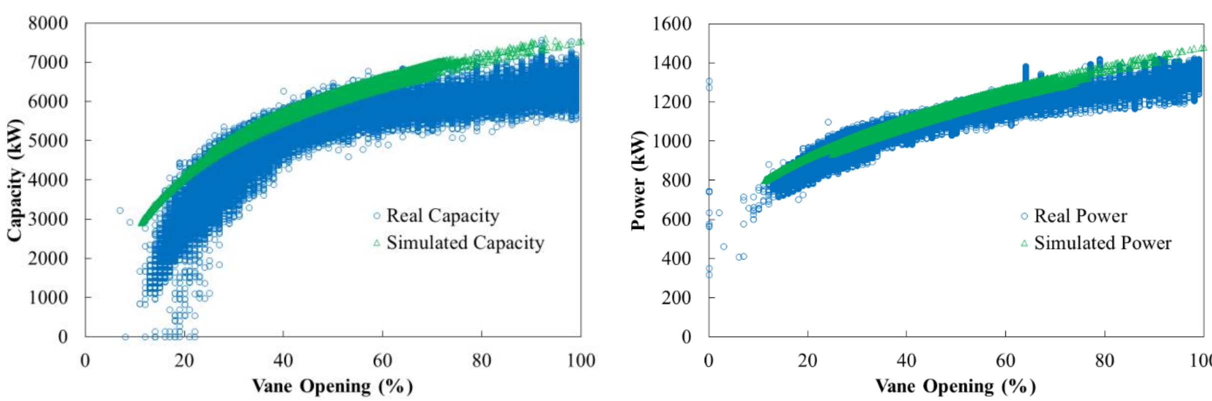


Fig. 7. Validation of the dynamic test platform

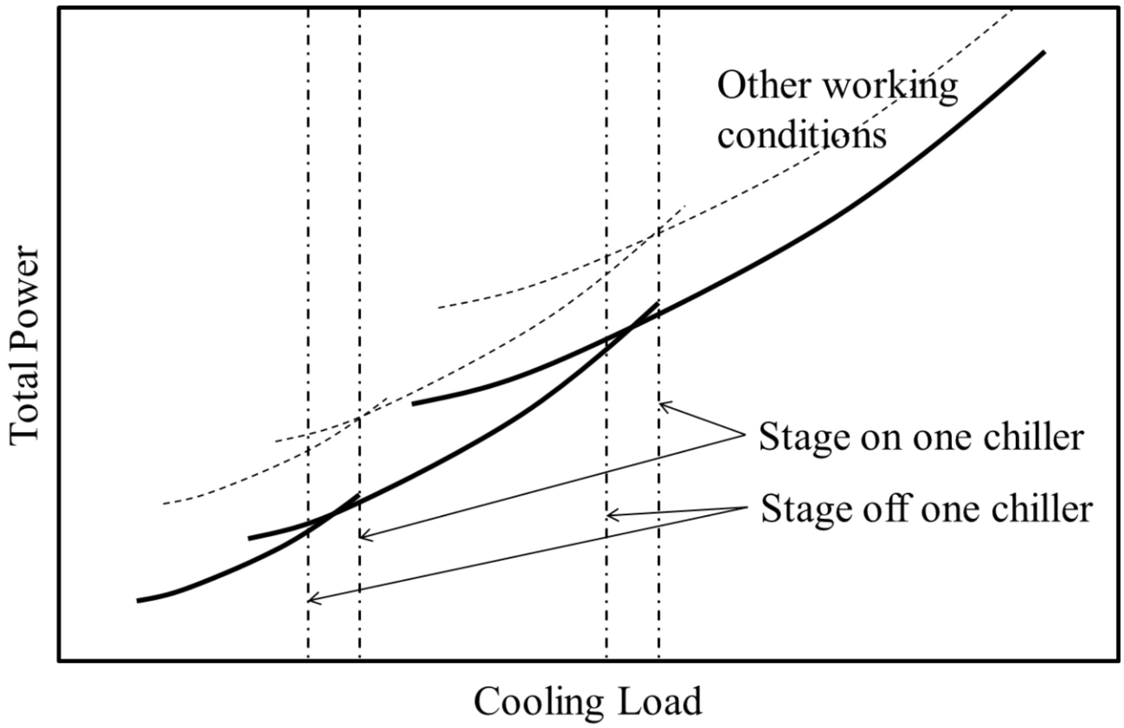


Fig. 8 Strategy S_R1: The strategy solely based on total cooling load

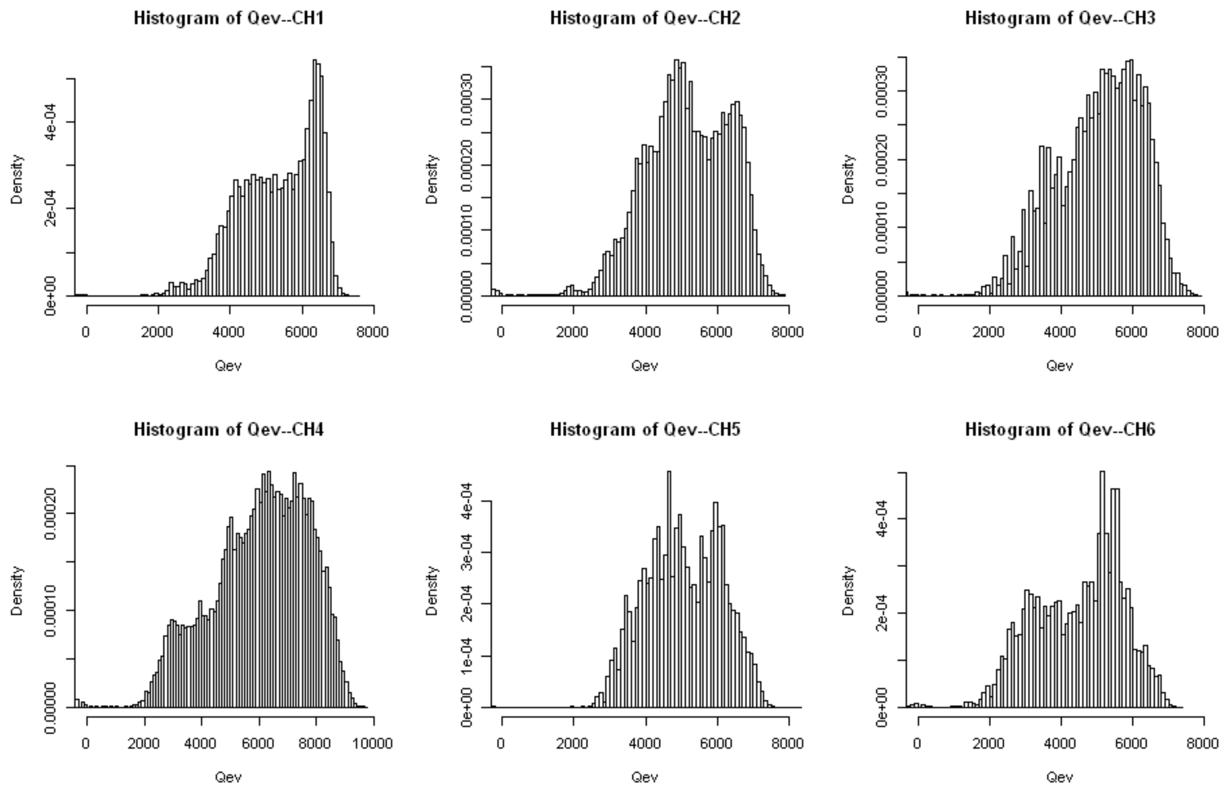


Fig.9. Cooling load distributions of individual chillers except only one chiller in operation

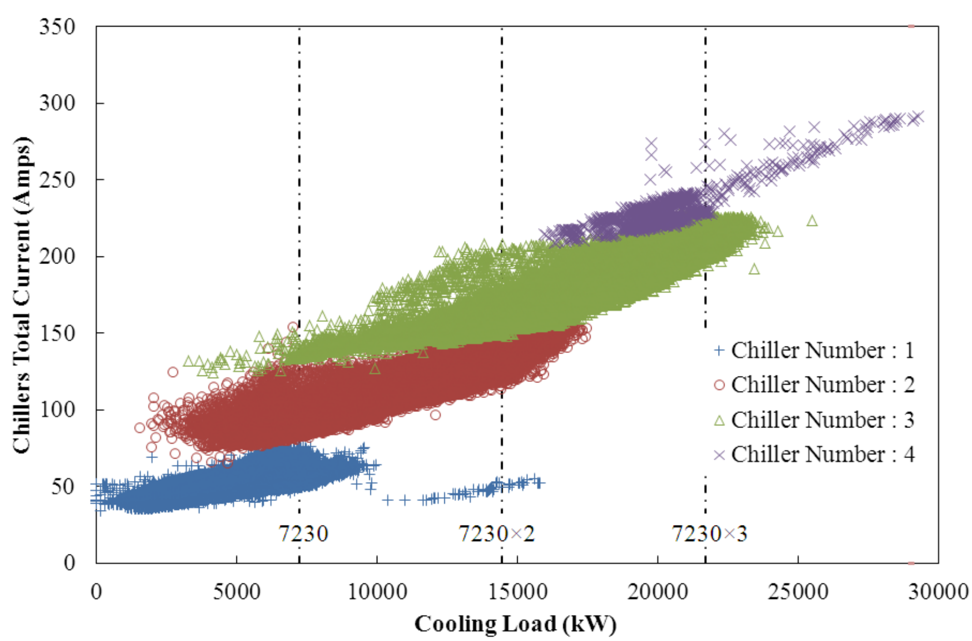


Fig. 10.Chiller total current *vs* total cooling load when strategy S_R2 is used

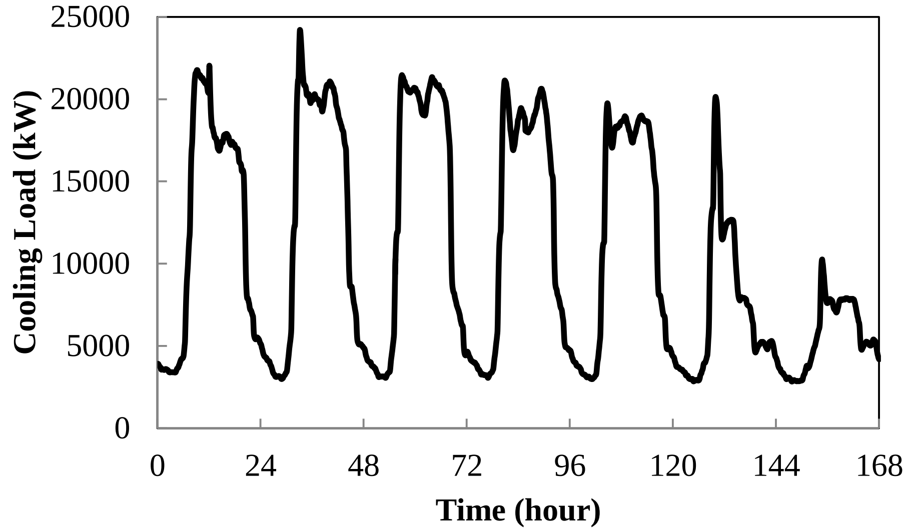


Fig.11. Cooling load used in the test

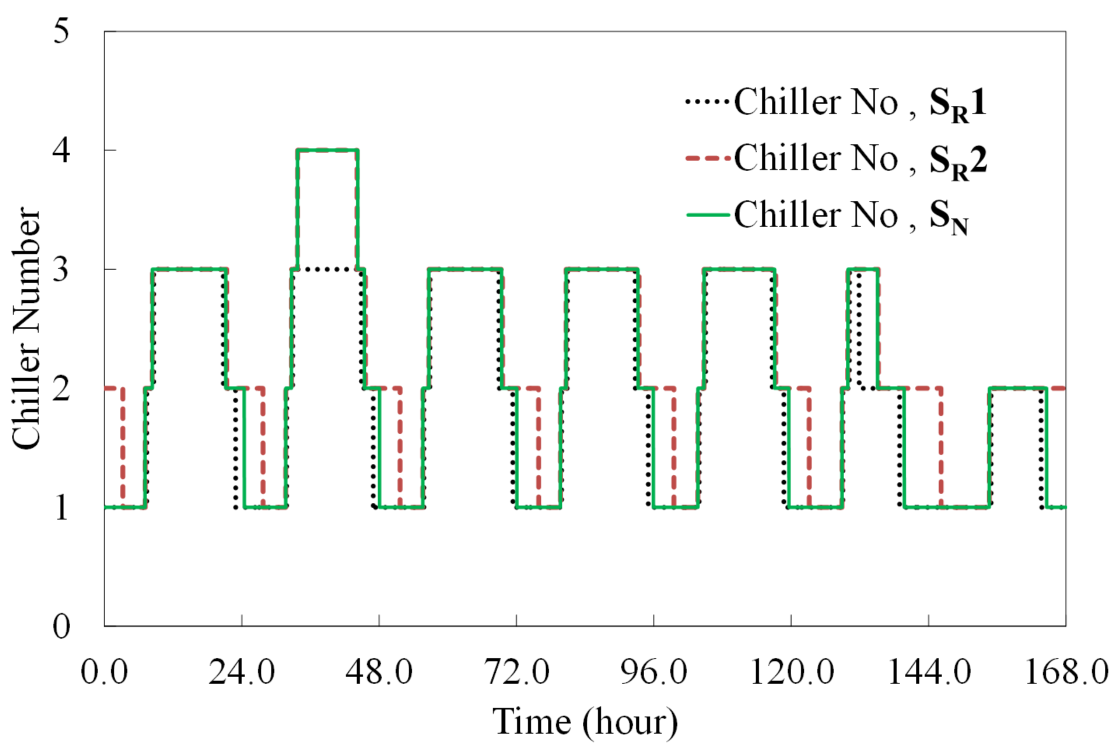


Fig. 12. Comparison on the numbers of operating chillers when using three strategies

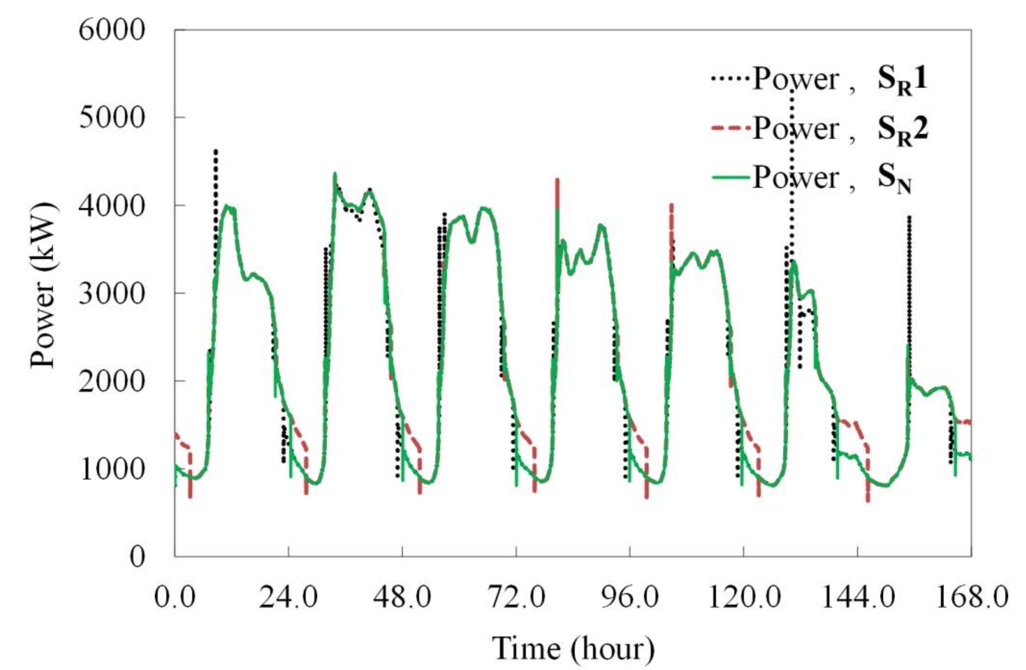


Fig. 13. Comparison on the power consumption of using the three strategies

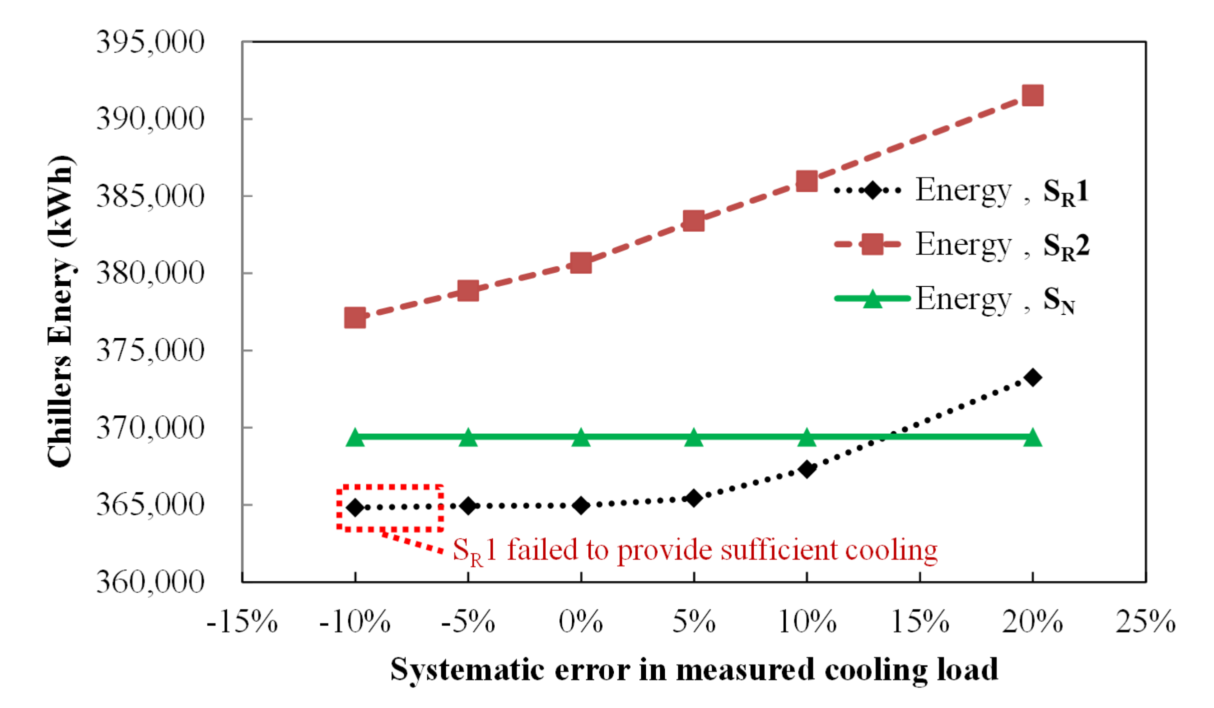


Fig. 14. Chiller energy consumptions when using three different strategies