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Probabilistic Approach for Uncertainty-based Optimal Design of Chiller Plants in Buildings

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Abstract: Conventional design of chiller plant is typically based on the peak cooling loads of buildings, while the cooling load reaches its peak level for only a small proportion of time in a year. This results in that even a perfectly designed chiller plant could be very significantly oversized in actual operation and it thus causes significant energy wastes. In this paper, an uncertainty-based optimal design based on probabilistic approach is proposed to optimize the chiller plant design. It ensures that the chiller plant operate at a high efficiency and the minimum annual total cost (including annual operational cost and annual capital cost) could be achieved under various possible cooling load conditions, considering the uncertain variables in cooling load calculation (i.e., weather conditions). On the premise of determining the minimum sufficient number of Monte Carlo simulation, this method maximizes the operating COP (coefficient of performance) and minimizing the annual total cost. A case study on the chiller plant of a building in Hong Kong is conducted to demonstrate the design process and validate the uncertainty-based optimal design method.

Keywords: Probabilistic approach; Uncertainty-based optimal design; Chiller plant; Simulation number; Energy efficiency

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1. Introduction

The building sector is the largest energy consumer in most countries and regions worldwide, especially in the metropolis such as Hong Kong [1, 2]. In commercial buildings, about 40-60% of the total electricity consumption is consumed by the heating, ventilation and air-conditioning (HVAC) systems [3]. Among all HVAC components and equipment, chiller plant is usually the major energy consumer, accounting for up to 50% of the total energy consumption of the entire HVAC systems [4]. It is found that a significant saving of chiller energy can be achieved by optimal design and energy efficient operation [5, 6].

The sizing and selection of chiller plants play the most important role in determining the energy performance of the HVAC systems [5]. The conventional design of chiller plant, proposed by ASHRAE [7], is usually based on sizing the components individually to meet a peak duty at a nominal operating point. Due to the inevitable uncertainty of weather data, indoor occupants and internal heat gain, designers tend to select a larger capacity than the peak duty (e.g., multiply a safety factor) in order that the plant can fulfil the cooling demand under any uncertain conditions for safety [8, 9]. This may result in significant oversizing of chiller plant and thus a large amount of energy wastes because the actual operating conditions are seldom the same as the design condition [10]. Oversizing of chiller plants is usually encountered as a result of cooling load calculation method, predefined weather data, and internal heat-gain criteria [11, 12]. Some measures, such as using a detailed simulation method, statistic weather data, model calibration and even the experiments, have been recommended to reduce the oversizing problems to a certain degree caused by uncertainties [8]. However, these methods cannot help to minimize the oversizing due to the adoption of conservative criteria for estimating the cooling loads of buildings.

Different from the early design methods which only address the peak cooling load of selected design day, some studies also have taken part load conditions into account in order to achieve a high efficiency in most of operating time of chiller plants [13, 14]. There are several approaches available to improve the energy performance of chiller plants under part load conditions since such conditions frequently occur throughout the entire cooling season [15]. In order to improve the systems PLR (part load ratio) that impacts the COP strongly, optimal sequence control is considered as an effective approach for the chiller plant with multiple chillers [16-19]. When the actual cooling load falls down from the peak duty, some of the chillers can be shut down so that each of the operating chillers can operate at a relatively higher PLR. Another important approach to ensure the performance of a chiller plant at high level is to use high efficiency chillers, particularly the chillers having good performance characteristics even under part load conditions [20]. For instance, variable-speed chillers may be employed to improve the energy efficiency when the chiller plant operates at part loads [21–24]. In addition, some studies show that the high COP of chiller plants can also be achieved by using hybrid chillers with different types of compressors or different energy sources, which can ensure all operating chillers within the optimum loading ranges [25].

When the part load conditions are considered in conventional optimal chiller design methods, they are typically based on the annual cooling load under the predefined conditions, which is commonly subject to a deterministic model-based simulation [26, 27]. The system may achieve a satisfactory performance when the actual operating conditions are the same or similar as the predefined conditions. However, when the actual conditions are different from predefined conditions caused due to various uncertain factors, the chiller plant is very likely to operate at a low efficiency [27, 28]. In order to address the problem caused by uncertainties, many researchers attempted to make the design to be more flexible, resilient and sustainable to achieve high operating performance under various load conditions [29, 30]. Several studies have taken the impact of uncertain variables into account when evaluating the chiller plant performance throughout the entire cooling season. Aaron and Li presented an analysis on a CCHP (combined cooling, heating and power) system model considering uncertainties of inputs and models [31, 32]. Case studies under different operating strategies were conducted to investigate the significance and sensitivity of uncertainties in predicting the CCHP system performance. Zhou [33] proposed a two-stage stochastic programming model for the optimal design of distributed energy systems, which uses genetic algorithm to perform the search in the first stage and Monte Carlo simulation to deal with uncertainties in the second stage. Burhenne [34] developed a Monte Carlo based methodology for uncertainty quantification to combine the building simulation and the cost-benefit analysis. However, the above studies have recognized and analyzed the impact of uncertainties on system performance, but they did not consider or propose effective approaches to overcome or reduce these impacts, which is the most important for improving the operating efficiency and robustness since uncertainties exist inevitably.

In order to achieve more flexible, resilient and sustainable design of the chiller plants, a cost related uncertainty-based optimal design method is proposed in this paper. It can ensure high chiller performance and achieve the minimum operation cost under various possible cooling load conditions, even though the load conditions deviating from the design conditions significantly due to various uncertainties of design information (i.e., weather conditions and number of occupants). In contrast to previous research, a probabilistic approach, which contains a wide range of so-called uncertainty “scenarios” generated by Monte Carlo simulation, is used for evaluating the performance of uncertainty-based optimal design. A statistical method is proposed to determine the number of Monte Carlo simulation for computational efficiency and accuracy. This design is based on two statistical principles, i.e., a maximization of the expected COP and a minimization of the expected value of the annual total cost. Meanwhile, an uncertainty-based optimization is conducted to identify the best configuration of number, sizes and types of chillers to achieve high operating efficiency and minimum total cost (including the operational cost and capital cost) under any cooling load conditions. Section 2 describes the concept of uncertainty-based optimal design in the HVAC domain. Section 3 presents the method of the uncertainty-based optimal design for chiller plants. Section 4 shows a case study on the uncertainty-based optimal design of the chiller plant of a building in Hong Kong. The last section draws the conclusion.

2. Concept of uncertainty-based optimal design

2.1 Uncertainties in HVAC field

Uncertainty is a term used to encompass many concepts [35]. It has been defined as a degree of ignorance [36], a state of incomplete knowledge [37], insufficient information [38], or a departure from the unattainable state of complete determinism [39]. In structure field, the various sources and categories of uncertainty identified in the literature can be classified into four categories [40]: epistemic uncertainty, variability, linguistic uncertainty [41] and decision uncertainty [42]. Epistemic uncertainty is the uncertainty associated with imperfect knowledge, which could be reduced by additional research and observation, i.e. model calibration and realistic data [43]. Variability is the uncertainty associated with diversity or heterogeneity, which cannot be minimized or even eliminated with additional research or observation [44, 45]. Considering the classification in structure field [40], HVAC fields contain epidemic uncertainty and variability only, and linguistic uncertainty and decision uncertainty are not considered in this study.

According to engineering practice, the uncertainties in the HVAC field could be divided into two types, including design uncertainties and operation uncertainties. Fig.1 presents an outline of uncertainties in the HVAC domain. Operation uncertainties mainly consist of information uncertainty and system reliability. This paper considers the design uncertainties only. Design uncertainties are mainly related to the cooling load uncertainty since the selection and sizing of HVAC subsystems (i.e., chillers, pumps, AHUs and cooling towers) mainly depend on the distribution of the annual cooling load. Cooling load uncertainty consists of the epidemic uncertainty and variability only. Variability mainly consists of the number of occupants and weather conditions, which cannot be minimized or even eliminated with additional research or observations. As for epidemic uncertainty, it concerns heat transfer performance of building envelopes and efficiency of air-conditioning equipment, which could be minimized and narrowed with additional research and observations, i.e. model calibration, realistic data and even correction factor.

2.2 Concept of uncertainty-based optimal design

Optimal design in HVAC field guarantees the optimization over predefined conditions (without considering the uncertainties) [26]. However, the operating conditions may change significantly throughout the lifetime of the building energy system. Concerning certain variables (e.g., weather conditions, number of occupants), HVAC systems could be possibly ensured to operate at a high efficiency using the statistic and historic data. However, given the fluctuations of weather conditions and number of occupants, the optimal design alone cannot guarantee the HVAC systems operating at high efficiency. Based on the predefined conditions, conventional design and even optimal design would result in obvious deviations between the design and the actual system performance and thus a large amount of energy wastes. Therefore, the uncertainties in these condition variables should not be ignored in the engineering practice.

Robust design is essential for improving engineering productivity [46]. The typical definition of robust design is described as "*a product or process is said to be robust when it is insensitive to the effects of sources of uncertainties, even though the design parameters and the process variables have large tolerances for ease of manufacturing and assembly*" [47-49]. Robust design improves the operating efficiency of a product by minimizing the uncertainties under various possible conditions, aiming at ensuring the mean performance at high level while maintaining feasibility with probabilistic constraints [46].

Combining the advantages of optimal design and robust design, a concept of uncertainty-based optimal design is proposed not only to ensure the chiller system performance at a high level under various possible cooling load conditions but also to achieve the minimum total cost in the lifecycle. The uncertainty-based optimal design can drive the chiller plants to operate at high COP and ensure that the minimum total cost could be achieved under various possible conditions, compared with conventional design and optimal design.

3. Uncertainty-based optimal design method for chiller plants

The uncertainty-based optimal design is performed by three steps as follows:

- *First step: generate the cooling load distribution involving uncertainties;*
- *Second step: determine the total design capacity of the chiller plant based on the cooling load distribution;*
- *Third step: determine optimal chiller plant configuration, i.e. number and sizes of chillers, types of chillers (constant speed chiller/variable speed chiller), by minimizing the life-cycle total cost of the chiller plant at the cooling load involving uncertainties.*

3.1 Generate cooling load distribution involving uncertainties

To conduct the proposed uncertainty-based optimal design, the first step is to obtain the cooling load distribution involving uncertainties. This step involves two modules, i.e. Module 1 for obtaining the uncertainties of input parameters and Module 2 for determining the minimum number of Monte Carlo simulations.

<u>*Module 1 – Obtain the uncertainties of input parameters*</u>

In order to consider various possible cooling load conditions under uncertainties (including variability and epidemic uncertainty), how to deal with the certain and uncertain factors is critical. Fig. 2 illustrates the functional scheme of a stochastic cooling load simulation. In this scheme, some input factors (e.g., building characteristics and equipment characteristics) are considered to be well-known or non-influential. Therefore the values are represented by scalar numbers [50]. In addition, some input factors (e.g., weather conditions, occupants and heat transfer coefficients of building envelopes) are uncertain, and they are therefore described by probability distributions of different types (normal, triangular, uniform, discrete uniform, etc.) [51]. Table 1 shows an example of the settings of uncertainties of the variables. When the certain and uncertain factors are determined, a more accurate model among alternative cooling load models is selected to calculate the cooling load in each scenario [52].

In order to generate the cooling load considering uncertainties, Monte Carlo simulation is employed. Monte Carlo simulation is a sampling-based technique that performs multiple model runs with random samples generated from the input distributions [52]. These simulations provide a series of possible results which involve uncertainties in the variables. In this study, the uncertainties of the input parameters are computed by Matlab.

Module 2 – Determine the minimum number of Monte Carlo simulations

When using a Monte Carlo simulation, a question that usually arises in connection with such simulations is to ask how many iterations of a particular Monte Carlo simulation are sufficient for accuracy. In this study, the output can be directly used to evaluate the variation of cooling load distribution and determine the minimum simulation number [53, 54]. Different from previous research which only used the mean value at one point to determine the number of simulations needed [53], in this study, both cooling load distribution profile and the mean value at a specific point, i.e. the peak cooling load in 99.6 percentile which represents the peak cooling load, are used for determining the minimum number of simulations needed. In this study, two deviations, called as convergence band width in Reference [53], are used for determining the minimum simulation number. The single-step deviation means the deviation between the average of i simulations and the average of i-1 simulations. The validation deviation (multi-step deviation) means the deviation between the average of i simulations and the average of $i+j$ simulations ($0<j\leqslant B_L$).The validation deviation at the "peak cooling load" is used to ensure the accuracy of the design capacity and the validation deviation of the cooling load distribution profile is used to ensure the accuracy of cooling load distribution for calculating the operation cost of different chiller plant configurations. Two criteria are defined as follows:

- The validation deviation of the cooling load distribution profile should be within its threshold B_{w1} over a number of simulation trials defined as convergence band length B_L.
- The validation deviation of the "peak cooling load" should be within it threshold B_{w2} over a number of simulation trials defined as convergence band length B_L.

The band length is expressed as a minimum number of simulations to verify whether the trials of Monte Carlo simulations are sufficient [53]. To achieve a desired level of confidence (i.e., 100(1-γ) %), the minimum simulation number B_L can be determined using the stopping rule as shown in Equation (1) [55]. In reference [54, 55], the minimum number is 50, corresponding to a confidence interval of 99. 5% (γ=0.0001).

$$0.9^{B_L}\left[-\mathrm{In}(0.1)B_L\right]^{-1} \leq \gamma \tag{1}$$

It is important to notice that both criteria request deviations is not over their thresholds over a number of simulation trials, defined as convergence band length B_L, to ensure reliability of convergence as shown in Fig.3. For the Region I from 0 to n_0, the single-step deviation is used for obtaining the initial simulation number n_0. The initial simulation number n_0 is the minimum number of simulations allowing the single-step deviation to be within the threshold. For the Region II (A) from n_0 to n, the validation deviation is over the threshold after a number of simulation trials (less than B_L) and thus the simulation number from n_0 to n is not sufficient. For the Region II (B) from n

to (n+B_L), the validation deviations are within the threshold after B_L simulation trials and thus the minimum sufficient simulation number is n.

A deviation index $f(n,m)$ is defined to represent the difference between average cooling load distribution profiles of n number of simulations and m number of simulations respectively, as shown in Equation (2) and Fig.4.

$$f(n,m)=\frac{\sum_{1}^{k}\left[\left|p_n(i)-p_m(i)\right|\cdot \Delta CL_i\right]}{\sum_{1}^{k}\left[p_m(i)\cdot \Delta CL_i\right]} \tag{2}$$

where, $p_n(i)$ is the probability at the load of CL_i of n trials of simulations, $p_m(i)$ is the probability at the load of CL_i of m trials of simulations, $\triangle CL_i$ is the cooling load interval and k is the total number of intervals. To validate if the number of simulations b is sufficient for obtaining accurate cooling load distribution profile, one should ensure that the deviation index $f(n,m)$ at each of B_L trials of simulations over the convergence band length falls within the threshold B_{w1}. Equation (3) presents this criteria in mathematic form, i.e. for all last B_L simulations, the deviation index is within the threshold B_{w1}.

$$f(b+j,b)\le B_{w1} \qquad \forall j,\ j=1,2,...,B_L \tag{3}$$

The second deviation index $g(x,y)$ is defined to represent the difference between the peak cooling load in 99.6 percentile of x number of simulations and y number of simulations respectively, as shown in Equation (4). It is worth noticing that the peak cooling load in 99.6 percentile is corresponding to the 30 unsatisfied hours per year.

$$g(x,y)=\frac{\left|CL_{x,99.6\%}-CL_{y,99.6\%}\right|}{CL_{y,99.6\%}} \tag{4}$$

where, $CL_{x,99.6\%}$ is the peak cooling load in 99.6 percentile at x trials of simulations, $CL_{y,99.6\%}$ is the peak cooling load in 99.6 percentile at y trials of simulations. To validate that the number of simulations a is sufficient for obtaining accurate “peak cooling load”, one should ensure that the deviation index $g(x,y)$ at each of B_L trials of simulations falls within the threshold B_{w2} over the convergence band length. Equation (5) presents the criteria in mathematic form, i.e. for all last B_L simulations, the deviation of the peak cooling load in 99.6 percentile is within the threshold B_{w2}..

$$g(a+j,a) \le B_{w2} \qquad \forall j,\ j=1,2,...,B_L \tag{5}$$

Fig.5 illustrates the scheme for determining minimum efficient simulation number in practical design optimization computation. At first, it is essential to obtain the initial simulation number a_0 and b_0, which can be computed by Equation (6).

$$f(b_0+i,b_0) < B_{w1} \quad and \quad g(a_0+i,a_0) < B_{w2} \tag{6}$$

where, i is the interval of simulation number. The initial numbers are increased further until the one-step deviations reach their thresholds. When the initial simulation number a_0 and b_0 are determined, the simulation number is validated from the initial value until the convergence condition is achieved. If the convergence condition is achieved, the larger one out of the two simulation numbers is chosen as the minimum sufficient simulation number.

Combining the output uncertainties from Matlab, the TRNSYS building model is used to generate the building cooling load distribution considering the uncertainties based on the determined simulation number. After conducting Max(a,b) trials of Monte Carlo simulations, the cooling load distribution involving uncertainties is determined. The peak cooling load is used for the determination of design capacity and cooling load distribution is used for calculating the operation cost of different chiller plant configurations.

3.2 Determine the total design capacity

The second step is to determine the total design cooling capacity, which plays a significant role in the design of chiller plant. If an inappropriate design capacity is selected, it may result in that a chiller plant is significantly oversized in actual operation and it thus causes significant energy and cost wastes.

To determine the total design cooling capacity, it is essential to obtain the design capacities with numbers of hours when the cooling demand cannot be met (marked as unmet hours). Based on the cooling load distribution, the “mean” design capacity of the total simulation trials are calculated and shown in Figure 6. The “mean” value represents the design capacity of chiller plant, corresponding to different unmet hours per year, based on the average cooling load distribution profile. The “max” value represents the maximum value among all the simulation trials. The “reference” value represents the design capacity determined using conventional method, i.e. based on the cooling load distribution of typical year. The peak cooling load in typical year is presented for comparison. It can be observed that when all the cooling load conditions are met, the design capacities based on average annual load profile (“mean”) and maximum load among all the simulation trials (“max”) are much higher than the peak cooling load in typical year. However, when certain number of unmet hour is allowed (as required in design guide), the design capacities based on the average annual load profile and the maximum load profile become significantly lower than the peak cooling load in typical year. Therefore, using the peak cooling load in typical year as the design capacity may lead to the oversizing of chiller plant. At most of the unmet hours, the design capacities based on the average annual cooling profile and that in typical year are very close.

3.3 Determine optimal chiller plant configuration

When the total design capacity is determined, the other key issue is to determine the optimal number, sizes and types of chillers in order to achieve minimum annual total cost. The annual total cost TC_n contains two parts, i.e. annual capital cost $f_s(N)$ and annual operational cost $OC_n(N)$, as shown in Equation (7).

$$TC_n = OC_n(N) + f_s(N) \tag{7}$$

The annual capital cost is the fixed expense in purchasing and installing the chillers and associated components, which is influenced by the number, sizes and types of chillers.

As for the annual operational cost, it is mainly related to the annual cooling load distribution and the energy efficiency. The energy efficiency is subject to the number, sizes and types of chillers.

The optimization of the chiller plant configuration is achieved, as shown in Fig.7, mainly based on three major modules. The optimization process and main assumptions are summarized as follows.

I. *Calculate the operating COP of chiller plant of the chiller number starting from two until the operating COP begins to decrease. At least two chillers are employed for convenient control and maintenance.*

II. *Under different number, optimize the sizes of chillers to maximize the operating COP. In practice, two types of sizes are preferred for the convenient maintenance and control. Besides, more (or same number) chillers with larger capacity and fewer (or same number) chillers with smaller capacity are reasonable and therefore assumed in the optimization trials.*

III. *Under different number and associated optimal sizes of chillers, optimize the types of chillers (e.g. constant speed chiller/variable speed chiller).*

IV. *Having optimal sizes and types of chillers for different chiller numbers, select the optimal chiller number to achieve the minimum total cost when the capital cost is considered.*

The operating COP mainly relates to the number, size and type of chillers. In common, these three factors should be optimized together to achieve high operating COP, which may result in that the calculations may be very complex. However, it is worth noticing that the number and size of chillers is subject to the total design capacity and the type of chillers mainly affects the operation efficiency of the chiller plant. To enhance the computation efficiency, the number and size of chillers are optimized together and then the type of chillers is optimized later, which may have no obvious impact on the optimization results compared with the situation that these three factors are considered together.

Module 1 – Optimization of number and sizes of chillers concerning energy efficiency

As mentioned above, the annual operational cost is mainly related to the annual cooling load distribution and system energy efficiency. The energy efficiency of chiller plants, usually evaluated by COP, strongly depends on the operating PLR. It is well known that the larger the PLR, the higher COP once the impact of other operating parameters (e.g. condensing and evaporating temperatures) are separated [56, 57], as shown in Equation (8).

$$COP_i = D_0 + D_1 \cdot PLR_i + D_2 \cdot PLR_i^{\ 2} + D_3 \cdot PLR_i^{\ 3} \tag{8}$$

where, D_0-D_3 are the coefficients that can be identified from chiller catalogue or field measurement data. The PLR is usually determined by the number and size of chillers. Therefore, the optimization of number and size of chillers is conducted to improve the operating PLR and thus COP.

PLR is simply defined as the ratio of the required cooling load (CL_i) to the available cooling capacity (CL_A) (i.e. that of operating chillers) as shown in Equation (9).

$$PLR_i = \frac{CL_i}{CL_A} = \frac{CL_i}{N_i \cdot CL_{\mathrm{Nominal}}} \tag{9}$$

where, $CL_{Nominal}$ is the nominal cooling capacity of each chiller. N_i is the number of operating chillers. It means that the more chillers are selected, the higher operating PLR can be achieved. On the other hand, selecting more chillers means that the size of individual chillers is smaller. Generally, the rated COP of chiller decreases when the nominal capacity of chillers reduces in certain extent [58]. Therefore, the operating COP increases when the number of chillers increases to certain value and it reduces when the number of chillers increases further, as shown in Fig.8. Since at least two chillers are used for convenient maintenance and control, the calculation of the chiller number starts from two until the operating COP begins to decrease.

The sizes of individual chillers, which determine the rated COP, influence the PLR and operating COP of the chiller plant. In practice, two types of sizes of chillers are proper for the convenient maintenance and control. Besides, the number of chillers of larger capacity is selected to be at least the same as that of smaller capacity in the optimization trials. To determine the optimal sizes of chillers at a given chiller number, the larger size increases gradually from the mean value (i.e., all the chillers are equally sized) until the operating COP achieves the maximum value in the optimization trials. At the same time, the smaller size decreases accordingly. The constraint of chiller plant configuration is shown in Equation (10).

$$\begin{gathered} n_1 \cdot C_1 + n_2 \cdot C_2 = CL_T \\ C_1 \geq C_2,\ \ n_1 \geq n_2 \end{gathered} \tag{10}$$

where, C_1 and n_1 are the nominal design capacity and number of the larger chillers respectively. C_2 and n_2 are the nominal design capacity and number of the smaller chillers respectively. CL_T is the total design capacity of the chiller plant. Equation (11) formulates the optimization problem for selecting the chiller number/sizes.

$$\begin{aligned} \text{find} \quad & C_1, C_2, n_1, n_2 \\ \text{that maximizes} \quad & COP_{op}(C_1, C_2, n_1, n_2) \\ \text{subject to} \quad & n_1 \cdot C_1 + n_2 \cdot C_2 = CL_T \\ & n_1 + n_2 \geq 2 \\ & C_1 \geq C_2, n_1 \geq n_2 \end{aligned} \tag{11}$$

where, COP_{op} is the operating COP based on annual cooling load distribution.

Module 2 – Optimization of types of chillers

It is well-known that the chiller plant usually operates at part load condition for most of time. Under the same operating PLR conditions (with the same cooling load distribution), chillers with better part load performance (e.g. variable-speed chillers) could be used. Fig.9 presents the COP profile of two typical types of chillers (i.e., variable-speed chiller and constant-speed chiller). The COP of constant-speed chillers may be even larger than that of the variable-speed chillers near the full load conditions while the variable-speed chiller performs much better under other load conditions, particularly the low PLR conditions. Therefore, both the constant-speed chillers and variable-speed chillers could be used to achieve a high operating COP.

In order to achieve high operating COP, more constant-speed chillers and fewer variable-speed chillers are used due to the higher COP of constant-speed chillers at nearly full load. In actual operation, the constant-speed chillers are maintained to operate at full load to achieve high COP. The insufficient cooling load, which is larger than the total capacity of operating constant-speed chillers, is covered by variable-speed chillers for their stable COP at part load condition. Equation (12) formulates the optimization problem for selecting chiller types. Where, N_c is number of constant-speed chillers, N_v is number of variable-speed chillers.

$$\begin{aligned} \text{find} \quad & N_C, N_V \\ \text{that maximizes} \quad & COP_{op}(N_C, N_V) \\ \text{subject to} \quad & N_C \geq N_V \geq 1 \\ & N_C + N_V = n_1 + n_2 \end{aligned} \tag{12}$$

Module 3 – Optimization of chiller plant configuration to achieve minimum total cost

As mentioned above, when number of chillers increases up to certain extent, the operating COP of operating chillers increases and the operation cost reduces. Normally, the capital cost of the chiller plant of given total capacity increases when more chillers are used. Therefore, there should be a compromised number of chillers when both the operating cost and the capital cost are considered.

Fig.10 illustrates the effects of number of chillers on minimum total cost. If the selected number of chillers is too small, the limited number of chillers will result in low energy efficiency and thus high operational cost while the capital cost of the chiller plant will be high if the selected number of chillers is too large.

4. Case study on the chiller plant design for a building in Hong Kong

A case study on the chiller plant design for a building in Hong Kong is conducted to test and evaluate the proposed uncertainty-based optimal design. At first, Monte Carlo simulation is used to generate the cooling load distribution profile for the assessment of proposed uncertainty-based optimal design. Then, the total design capacity is determined according to the cooling load distribution profile. Finally, optimal chiller plant configuration is conducted to achieve the minimum total cost.

4.1 Description of stochastic input parameters

The uncertainties in the building load calculation involve:

a) Number of occupants and weather conditions, which cannot be predicted accurately;
b) Infiltration flow rate between outdoor environment and indoor air, heat rejection by equipment, etc., which can be narrowed through some proper measures but cannot be eliminated.

As mentioned above, the uncertain variables might be divided into two parts, i.e. variability and epidemic uncertainty. For variability which mainly includes weather conditions and number of occupants, it may not be accurately predicted due to the irregular fluctuations. The weather conditions may be assumed to be subject to normal distribution, described by the mean value and standard deviation. The number of occupants may be assumed to be subject to triangular distribution, described by the mean value, minimum value and maximum value. As for epidemic uncertainty (i.e., infiltration flow rate), it usually fluctuates around the mean value, and can be predicted according to the regular fluctuation. Uniform distribution is used to consider this type of uncertainties in cooling load calculation.

4.2 Implementation and evaluation of uncertainty-based optimal design method

4.2.1 Generate the cooling load distribution involving uncertainties

To conduct the Monte Carlo simulations to obtain the cooling load distribution, it is essential to determine the settings of uncertainties of the variables. According to the settings in Table 1, the uncertainties of the input parameters are computed by Matlab. Combining the output uncertainties from Matlab, the TRNSYS building model is used to generate the building cooling load considering the uncertainties.

In order to obtain the reasonable cooling load distribution, a sufficient simulation number should be selected for computational efficiency and accuracy. In this study, both validation deviation thresholds for the cooling load distribution profile and peak cooling load in 99.6 percentile are chosen to be 0.5%.

The test results show that the initial simulation number should be 20. Then the minimum simulation number can be obtained until the convergence condition is achieved, as shown in Table 2. It can be seen that 20 trials of simulations are sufficient as the corresponding validation deviation is within the threshold over 50 validation trials of simulations.

In order to obtain the accurate operational cost, the validation deviation of cooling load distribution profile $f(n,m)$ is used to select the minimum simulation number. Fig.11 shows the results in determining the initial simulation number of cooling load distribution. It can be observed that the initial simulation number should be 350. Then the minimum simulation number can be obtained when the convergence condition is achieved, as shown in Table 3. It can be observed that 780 trials of simulations are sufficient for the cooling load distribution profile as the corresponding validation deviation is within the threshold over 50 validation trials of simulations.

Compared with the minimum simulation number for accurate “peak cooling load”, the minimum simulation number for accurate cooling load distribution is much larger. To obtain the accurate cooling load distribution and peak cooling load, at least 780 times of Monte Carlo simulations are required to achieve the computational efficiency and accuracy. Table 4 shows the minimum simulation number of other thresholds for your reference. In some literatures [59], the researchers assumed that 1000 simulation trials are sufficient without a quantized index to evaluate the accuracy and attempted to use 1000 simulation trials to generate the required cooling loads.

After conducting 780 times of Monte Carlo simulations, the cooling load distribution is obtained, as shown in Fig.12. The reference case is the normal cooling load distribution without considering the uncertainties. It can be seen that the cooling load distribution profile of 780 simulation trials is smoother than that of reference case because more cooling load conditions are considered. The cooling load distribution mostly locates between about 2200kW and 4500kW.

4.2.2 Determine the total design capacity

The second step is to determine the total design capacity of the chiller plant. The design capacities corresponding to different unmet hours are presented in Fig.13. The meanings of the symbols can be found in Section 3.2. It can be seen that using the peak cooling load of typical year (i.e. 5600kW) as design capacity may lead to the oversizing of chiller plant. When the annual unmet hours is equal to 0, the design capacity of the "mean" and the "max" can be much higher than the peak cooling load of typical year in conventional design, which could result in the serious oversizing of chiller plant. It can be also observed that the profile of "mean" is close to that of the reference case. The decision makers can size the chiller plant based on their specific requirements. In this study, the number of unmet hours should be no more than 50. The chiller plant can be sized based on the load of 5121 kW according to the "max". If the requirement is very strict, smaller number of unmet hours can be used in determining the design capacity.

4.2.3 Determine the optimal chiller plant configuration

The third step is to optimize the number, sizes and types of chillers to achieve the minimum total cost. The capacity of all the chillers is subject to the design capacity 5100kW. As shown in Fig.8, the operating COP increases when the number of chillers increases in certain extent. It decreases when the number of chillers increases further. To facilitate the operation and control, at least two chillers are employed for practical reasons. The tried number of chillers starts from 2 until the number where the operating COP begins to decrease. The sizes of chillers are also optimized under each given chiller number based on the rated chiller COP of different capacities, as shown in Fig.14.

Using Module 1 described in Section 3.3, the optimization of number and sizes of chillers is conducted. The results are listed in Table 5. It can be observed that the operating PLR increases when the number of chillers increases and the operating COP increases when the number of chillers increases from 2 to 5. When the number of chillers increases up to 6, the operating COP reduces. Therefore, the number of chillers is tried between 2 and 6. Combining the chiller plant options from 5 to 8, the chiller plant options consisting of some chillers of larger capacity and one chiller of smaller capacity have a larger operating COP compared with the other options. It means that the optimal chiller plant option consists of more chillers with larger capacity and one chiller with smaller capacity. Among these options, the option 6 has the largest operating COP (6.09) although its PLR (0.91) is not the largest among options. The options 4, 6 and 8 have the better energy performance than options 3, 5 and 7 correspondingly under their chiller numbers. Therefore, the options 3, 5 and 7 will not be considered and the options 1, 2, 4, 6 and 8 are selected for the optimization of types of chillers.

After the number and sizes of chillers are determined, what needs to do is to optimize the types of chillers to improve the COP at part load conditions. Fig.15 presents the typical COP profiles of a constant-speed chiller (1200kW) and a variable-speed chiller (1200kW) according to the data from the chiller manufacturer. In this study, under the same PLR, the COPs of constant-speed chillers are assumed to be proportional to their capacities.

Using module 2 described in Section 3.3, the optimization of chiller types is conducted to achieve a higher COP. Table 6 summarizes the optimization results of types of chillers. The COP distribution is shown in Fig.16. The result of conventional design is also presented for the comparison. It can be observed that the option consisting of four constant-speed chillers (1100kW) and one variable-speed chiller (700kW) has the largest operating COP (6.15) compared with other options. The option consisting of six chillers has a more concentrated COP distribution (from 5.45 to 6.4) than that consisting of two chillers. From Table 6, the optimal chiller plant option consists of more constant-speed chillers and one variable-speed chillers to achieve minimum operation cost.

According to the cooling load distribution shown in Fig.12 and the COP distribution shown in Fig.16, the annual operation costs of the chiller plants are computed, as listed in Table 7. It can be seen that the chiller plant of four constant-speed chillers (1100kW) and one variable-speed chiller (700kW) has the lowest annual operation cost (3,474,483kW) compared with that of other options, while the design option with one constant-speed chiller and one variable-speed chiller has the highest annual operation cost (4,501,630kW). Considering the electricity price (0.8 HK$/kWh), Table 7 also shows the annual electricity cost.

The annual total cost also contains the annual capital cost of chiller plants. The capital cost contains the equipment, relevant accessories and space rent fees. The life cycle of the chiller plant is assumed to be 10 years. The capital cost of 900kW variable-speed chiller is HKD 1.2M and the capital cost of 900kW constant-speed chiller is HKD 0.9 M, referring to the data from a manufacture. As for the capital cost of other constant-speed chillers and variable-speed chillers, they are computed by Equation (15) [60, 61].

$$CC = CC_0 \cdot \left(C / C_0\right)^{\alpha} \tag{15}$$

where, CC_0 is the capital cost of a reference chiller with the capacity C_0. CC is capital cost of chiller with the capacity C. α is the coefficient, which set to be 0.4 in this study [62, 63]. The annual total costs under the different options are computed using Equation (15) and presented in Table 8. It can be seen that the option consisting of one constant-speed chiller and one variable-speed chiller has the lowest annual capital cost (311k HK$). From Table 8, the annual capital cost increases when chiller number increases at given total capacity.

Combining the annual operational cost shown in Table 7 and the capital cost shown in Table 8, the annual total costs under the different options are computed and presented in Table 9. It can be observed that the option with three constant-speed chillers (1400kW) and one variable-speed chiller (900kW) is the optimum design option.

From Table 9, the plant option with one constant-speed chiller (3200kW) and one variable-speed chiller (1900kW) has the least annual capital cost while the option with four constant-speed chillers (1100kW) and one variable-speed chiller (700kW) has the least annual operation cost. To achieve a compromised annual operational cost and annual capital cost and thus the minimum annual total cost, the chiller plant option with three constant-speed chillers (1400kW) and one variable-speed chiller (900kW) can be considered as the optimum selection for the design, and the minimum annual total cost is reduced by 17.7% compared with the conventional design option.

Conclusion

This paper presents an uncertainty-based optimal design method based on a probabilistic approach to ensure the high performance of chiller plants and achieve the minimum annual total cost under various possible cooling load conditions by optimize the capacity and configuration of chiller plants. A new method to determine the minimum sufficient simulation number is proposed to obtain the cooling load distribution of required accuracy considering the uncertainties in inputs. A case study is given as an example to demonstrate the proposed method. Conclusions can be made as follows:

- Determining the minimum simulation number is very important for obtaining the accurate peak cooling load and cooling load distribution. 780 simulation trials are found and used and to achieve an accuracy of 0.5% for both of them.

- Having the quantitative relation between unmet hours and the design capacity, decision makers can properly size the chiller plant with quantified confidence according to their specific requirements.

- The configuration of the chiller plant can be selected by achieving the minimum total cost when considering uncertainties. The selected chiller plant can perform well under various possible cooling load conditions. The results of the case study show that the total cost of optimized chiller plant can be reduced significantly (i.e. 17.7%) compared with the conventional design.

The test results and experiences from the case study also show that the proposed optimization method can determine the optimal design of the chiller plant effectively in terms of the human effort of programming for implementing the method and the computing effort in using the method for optimizing a chiller plant design. The optimization is conducted by separating optimizing trials into three steps, i.e. plant cooling capacity, number and size of chillers and type of chillers. The computation efficiency is dramatically improved and the computation for the optimization of a chiller plant can be completed within about 10 minutes performed completed execution. It is worth noticing that the optimization output may not the perfect one as not all options/combinations are tested.

Acknowledgements

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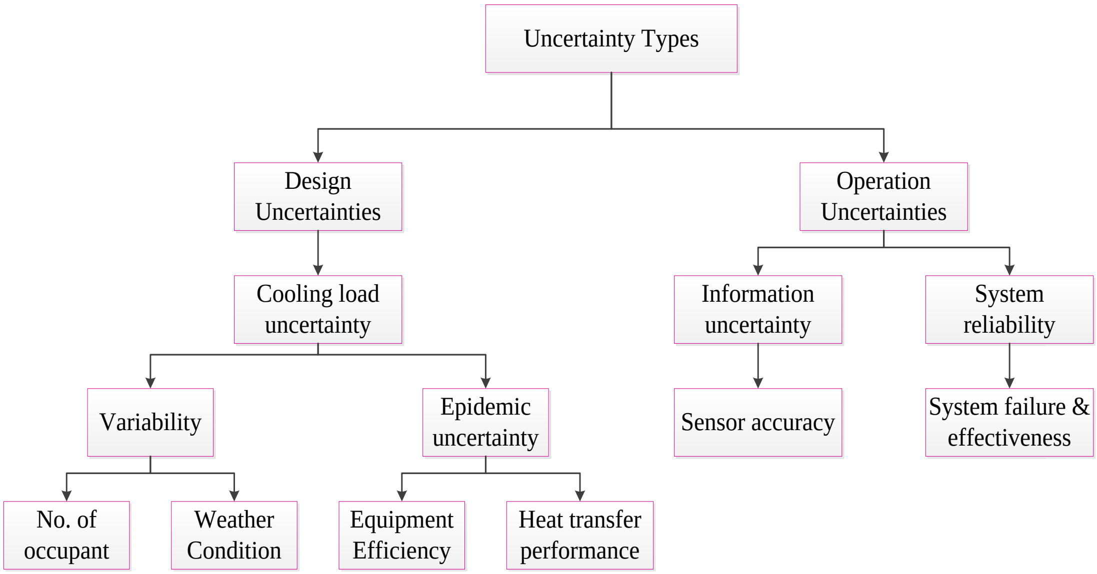

Fig.1 Types of uncertainties in HVAC field

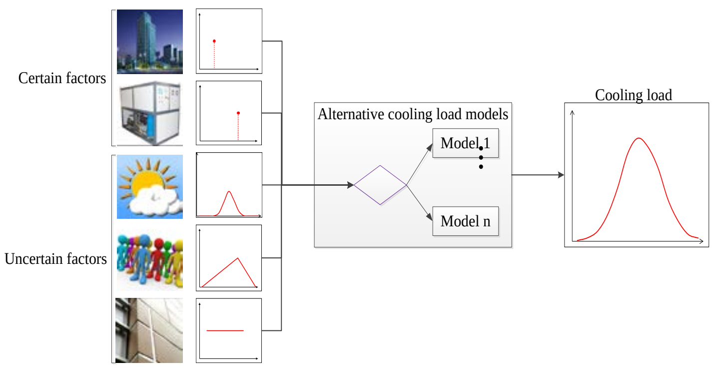

Fig.2 Scheme of the framework for cooling load simulation

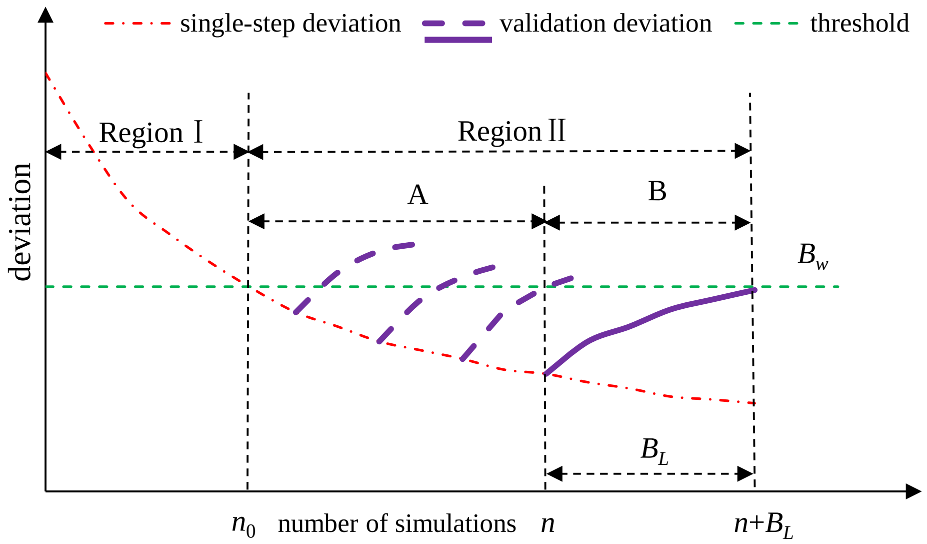

Fig.3 Scheme of threshold and convergence band length

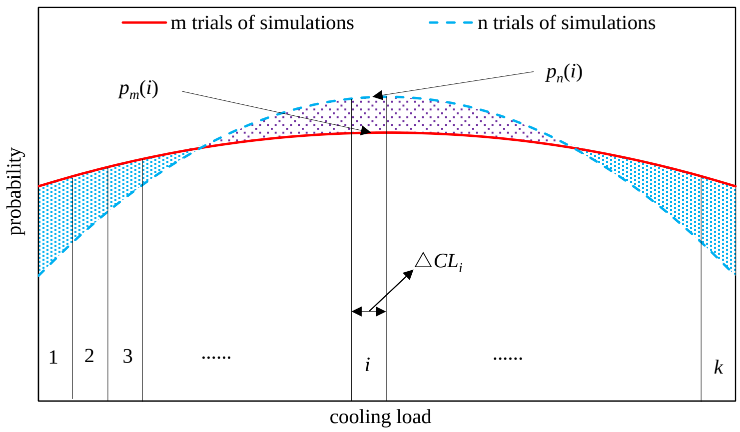

Fig.4 Difference of cooling load distribution with different simulation numbers

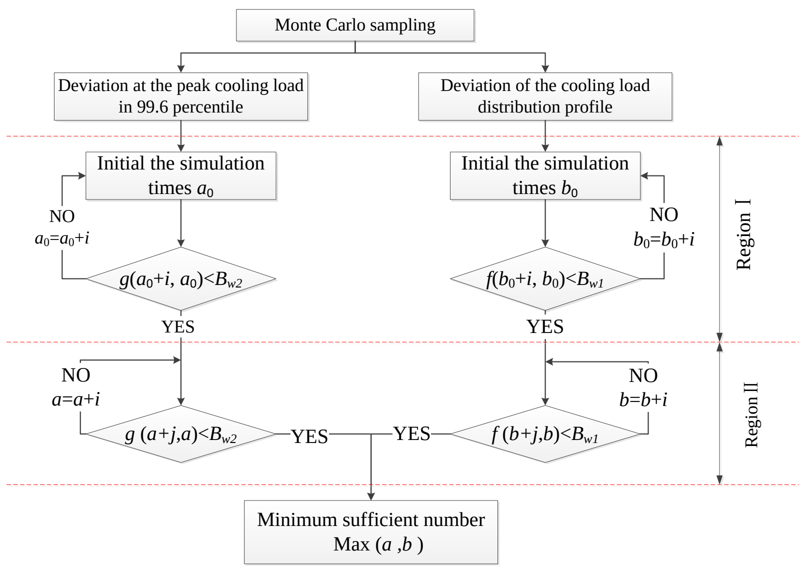

Fig.5 Scheme for determining minimum efficient simulation number

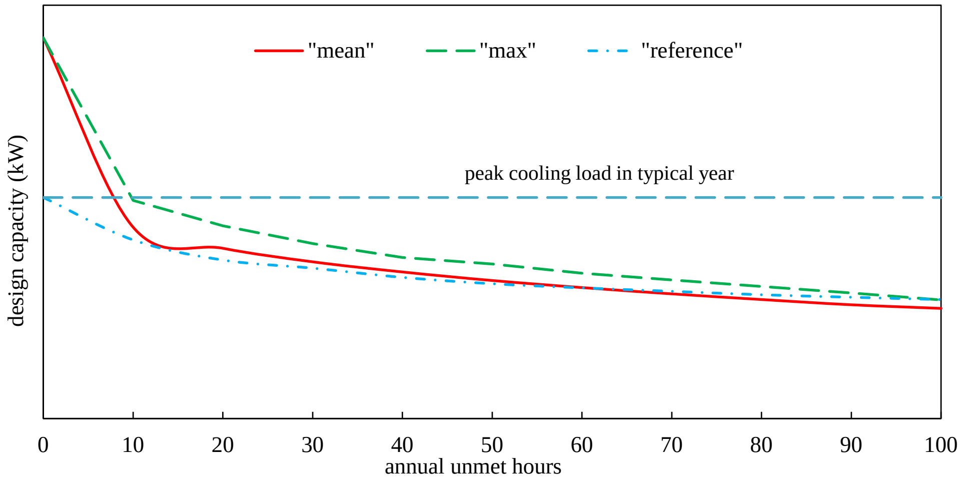

Fig.6 Design capacity vs. annual unmet hours

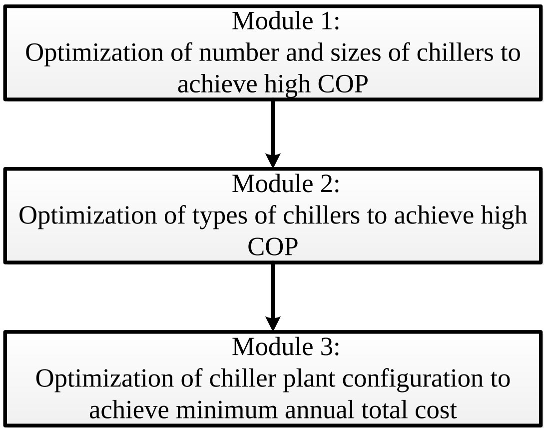

Fig.7 Determination of optimal chiller plant configuration

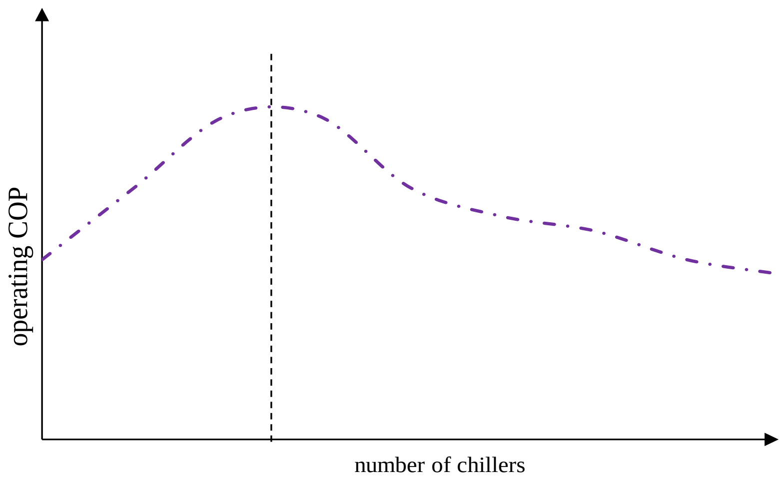

Fig. 8 Effects of number of chillers on the operating COP

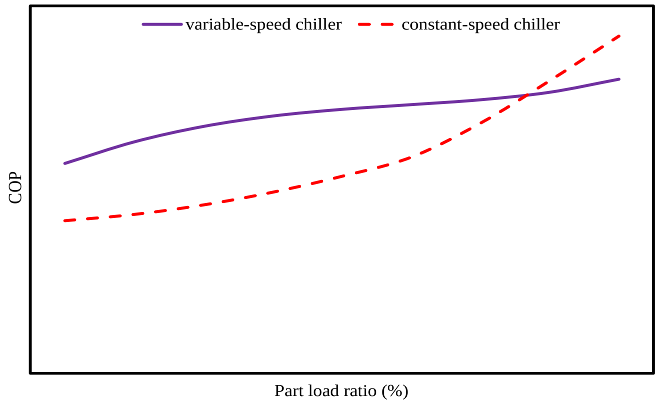

Fig. 9 COP of constant-speed chiller and variable-speed chiller

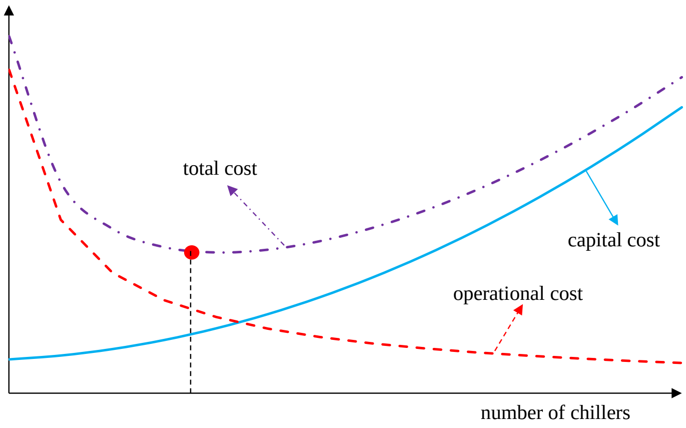

Fig.10 Effects of number of chillers on minimum total cost

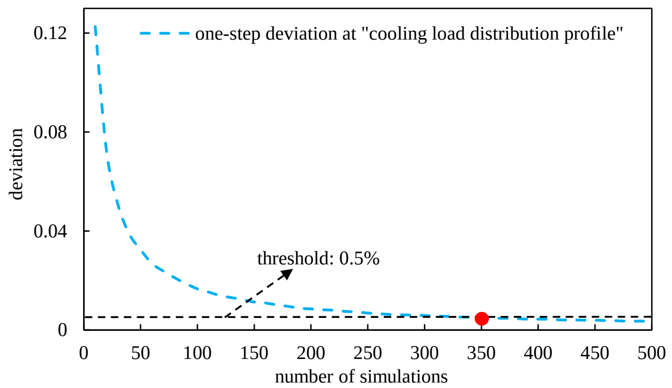

Fig.11 Determination of initial simulation number for cooling load distribution

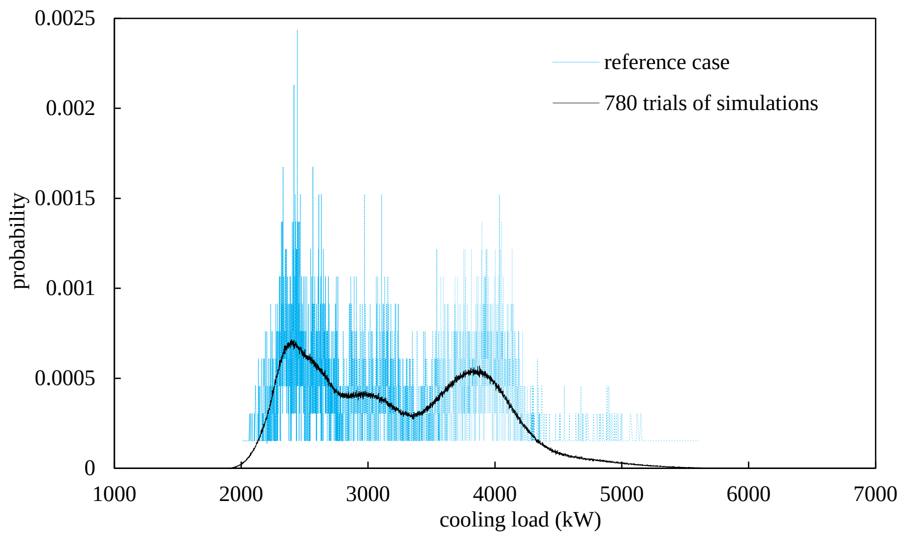

Fig.12 Distribution of cooling load considering uncertainties

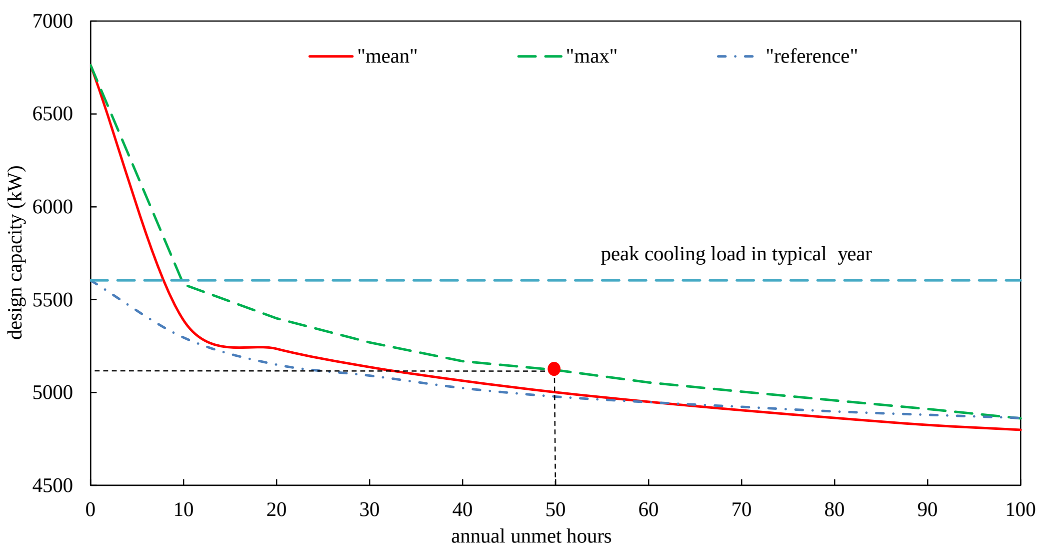

Fig.13 Design capacity vs. number of annual unmet hours

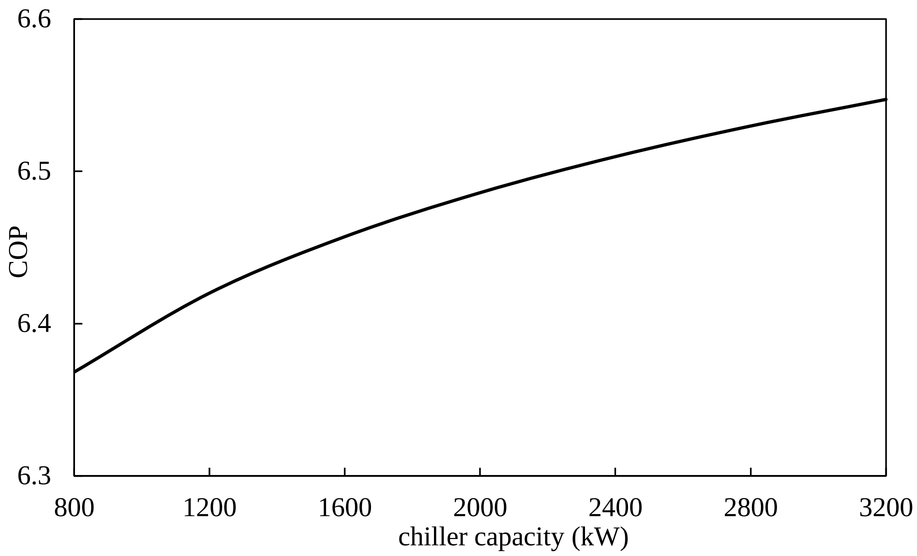

Fig.14 Rated COP vs. chiller capacity

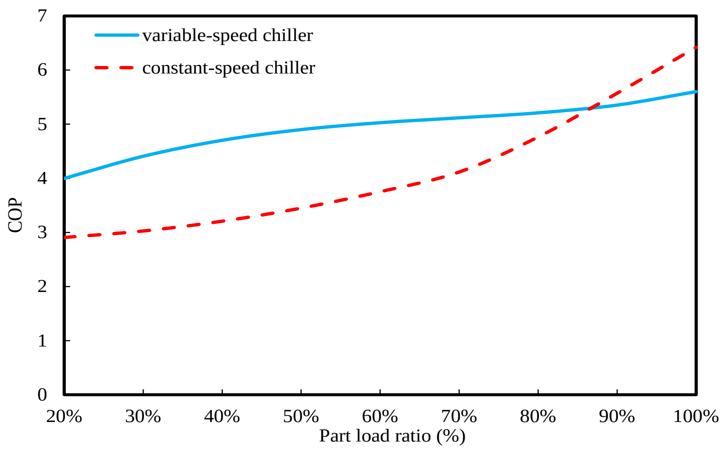

Fig.15 COP of constant-speed chiller and variable-speed chiller (1200kW)

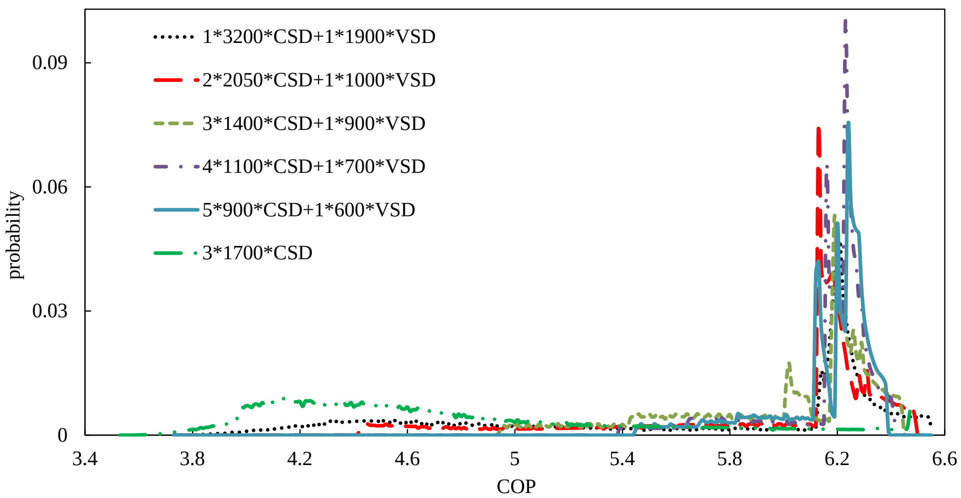

Fig.16 Distribution of COP

Table 1 Distributions of stochastic input parameters

Parameters	Distributions
Outdoor temperature (℃)	$N(0,1)$
Relative Humidity (%)	$N(0,1.35)$
Number of Occupants	$T(0.3,1.2,0.9)$
Infiltration rate (m^3/s)	$U(2.7, 3.3)$
Equipment rejection load (kW)	$U(376, 464)$
Remarks: $N(\mu, \sigma)$ - normal distribution with mean value μ and standard deviation σ; $U(a, b)$ - uniform distribution between a and b; $T(a, b, c)$ - triangular distribution with lower limit a, upper limit b and mode c.	

Table 2 Minimum simulation number for the "peak cooling load"

Simulation time	20	30	40	50	60	70
"Peak cooling load"	5177	5179	5179	5178	5177	5176
Deviation	-	0.0004	0.0004	0.0002	0	0.0002

Table 3 Minimum simulation number for the cooling load distribution

Simulation time	780	790	800	810	820	830
cooling load distribution	3231	3231	3231	3231	3231	3231
Deviation	-	0.0020	0.0032	0.0037	0.0041	0.0048

Table 4 Minimum simulation number for the other thresholds

Thresholds	1%	0.9%	0.8%	0.7%	0.6%	**0.5%**	0.4%
Initial simulation number	180	190	220	250	300	**350**	440

Minimum simulation number	380	420	470	510	620	**780**	1020

Table 5 optimization of number and sizes of chillers

Option No.	Chiller Number	Chiller plant option	PLR_{op}	COP_{op}
1	2	1*3200+1*1900	0.790	5.56
2	3	2*2050+1*1000	0.863	5.84
3	4	2*1500+2*1050	0.919	5.89
4	4	3*1400+1*900	0.921	5.95
5	5	3*1200+2*750	0.941	5.95
6	5	4*1100+1*700	0.910	6.09
7	6	4*950+2*650	0.956	6.05
8	6	5*900+1*600	0.932	6.07

Table 6 Optimization of types of chillers

Chiller Number	Chiller plant option	COP_{op}
2	1*3200*CSD+1*1900*VSD	5.65
3	2*2050*CSD+1*1000*VSD	5.91
4	3*1400*CSD+1*900*VSD	5.98
5	**4*1100*CSD+1*700*VSD**	**6.15**
6	5*900*CSD+1*600*VSD	6.12
3	3*1700*CSD (conventional design)	4.75

Table 7 Annual operation cost and electricity cost of different design options

Types	Annual operation cost (kW)	Electricity cost (*k* HK$)
1*3200*CSD+1*1900*VSD	3,729,780	3,006
2*2050*CSD+1*1000*VSD	3,627,834	2,902
3*1400*CSD+1*900*VSD	3,512,582	2,810

4*1100*CSD+1*700*VSD	**3,474,483**	**2,780**
5*900*CSD+1*600*VSD	3,492,110	2,794
3*1700*CSD (conventional design)	4,501,630	3,601

Table 8 Capital cost of constant-speed chillers and variable-speed chillers

Types	Annual capital cost (*k* HK$)
1*3200*CSD+1*1900*VSD	311
2*2050*CSD+1*1000*VSD	375
3*1400*CSD+1*900*VSD	442
4*1100*CSD+1*700*VSD	499
5*900*CSD+1*600*VSD	552
3*1700*CSD (conventional design)	348

Table 9 Annual total costs of the chiller plants

Types	Annual operation cost (k HK$)	Annual capital cost (k HK$)	Annual total cost (k HK$)
1*3200*CSD+1*1900*VSD	3,006	311	3,317
2*2050*CSD+1*1000*VSD	2,902	375	3,277
3*1400*CSD+1*900*VSD	**2,810**	**442**	**3,252**
4*1100*CSD+1*700*VSD	2,780	499	3,279
5*900*CSD+1*600*VSD	2,794	552	3,346
3*1700*CSD (conventional design)	3,601	348	3,949

Highlights

- A wide range of uncertainties is generated by Monte Carlo simulation.

- A new method is proposed to determine the minimum simulation number.
- An optimization is conducted to select the best configuration of chiller plant.
- The total cost is reduced significantly compared with the conventional design.
- This method can be automatically conducted with computation efficiency.