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Robust optimal design of district cooling systems and the impacts of uncertainty and reliability

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Abstract: Uncertainty exists widely in the design of district cooling systems. Due to failures or improper maintenance of components or subsystems, the cooling systems may mal-function or work with reduced performance. In the conventional design method of district cooling systems, both aspects are often ignored or considered roughly. To ensure that district cooling systems achieve the expected performance as closely as possible, a robust optimization method is proposed in this paper. This approach relies on quantifying the uncertainty at the design stage and the reliability of the cooling system in operation. By taking the total annual cost (including the capital cost, operation cost and availability risk cost) as the objective, the robust optimal design of district cooling systems can be obtained. Uncertainties in weather, building design/construction and indoor conditions are considered and reliabilities of major equipment in the systems are dealt with as well. Individual cooling systems are often alternative to district cooling systems while uncertainty and reliability issues also exist at the design stage. The role of uncertainty and reliability in the design of district cooling systems and individual cooling systems are assessed and compared. Results show that both uncertainty and reliability have greater impacts on the design of individual cooling systems.

Keywords: Design optimization; District cooling system; Individual cooling system; Uncertainty ; Reliability; Robust optimal design

1. Introduction

Appropriate design and control are the key measures to guarantee high efficiency of district cooling systems (DCSs). In the conventional design method, conditions or data used at the design stage are certain values. For example, the outdoor weather conditions are usually described using a typical meteorological year (TMY) or a typical design day [1, 2] for the design location. However, the actual weather in a given year can be significantly different, for instance extreme heat waves with low occurrence may not be well represented in the standard weather data. Such difference between the data used at the design stage and that in actual operation can be very significant and it should therefore be quantified and treated as uncertainty at the design stage. In fact, many other sources of uncertainty need to be dealt with when designing DCSs, such as stemming from imprecise knowledge of physical properties of individual components and the network as a whole. Another important issue to be looked at in the system design is system reliability, which refers to the capability that the system performs properly in case of certain component failures. As a consequence, the component or sub-system may not always be available due to maintenance and failures that lead to system outages [3]. The common solution is to add redundancy, e.g. by adding one or more extra groups of equipment which serve as standby. This is simple but not necessarily the best. Improved design methods need to be developed by incorporating uncertainty and reliability and thus be able to identify failure risks, outage time and the need for redundant equipment. The reliability of systems, specially related to failures, also can be regarded as a type of uncertainty. In this paper it is separated from the general uncertainties because such uncertainty has rather different numerical nature and is discrete (i.e. failed state or normal state for a component). It is addressed separately and quantified using a different method.

Concerning uncertainty and reliability issues, design methods can be classified into four groups: methods without quantifying uncertainty and reliability (*the conventional design*), methods only quantifying uncertainty (*uncertainty-only design*), methods only quantifying reliability (*reliability-only design*), and methods quantifying both uncertainty and reliability (r*obust optimal design*). The conventional method determines the optimal system without quantifying uncertainty and reliability. The *reliability-only/uncertainty-only* design method moves one step forward but only quantifies either reliability or uncertainty and involve it into the design optimization. The design method that quantifies both aspects is regarded as the robust optimal design method, which is the target of this study. Using this method, the performance of the cooling systems can be guaranteed within certain performance tolerances, based on the probability distributions of uncertainty in the system parameters, and/or occurrence of component failures.

For the conventional individual cooling systems (ICS), several studies dealing with design optimization under uncertainty are reported in the literature [4, 5]. Robust optimal design considering both uncertainty and reliability is investigated by Gang et al. [6]. For the design of DCSs, the conventional method is the most commonly used. *Uncertainty-only* and *reliability-only* design methods are not studied, not to mention robust optimal methods. Therefore a robust optimal design method is proposed and implemented in DCSs. The impacts of uncertainty and reliability on the design optimization of DCSs and ICSs are assessed and compared.

This study attempts to achieve two objectives. One objective is to propose and implement a new design method for DCSs by quantifying both uncertainty and system reliability. The other objective is to compare the impact of uncertainty and reliability on the design optimization of DCSs, and that on the design optimization of ICSs. The organization of this paper is as follows. In Section 2, studies on DCSs and applications of uncertainty and reliability quantification in building energy systems are reviewed. In Section 3, the robust optimal method and its main steps are introduced. In Section 4, a DCS is selected to demonstrate the application of the new method. In Section 5, the cooling load distribution of the DCS considering uncertainty is analyzed. The performance of the robust optimal design for the DCS is investigated. The impacts of uncertainty on the cooling loads of the DCS and ICS, and the effects of uncertainty and reliability on the design optimization of the DCS and the ICS are analyzed. Conclusive marks are summarized in Section 6.

2. Literature review

2.1 Studies and applications on DCSs

Existing studies on DCSs can be classified into the following three categories:

- *Performance assessment and comparison with conventional systems.* District cooling and heating systems in North China using seawater were compared with traditional cooling and heating systems (such as coal-fired heating system & a conventional air conditioning system, etc.) [7, 8]. A district cooling and heating system in Japan was investigated and its performance was verified by comparing it with individual systems. Influential factors for the system efficiency were presented [9]. Performance assessment of DCSs is necessary at the early planning and design stages, which was investigated by several researchers [10-12].
- *Systematic optimization of design and operation.* By optimizing the location of the cooling plants, the cooling capacities of the plants, the cold storage location, the storage capacity, etc., the optimal DCS was obtained by using a mixed integer linear programming model [13]. By taking the operational planning problem of district cooling and heating plants as a mixed 0–1 linear or non-linear programming problem, the operation of district cooling and heating systems was optimized with multiple objectives using genetic algorithms, etc. [14, 15].

- *Design and control optimization of chilled water systems*. Chilled water pumps in DCSs are the major additional energy-consuming parts compared with that in ICSs [10]. Therefore, design and control optimization of chilled water systems is necessary to reduce the energy consumption. This can be realized by decreasing the resistance of pipelines via adding some specific surfactants [16], optimally organizing the layout of pipelines [17, 18], limiting the remote distance of consumers, adopting more reasonable pump connection ways and using a larger supply and return chilled water temperature difference [19].

Design optimization of the central cooling plant of DCSs is still not sufficiently studied yet. Any useful literature on the design optimization with consideration of uncertainty or reliability of DCSs is not found yet to the best knowledge of authors.

2.2 Uncertainty and sensitivity analysis of building energy systems

An uncertainty study can help to assess the performance of building energy systems at different risk levels by presenting the performance distributions [20-22]. The most influential factors can be identified through a sensitivity analysis. The uncertainty study is also used to improve the design or retrofit of building energy systems [23, 24]. By presenting the risk and benefit distribtuions of different design schemes, stakeholders can make decisions using quantified risk measures [24-27].

For the design of building cooling systems, reliable cooling load calculation is very important since it is the basis for determining the capacity and configuration of the cooling systems. Many variables are used in the cooling load calculation and most of them contain uncertainties [5, 28-30]. The peak cooling load distribution was studied by Domínguez-Muñoz et al. [31] considering uncertainties in the building material, heat transfer coefficients of external and internal wall, internal heat gain sources, etc. Hopfe [32] investigated the annual cooling/heating load considering the physical, design and scenario uncertainties. The distribution of the annual cooling/heating load and weighted over-heating/under-heating hours were analyzed. Sun et al. [5] proposed a method to size cooling/heating systems by considering uncertianties in the load calculations. Gang et al. [4] investigated impacts of uncertainty on the capacity and configuration selection of ICSs. However, studies on the uncertainty in the cooling load calculation of DCSs and corresponding impacts on the design optimization have not been reported.

2.3 Reliability assessment of building energy systems

Reliability refers to "*the probability of successful operation or performance of systems and their related equipment, with minimum risk of loss or disaster or of system failure*" [33]. Reliability design has been widely adopted in engineering of critical systems, and applied to different domains such as structures, power systems, computer science, etc. [34, 35]. Reliability analysis or assessment is also concerned in the field of building energy systems. A multi-criteria approach was used to select the space heating system for an industrial building and the criteria included reliability, operational cost, comfort, etc. [36]. A method based on reliability assessment was proposed to predict an optimal inspection period for condition-based preventive maintenance for air-conditioning facilities in office buildings [37]. The expected profit produced by the method was also analyzed. Reliability assessment can be used to improve the system design, which can be found in the fields such as the power system, chemical process, etc. [33]. There is some work reported related to the design of ICSs to achieve robust optimal systems [6]. However, no application in the DCSs can be found.

3. Robust optimal design method and steps

The approach and steps of the robust optimal design for DCSs are shown in Fig. 1. In the initial stage, all variables used in the design performance modelling, that are not known with certainty are identified. By quantifying the uncertainties of these variables based on probability distributions, the design model can be used to propagate the combined effect of all uncertainties through the model. This follows a standard Monte Carlo approach [38] that is based on sampling over the ranges of all parameters and importing the samples into the design performance calculation, typically a simulation program. In the first step a simulation model of all buildings is used to find the aggregated cooling load for the DCS. By using this simulation model in the Monte Carlo method, the distribution of aggregated cooling load is obtained. The resulting probability distribution quantifies the uncertainty of the cooling load.

Knowing the failure rates and repair rates of the components or sub-systems (typically based on expert knowledge), the probabilities for all the states of the DCS and their performance are obtained. The reliability of the DCS is then quantified using an appropriate reliability measure. By minimizing the total cost including the capital cost, operation cost and availability risk cost, the robust optimal design of the DCS is achieved. Detailed processes for uncertainty and reliability quantification are introduced as follows.

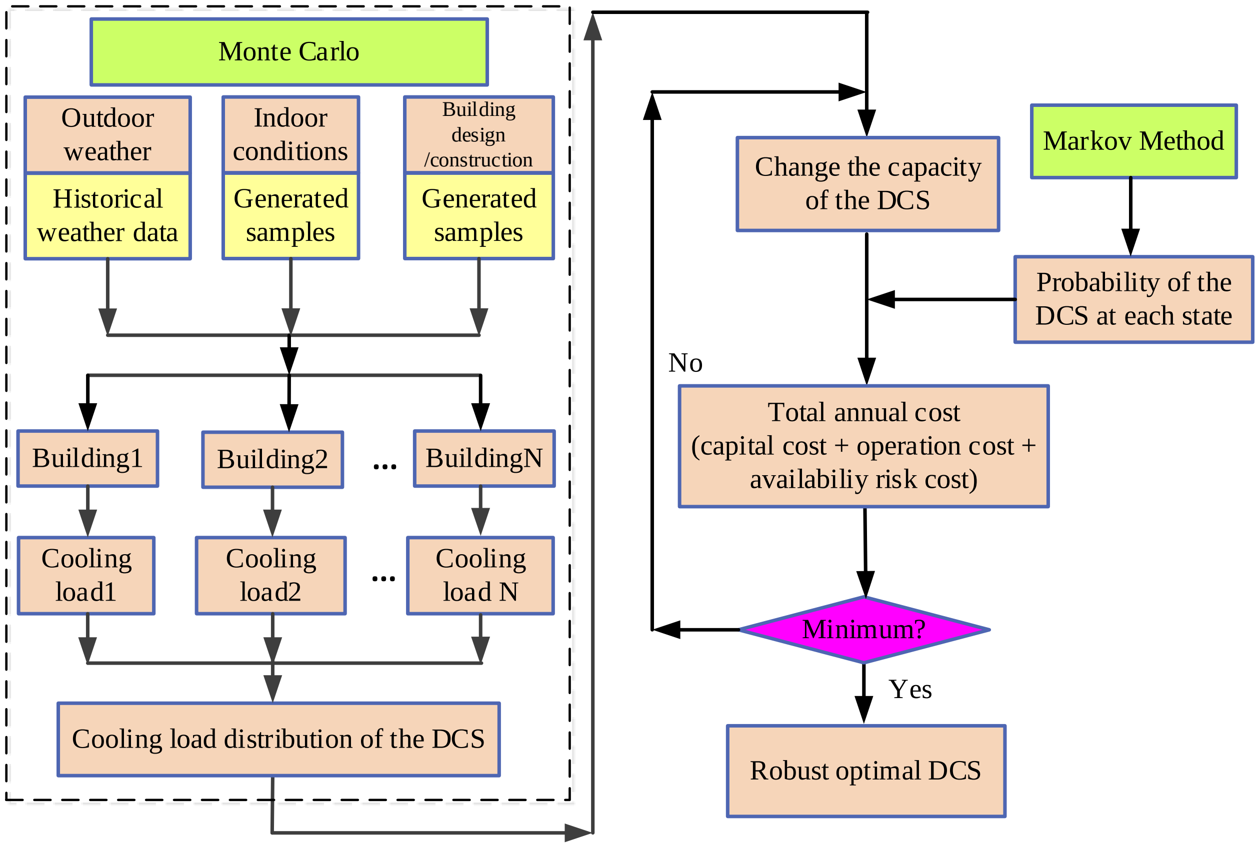

Fig. 1 Illustration of the robust optimal design method for DCSs

3.1 Uncertainty quantification

For a new district/community to be developed, limited information is available and many variables used for the design of DCSs (such as the weather condition, the building envelope material, the occupants for each building, etc.) are only approximate assumptions. We represent this lack of knowledge as uncertainty. This results in uncertainty of the cooling load, which is the primary factor used for the design of the central cooling plant(s) of a DCS.

The following variables with uncertainty can be classified into three categories:

- *Outdoor weather*. Weather data of TMY are used in the conventional design method. However, the weather data in actual operation of the DCS can be very different. Such difference is regarded as uncertainties in the weather data. Actual measurements are recommended (instead of the statistically representative TMY) [5] to quantify uncertainty in the outdoor weather. Actual measurements in the past several decades are adopted in this study to estimate the uncertainty in the weather data. In this way we guarantee that occurrences of extreme weather events are represented in the weather data that drive the design.

- *Building design/construction.* At the planning stage, limited information of the buildings that are going to be served by the DCS can be obtained. Typically, only floor area and types of building functions are known at that stage. When meeting the requirement of investors or governments, the building designs can take different forms to realize the designated functions and floor area. Major variability will result in for instance the surface-area-to-volume ratios (external surface areas divided by the volume), or the building envelope materials. These are therefore regarded as uncertainties in the building design/construction, i.e. the realization which is unknown at the design stage of the DCS. Values for this group of variables are hard to determine but their ranges can be obtained by referring to design guidelines and local policies. Due to lack of more precise information, uniform distributions are used to quantify uncertainties in these building realization parameters [22].
- *Indoor conditions.* Internal heat gain sources including occupants, lighting, ventilation and plug-in equipment are the primary factors affecting cooling loads. When conducting cooling/heating load calculation, variables representing these sources are assigned certain values according to the design guidelines or manuals. Actual values of these variables can be different when the DCS is in operation. Such difference is regarded as uncertainty in the indoor conditions. Normal distributions are used to quantify uncertainties of these variables [39].

The propagation of all uncertainties through the load calculation program is done with a Monte Carlo approach as explained earlier. As explained, this method requires an appropriate sampling method over the ranges of all uncertain inputs. For uncertainties of variables fitting normal distributions, the Latin Hypercube Sampling (LHS) method [40] is used for sampling because it can achieve a better coverage of samples. The sample space is partitioned into several dis-joint intervals with equal probability. One random sample is selected from each interval and the process repeats. By using LHS method, the characteristics of outputs can be obtained with much less computation. This is especially helpful when each trial takes a long time.

3.2 Reliability quantification

Reliability quantification of components is based on Markov method due to its wide application in reliability analysis of multi-state systems [3, 35, 41, 42]. The function of the Markov method is to obtain the probability of each state of a multi-state system at a specific period. This information is then used to estimate the system reliability performance, given a certain reliability measure. The simplest approach is to define a “working state” and a “down state” and define the measure of reliability as the rate of down state to working state. In reality one will encounter many different levels of down state with different levels of severity and hence different repair time durations.

Several steps are required in the use of the Markov method, including:

i. List all the possible states of a DCS;

ii. Determine the state transition density matrix, which is determined by failure rates and repair rates of components in the DCS;

iii. Obtain the probability of each state of the DCS;

iv. Calculate the mean steady-state performance of the DCS.

The probability of the DCS at each state at time t can be expressed with a vector $P(t)$ (Eq. 1) (k is the number of total states). $p_i\ (t)$ is the probability of the system at state i. It can be deduced from the initial state by Eq. (2~4), where A (Eq. 3) is the state transition density matrix and determined by the failure rate (λ) and repair rate (μ) of the component in the DCS. $P(0)$ is the initial state of the DCS. When the time approaches infinity, the state of the DCS will keep stable and the vector $P(\infty)$ will approach constant (Eq. 5). By transforming Eq. 5, Eq. 6 can be obtained. Eq. 7 indicates that the sum of probabilities of all the states is 1. By solving the linear algebraic equations (Eq. 6 and Eq. 7), the steady-state probability vector $P(\infty)$ is obtained. The mean steady-state system performance (E_∞) of the DCS can thus be evaluated using Eq. 8, which is the sum of products of the system performance at each state and the state probability. Then the deficiency due to failures can also be calculated. Where, g_i is the performance of the DCS (such as the energy consumption or the cost) at state i. The key issue is to determine the transition density matrix A *(Eq. 3)*. When the repair rate and failure rate are regarded as time-independent, the two variables can be obtained by Eq. (9~10) [3]. Where, the *MTTF* is the "mean time to failure" and *MTTR* is the "mean time to repair".

$$P(t)=\left[p_1(t), p_2(t)\ldots p_k(t)\right]^T \tag{1}$$

$$P(1)=P(0)A \tag{2}$$

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} \end{bmatrix} \tag{3}$$

$$P(m)=P(m-1)A = P(0)A^m \tag{4}$$

$$P(\infty)=P(\infty\text{-}1)A = P(\infty)A \tag{5}$$

$$P(\infty)(A\text{-}I)=0 \tag{6}$$

$$\sum_{i=1}^{k} p_i(\infty) = 1 \tag{7}$$

$$E_\infty = \sum_{i=1}^{k} g_i p_i \tag{8}$$

$$\lambda = 1/MTTF \tag{9}$$

$$\mu = 1/MTTR \tag{10}$$

3.3 Design optimization objective and steps

The robust optimal design is obtained by minimizing the total cost in the life cycle or the average annual cost. The total annual cost (C_{toal}) is the sum of the annual capital cost, annual operation cost (C_o) and annual availability risk cost (C_{ar}), as shown in Eq. 11. The annual capital cost is the total capital cost (C_c) of the DCS divided by the number of years (a), which is 20 in this study. The capital cost is determined by the system capacity (CAP). The annual operation cost is calculated by using the annual electricity consumption times the electricity price. It is determined by CAP and the cooling loads of the DCS ($LOAD$). The availability risk cost (C_{ar}) is introduced to quantify the losses caused by the unmet cooling demand. The unmet cooling demand consists of two parts: one is due to the under-sized capacity of the DCS, the other is due to the unavailability (failures, faults, etc.) of the DCS. It is calculated based on the actual cooling load ($Load(\hat{\imath})$) and the available capacity of the DCS ($CAP_a(i)$) at specific time (Eq. 12). P_{ar} ($/kW) is the price of the availability risk cost.

$$C_{toal} = C_c(CAP)/a + C_o(CAP, Load) + C_{ar}(CAP, Load) \tag{11}$$

$$C_{ar} = \sum_{i=1}^{8760} \left[P_{ar} \times max\left(0, Load(i) \text{-} CAP_a(i)\right)\right] \tag{12}$$

By quantifying uncertainty and reliability of the cooling system, the robust optimal design can be achieved by minimizing the total annual cost. As shown in Fig. 1, detailed steps are as follows:

i. Buildings connected to a DCS are modelled via the simulation programs.

ii. Variables, which have uncertainties and are used in the cooling load calculation, are identified.

iii. Samples for the identified variables are generalized and imported into the simulation program. The sampling methods may be different for variables with uncertainties. The cooling load profiles of the DCS considering uncertainty can be obtained using the Monte Carlo method.

iv. With the repair rate and failure rate of primary components (i.e. chillers in this study), the steady-state probability of the DCS at each state can be obtained using Markov method.

v. With the cooling load distribution, the annual operation cost and availability risk cost of the DCS at each state can be evaluated at a given capacity. By summing the products of the annual cost of the DCS at each state and the steady-state probability at this state, the total annual cost of the DCS can be obtained.

vi. By minimizing the total annual cost via changing the capacity, the robust optimal DCS can be achieved.

The performance of the DCS using other three design methods (i.e., conventional design method, *uncertainty-only* method and *reliability-only* method) is also presented for comparison. The conventional method determines the DCS capacity using a safety factor. The *uncertainty-only* method determines the optimal design by minimizing the total annual cost, where the process is similar to that of the robust optimal design explained above except that all the chillers are assumed to be always available. The availability risk cost then arises from the unmet cooling demand caused by the under-sized capacity of the DCS. The *reliability-only* method determines the optimal design by minimizing the total annual cost, where the process is similar to that of the robust optimal design except that the cooling load is on the basis of the reference case.

4. System description and parameters used in the case study

Several new urban areas are being developed to accommodate the increasing population and promote the development in Hong Kong. DCSs are proposed to supply cooling for these areas. One of these areas is selected to test the proposed robust optimal design method. The area is shown in Fig. 2, which is Kwu Tung North area in the North East New Territories region of Hong Kong [43]. It shows that the area will be used for residential, commercial and industrial development. Both commercial and residential buildings are planned in this area but only public and commercial buildings will be served by the DCS. Users of the DCS include office buildings, government buildings, hospitals, research buildings, hotels, metro stations, etc. In total, 37 buildings are involved and detailed information can be found in the reference [10], including the government buildings, commercial malls, shops, hotels, metro stations and so on. Based on the initial planning information including the floors of buildings, building functions, gross floor areas, the cooling load of the DCS is estimated based on load simulation as described above.

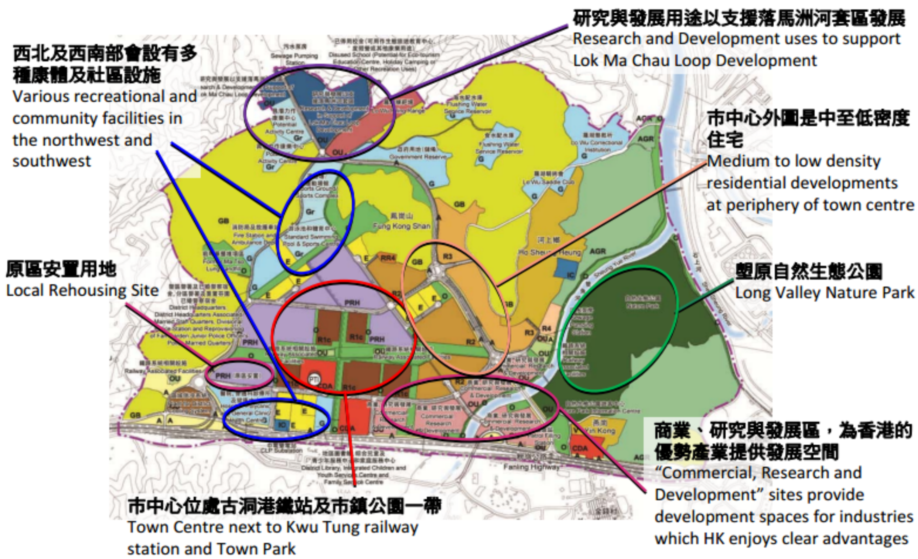

Fig. 2 Land use planning information of a new development area in Hong Kong

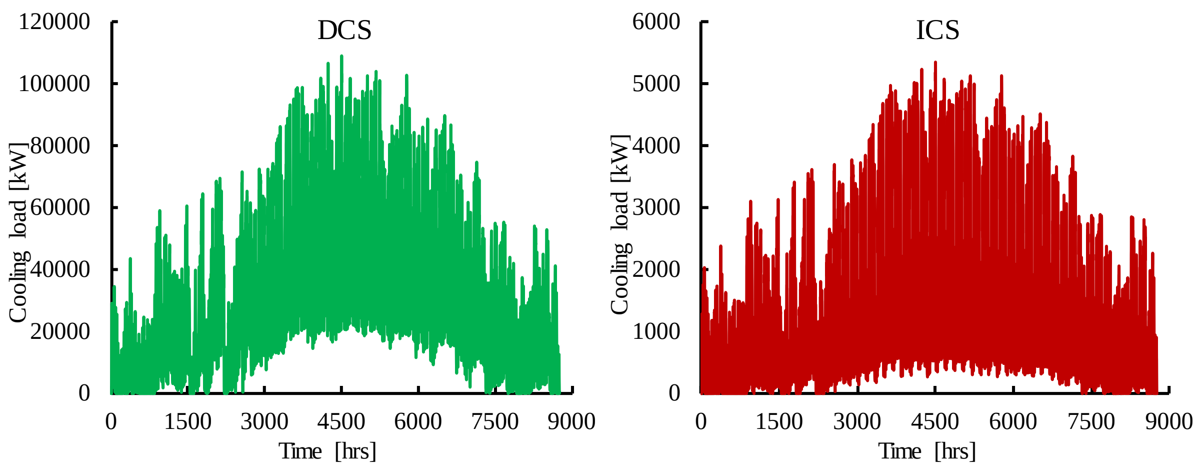

Fig. 3 Annual hourly cooling loads of the DCS and ICS in the reference case

The software EPC [44] is adopted to calculate the cooling load of the cooling system. It is developed by the High Performance Building Group in Georgia Institute of Technology. It is based on a reduced-order building energy model following the ISO 13790:2008. Annual hourly cooling loads of the DCS without considering uncertainty (marked as the reference case) are shown in Fig. 3. One of objectives of this study is to compare the impacts of uncertainty and reliability on the design of DCSs and that on the design of ICSs. Therefore, one office building with eight floors in the new development area served by the DCS is selected and the ICS for this building is designed. The annual hourly cooling loads of the ICS is also shown in Fig. 3. It can be seen that cooling is required almost all the year for both the DCS and ICS due to the subtropical climate. For the uncertainty quantification, totally 580 sets (29x20) of samples are used to get the cooling load distribution. Weather data from 1979 to 2007 (29 years) are collected and used to represent the uncertainties in the weather. For each trial (which can be regarded as each year), weather data of one of the 29 years are used. To conduct sufficient trials (i.e., sufficient to represent the uncertainty of variables in other two groups), multiple trials (i.e. 20 trials) are made for the weather data of each year. Detailed information for the inputs used in the reference case and the uncertainty study is shown in Table 1.

To compare the impacts of uncertainty and reliability, and to test the robust optimal design method, the central cooling plants of the DCS and the ICS need to be simulated. For both the DCS and the ICS, chilled water systems with primary constant speed pumps are designed. Chillers with different capacities are used in both systems. Chillers with larger capacities usually have higher nominal coefficients of performance (COPs). Fig. 4 shows the nominal COPs used in this study for chillers with different capacities in the DCS and the ICS. The COP of a chiller at different part load ratios is shown in Fig. 5. The nominal COP may be different for different chillers and the same curve then moves vertically. The COP increases with the increase of part load ratio and reaches the largest at around 80%.

Table 1 Information of inputs used in the reference case and uncertainty study

Group	Parameter	Reference case	Uncertainty study	
			Distribution	**Values**
Outdoor weather	Dry bulb temperature of outdoor air	TMY	Actual data:1979~2007	
	Humidity of outdoor air			
	Global radiation			
Building design/ construction	Building floor	Based on the plan	Relative normal	(1,0.04)
	Building length	Based on the plan	Relative normal	(1,0.04)
	Window wall ratio	0.5	Uniform	(0.3,0.7)
	Wall conductivity ($W/(m^2.K)$)	1.5	Uniform	(1,1.5)
	Window conductivity ($W/(m^2.K)$)	3	Uniform	(1.5,3)
	Roof conductivity ($W/(m^2.K)$)	0.9	Uniform	(0.4~0.9)
	Absorption coefficient of wall	0.9	Uniform	(0.4~0.9)
	Absorption coefficient of roof	0.8	Uniform	(0.4~0.8)
	Solar transmittance of window	0.8	Uniform	(0.4~0.8)
Indoor condition	Occupant density	Varying in 4~15 m^2/person for different buildings	Relative normal	(1,0.04)
	Lighting density	Varying in 10~20 W/m^2 for different buildings	Relative normal	(1,0.04)
	Power density of plug-in equipment	Varying in 8~20 W/m^2 for different buildings	Relative normal	(1,0.04)
	Ventilation rate	Varying in 1~4 ACH for different buildings	Relative normal	(1,0.04)

Note: for uniform distributions (*a*, *b*), *a* is the lower limit and *b* is the upper limit; for normal distributions (*c*, *d*), *c* is the mean value and *d* is the variance. Relative normal distribution [5] means that the distribution of the variable is obtained by multiplying the value in the reference case by certain factors. These factors fit the listed distributions in the Table.

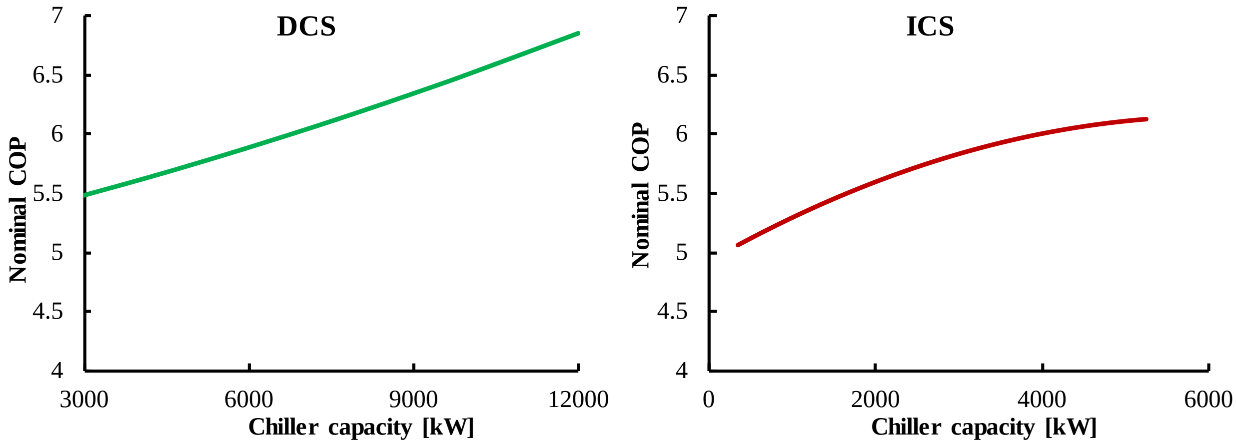

Fig. 4 Nominal COP of chillers at different capacities for the DCS and ICS

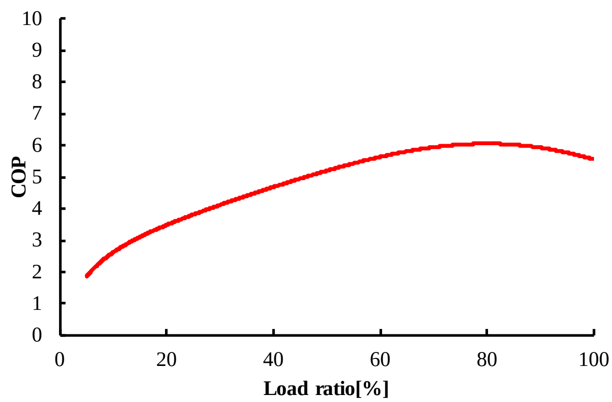

Fig. 5 Performance curve of chillers at different part load ratios

Capital costs of the DCS and the ICS of different capacities can be estimated based on the empirical relation shown in Fig. 6, which is obtained based on the cost information of major suppliers in the market. It shows that the unitary cost decreases with the increase of the system capacity. The operation cost is estimated based on the local electricity price, which is about 0.15 $/kWh in Hong Kong. The availability risk cost is estimated using the introduced availability risk price, which is up to the preference of actual stakeholders of a project. The difference between the availability risk price and the electricity price affects the optimization results. Therefore, the total annual costs for the DCS and ICS at different availability risk prices are estimated and analyzed. The failure rate of

0.0001(1/h) and repair rate of 0.002 (1/h) are used to quantify the reliability of chillers in this study, which are based on but larger than the data in the reference [45]. That's because the failure rate of equipment usually follows a bathtub curve and it can be very large at the early and wear-out stage of its life cycle [46].

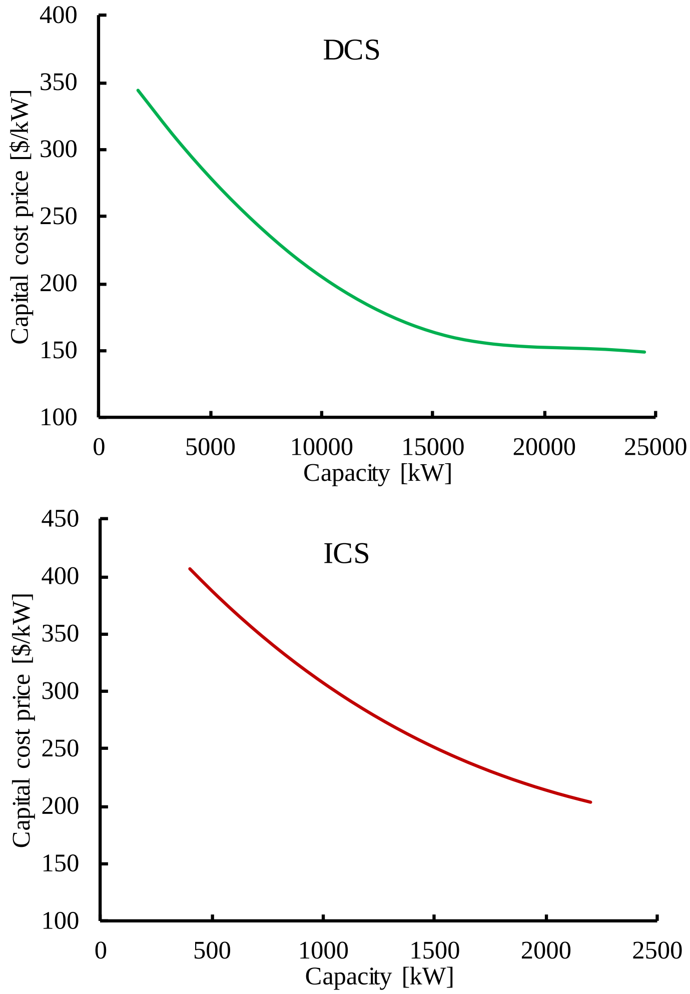

Fig. 6 Unitary capital costs for the DCS and ICS at different capacities

5. Results and discussions

5.1 Cooling load distribution of the DCS considering uncertainty

The peak cooling load is the basis for the capacity of cooling systems. The annual average cooling load is the basis for energy consumption estimation and configuration optimization. Therefore, distributions of the peak cooling load and annual average cooling load of the DCS considering uncertainty are analyzed. The impacts of uncertainty on the cooling loads of the DCS and ICS are also compared.

The distribution of the peak cooling load of the DCS is shown in Fig. 7a. The peak cooling load of the DCS varies between 87 MW and 120 MW. It corresponds to a relative difference between -21% and 9% compared with the peak cooling load in the reference case. The peak cooling load has high frequency between 98 MW and 105 MW. It means that the peak cooling load of the DCS has a high probability to fall in this range. The peak cooling load of the reference case locates at over 90% of the cumulative distribution function (CDF). It shows that if the cooling load is calculated using data in the reference case and without considering uncertainty, the peak cooling load can be over-estimated with a probability of 90%. However, if the decision maker wants to limit the risk of under-estimation to be less than 5%, the peak cooling load of the reference case can be not large enough.

As shown in Fig. 7b, the peak cooling load of the ICS varies between 3100 kW and 7000 kW. It corresponds to a relative difference between -44% and 30% compared with the peak cooling load in the reference case. The peak cooling load has high frequency between 4600 kW and 5500 kW. It means that the peak cooling load of the ICS has high probability to fall in this range. Fig. 7 shows that the peak cooling load of the ICS varies much more significantly than that of the DCS when uncertainties of input variables have similar distributions. It means that the uncertainty has even larger impacts on the cooling load of the ICS. Involving uncertainty in the design of ICSs is therefore more important. It also demonstrates that DCSs have a higher capability to accommodate uncertainties than ICSs. That is because multiple buildings are connected to a DCS and the cooling load of the DCS is the sum of that of all individual buildings. The variation caused by uncertainty is reduced due to averaging facts. It can predict that, if the number of buildings keeps increasing, uncertainty will have limited impact on the cooling loads of DCSs.

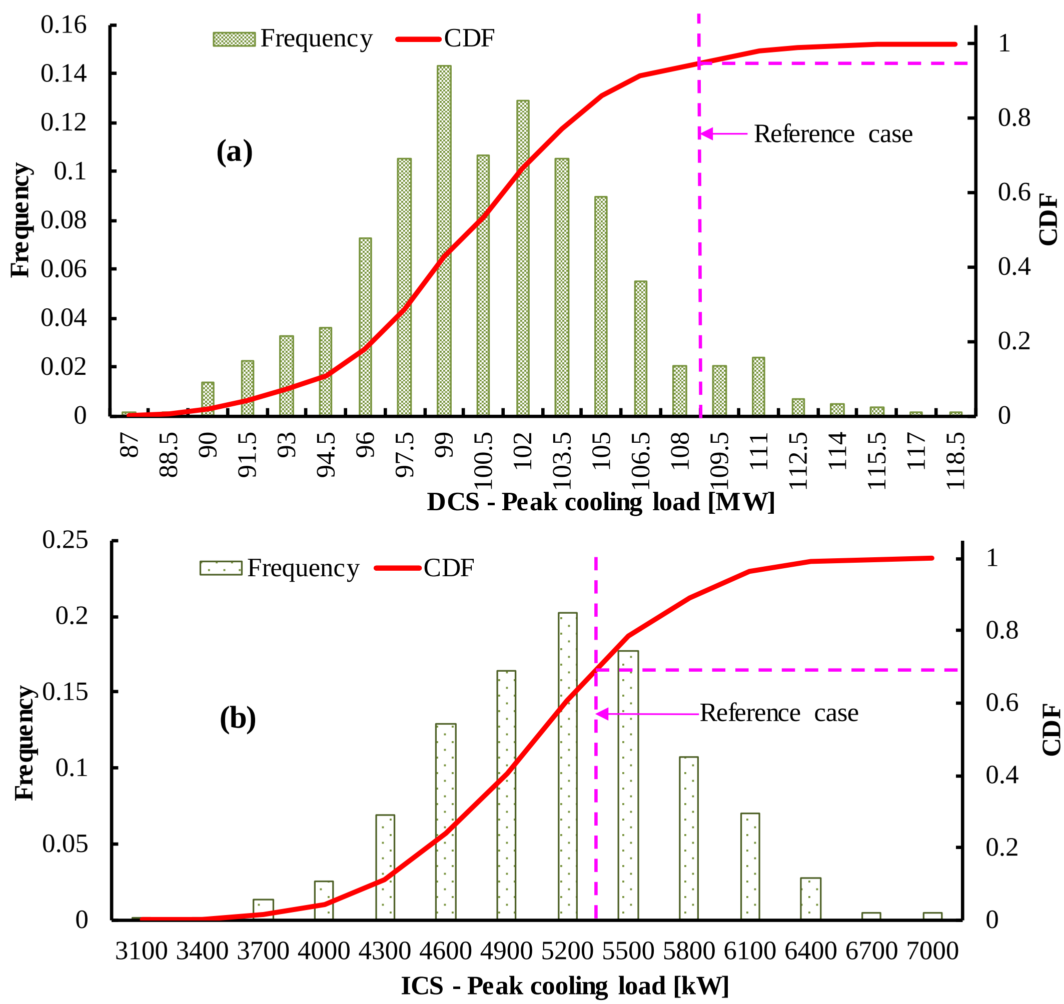

Fig. 7 Peak cooling load distribution of the DCS and the ICS

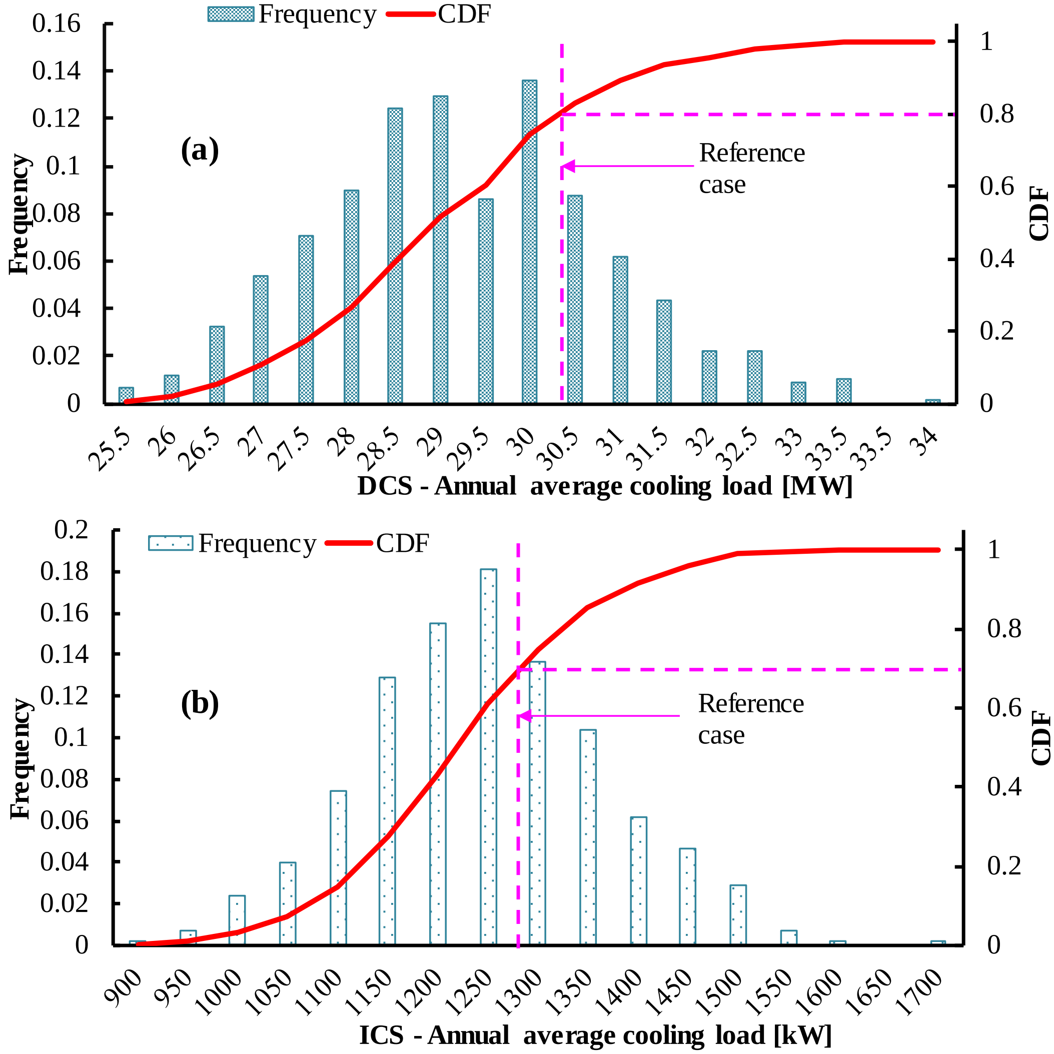

Fig. 8 Annual average cooling load of the DCS and the ICS

The distribution of the annual average cooling load of the DCS is shown in Fig. 8a. It shows that the annual average cooling load of the DCS varies between 25.5 MW and 34 MW. It corresponds to a relative difference between -16% and 12% compared with the annual average cooling load in the reference case. The cooling load has high frequency between 28 MW and 30.5 MW, which means that the annual average cooling load of the DCS has high possibility to fall in this range. The annual average cooling load of the reference case locates at around 80% of the CDF. With the results in Fig. 8a, the decision maker can obtain the annual average cooling load at different risk levels. A larger load can be used if the under-estimation risk should be controlled within a low interval. For instance, if the risk should be less than 5% (the 95% of CDF), the annual average cooling load of the DCS should be larger than 32 MW. The cooling load obtained using the conventional method cannot make this without quantifying uncertainties.

Fig. 8b shows that the annual average cooling load of the ICS varies between 900 kW and 1700 kW. It corresponds to a relative difference between -36% and 30% compared with the annual average cooling load in the reference case. The annual average cooling load has high frequency between 1150 kW and 1300 kW, indicating high probability in this range. Fig. 8 shows that the annual average cooling load of the ICS varies more significantly than that of the DCS when uncertainties of input variables have similar distributions. It proves again that the uncertainty has larger impacts on ICSs and involving uncertainty in the design of ICSs is more important.

5.2 Robust optimal design of the DCS

Performance of the robust optimal design of the DCS is analyzed in this section. It is compared with the system performance obtained using the conventional method, the *uncertainty-only* method and the *reliability-only* method. Performance of the DCS with identical chillers is investigated here. In total, the 7-chiller DCS has 8 states considering failures of chillers, where the number of available chillers can be 0, 1, 2, 3, 4, 5, 6 and 7. The steady-state probability of the DCS at each state can be evaluated.

Capacities of the DCS determined using the four design methods are shown in Fig. 9. The horizontal axis is the availability risk price ratio (ARPR), which is the availability risk price divided by the electricity price. The capacity obtained using the conventional method is determined by multiplying the peak cooling load of the reference case by factor of 1.1 [47]. It can be seen that the optimal capacity of the DCS increases with the increase of ARPRs, when the DCS is designed and optimized using the *uncertainty-only* method, *reliability-only* method and r*obust optimal* method. The capacity of the DCS using *robust optimal* method is larger than that using *uncertainty-only* method, and smaller than that using *reliability-only* method. When the ARPR exceeds 10, the capacity of the DCS using the *robust optimal* method is larger than that using the conventional method. It demonstrates that if the availability risk price is very high, or the requirement for the thermal comfort is very strict, the capacity of the DCS determined using the conventional method is still not enough.

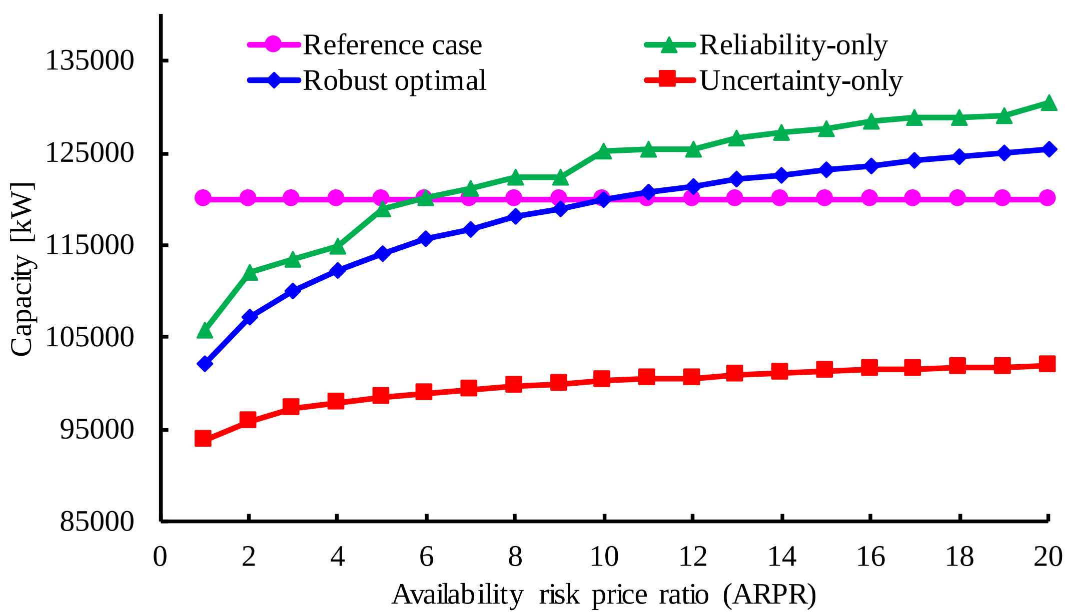

Fig. 9 Optimal capacities of the DCS at different ARPRs using four design methods

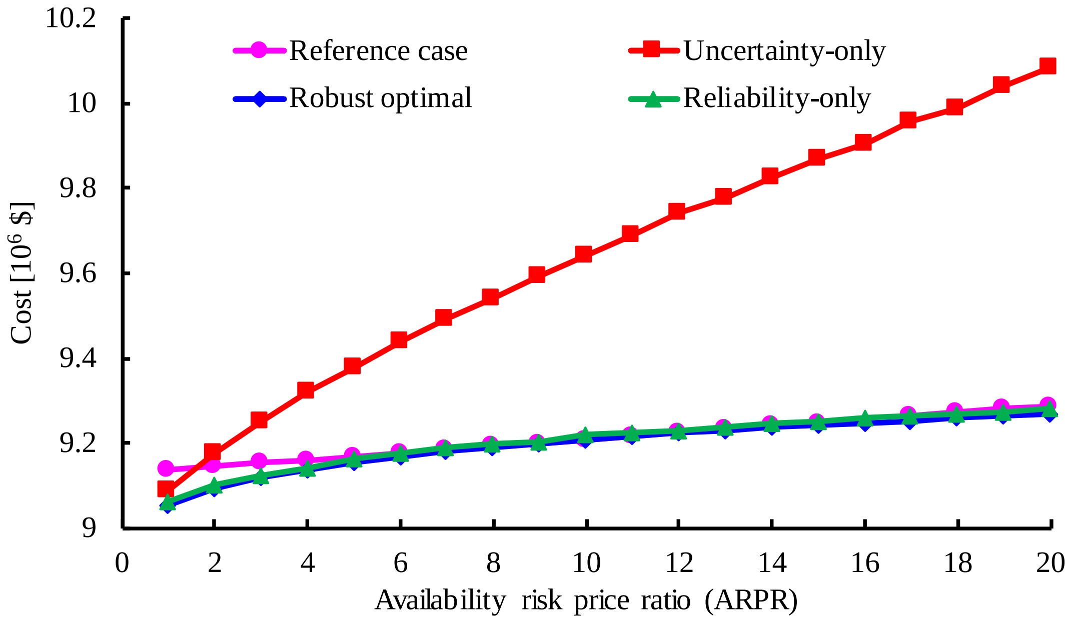

Fig. 10 Total annual costs of the DCS at different ARPRs using four design methods

The total annual costs of the DCS designed using four methods are shown in Fig. 10. It can be seen that the cost of the DCS designed using the *uncertainty-only* method increases largely. It results from the lower capacity obtained at the design stage and the higher insufficient capacity in operation. For the other three methods, the total annual costs are close to each other. That is because that the capital cost contributes to a very small portion of the total annual cost. Even if a larger capacity is used, the total annual cost increase is not obvious.

5.3 Impacts of uncertainty and reliability on the design optimization of the DCS compared with the ICS

The deliverables of the DCS design, considering uncertainty only as well as considering both uncertainty and reliability, are introduced in this section. Impacts of the uncertainty and reliability on the design optimization of the DCS and the ICS are assessed and compared.

It has been established that using chillers of different capacities can improve the system efficiency of ICSs [4]. This is tested on the DCS here. The performance of the ICS is also presented for comparison. The capacities of the DCS and ICS are determined by limiting the unmet hours to 35 with a probability of 100%. By sorting the annual hourly cooling loads of the DCS and ICS in a descending order, the cooling loads at the 35th hour of each trial are selected. The maximum ones among the selected 580 samples (corresponding to 580 trials) are taken as the capacity of the DCS and ICS. It is 10500 kW for the DCS and 6300 kW for the ICS. For the DCS, 7 chillers are selected which is inferred from a real DCS project with a similar capacity. The DCS with 7 identical chillers is marked as S_{dcs1}. The system with 6 large chillers and one small chiller is marked as S_{dcs2} (the capacity of the small one is half of that of the large one). For the ICS, the system with 3 identical chillers is marked as S_{ics1}. The system with 2 large chillers and 1 small chiller is marked as S_{ics2} (the capacity of the small one is half of that of the large one). Considering uncertainty, energy saving of systems using chillers of different capacities in both the DCS and ICS is shown in Fig. 11.

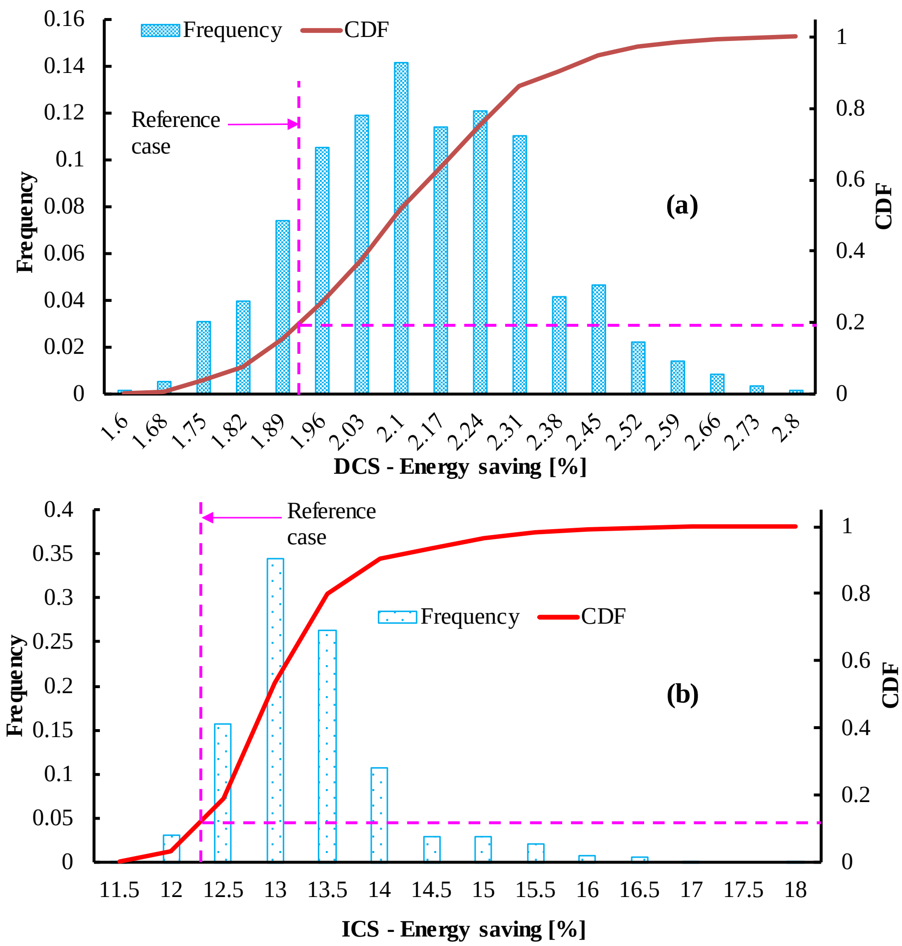

Fig. 11 Energy saving distributions of the DCS and ICS using chillers of different capacities

Fig. 11a shows that the energy saving of S_{dcs2} varies between 1.6% and 2.8%, which is not very promising. Energy saving has high frequency between 1.96% and 2.31%, which indicates that it has high possibility to fall in such a range. For the ICS in Fig. 11b, the energy saving of S_{ics2} is between 11.5% and 18%, which is quite promising. The energy saving has high frequency between 12.5% and 14%. Energy saving of S_{dcs2} is not as large as that of S_{ics2}. It shows that using chillers of different capacities in DCSs makes no big difference from the viewpoint of energy saving.

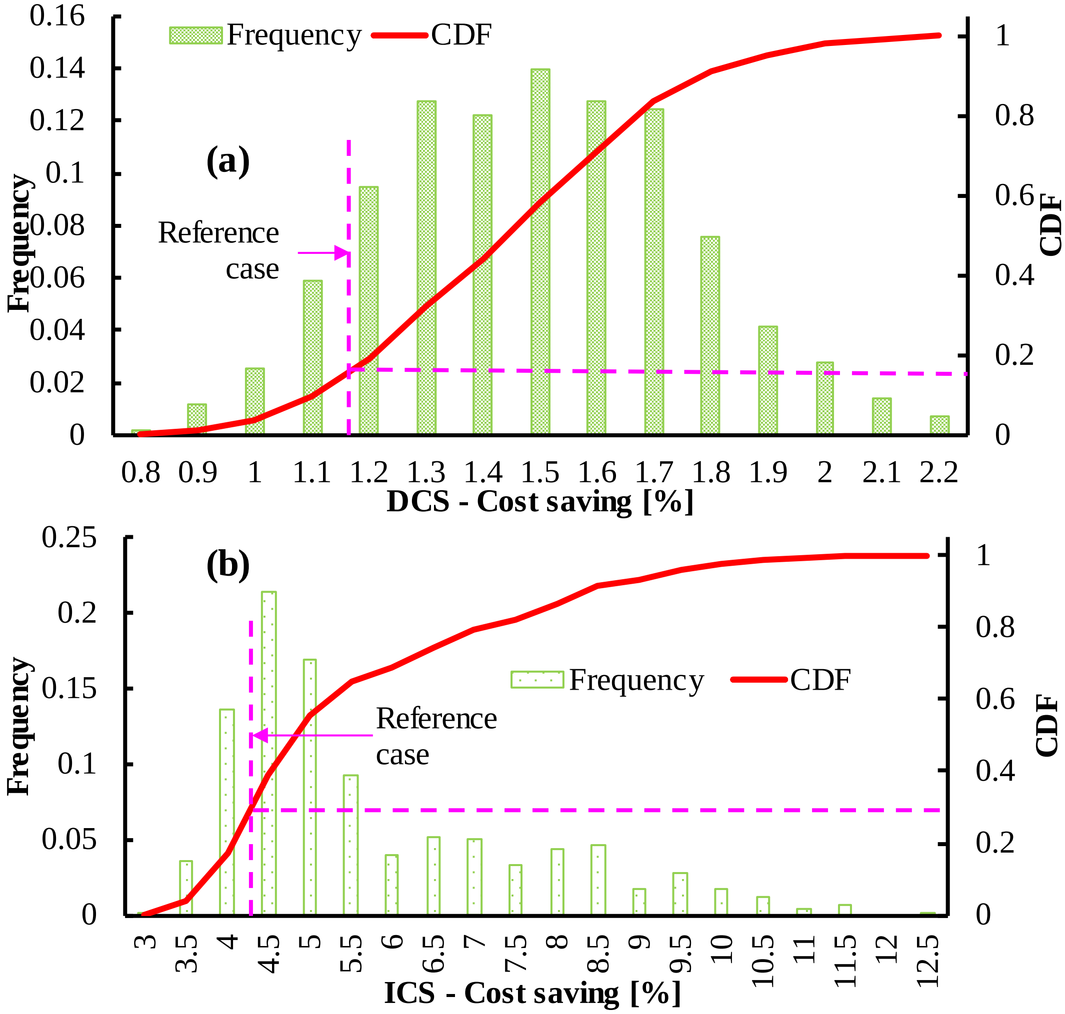

Fig. 12 Cost savings of the DCS and ICS using chillers of different capacities

When both uncertainty and reliability are considered in the design stage, cost saving of the DCS and ICS using chillers of different capacities is shown in Fig. 12. The availability risk price is assumed as 1.5 \$/kWh, which is 10 times of the electricity price. It shows that the cost saving of S_{dcs2} varies between 0.8 % and 2.2%. The percentage is less than that of energy saving. Cost saving of S_{ics2} ranges from 3% to 12.5%, which is also lower than the percentage of energy saving. It indicates that, considering reliability, the advantage of systems using chillers of different capacities becomes less.

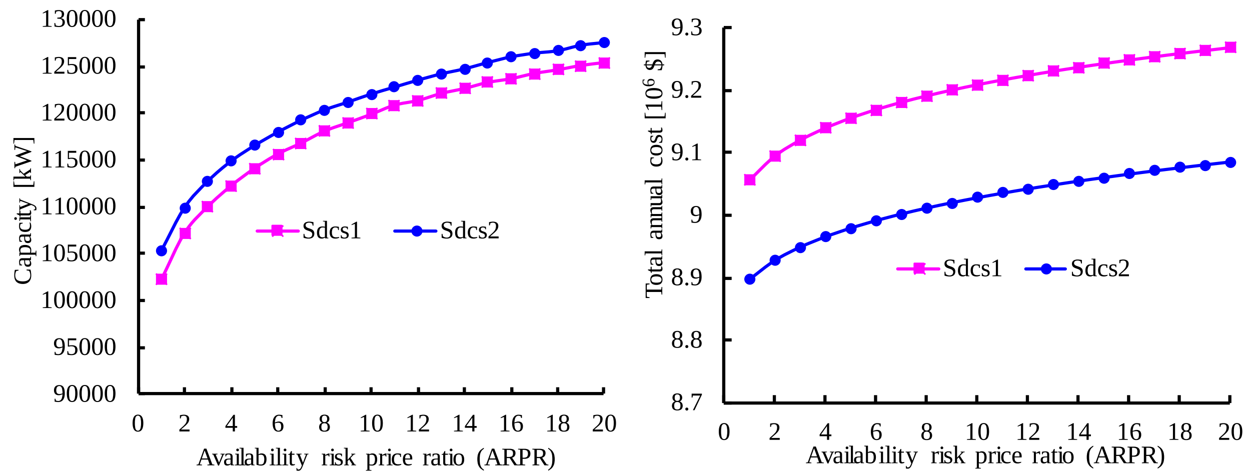

Fig. 13 Optimal capacities and total annual costs at different ARPRs - *DCS*

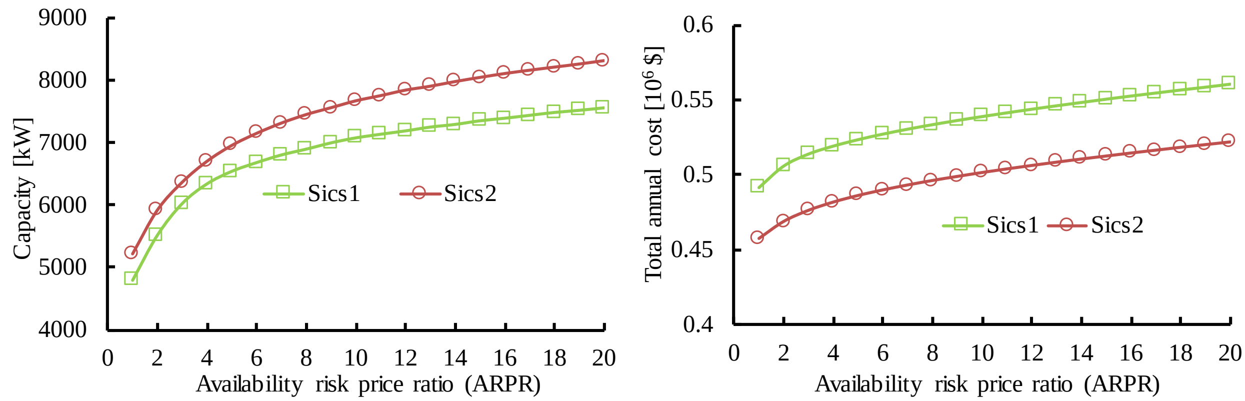

Fig. 14 Optimal capacities and total annual costs at different ARPRs - *ICS*

The difference between the electricity price and availability risk price affects the results. Therefore, capacities and total annual costs at different availability risk prices are calculated and shown in Fig. 13 and Fig. 14. Fig. 13 shows that with the increase of ARPRs, the optimal capacities and the total annual costs of the DCS increase. At the same ARPR, the optimal capacity of S_{dcs1} is about 3% less than that of S_{dcs2} while the cost is 2% higher. The relative cost saving decreases with the increase of ARPRs. The optimal capacities and the annual total costs for the ICS are shown in Fig. 14. It shows the similar trend to that for the DCS. Both the capacity and cost increase with the increase of ARPRs. At the same ARPR, the capacity of S_{ics2} is about 9% higher than that of S_{ics1} while the cost is about 7% lower. It proves that even considering reliability, using chillers of different capacities in ICSs is still preferred due to the lower cost. Fig. 13 and Fig. 14 show that the impacts of uncertainty and reliability on the design optimization of ICSs are higher than that of DCSs.

6. Conclusions

In this paper, a robust optimal design method is proposed and demonstrated for DCSs by considering uncertainty at the design stage and system reliability. Performance of the robust optimal design of DCSs is analyzed. The impacts of uncertainty and reliability on the design of DCSs and that on the design of ICSs are evaluated and compared. The following conclusions are made through a case study:

1) Uncertainty at the design stage affects the cooling load predictions of DCSs and ICSs significantly. The cooling load variation of DCSs is smaller than that of ICSs when the uncertainties of input variables fit similar distributions. It is therefore more important to consider uncertainty in the design of ICSs. DCSs have a higher capability to accommodate uncertainty.
2) DCSs and ICSs using chillers of different capacities are more energy and cost efficient. Energy saving of DCSs using chillers of different capacities is not promising. It is not recommended to use chillers of different capacities in DCSs.
3) Considering reliability, systems using chillers of different capacities are still preferred but the advantage decreases. The cost saving is smaller than energy saving.
4) The impact of uncertainty and reliability on the design optimization of DCSs is smaller than that on the design optimization of ICSs.
5) The capacities of DCSs obtained using the robust optimal method are larger than that using *uncertainty-only* method and smaller than that using *reliability-only* method. When the

availability risk price is very high, the capacity of DCSs using the conventional design method may not be sufficient.

When quantifying uncertainty and reliability, the distributions for the inputs and failure/repair rates of chillers are required. For DCS projects in different countries and climate regions, the distributions need to be selected according to the local policy, design practice, etc. The failure/repair rates should be checked because the values can also be different for chillers produced by different manufacturers. With updated information, the design method proposed in this paper can be generalized to achieve robust optimal DCSs.

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