GANG, Wenjie, et al. An uncertainty-based design optimization method for district cooling systems. Energy, 2016, 102: 516-527.

https://doi.org/10.1016/j.energy.2016.02.107

An Uncertainty-Based Design Optimization Method for District Cooling Systems

Wenjie Gang[1], Godfried Augenbroe[2], Shengwei Wang[1,*], Cheng Fan[1] and Fu Xiao[1]

[1] Department of Building Services Engineering, the Hong Kong Polytechnic University, Kowloon, Hong Kong

[2] College of Architecture, Georgia Institute of Technology, Atlanta, USA

Abstract: Uncertainties exist widely at the planning and design stages of district cooling systems, which have significant impacts on the design optimization. This paper therefore proposes a design method for district cooling systems by quantify the uncertainties, which is so-called uncertainty-based design optimization method. Uncertainties in the outdoor weather, building design/construction and indoor conditions are considered. The application of the uncertainty-based design optimization method is examined in several aspects: the performance assessment, system sizing, configuration selection and technology integration. With the performance distribution at different risk levels, the design of district cooling systems can be determined by the stakeholders based on the compromise between quantified risk and benefit. Sensitivity analysis is conducted to identify influential variables with uncertainties for the cooling loads of district cooling systems. Results show that the uncertainties in the indoor condition are the most important and the uncertainties in building design/construction have the least impact.

Keywords: uncertainty quantification; uncertainty-based design method; district cooling system; sensitivity analysis; cooling load

[*]Correspondence author: Email: beswwang@polyu.edu.hk, Phone: +852-2766 5858

Address: Department of Building Services Engineering, the Hong Kong Polytechnic University, Kowloon, Hong Kong.

1. Introduction

A district cooling system (DCS) generates the chilled water centrally and serves a group of buildings for cooling and dehumidification purposes [1]. It is regarded as a cooling system with high efficiency due to the concentration effect of cooling loads and the feasibility to integrate with local energy resources [2, 3]. Appropriate design of DCSs is very important because it determines the capital cost, operational cost, energy usage, green-house gas emission, and thermal comfort of users. However, uncertainties exist widely in the design of DCSs and will affect the performance of DCSs. Without quantifying these uncertainties, the decision on the design of DCSs cannot be made with confidence. The performance of DCSs may fail to achieve the expectation, together with high costs and low benefits. It is therefore necessary to develop a design method for DCSs by quantifying the uncertainties at the design stage, which is the uncertainty-based design optimization method.

Studies on DCSs at the early design stage

At the early design stage, performance assessment of DCSs is required, especially when the decision is made between the DCS and conventional individual cooling systems (marked as ICSs) [4]. District cooling and heating systems (DCHSs) using seawater in China were compared with traditional cooling and heating systems (such as coal-fired heating system & conventional air conditioning system) [5, 6]. Performance of a DCHS plant in Japan was verified and compared with individual systems [7]. Another important task at the design stage is the design optimization of central cooling plants. However, very limited studies are found in DCSs. Soderman [8, 9] used a mixed integer linear programming model to optimize the DCS design in an urban area, including the locations of cooling plants, the cooling capacity of the plants, the cold media storage locations, etc. Chow et al.[10] tested the feasibility of using ice storage system in a DCS under a specific tariff.

All the above studies are based on certain conditions without concerning uncertainties. However, uncertainties exist generally in DCSs at the design stage. Without taking these uncertainties into account, performance of DCSs will deviate from the expectation. One case is that the capital cost of a DCS project was reported to be increased again and again because the installation cost of chilled water pipelines is much higher than the budget. Therefore, it is highly necessary to take uncertainties into account at the design stage and involve them into the design of DCSs.

Studies on uncertainty analysis in cooling/heating systems of buildings

Uncertainty analysis in building energy systems attracts increasing attention in the past decade. It can help assess the building energy system performance (i.e. thermal comfort, cost, energy consumption) by presenting the performance distributions at different probabilities [11-13]. It can also be used to improve the design or retrofit of building energy systems[14-17]. At the design stage of cooling/heating systems, the cooling/heating loads are the most important factors that contain uncertainties. Uncertainties in the cooling loads of one building or ICSs have been studied thoroughly [18-20]. However, uncertainties in the cooling loads of DCSs are not studied yet. Design optimization considering uncertainties was reported in building energy fields. Impacts of the uncertainties on the design of heating, ventilation and air conditioning (HVAC) systems were investigated by Sun et al. [21]. A multi-criteria design optimization method considering uncertainties for net zero energy buildings was studied by Sun et al. [22]. The design method for ICSs based on uncertainty quantification was investigated by the authors [23]. However, for the design optimization of DCSs, no studies are reported yet.

Summary of limitations of existing studies

From the above review it can be found that the work on the cooling load, and central plant design of DCSs is rarely reported. No studies are found to address the uncertainties at the design stage of DCSs, not to mention to involve the uncertainty quantification into the design method. Although the design optimization method for ICSs was proposed [23], there is still large space to improve the method by considering more sources of uncertainties and adopting more reasonable samples. In addition, DCSs have unique characterises compared with ICSs and the connected buildings are often with very different functions. Another problem is that the importance of each variable with uncertainties on the performance of DCSs is still not analysed and compared. Influential variables need to be identified.

Objectives of this study

According to the above limitations, this study therefore attempts to develop a design optimization method for DCSs based on uncertainty quantification. The objectives are summarized as follows:

- An uncertainty-based design optimization method is proposed for DCSs by quantifying uncertainties at the design stage. With the proposed method, the DCS can be then designed and optimized at different risk levels. The stakeholders can make decisions based on their specific requirements.
- The method to quantify the uncertainties of the cooling loads of DCSs is developed. Uncertainties in the input variables for cooling load calculation are categorized and different methods to address these uncertainties are introduced.
- The importance of variables with uncertainties is analysed and quantified by conducting sensitivity analysis. Influential factors are identified, which provides a better understanding of

these uncertainties. Attention can be paid to these influential factors to reduce the performance variation of DCSs.

- The application of the uncertainty-based design method is examined in four aspects, including the system performance assessment, system sizing, configuration selection and technology integration. The performance of DCSs using the proposed method is compared with that using the conventional method.

Organization of this paper

The paper is organized as follows. In Section 2, the uncertainty-based design optimization method is presented and detailed steps are introduced. In Section 3, methods to conduct the sensitivity analysis are presented. In Section 4, a case study on a DCS in a new district under planning in Hong Kong is introduced to demonstrate the uncertainty-based method. In Section 5, the cooling load distribution of DCSs considering uncertainties is analysed. Results of the sensitivity analysis are presented. In Section 6, performance of the DCS based on the uncertainty-based design optimization method is analysed and compared with the conventional design method. Conclusive remarks are given in the final section.

2. The uncertainty-based design optimization method and steps

The conventional method determines the design schemes of DCSs based on certain cooling loads. The inputs of the cooling load calculation use values according to the planning information, HVAC design guidelines or manuals. Sometimes, a safety factor (over 1) may be assigned to the peak cooling load to determine the capacity of DCSs. Compared with the conventional design method, the uncertainty-based method attempts to improve the DCS design by quantifying uncertainties at the design stage.

2.1 Classification of variables with uncertainties and quantification method

Many variables used in the cooling load calculation contain uncertainties. All these uncertainties can be classified into three groups based on the physical location of these variables.

1) Outdoor weather

In the conventional method, weather data of the typical meteorological year (TMY) are used in the annual hourly cooling or heating load calculation. However, the actual weather can be very different. These differences are regarded as uncertainties in the outdoor weather. Cooling loads and energy consumption of DCSs can be over-estimated or under-estimated by using the TMY data.

2) Building design/construction

At the design stage, limited information about buildings in DCSs is available, such as the gross floor area, the number of floors or the orientation. Even for such information, values used at the design stage are very hard to be the same with that actually used when the buildings are constructed. By meeting the requirements of developers or governments, the building design cannot be the same for different architects. For example, the building shapes and the material of building envelopes can vary for different architects. All these differences will affect the cooling loads and then cause energy consumption deviation. These are regarded as uncertainties in the building design/construction.

3) Indoor conditions

Internal heat gain from occupants, lighting and plug-in equipment is a primary source of the cooling load. Values of variables representing the internal heat gain sources are usually selected according to design guidelines or manuals. However, the actual values will be different from that used at the design stage. These differences are regarded as uncertainties in the indoor conditions.

2.2 Detailed steps of the uncertainty-based design optimization method

Steps to implement the uncertainty-based design optimization method are illustrated in Fig. 1. Detailed explanations are introduced as follows.

1) The input variables that have uncertainties are selected and samples are generated. Different methods are used to quantify uncertainties in the three groups of variables. For the outdoor weather, historical measurements of weather data are used which is proved to be a better way to account for uncertainties in the weather [21]. For other variables, normal distributions and uniform distributions are used. For the normal distributions, Latin Hypercube Sampling (LHS) method is used to improve the calculation efficiency [24].
2) Samples are imported into the cooling load calculation software. For a DCS, many buildings with different functions are involved and need to be simulated. For each building, uncertainties of cooling loads result from the uncertainties in the three groups of variables.
3) The cooling load of the DCS can be obtained. The cooling load of the DCS in one hour is the sum of the cooling loads of all the individual buildings in this hour. Then the annual hourly cooling load distribution of the DCS can be obtained.
4) The distributions of the peak cooling load and annual cooling load profile are analyzed.
5) According to the peak cooling load distribution, the capacity of the DCS can be determined at different risk levels. Based on the annual cooling load distribution, the performance distribution of the DCS with different configurations and technologies can be obtained. The optimized DCS is therefore determined by balancing the risk and benefit.

3. Sensitivity analysis

The primary purpose of sensitivity analysis is to identify important variables for outputs such as the energy consumption, the cooling/heating load, etc. By ranking the importance of input variables, important ones can be obtained and measures can be followed up to reduce the variation bands of the design outcomes. Both global and local methods can be used to conduct sensitivity analysis. Two global methods are adopted in this study due to their ability to handle the interaction of inputs [25].

The first method is based on ANalysis of VAriance (ANOVA). The sensitivity analysis contains three primary steps: 1) To obtain the regression model representing the relationship between the inputs and outputs; 2) To select significant ones out of all the inputs using parameter screening methods; 3) To rank the sensitivity of selected variables based on some reasonable sensitivity index (SI). Parameter screening is necessary to remove insignificant input variables. This is especially important when there are many inputs but the samples or trials are limited. A very effective screening method Lasso is used [26] because it can always choose the most correlated parameters to enter the model. The regression model of the cooling loads of DCSs can be expressed with Eq. (1). Where, y is the output, x_1, x_2 …x_n are the input variables, a_1, a_2 … a_n are the regression coefficients.

$$y_1 = a_1 x_{i1} + a_2 x_{i2} \ldots\ldots + a_n x_{in} \quad (1)$$

The importance or sensitivity index is calculated using Eq. (2) and Eq. (3). The total sum of squares (SST) indicates the uncertainty associated with the outputs. SST is consisted with two parts: the regression sum of squares (SSR) and the error sum of squares (SSE). The ratio of SSR to SST (R^2) indicates the accuracy of the regression model. The uncertainty in the output caused by the variable

j can be calculated by decomposing SSR, which is expressed as SS_j. The SI can be obtained using Eq. (3). A larger SI indicates a higher sensitivity of the variable for the output. Detailed explanations can be found in the reference [21] .

$$R^2 = \frac{SSR}{SST} \tag{2}$$

$$\mathrm{SI}_j = \frac{SS_j}{SST} \times 100\% \tag{3}$$

For comparison purposes, another method *random forest* is used to identify the influential variables, which is frequently used to rank the importance of variables. Random forest is a very popular and efficient ensemble learning method for classification, regression and other tasks based on model aggregation ideas, which is introduced by Breiman [27]. A multitude of decision trees is constructed considering two randomization processes, i.e., random selection of training samples and features for tree development. A certain unification scheme will be used to generate the final outcome, e.g., the majority votes for classification tasks and mean aggregation for regression tasks. One advantage of random forests is that it can avoid over-fitting by using the out-of-bag observations for validation. Quantification of the variable importance is one of the common applications of random forests. The principle is to test the increase of the mean error or mean square error when the inputs are randomly permuted. Detailed processes and explanations can be found in [27].

4. A Case study on a DCS in a new development area

A DCS in Hong Kong is taken as a case to demonstrate the uncertainty-based design optimization method. To accommodate the increasing population and promote the development of Hong Kong, the government has launched a land reclamation program which turns remote mountain areas into new development areas. DCSs are proposed to supply cooling for these new development areas. The planning layout of one district is shown in Fig. 2. Both commercial and residential buildings are planned in this district. However, only public and commercial buildings will be served by the DCS, including office buildings, government buildings, hospitals, research buildings, hotels, metro stations, etc. According to the initial plan and hypothesis, totally 37 buildings are connected to the DCS and detailed information of these buildings can be found in the reference [4].

A software EPC [28] is used to calculate the cooling load of the DCS, which is developed by the High Performance Building Group in College of Architecture, Georgia Institute of Technology. It is based on a reduced-order building energy model, which follows the BS EN ISO 13790:2008 standard. Annual hourly cooling loads of the DCS without uncertainties (marked as the reference case) are shown in Fig. 3.

Detailed values for inputs used in the reference case and the uncertainty study are shown Table 1. For the outdoor weather data, the actual measured data from 1979 to 2007 (29 years) are used. For the building design/construction, the number of floors and the building size are based on the initial plan. The ranges of thermal properties of building materials are from the design manual for hot summer and warm winter areas of China (which is the climate for Hong Kong). When there are no accurate distributions, values in the ranges should be given the same chance so uniform distributions are adopted. The mean values and variances for variables representing indoor conditions vary largely in different papers so they are determined based on the local design guideline, designers' experiences and assumptions. Totally 580 trials (20 times of 29) are conducted for the uncertainty study.

To demonstrate the uncertainty-based design optimization method, the DCS is modelled and several design schemes are compared. Chillers are the most energy-consuming and the performance curve of chillers is shown in Fig. 4, which is obtained from a simplified regression model by fitting manufacture data. The chilled water system is assumed to be primary only with constant-speed flow rate. Pumps for the chilled water system with a hydraulic head of 40m are selected. For the cooling water system, pumps with a hydraulic head of 20m are selected.

5. Results of the cooling load distribution and sensitivity analysis

Before the cooling load and design results are presented, actual weather data from 1979 to 2007 are compared with the TMY data, as shown in Fig. 5. It shows that the actual data during some periods distribute evenly around the TMY data, where the TMY data locate in the middle of the actual measurements and they can be taken as the mean values. During some other periods (most of the time), the actual data can be much larger or smaller than the TMY data. If the cooling loads are evaluated using the TMY data, they can be over-estimated or under-estimated. The comparison demonstrates again that it is necessary to quantify uncertainties of the outdoor weather in the DCS design.

5.1 Distributions of cooling loads

The frequency and cumulative distribution function (CDF) of the annual average cooling loads are shown in Fig. 6. It shows that the annual average cooling load varies between 25.5 MW and 34 MW, which is 0.84 and 1.12 times of that in the reference case. The frequency of the load between 28.5 MW and 30 MW (0.94 and 0.99 times of that in the reference case) is high. It indicates that the annual average cooling load has a strong probability to fall in such a range. The annual average cooling load of the reference case is 30.4 MW, corresponding to the CDF of around 0.8. It indicates that the annual average cooling load considering uncertainties has a probability of 80% to be less than that of the reference case if it is calculated using similar settings.

The distributions of annual hourly cooling loads for each trial are shown in Fig. 7. The cooling loads of the reference case are highlighted with red. It can be seen that at the same CDF, the cooling load of the reference case is larger than the mean of cases with uncertainties. Usually the larger cooling loads are used to size the DCS. For example, the annual 0.4% cooling design day can be used to determine the capacity of the cooling system [29]. The cooling load distributions with a CDF of over 99.6% are shown in Fig. 7b. It shows that the cooling loads vary significantly. If the DCS is sized based on the load of the reference case, no quantified risks can be obtained. In addition, Fig. 7b shows that it has a high probability to oversize the DCS if the capacity of the DCS is determined using the conventional method.

The frequency and CDF of the peak cooling load are shown in Fig. 8. It can be seen that the peak cooling load varies between 86 MW and 119MW, which is 0.79 and 1.1 times of that of the reference case. The frequency of the peak load between 98 MW and 104 MW is high, which is 0.9 and 0.95 times of that of the reference case. It means that the peak cooling load has a strong probability to fall in the range. The peak cooling load of the reference case is 109 MW, corresponding to the CDF of over 0.9. It indicates that in consideration of uncertainties, the peak cooling load of the DCS has a probability of 90% to be less than that of the reference case. It proves again that using the conventional method has a high probability to oversize the DCS.

5.2 Sensitivity analysis results

Sensitivity analysis is conducted to identify important variable with uncertainties for the cooling loads of DCSs. Results on the annual average cooling loads are shown in Fig. 9. The left figure indicates that the indoor conditions (the occupant density, lighting density, plug-in load density and ventilation rate) are the most important for the annual average cooling load of the DCS. Uncertainties in building design/construction have the least impact. Among the variables of building design/construction, the most important ones are the window wall ratio (WWR) and transmittance of windows. It indicates that windows should be designed carefully to decrease the cooling load and achieve green buildings. Sensitivity analysis results for one building are also presented and shown in the right figure for comparison purposes. It shows that the importance ranking is similar. The descending sequence of the importance is also the indoor condition, outdoor weather and building design/construction.

The importance ranking of input variables on the peak cooling load is shown in Fig. 10. It can be seen that the most important variable is the ventilation rate of the outdoor air. With higher rankings of the outdoor dry-bulb temperature and humidity, the uncertainties in the outdoor weather play a more important role in the peak cooling load of the DCS than that in the peak load of one building. That is because one year's outdoor weather data are used in one trial for each building in the DCS, which is the same in the load calculation of one building. However, variables representing the building design/construction and indoor conditions are randomly sampled for all the 37 buildings in one trial. By summing the cooling load of all individual buildings, the randomness of the uncertainty of each variable is averaged. The uncertainties in the building design/construction are still less important than that in the other two groups of variables.

Results of the sensitivity analysis using random forests are shown in Fig. 11. The values of the horizontal axis are the increase of mean squared errors when the variables are permuted randomly. A larger value mean greater importance for the outputs. In general, uncertainties in the outdoor weather and indoor conditions have greater impacts on the cooling loads than that in building design/construction. Uncertainties in the outdoor weather play a more important role in the cooling load of the DCS than that in the cooling load of one building. The conclusion is similar to that using the ANOVA method. Detailed ranking for some variable may be different due to working mechanisms of these two methods.

6. Performance of the DCS using the uncertainty-based design optimization method

The application of the uncertainty-based design optimization method is examined in four aspects: system performance assessment, sizing, configuration selection and technology integration. Performance of the DCS is analyzed and compared with that based on the conventional design method.

6.1 Performance assessment of DCSs

The performance of DCSs can be evaluated based on the annual cooling load distribution. Accurate estimation of the energy consumption of DCSs is important for the government, investors and users. The government needs to know how much electricity will be required by constructing this new district and whether the existing grid has enough capability. The investors need to know when the investment can be paid back and how much benefit they can get. For users, the annual energy consumption relates closely to the bills to pay.

The energy consumption distribution of the DCS at different risks is shown in Fig. 12. It can be seen that the energy consumption varies between 47 (10^6 kWh) and 61 (10^6 kWh) (0.84 and 1.1 times of that of the reference case). It has a high frequency between 51.8 (10^6 kWh) and 55 (10^6 kWh) (0.93 and 0.99 times of that of the reference case), which means that it has a strong probability to fall in the range. The energy consumption of the DCS in the reference case is also shown in Fig. 12, corresponding to the CDF of about 0.8. It means that the annual energy consumption of the DCS considering uncertainties has a probability of 80% to be lower than that of the reference case. In other words, the energy consumption of the DCS can be over-estimated with a chance of 80% using the conventional method. By using the uncertainty-based design method, the stake holders can obtain the energy consumption of the DCS at different risk levels.

6.2 Sizing optimization of DCSs

By using the uncertainty-based design optimization method, the DCSs can be sized with quantified confidence. The capacity of the DCS at different risk levels is shown in Fig. 13. It shows that the capacity of the DCS reduces with the increase of unmet hours, which are hours that the cooling loads exceed the capacity of the DCS. For a given number of unmet hours, the required capacity of the DCS increases with the decrease of allowed risks. According to such quantified information shown in Fig. 13, the DCS can be sized based on the risk requirements of decision makers. For a given capacity, the uncertainty-based design method can provide the quantified risks under certain number of unmet hours. For example, if the DCS has a capacity of 105 MW, the number of unmet hours can hardly be over 16 per year and has a chance of 5% to be over 5 per year (or a chance of 95% to be less than 5). For a specific number of unmet hours, the capacity can be obtained at different risk requirements. For example, if the number of unmet hours is set to 10, the risk that the number exceeds 10 can be reduce to 0 if the capacity of the DCS is no less than107MW. If designers want to keep the risk less than 10%, the capacity should be not less than 101MW. By using the uncertainty-based design optimization method, the DCS can be sized based on quantified risk and comfort requirements. In contrast, the conventional method can tell nothing more except offering certain design capacities.

6.3 Configuration selection of DCSs

Another important task of design optimization is to select the configuration of DCSs. The configuration relates to the operational cost of DCSs in the life cycle. It is often suggested to install chillers with different capacities in ICSs to guarantee high energy efficiency at partial loads. The capacity of DCSs is usually much larger than that of ICSs and much more chillers need to be installed. The necessity to install chillers with different capacities in the DCS is investigated by using the uncertainty-based design optimization method. In the DCS of this study, totally seven chillers are selected, referring to a DCS project in Hong Kong which has a similar capacity. Five chillers with an individual capacity of 17500 kW (5000 ton) and two chillers with an individual capacity of 8750 kW (2500 ton) are selected, which is marked as *Configuration 1*. The performance of *Configuration 1* is compared with the DCS using seven identical chillers with an individual capacity of 15000 kW (marked as *Configuration 2)*. The energy saving by *Configuration 1* is shown in Fig. 14.

From Fig. 14 it can be seen that the energy saving is about 1.6% in the reference case. No further information is provided by the conventional design method. However, by using the uncertainty-based design optimization method, the energy saving distribution at different risk levels can be obtained. Fig. 14 shows that the energy saving varies between 1.2% and 2.5%, which is not promising and hard to be over 2.5%. Considering complicated control and maintenance issues, *Configuration 1* may be not suitable in the DCS. From the curve of CDF it shows that the energy saving in the reference case can be under-estimated with a chance of about 80%, which indicates that *Configuration 1* has a probability of about 80% to save as much energy as that of the reference case. By using the uncertainty-based design optimization method and following results in Fig. 14, the decision makers can select appropriate configuration of DCSs with quantified risks.

6.4 Technology integration of DCSs

DCSs are often integrated with different technologies to reduce the operational cost. Accurate cost saving prediction of the integrated system is very important for investors, which will affect the payback period of the investment. The uncertainty-based design optimization method can provide the cost saving distribution of the integrated system at different risk levels. Performance of the DCS integrated with the ice storage system is investigated in this study to illustrate the uncertainty-based design optimization method. The systematic COP of the ice storage system is assumed to be 3. The peak period is from 8 a.m. to 8 p.m. on weekdays and the rest of time is off-peak period. The electricity price is 0.16 $/kWh for the peak period and 0.08 $/kWh for the off-peak period. Annual operational costs of the DCS with the ice storage system are shown in Fig. 15.

Fig. 15 shows that the annual operational cost of the DCS with the ice storage system varies in a quite large range, i.e. between 5.4 (10^6 $) and 7.2 ($10^6$ $). The frequency of the cost between 6 (10^6 $) and 6.5 ($10^6$ $) is high, which means that the annual operational cost of the DCS has a strong probability to be in this interval. The annual operational cost of the reference case is also illustrated in Fig. 15, corresponding to the CDF of over 0.8. It means that the annual operational cost of the DCS with the ice storage system has a probability of 80% to be lower than that of the reference case. Without quantifying the uncertainties at the design stage, the annual operational cost has a strong possibility to be over-estimated.

7. Conclusions

An uncertainty-based design optimization method for DCSs is proposed in this paper by quantifying uncertainties in the outdoor weather, building design/construction and indoor conditions. By using the uncertainty-based design optimization method, the performance of DCSs can be evaluated with quantified confidences. The sizing and configuration of DCSs can be determined based on the risk and benefit analysis. Uncertainties in the indoor conditions are the most influential for the cooling loads of DCSs. Uncertainties in building design/construction have the least impact on the cooling loads of DCSs, among which the uncertainties in windows are the most important.

The originalities of this paper are summarized as follows:

- An uncertainty-based design optimization method for DCSs is developed, which is the first time to involve the uncertainty quantification into the design of DCSs.
- An improved method is proposed to quantify the uncertainties of the cooling load of cooling systems. Historical weather data are used to quantify uncertainties in the weather. Uncertainties in the building design are also considered, which is never done before.
- Influential variables are identified for the cooling loads of DCSs and ICSs. Similarities and differences are analyzed.

The uncertainty-based design optimization method can be generalized in DCSs. The relative results are useful for DCSs in subtropical areas. However, distributions should be checked based on local design practice and policy before using this method in other areas, especially on the important variables identified by the sensitivity analysis. Occupant's behavior attracts increasing attention recently because it affects the cooling/heating loads and then the energy consumption of buildings [30-32]. How to quantify it and involve it into the design of building cooling or heating systems, or DCSs is also worth of concern. In addition, the design of DCSs relates to many aspects and only uncertainties in the cooling load are concerned in this paper. Uncertainties in the performance of subsystems or components of DCSs also affect the system performance. The comprehensive design optimization method considering all these uncertainties should be further studied.

Acknowledgements

The research presented in this paper is financially supported a PhD fellowship grant of the Research Grant Council (RGC) of the Hong Kong SAR and a grant of the MTR Corporation Limited.

References

[1] ASHRAE. District cooling guide. Atlanta, GA. 2013.

[2] Rezaie B, Rosen MA. District heating and cooling: Review of technology and potential enhancements. Appl Energy 2012; 93: 2-10.

[3] EMSD. Benefits of DCS. http://www.energyland.emsd.gov.hk/en/building/district_cooling_sys/dcs_benefits.html.

[4] Gang WJ, Wang SW, Gao DC, Xiao F. Performance assessment of district cooling systems for a new development district at planning stage. Appl Energy 2015; 140: 33-43.

[5] Li Z, Duanmu L, Shu HW, Shuang J, Zhu YX. District cooling and heating with seawater as heat source and sink in Dalian, China. Renew Energy 2007; 32(15): 2603-2616.

[6] Shu HW, Duanmu L, Zhang CH, Zhu YX. Study on the decision-making of district cooling and heating systems by means of value engineering. Renew Energy 2010; 35(9): 1929-1939.

[7] Shimoda Y, Nagota T, Isayama N, Mizuno M. Verification of energy efficiency of district heating and cooling system by simulation considering design and operation parameters. Build Environ 2008; 43(4): 569-577.

[8] Söderman J. Optimisation of structure and operation of district cooling networks in urban regions. Appl Therm Eng 2007; 27(16): 2665-2676.

[9] Söderman J. Pettersson F. Structural and operational optimisation of distributed energy systems. Appl Therm Eng 2006; 26(13): 1400-1408.

[10] Chow TT, Au WH, Yau R. Cheng V, Chan A, Fong KF. Applying district-cooling technology in Hong Kong. Appl Energy 2004; 79(3): 275-289.

[11] Brohus H, Frier C, Heiselberg P, Haghighat F. Quantification of uncertainty in predicting building energy consumption: A stochastic approach. Energy and Buildings 2012; 55:127-140.

[12] Heiselberg P, Brohus H, Hesselholt A, Rasmussen H, Seinre E, Thomas S. Application of sensitivity analysis in design of sustainable buildings. Renew Energy 2009; 34(9): 2030-2036.

[13] Pettersen TD. Variation of energy consumption in dwellings due to climate, building and inhabitants. Energy Build 1994; 21(3):209-218.

[14] Hopfe CJ, Augenbroe GLM, Hensen JLM. Multi-criteria decision making under uncertainty in building performance assessment. Build Environ 2013; 69: 81-90.

[15] Rezaee R, Brown J, Augenbroe G. Building Energy Performance Estimation in Early Design Decisions: Quantification of Uncertainty and Assessment of Confidence. Construction Research Congress 2014: 2195-2204.

[16] De Wit S, Augenbroe G. Analysis of uncertainty in building design evaluations and its implications. Energy Build 2002; 34(9): 951-958.

[17] Zhang Y, Augenbroe G. Right-sizing a residential photovaltaic system under hte influence of demand response programs and in the presence of system uncertainties. ASHRAE/IBPSA-USA Building Simulation Conference Atlanta, GA September 10-12, 2014.

[18] Hopfe CJ. Uncertainty and sensitivity analysis in building performance simulation for decision support and design optimization. PhD dissertation, Eindhoven University. 2009.

[19] Domínguez-Muñoz F, Cejudo-López JM, Carrillo-Andrés A. Uncertainty in peak cooling load calculations. Energy Build 2010; 42(7):1010-1018.

[20] Li DHW, Wong SL, Lam JC. Climatic effects on cooling load determination in subtropical regions. Energy Convers Manag 2003; 44(11):1831-1843.

[21] Sun Y, Gu L, Wu C, Augenbroe G. Exploring HVAC system sizing under uncertainty. Energy Build 2014; 81:243-252.

[22] Sun Y, Huang P, Huang G. A multi-criteria system design optimization for net zero energy buildings under uncertainties. Energy Build 2015; 97: 196-204.

[23] Gang WJ, Wang SW, Shan K, Gao DC. Impacts of cooling load calculation uncertainties on the design optimization of building cooling systems. Energy Build 2015 94: 1-9.

[24] Iman RL. Latin hypercube sampling. John Wiley & Sons, Ltd, 2008

[25] Tian W. A review of sensitivity analysis methods in building energy analysis. Renew Sust Energ Rev 2013; 20: 411-419.

[26] Tibshirani R. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society 1996; 267-288.

[27] Breiman L. Random forests. Machine Learning 2001; 45(1): 5-32.

[28] Quan SJ, Li Q, Augenbroe G, Brown J, Yang PPJ. Urban Data and Building Energy Modeling: A GIS-Based Urban Building Energy Modeling System Using the Urban-EPC Engine, in Planning Support Systems and Smart Cities. Springer International Publishing, 2015; 447-469.

[29] ASHRAE. ASHRAE Handbook-HVAC systems and equipment. Atlanta, GA. 2012.

[30] Yan D, O'Brien W, Hong T, Feng X, Gunay H.B, et al. Occupant behavior modeling for building performance simulation: Current state and future challenges. Energy Build 2015; 107: 264-278.

[31] Hong T, D'Oca S, Turner W.J, Taylor-Lange S.C. An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework. Build Environ 2015; 92: 764-777.

[32] Ding Y, Wang Z, Feng W, Marnay C, Zhou N. Influence of occupancy-oriented interior cooling load on building cooling load design. Appl Therm Eng 2016; 96: 411-420.

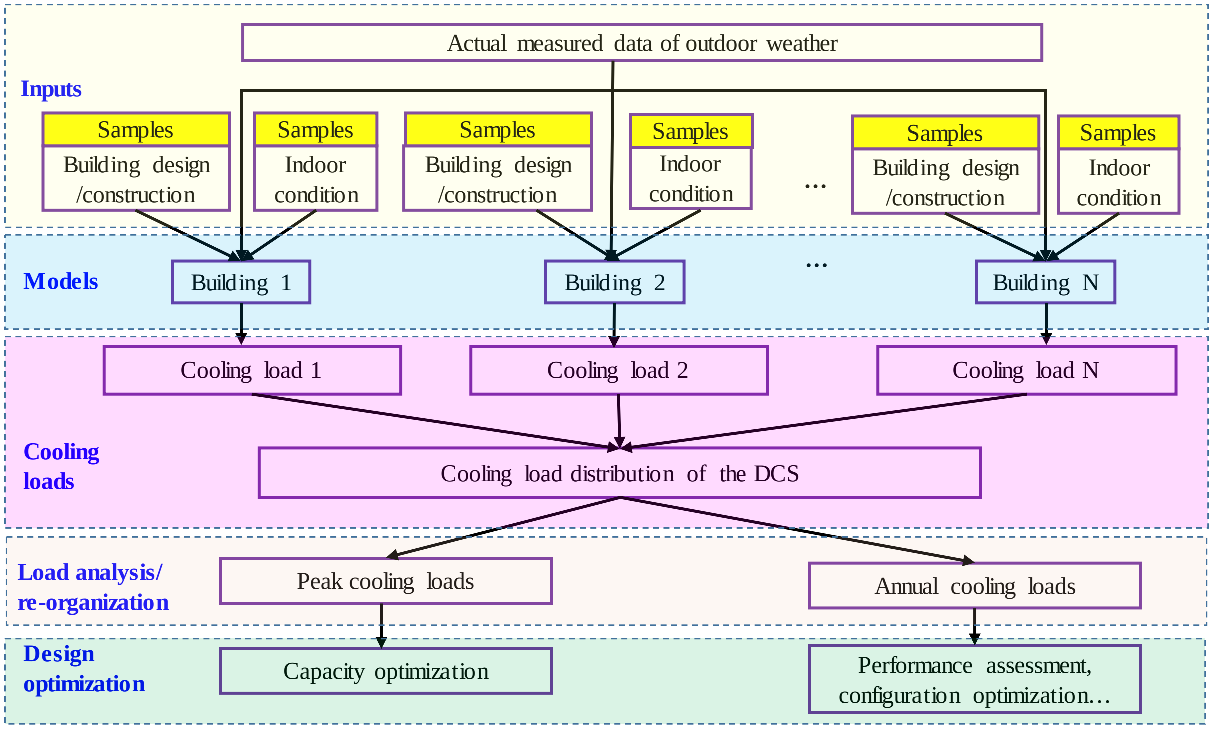


Fig. 1 Steps of the uncertainty-based design optimization method

Fig. 2 Initial planning scheme of the new district investigated in this study

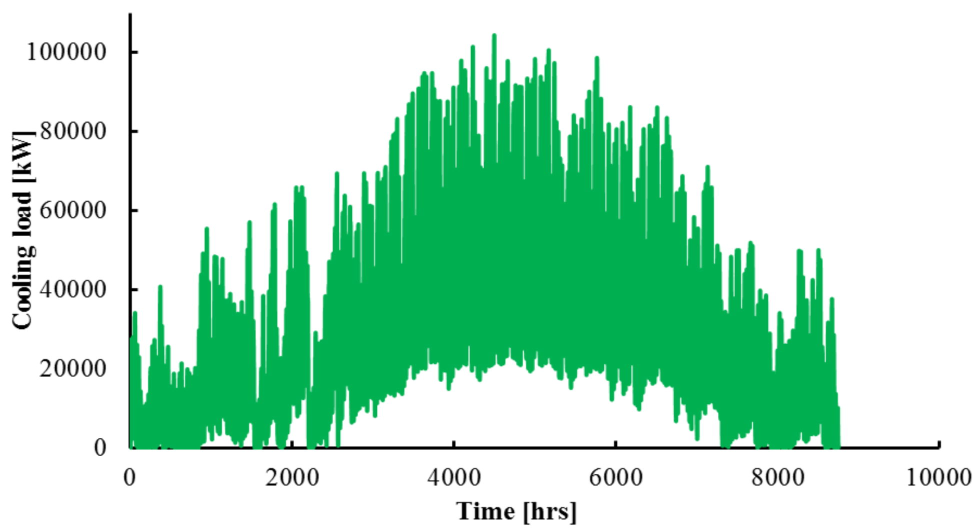


Fig. 3 Annual hourly cooling loads of the DCS in the reference case

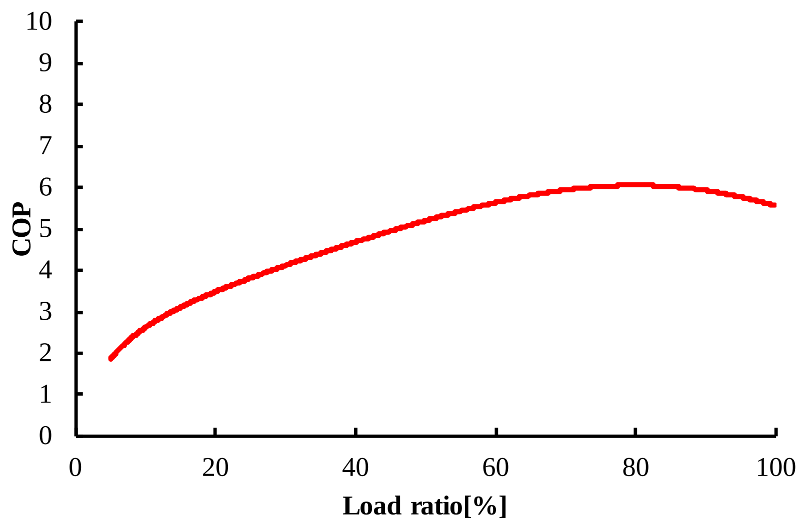


Fig. 4 Performance curve of chillers at different part load ratios

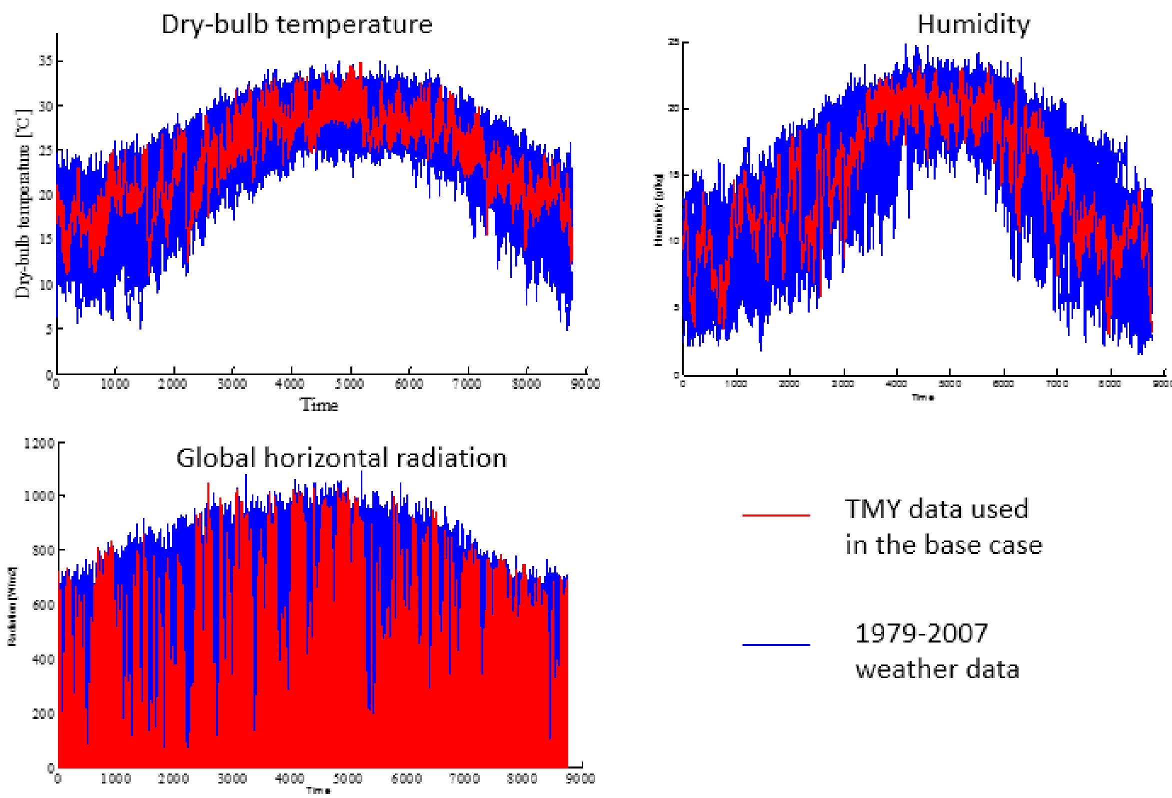


Fig. 5 Actual weather data from 1979 to 2007 vs. TMY

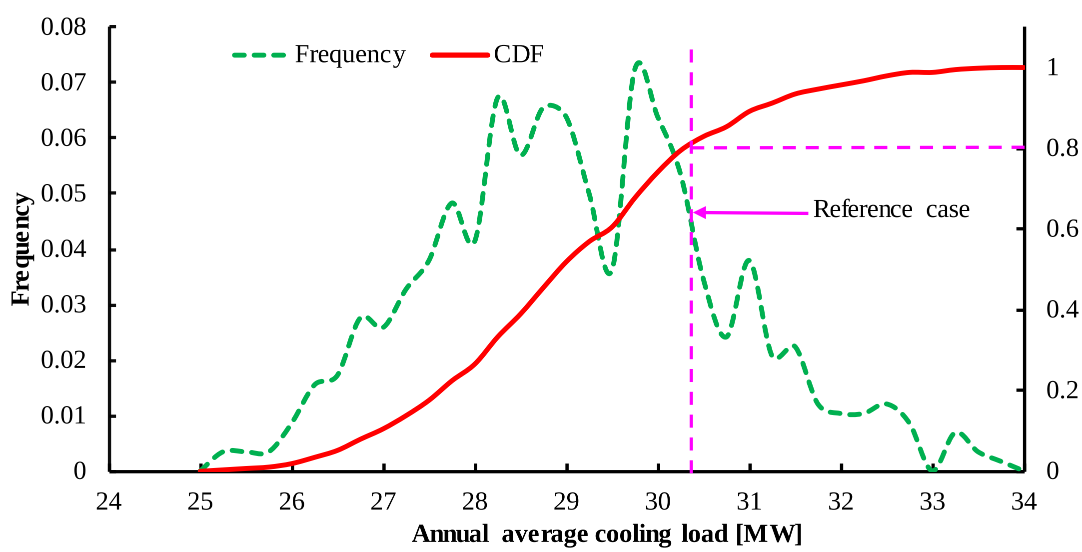
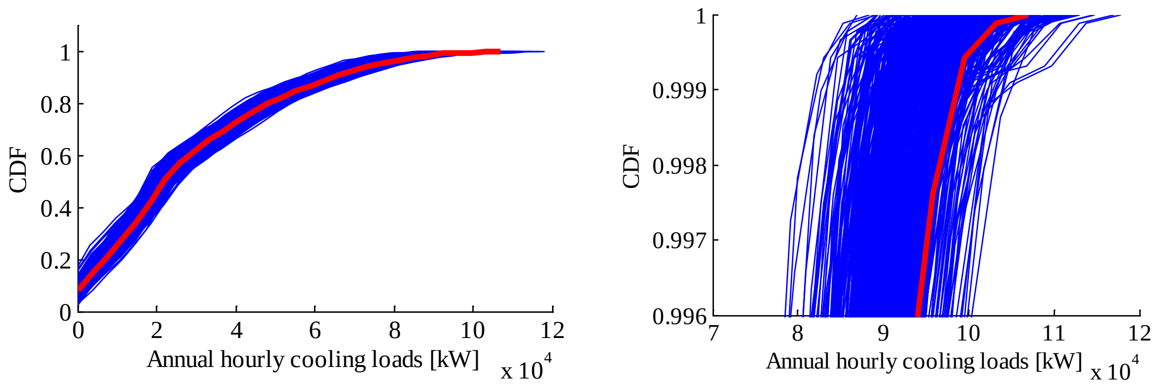


Fig. 6 Distribution of the annual average cooling loads



(a) (b)

Fig. 7 Annual cooling load distribution

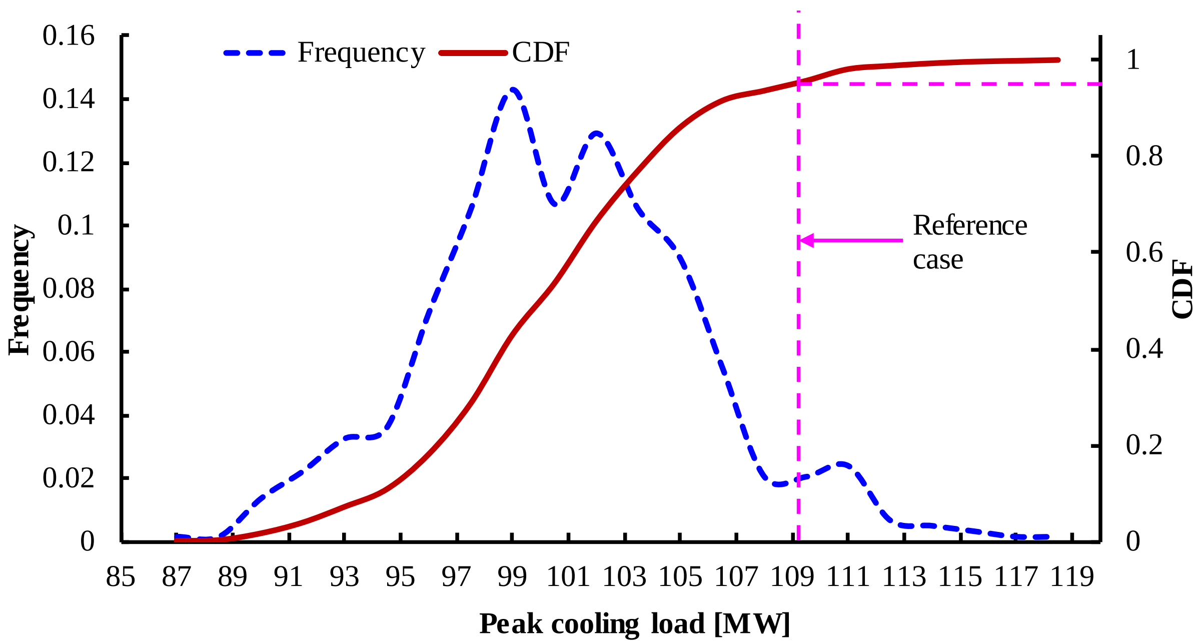
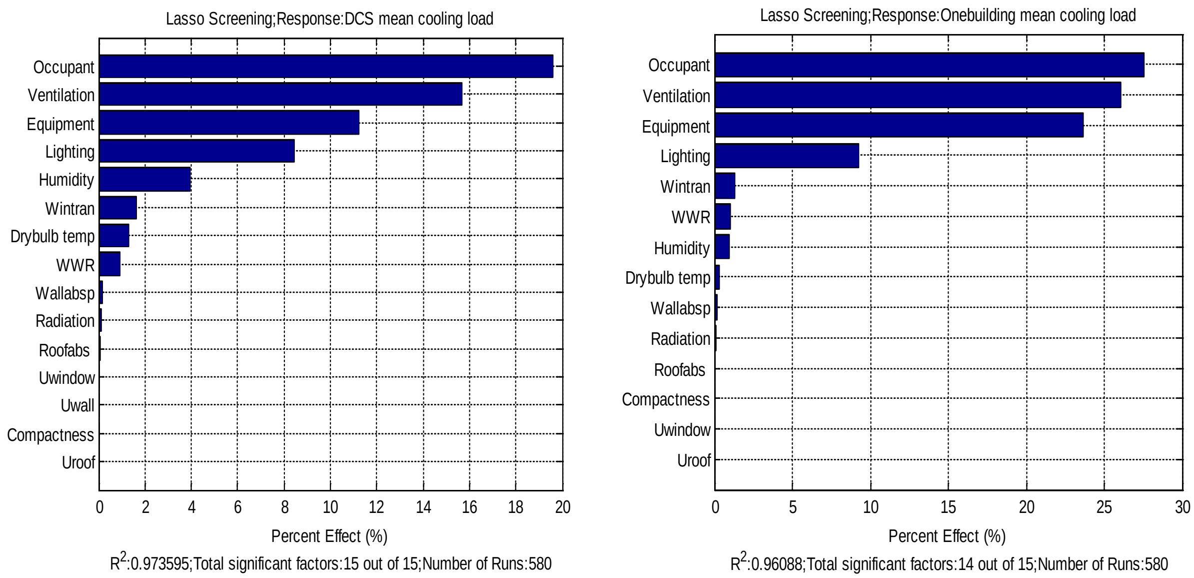
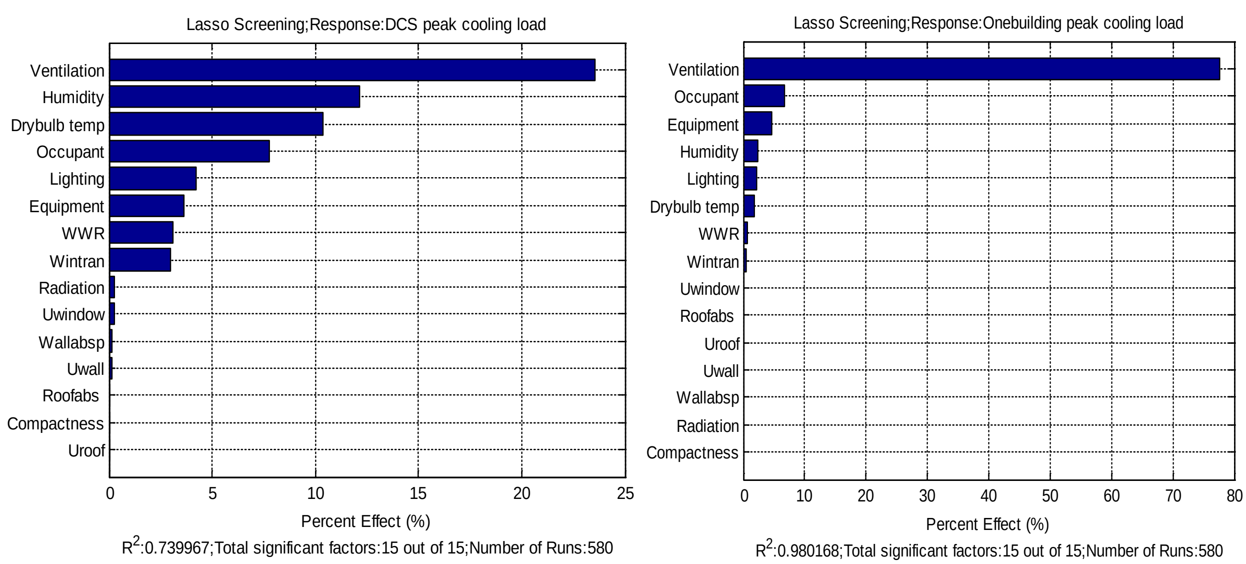


Fig. 8 Distribution of the peak cooling load of the DCS



Left: Annual average cooling load of the DCS; Right: Annual average cooling load of one office building

Fig. 9 Importance ranking of the input variables for the annual average cooling load



Left: Peak cooling load of the DCS *Right: Peak cooling load of one office building*

Fig. 10 Importance ranking of the input variables for the peak cooling load

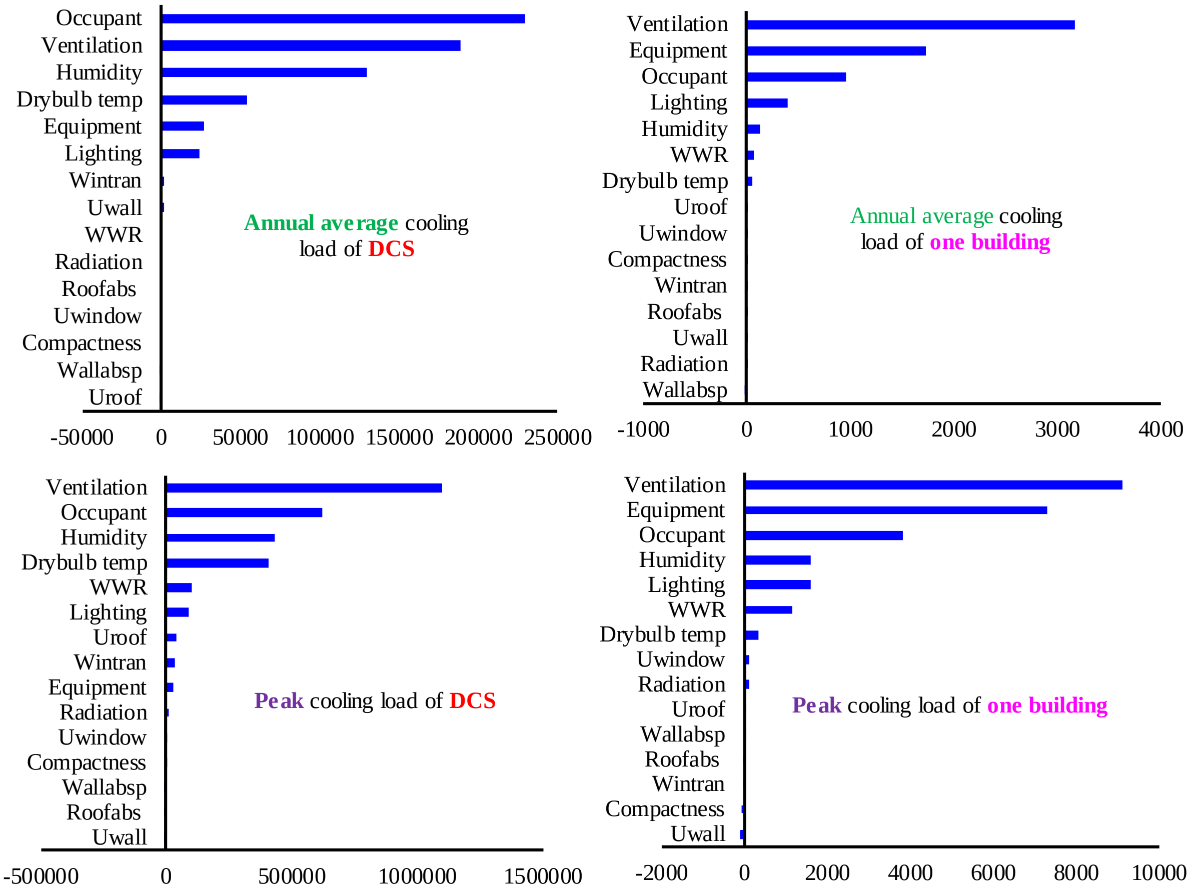


Fig. 11 The ranking of variable importance using random forests

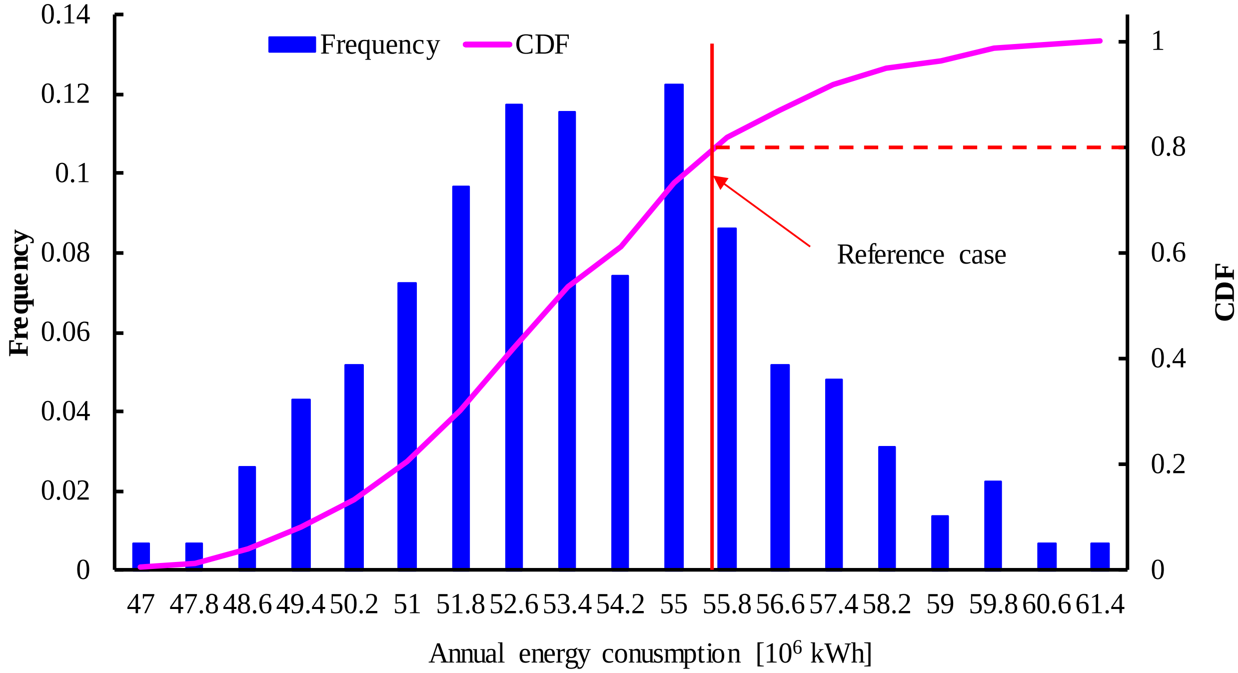


Fig. 12 Distributions of energy consumption of the DCS considering uncertainties

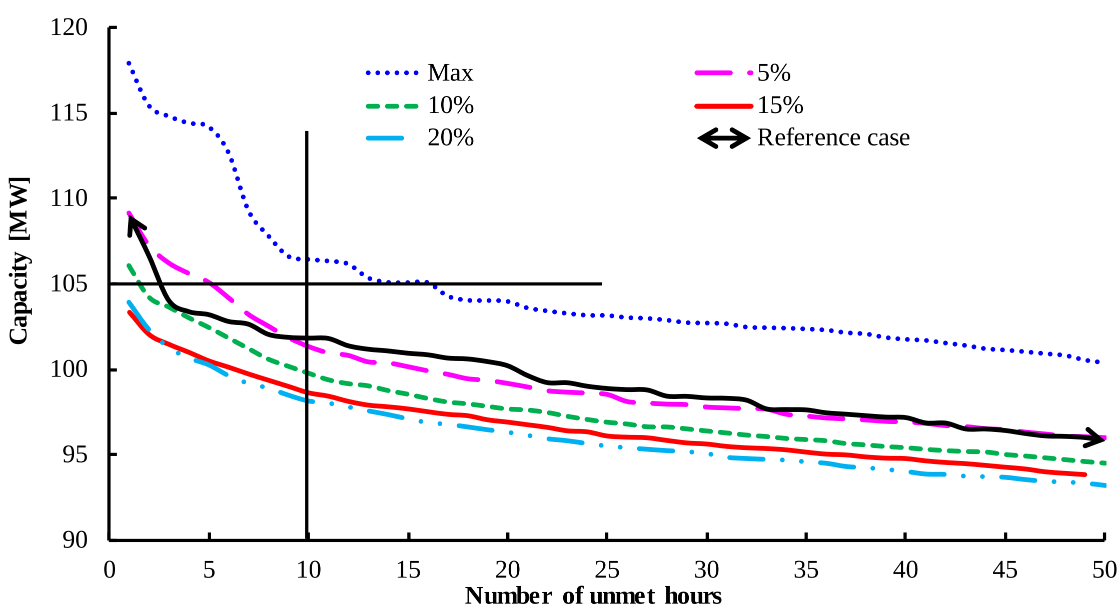


Fig. 13 Capacities of the DCSs at different risk levels and numbers of unmet hours

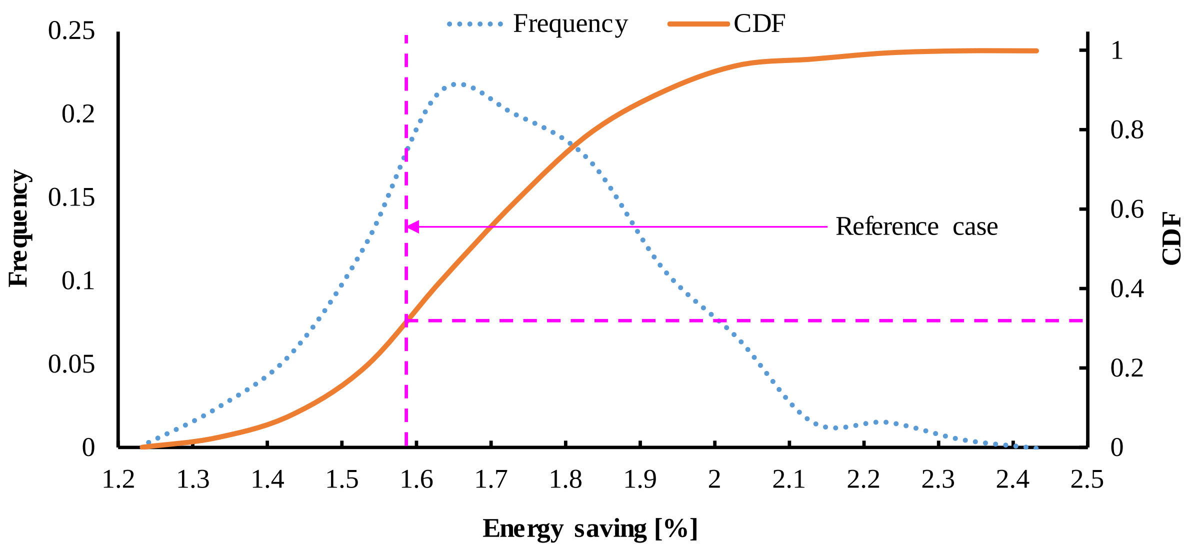


Fig. 14 Energy saving distribution by the DCS using chillers with different capacities

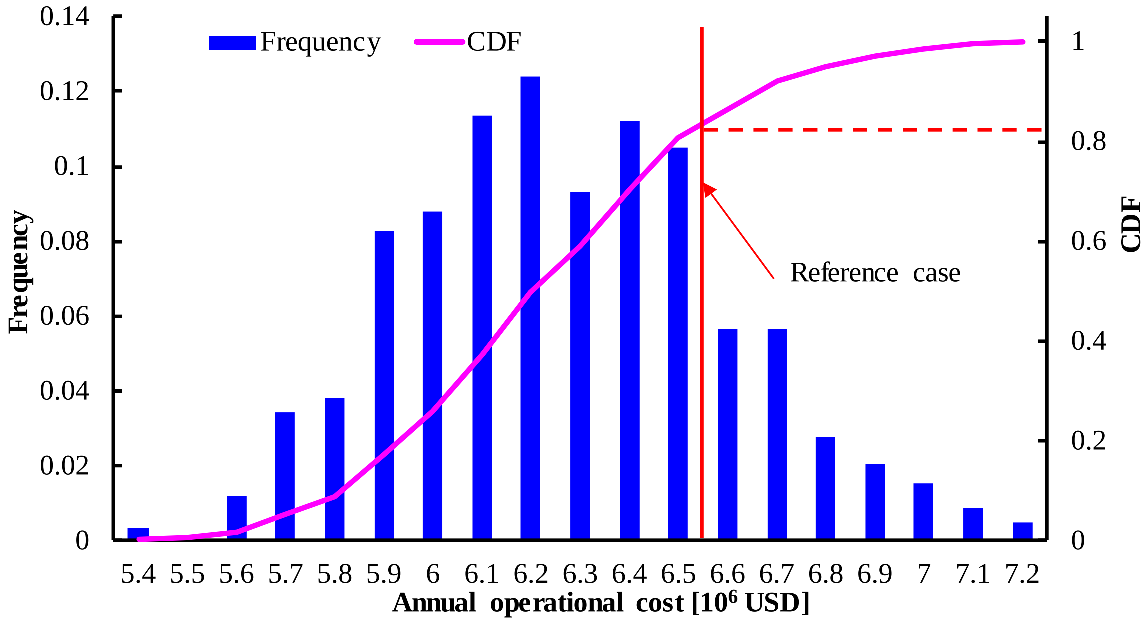


Fig. 15 Annual operational costs of the DCS integrated with the ice storage system

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

Group	Abbreviation	Parameter	Reference case	Uncertainty study	
				Distribut-ion	**Values**
Outdoor weather	Drybulb temp	Dry-bulb temperature of outdoor air	TMY	Actual data:1979~2007	
	Humidity	Humidity of outdoor air			
	Radiation	Global radiation			
Building design/ construct-ion	Building floor	Building floors	Based on the plan	Relative normal	(1,0.04)
	Building length	Building length	Based on the plan	Relative normal	(1,0.04)
	WWR	Window wall ratio	0.5	Uniform	(0.3,0.7)
	Uwall	Conductivity of wall (W/(m^2.K)	1.5	Uniform	(1,1.5)
	Uwindow	Conductivity of window (W/(m^2.K)	3	Uniform	(1.5,3)
	Uroof	Conductivity of roof (W/(m^2.K)	0.9	Uniform	(0.4~0.9)
	Wallabsp	Wall absorption coefficient	0.9	Uniform	(0.4~0.9)
	Roofabs	Roof absorption coefficient	0.8	Uniform	(0.4~0.8)
	Wintran	Window solar transmittance	0.8	Uniform	(0.4~0.8)
Indoor condition	Occupant	Occupant density	Ranging from 4~15 m^2/person for different types of buildings	Relative normal	(1,0.04)
	Lighting	Lighting density	Ranging from 10~20 W/m^2 for different types of buildings	Relative normal	(1,0.04)
	Equipment	Plug-in equipment density	Ranging from 8~20 W/m^2 for different types of buildings	Relative normal	(1,0.04)
	Ventilation rate	Ventilation rate	Ranging from 1~4 ACH for different types of buildings	Relative normal	(1,0.04)

Note: for the uniform distribution (a, b), a and b are the lower limit and upper limit; for the normal distribution (c, d), c is the mean and d is the variance; the relative normal distribution means that the samples of the variable are obtained by multiplying the value in the reference case by certain factors [21]. *These factors fit the listed distribution in the Table.*