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Uncertainty-based robust optimal design of cleanroom air-conditioning systems considering life-cycle performance

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Abstract:

Strict and simultaneous space temperature and humidity controls are often required in many applications, such as hospitals, laboratories, cleanrooms for pharmaceutical and semiconductor manufacturing. The energy intensity in such applications can be up to 100 times than typical office buildings, mainly due to the improper system design and control. Although some uncertainty-based design methods have been developed for air-conditioning systems, most of the existing systems are designed based on a certain ventilation mode while neglecting the life-cycle performance of the components. This study, therefore, proposes a robust optimal design method for cleanroom air-conditioning systems considering the uncertainties in design parameters for inputs and operation strategies as well as the life-cycle performance of the components. An adaptive full-range decoupled ventilation (ADV) strategy, which incorporated five operation modes, was adopted in the design optimization. Two maintenance modes were adopted and compared to consider the flexibility of maintenance. The proposed design method has been implemented and validated in the design optimization of an existing air-conditioning system. The results showed that, compared with the conventional design, up to 54% reduction of life-cycle costs and superior satisfaction of services could be achieved by using the proposed method.

Keywords: Optimal design method, Cleanroom, air-conditioning systems, Life-cycle performance, Adaptative ventilation strategy, Uncertainty design parameters, Maintenance

Introduction

Strict and simultaneous space temperature and humidity controls are needed in many applications, such as cleanrooms for pharmaceutical/semiconductor manufacturing, biological/chemical labs, hospitals and museums (hereafter denoted as "cleanrooms" for brevity). Such applications can be up to 100 times as energy-intensive as typical office/educational buildings as shown in Fig. 1. The data in this figure were collected from USDOE/EIA Commercial Buildings Energy Consumption Survey (office, educational building, hotel, mall and hospital) [1], Labs21 benchmarking tool (Laboratory) [2] as well as Mathew [3] and Mills (Cleanroom) [4]. However, the energy intensity has no significant reduction over 17 years (1993 to 2010) due to the neglect of highly cost-effective energy efficiency opportunities.[5] In addition, the total floor area of cleanrooms has been growing very fast worldwide. In New York, the total floor area of cleanrooms increased from 15 thousand m^2 in 2003 to the estimated 22.5 thousand m^2 in 2010,[3] and the rate of increase is even faster in China due to the rapid growth of the semiconductor industry.[6]

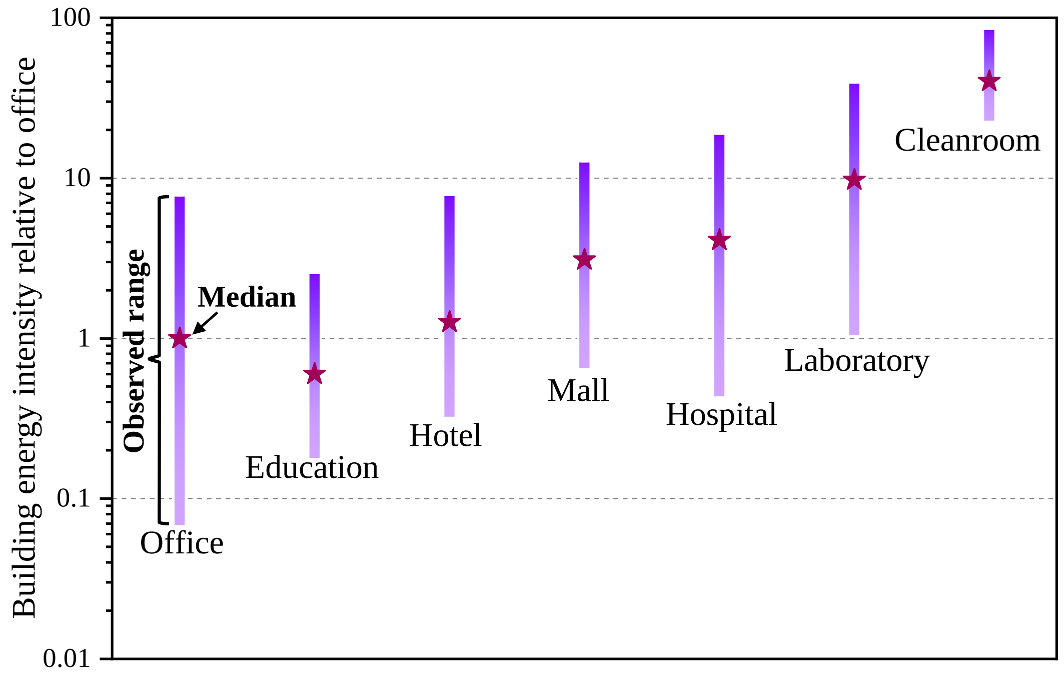

Fig. 1 Energy intensities of different types of buildings [1-4]

Heating, ventilation and air conditioning (HVAC) systems in cleanrooms account for more than 50% of total building energy.[7] Proper design and selection of air-conditioning systems are critical to achieving energy-efficient and reliable operation in cleanrooms. For instance, an under-sized air-conditioning system might result in insufficient cooling and dehumidification under hot and humid outdoor air conditions, while an over-sized system might cause low energy-efficiency and high capital costs [8,9]. Neme et al. [10] estimated that improper sizing could yield as much as a 10% overall energy increase.

Facilitating a proper ventilation strategy is a key issue to ensure an appropriate system design. For cleanroom air-conditioning systems, different components are highly interactive and coordinative to achieve strict and simultaneous humidity and temperature controls. The authors of this paper explored the influence of the selected ventilation strategy on the design of systems.[11] For instance, the required cooling coil capacity of the make-up air-handling unit (MAU) is the least when adopts the interactive control (IC) strategy, and is the largest when adopts the dedicated outdoor air ventilation control (DV) strategy. The sizing of the components is determined basically using the annual maximum cooling/heating demand, by considering the year-around operation conditions which are certain and presumed at the design stage. However, the proper and optimal design for cleanroom air-conditioning systems is particularly associated with ever-changing working conditions and the uncertainties of information used.

Accurate prediction of cooling load is also a key issue to ensure an appropriate system design. Under current engineering practice, to design and select a properly sized air-conditioning system, the peak or maximum load of buildings are computed based on a given indoor and prevailing outdoor design condition.[12] A safety factor is assigned to the design cooling load when determining the capacity of the cooling system, considering the future extension, uncertainties/assumptions in the preliminary design stage and potential cooling loss.[13,14] However, this method may often overestimate the actual cooling load as indicated in previous studies,[15,16] due to the neglect of uncertainty. Uncertainty can be defined as *"being any departure from the unachievable ideal of complete determinism"*. [17] In terms of cleanroom air-conditioning system design, uncertainty exists in weather conditions, physical properties of the building envelop, internal sensible/latent loads, load diversities of multiple spaces, etc.. [18] Neglecting the uncertainty may cause mismatches between air-conditioning system design and operation/control, and thus the degraded system performance. Previous studies mainly focused on the design of the central cooling plant (water-side) considering uncertainties.[15,16,19] The basic principle of selecting the cooling plant is based on the distributions of predicted total cooling load (i.e. selecting the cooling capacity with the likelihood that the system fails to provide the required service to be less than a threshold). However, for the air-side component design, due to the counteraction and interaction (i.e. overcooling and reheating process) among different components as well as the diversity behaviours of different spaces, the total cooling demand of air-side components may significantly exceed the total cooling load, particularly for the building with spaces requiring simultaneous temperature and humidity controls.

Performance degradation of components/equipment, which is defined as the reduction of components/equipment outputs over a long period of operation, often leads to lower energy efficiency and higher life cycle costs of the systems. For instance, the overall energy efficiency of a ground-source heat pump would decrease by 13% after 20-year operation as indicated by Zhou et al. [20]. The energy efficiency ratio of chillers systems may decrease by 5-20% over 20 years as reported in reference.[21] Proper maintenance is beneficial to improve the system performance, satisfy control requirements of the indoor environment and prolong component/equipment service life. Comprehensive maintenance of chillers (i.e. tube cleaning, balanced water treatment, refrigerant leak monitoring, etc.) would improve the chiller energy savings by 20 to 25% [22] and can extend chiller lifetime by 50%.[23] Mowris et al. [24] showed that through duct sealing, airflow adjustment and condenser coil cleaning, up to 27% of HVAC energy use can be saved. Eleftheriadis et al. [25] found that building energy consumption can be 18 - 47% higher than a scenario without degradation, depending on the maintenance quality. To offer better maintenance quality, Salah et al. [26] recommended different maintenance durations/intervals for different air-conditioning components based on their failure risks. However, the component life-cycle performance, as one of the main concerns in practical applications, are not well integrated into the current design practice, especially for the air-side air-conditioning systems.

To address the aforementioned challenges, this study proposes a robust optimal design method based on life-cycle performance analysis for cleanroom air-conditioning system design. The objective of design optimization is to achieve a cost-effective design that ensures the system operates at high performance over its life cycle, considering the wide ranges and uncertainties of working conditions, component performance degradation and proper maintenance. Uncertainties of design inputs, load diversities of multiple spaces, as well as component performance degradation and maintenance over the system life cycle were quantified using probabilistic methods. Monte Carlo simulation was adopted to model the uncertainty propagation in the air-conditioning system design process and generate the stochastic component performance data. Two maintenance modes were adopted and compared to consider the flexibility of maintenance. A robust optimization process was then used to identify the optimal sizes of cleanroom air-conditioning components with minimal life-cycle costs. This method was tested and validated using an existing pharmaceutical building as a reference in Hong Kong, a typical city in subtropical regions. The economic benefits and service satisfaction of the cleanroom air-conditioning system over the system life cycle, designed based on the proposed method, were compared with that of the conventional design without considering the life-cycle performance. The major innovations and original contributions of this study can be summarized as follows:

- The life-cycle performance of the components, which includes performance degradation due to ageing effects and performance improvements due to the maintenance, was considered and were built into the design optimization for cleanroom air-conditioning systems.
- The interaction between ventilation strategy and component performance variations was considered, to provide systems with the robustness to operate at high energy efficiency and high reliability to meet the requirements of the indoor environment.
- The impacts of multiple sources of uncertainty, including the uncertainties of building design variables, load diversities and performance variations were comprehensively considered in the proposed design method. This method can be used to identify the optimal system with the best performance expectation under all possible working conditions.
- Different maintenance modes were adopted and compared in design optimization, offering more flexible maintenance schemes for cleanroom air-conditioning systems.

A typical cleanroom air-conditioning system in subtropical regions

Fig. 2 shows a typical multi-zone cleanroom air-conditioning system (i.e. serving to meet the ISO 14644-1: 2015, class 8 specifications [27]) in subtropical regions, where the climatic conditions are hot and humid. The system consists of a make-up air-handling unit (MAU) and multiple supply air-handling units (AHUs). Each AHU serves for one zone containing multiple spaces. The outdoor air is first processed by the MAU and then is mixed with recirculation air, before being conditioned by the AHU, to reach the target supply air set-points. A MAU mainly consists of filters, cooling coils and a fan, and an AHU mainly consists of filters, cooling coils, heaters and a fan.

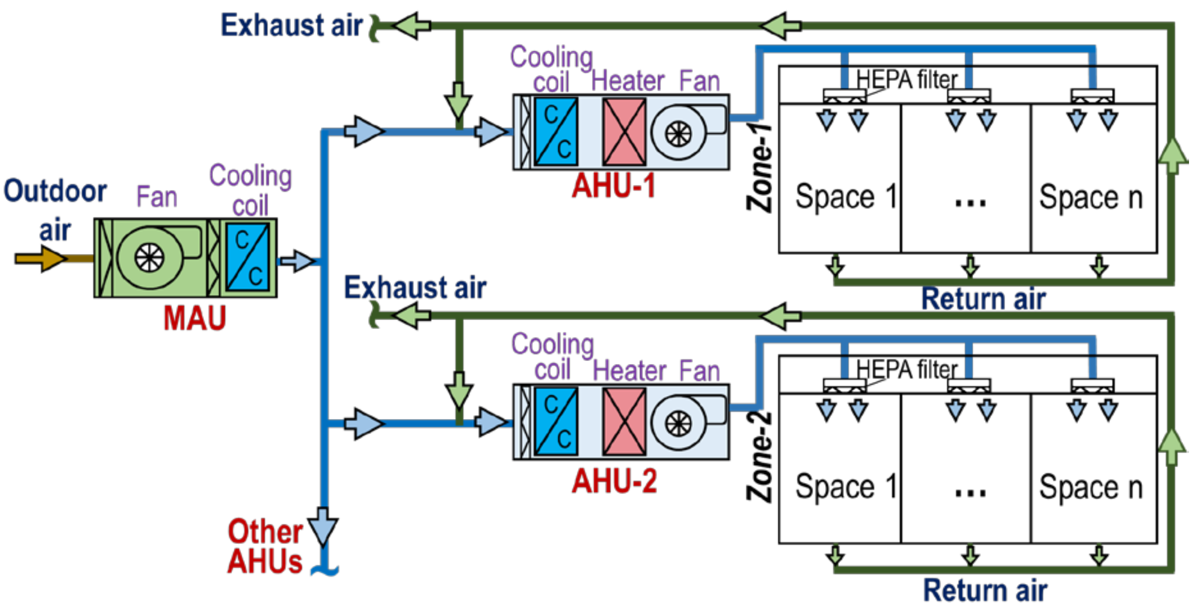

Fig. 2 A typical multi-zone cleanroom air-conditioning system in subtropical regions

The cleanrooms have strict control requirements on indoor temperature, humidity, pressure and cleanliness. To reach the control requirements, the indoor temperature and humidity are controlled by the coordinated use of the MAU and AHUs (i.e. cooling and heating). The indoor pressure is maintained by adjusting the amount of outdoor airflow and exhaust airflow. The indoor cleanliness is achieved by setting the supply airflow higher than a threshold (i.e. 20 air change rates per hour (ACH)) and installation of high-efficiency particulate air (HEPA) filters. Cleanroom air-conditioning systems of such configuration are usually designed as constant air volume (CAV) systems due to the cleanliness requirement.

Description of robust optimal design method based on life-cycle performance analysis

The objective of the design optimization is to minimize the life-cycle cost (C_{lc}, USD) of the cleanroom air-conditioning systems as expressed by Eq. (1). Where, C_{in} is the initial cost (USD) of the components. C_{op} is the operation (electricity) cost (USD) of the system. C_{pe} is the penalty cost of the system which is a visual expense to quantify the dissatisfaction of the service due to insufficient capacities. C_{ma} is the maintenance cost (USD) of the system. i is the operating year. T is the service life of the system (i.e. 25 years). PWF is the present worth factor that is used to calculate the present value as shown in Eq. (2). r is the interest rate.

$$C_{lc} = C_{in} + \sum_{i=1}^{T} PWF(i)\, C_{op,i} + \sum_{i=1}^{T} PWF(i)\, C_{ma,i} + \sum_{i=1}^{T} PWF(i)\, C_{pe,i} \tag{1}$$

$$PWF(i) = \frac{1}{(1+r)^i} \tag{2}$$

Fig. 3 presents the process and main steps of the proposed robust optimal design method for cleanroom air-conditioning systems considering life-cycle performance. *In the first step*, the design inputs, including the search ranges of component capacity and uncertain design parameters, are selected and the uncertain design parameters are quantified. The uncertain design parameters consist of building design parameters, load diversities and component performance variations. For different uncertainty sources, the probabilistic theory provides an appropriately rigorous basis to characterize the uncertainty.[15] The uncertainties in building energy model parameters can be quantified using real measurements,[28] Bayesian calibration [29,30] and expert judgment.[31]

In this study, the design parameter uncertainties were modelled using the stochastic distributions (e.g. normal distribution, triangular distribution, uniform distribution, etc.) following the recommendation by Gang et al. [16] and Kang et al. [32]. *In the second step*, uncertain cooling demands (i.e. sensible and latent cooling demands) were calculated using the cooling loads (i.e. obtained from building energy simulation software) multiplied by the space load diversity factors (with quantified distributions). *In the third step*, the “optimizer” determines the best component sizes and maintenance intervals facilitating the adaptive full-range decoupled ventilation (ADV) strategy [11] and considering the component life-cycle performance. These steps were repeated until the objective is minimized while reaching the convergence tolerance. More detailed descriptions are shown in the following sections.

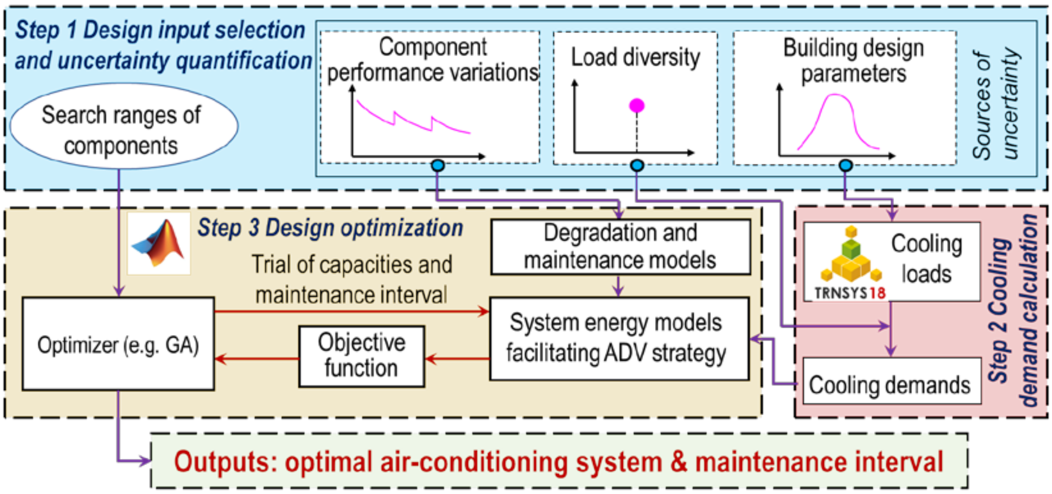

Fig. 3 Process and steps of proposed robust optimal design method considering life-cycle performance.

Uncertainty quantification and cooling demand calculation

Three types of uncertainty were considered in this study: building design parameters uncertainty, load diversities and performance variations. Building design variables (*X*), including outdoor weather, physical parameter and indoor conditions, would highly influence the space cooling load (*Y*) as expressed by Eq. (3). Each variable may follow a certain distribution function *G*. The load diversities, including the sensible and latent load diversities, represent the asynchronous behaviours of multiple spaces. Probabilistic diversity factors (β) were used to quantify uncertain space load diversities, in order to estimate the space cooling demands. The distribution functions (*H*) of diversity factors can be found in reference.[18] Component performance variations include performance degradation due to the ageing effects and performance improvement due to maintenance. These uncertain parameters were assigned with proper probability distribution functions (PDFs). The samples were generated from the uncertain parameters adopting Monte Carlo simulation and then they were used as inputs for calculating uncertain cooling demands. Latin Hypercube Sampling (LHS) method [33] was used to reduce the number of samples.

$$Y = f(X_1, X_2, \dots, X_n) \qquad X_i \sim G_i \tag{3}$$

Each set of samples was imported into the cooling load calculation software (e.g. TRNSYS, EnergyPlus, etc.). The zone sensible and latent cooling loads (*Y*) could then be obtained.

For CAV systems, the actually required cooling demands of a zone are often significantly larger than the cooling loads due to the overcooling and over-dehumidification for some spaces inside a zone.[34]

To simplify the calculation of the cooling demands, the cooling demands (Z) were calculated by the cooling loads (Y) multiplied by diversity factors (β) as shown in Eq. (4).

$$Z = Y \times \beta \qquad \beta_i \sim H_i \tag{4}$$

Design optimization over life cycle

The optimization of cleanroom air-conditioning systems aims to ensure that the systems can operate in the best mode over its life cycle. In this study, the interaction between the ADV strategy and component performance variations were considered into the design optimization, to ensure the system operates at a high energy efficiency over its life cycle.

<u>Basic principle of the ADV strategy</u>: The ADV strategy overcomes the limitations of existing ventilation strategy (e.g. interactive control) by avoiding sub-cooling and reheating as far as beneficial via the best use of MAU and economizer for cooling and dehumidification. It incorporates five operation modes, such as partially decoupled control (PD), dedicated outdoor air ventilation (DV) and three adaptive economizer control modes (following sensible load, following latent load and lower-limit humidity control), and selects the best operation mode adaptive to the working conditions and component capacities. More detailed information on the ADV strategy can be found in reference [11].

<u>Component performance over system life cycle</u>: The component performance (i.e. represented by capacity) can be influenced by the degradation and maintenance. In this study, a random degradation rate method [35] was used to model the degradation. This method has no requirement for actual measurements and thus can be applied at the design stage. Using this method, the output of a component is reduced by a degradation rate (i.e. presented by a random quantification) per operating year. The capacity of the component in Year t was estimated by Eq. (5). The pre-scheduled preventive maintenance, which is cost-effective and flexible, was adopted to improve the component performance (represented by capacity).[36] The maintenance each time is expected to improve the system performance by some percentage, as expressed by Eq. (6). [37] Where, CAP_O is the component when newly installed. D_a is the annual degradation rate while i is the year of operation. CAP_i is the amount in the i^{th} year considering degradation. CAP_i^m is the capacity in the i^{th} year after maintenance. The uncertainty of degradation rate (D_a) can be quantified as a stochastic distribution.

$$CAP_i = CAP_o \times (1 - D_a)^i \tag{5}$$

$$CAP_i^m = min\,(CAP_o, CAP_i(1 + \beta)) \tag{6}$$

In this study, two maintenance modes were adopted to consider the flexibility of maintenance. The first mode is to set the same maintenance interval (year) for the whole system, which was easier to be implemented. The second mode is to set different maintenance intervals for different equipment (i.e. MAU and AHUs), which is flexible allowing for the adjustment of maintenance periodicity according to the significance of equipment (i.e. MAU/AHUs) although it may be labour-intensive. For the second mode, the maintenance intervals for the MAU and AHUs were different while the maintenance interval of components inside the same MAU and AHU was the same.

Procedure and main steps of optimization: The detailed design optimization based on life-cycle performance analysis is presented in Fig. 4. A genetic algorithm (GA) was used to minimize life-cycle costs (C_{lc}, Eq. (1)). The initial cost of the components (C_{in}) includes the cost of the major components, such as MAU/AHU cooling coil, AHU heaters and MAU fan. The unit prices of air-conditioning components were estimated based on RSMeans Mechanical Cost Data [38] as shown in Appendix A. The component cost for maintenance (C_{ma}) each time was assumed as 5% of the initial cost of the corresponding component.[39,40] The operation cost (C_{op}) of the system was calculated by the local electricity price multiplied by the total electricity consumption. The equivalent total electrical load (E_{tot}, Eq. (7)) includes the equivalent electrical loads of fans, cooling coils and heaters. The equivalent electrical loads of components were calculated according to their inlet and outlet air states and the cooling/heating system overall COPs using Eqs. (8) - (10). Where, W_f is the total fan power (kW). V is the air volumetric flowrate (m^3/s). Δp is the total pressure rise (kPa). η_f is fan efficiency. h_{out} and h_{int} are inlet and outlet air enthalpy, respectively (kJ/kg). ρ is air density (kg/m^3). COP_c and COP_{he} are the overall coefficient of performance of the cooling system and heating system, respectively. The inlet/outlet air states and the air flowrates were determined following the principle of the ventilation mode adopted, as illustrated in reference [11]. The penalty cost (C_{pe}) was quantified by the accumulation of unmet demand multiplied by a penalty price (*£pe*) (Eq. 11).

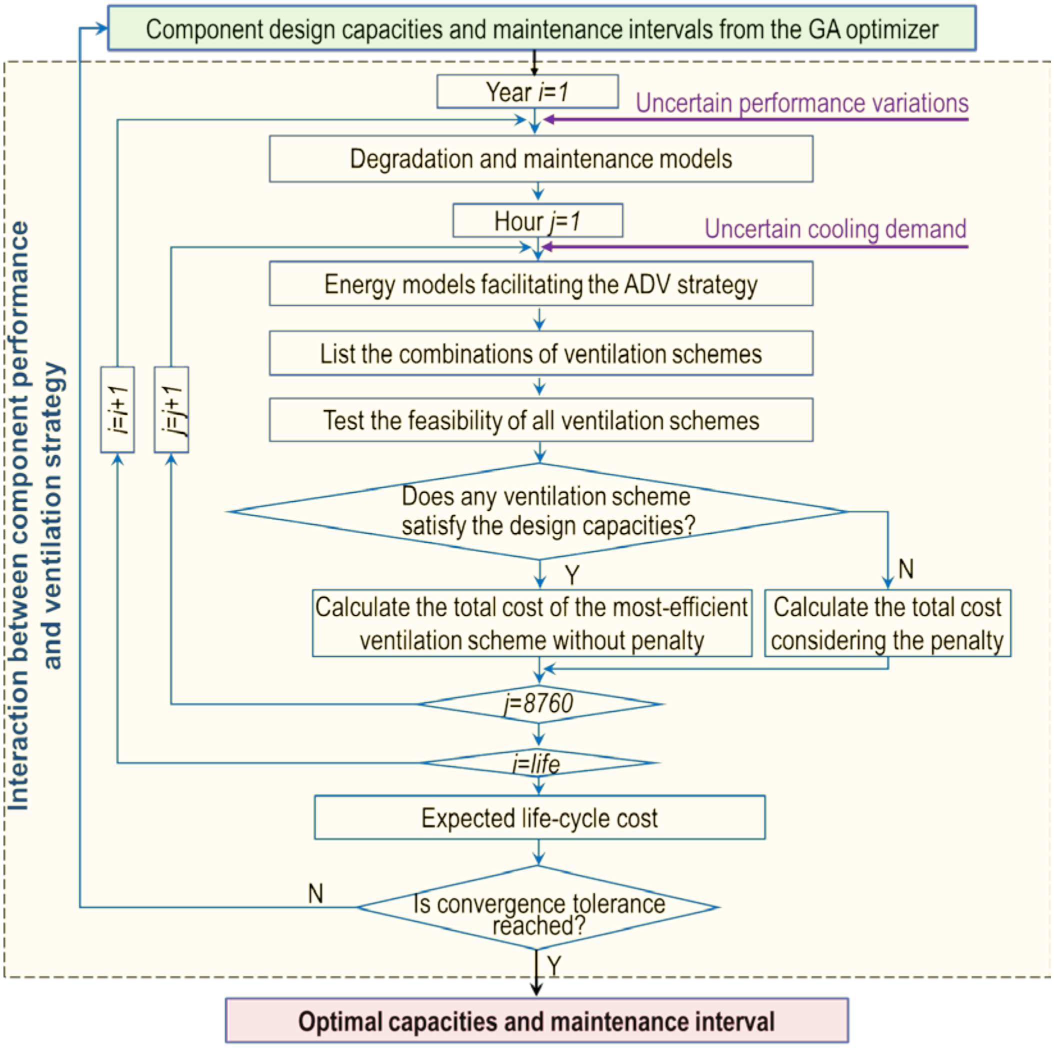

Fig. 4 Detailed process of optimal design based on life-cycle performance analysis

$$E_{tot} = E_{f,MAU} + E_{f,MAU} \sum_{j=1}^{M} (E_{cc,AHU,j} + E_{he,AHU,j} + W_{f,AHU,j}) \tag{7}$$

$$W_f = \frac{V\Delta p}{\eta_f} \tag{8}$$

$$E_{cc} = \frac{Q_{cc}}{COP_c} = \frac{\rho V(h_{out,cc} - h_{int,cc})}{COP_c} \tag{9}$$

$$E_{he} = \frac{Q_{he}}{COP_{he}} = \frac{m(h_{out,he} - h_{int,he})}{COP_{he}} \tag{10}$$

$$C_{Pe} = £_{pe} \sum_{j=1}^{8760} max(0, D_{emand}(j) - C_{apacity}) \tag{11}$$

At each time step, the component capacities and maintenance intervals were obtained from the GA optimizer. The actual component performances were then updated using the degradation and maintenance models. Under the given cooling demands and component capacities, each zone could select the optimal ventilation mode from several alternative modes adopting the ADV strategy. The combinations of ventilation schemes were listed (i.e. different zones may operate adopting different ventilation modes in each scheme) and then the energy performances of all schemes were evaluated. If the design capacities could not meet the requirements of the most energy-efficient ventilation scheme, then the system would test the feasibility of the suboptimal ventilation scheme. If the design capacities failed to meet requirements of all ventilation schemes, the service dissatisfaction might occur (i.e. indoor temperature/ humidity could not be controlled at the required ranges) and hence the penalty cost (C_{pe}) would be given (i.e. this hour was marked as an unmet hour). The design option corresponding to the minimal expected life-cycle cost was identified as the optimal design alternative.

Case study and results

A cleanroom air-conditioning subsystem of a pharmaceutical factory building located in Tai Po Industrial Estate of Hong Kong was selected to demonstrate the performance of the robust optimal design method. All the production areas in the subsystem were designed as ISO 14644-1: 2015, Class 8 cleanrooms.[27] This subsystem serving for three zones, each zone containing several spaces, have the same configuration as shown in Fig. 2. The configuration and control requirements of the subsystem are shown in Table 1.

Table 1 Cleanroom subsystem configuration and control requirements

Envelope details	Wall (W/m^2·K)	1.5
	Roof (W/m^2·K)	0.8
	Window (W/m^2·K)	2.7
	Window to wall ratio (WWR)	0.2
Floor area of the zones	Zone 1 with 9 spaces: total area 100.5 m^2	
	Zone 2 with 8 spaces: total area 121 m^2	
	Zone 3 with 8 spaces: total area 151 m^2	
Height of the zones	2.8 m	
Operating schedule	9:00-18:00	
Fan specification	Fan pressure drops (Pa)	1600 (MAU) /1350 (AHU)
	Fan efficiency (%)	60
The overall coefficient of performance (COP) of systems	Cooling system (central cooling)	2.5
	Heating system (electric heater)	1
Space control requirements	Temperature (°C)	20±3
	Relative Humidity (%)	55±10
	Supply airflow rate (ACH)	≥20
	Outdoor airflow rate (ACH)	≥2

Totally 950 (38 × 25) sets of samples were generated and used to get the cooling load distribution, based on the uncertainty distributions as summarized in Table 2. The local historical weather data from 1979 to 2016 (38 years) were collected and used to account for the weather uncertainties. For each trial (i.e. also regarded as each year), one of the 38-year weather data was used. To sufficiently consider the uncertainties of physical parameters and indoor conditions, multiple trials (i.e. 25 trials) were made (sampling over the ranges of corresponding parameters) associated with the selected weather data of each year. Table 3 presents the quantified degradation rates and the expected percentage of performance improvements from maintenance.[21] The case cleanroom air-conditioning subsystem was assumed to serve for 25 years.[41] The interest rate r was set as 3.75%.[42] The penalty price was set as 20 times of local electricity price, as the optimal system size varies only within a small range when the penalty price is higher than a threshold.[18] The local electricity price was taken as the average price of 0.141 USD/kW in Hong Kong. [38]

Two maintenance modes were considered in design optimization using the proposed robust optimal design method. The first design (marked as Robust Design #1) assumed that the same maintenance interval was set for the whole system (MAU and AHUs). The second design (marked as Robust Design #2) assumed that different maintenance intervals were set for MAU and AHUs. A conventional design which neglected the impacts of degradation and maintenance (i.e. the degradation rate was set to 0, and the maintenance interval was set to 0) was used for comparison.

Table 2 Classification and quantification of uncertain parameters

Category		Parameter	Uncertainty/distribution
Building design variables	Outdoor weather	Outdoor dry-bulb air temperature (°C)	Historical data: 1979–2016
		Outdoor air relative Humidity (%)	
		Global radiation (W/m^2)	
		Diffuse radiation (W/m^2)	
	Physical parameter	Internal shading coefficient	*N (0.5, 0.1^2)*
		External shading coefficient	*N (0.2, 0.05^2)*
		Conductivity of window (W/(m^2·K))	*U (1.5,3)*
	Indoor condition	Occupant density (m^2/person)	*10×T(0.3, 1.2, 0.9)*
		Lighting density (W/m^2)	*14×T (0.3,1.2, 0.9)*
		Process sensible load (W/m^2)	*45×N (1,0.06^2)*
		Process latent load (W/m^2)	*15×N (1,0.06^2)*
Load diversity		Sensible cooling load diversity	The distributions referring to reference [18]
		Latent cooling load diversity	
Component performance		Degradation rate (due to aging)	As presented in Table 3
		Performance improvement (due to maintenance)	

Table 3 Component performance degradation rates and performance improvements [21]

Component	Degradation rate	Percentage of performance improvement
Cooling coil	N (0.01, 0.001)	N (0.031,0.0031)
Heater	N (0.002, 0.0002)	N (0.004,0.0004)
Fan	N (0.005, 0.0005)	N (0.012,0.0012)

Optimal design alternative and maintenance interval

A Genetic Algorithm (GA) was applied to find the optimal design alternatives and maintenance intervals of both the conventional and proposed designs. The parameters to be optimized in the GA simulations for three designs are listed in Table 4. The AHU fan capacity was not involved in design optimization. Due to the indoor cleanliness requirements, the AHU fan is usually a constant speed fan to ensure a sufficient airflow rate.

Table 4 The parameters to be optimized in the GA simulations

Method	Parameters to be optimized
Conventional design	MAU fan, MAU cooling coil, AHU-1/2/3 cooling coils, AHU-1/2/3 heaters
Robust optimal design #1	MAU fan, MAU cooling coil, AHU-1/2/3 cooling coils, AHU-1/2/3 heaters, system maintenance interval
Robust optimal design #2	MAU fan, MAU cooling coil, AHU-1/2/3 cooling coils, AHU-1/2/3 heaters, MAU and AHU-1/2/3 maintenance intervals

Fig. 5(A) presents the design capacities adopting the conventional design and proposed design methods. The design cooling coil and heater capacities of the conventional design were smaller than that of the proposed designs. For instance, for AHU-1, the design cooling coil capacity of conventional design is 0.75 and 0.60 times that of the proposed robust optimal design #1 and #2, respectively. The design heater capacity of the conventional design is 0.65 and 0.71 times that of the proposed robust optimal design #1 and #2, respectively. Due to the neglect of component performance degradation, the design component capacities adopting the conventional design method are of high probability to be under-sized. In contrast, the design component capacities adopting the proposed robust optimal design method are larger than that of adopting the conventional design method by considering the penalty (i.e. due to the dissatisfaction of services).

Fig. 5(B) shows the optimal maintenance intervals for the proposed designs. For the proposed robust optimal design #1, the maintenance interval was set as 3 years for the whole system (including MAU and three AHUs). For the proposed robust optimal design #2, the maintenance intervals were set as 2, 6, 4 and 3 years for the MAU, AHU-1, AHU-2 and AHU-3, respectively. The optimal maintenance intervals for three AHUs are different. The reason is that the cooling load/demand profiles of zones (i.e. served by AHUs) are different, and thus the impacts of component capacity degradations on system energy performance are different. The energy performance of the critical zone (i.e. with high cooling and dehumidification demand) is more sensitive to the changes of component performance. The system designed based on the robust optimal design #2 could have a more flexible maintenance scheme compared with robust optimal design #1.

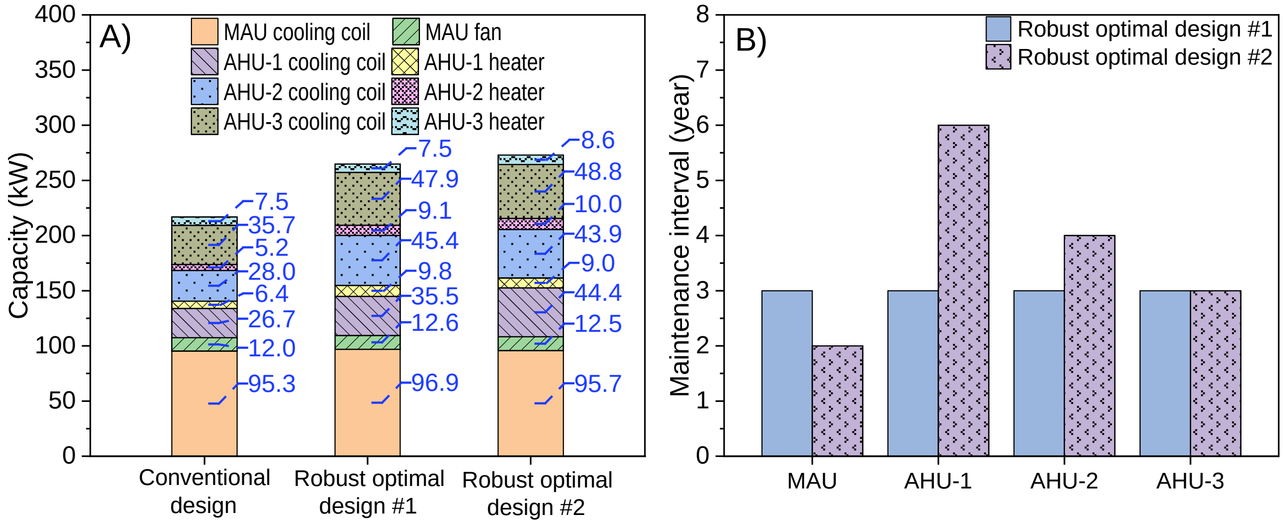

Fig. 5 Conventional design and the proposed optimal designs A) optimal capacity B) maintenance interval

Performance comparisons between conventional design and proposed design method

The life-cycle costs for each design are presented in Fig. 6. The life-cycle costs of the conventional design, robust optimal design #1 and robust optimal design #2 are 1028.3 *kUSD*, 475.1 *kUSD* and 474.2 *kUSD*, respectively. Compared with adopting the conventional design, the system adopting the proposed optimal design method can save the life-cycle cost for more than 54%. Although the system adopting the conventional design requires minimal initial cost compared with that of the system adopting the proposed two designs, it incurs the highest penalty cost, which accounts for 59% of its life-cycle cost. Therefore, if the component performance degradations and maintenance were not considered in design optimization, the system sizes may have a high probability to be under-estimated, resulting in serious service dissatisfaction. In contrast, both the robust optimal design #1 and #2 can offer satisfactory services (i.e. represented by the comparatively low penalty cost). The system adopting the robust optimal design #2 requires a higher initial cost (1.0%) and maintenance cost (13.5%) than the corresponding cost of the system adopting the robust optimal design #1.

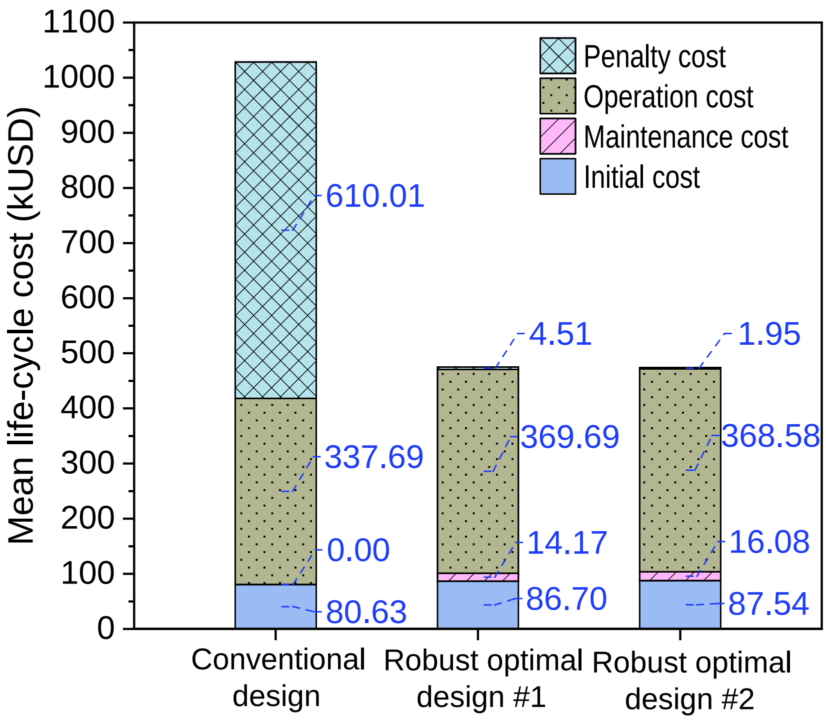

Fig. 6 Mean life-cycle cost of the conventional design and the proposed optimal designs

In some design practices, especially for cleanroom air-conditioning systems, the number of hours when the cooling or heating capacity cannot meet the required demands (namely unmet hour) is especially concerned by the designers to ensure the quantity of service. Fewer unmet hours indicate a better performance of air-conditioning systems. The annual mean unmet hours for conventional design, proposed robust optimal design #1 and #2 over the life cycle are presented in Fig. 7. The conventional design method can only provide the system with satisfactory service in the first year, while the unmet hours would exceed 100 in the entire years due to the component performance degradations and lack of maintenance. The proposed robust optimal design #1 and #2 can offer the system more satisfactory services over its life cycle compared with the conventional design. The annual mean unmet hours over the life cycle of the conventional design, proposed robust optimal design #1 and #2 are 2162, 62 and 35 hours, respectively. For the robust optimal design #1, the annual mean unmet hour is less than 10 hours in the first thirteen years, while the annual mean unmet hour of the system would increase and eventually reach the maximum 381 hours. For the robust optimal design #2, the annual mean unmet hour is less than 10 hours in the first sixteen years, while the mean annual unmet hour of the system would increase and eventually reach the maximum 221 hours. By setting different maintenance intervals for different components (robust optimal design #2), the unmet hours can be significantly decreased, especially when the system operates close to its life span.

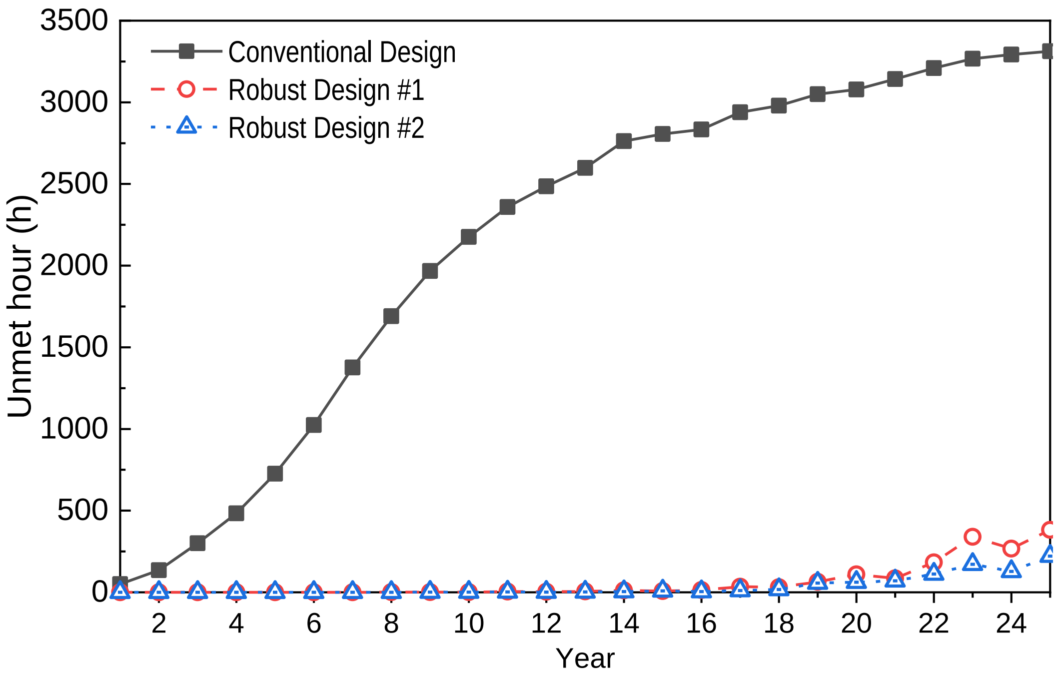

Fig. 7 Annual mean unmet hours over the system life cycle

A sensitivity study was conducted to show the effects of the maintenance intervals on the overall performance of the system as shown in Fig. 8. The results were obtained based on the design capacities of the robust optimal design #1. For each boxplot, the central line indicates the mean value, the peripheries of each box are the 25th and 75th percentiles. As shown in Fig. 8, with the increase in the maintenance interval, the life-cycle cost first decreases and then increases, while the annual mean unmet hour always increases due to the insufficient component capacities. The mean life-cycle cost and annual unmet hour under the maintenance interval of 9 years can be 17.3% and 4.4 times more than that of the optimal solution (i.e. maintenance interval of 3 years), respectively. The proper selection of maintenance intervals is a key issue to ensure the system with low life-cycle costs and good satisfaction of services.

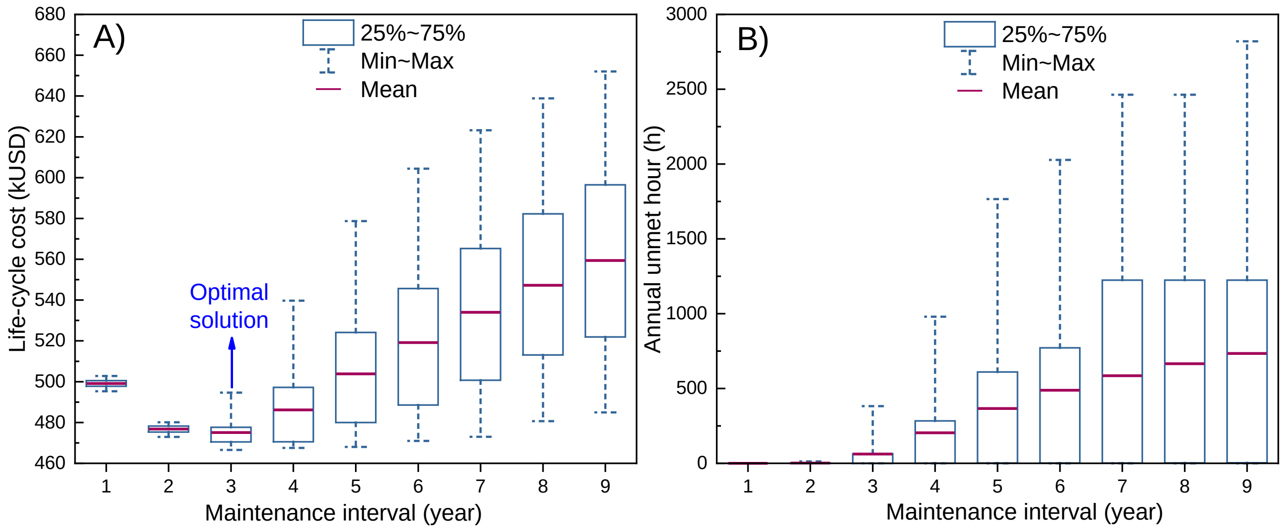

Fig. 8 Life-cycle cost and annual mean unmet hour under different maintenance intervals

Discussion

As one of the measures to achieve energy-efficient operation in cleanrooms, the robust optimal design method developed in this study could offer the air-conditioning systems with high performance over its life cycle. Suggestions are highlighted for the future development of energy-efficient measures for cleanroom air-conditioning systems.

The results of the case study indicate that, compared with the conventional design method, adopting the robust optimal design can significantly reduce the life-cycle cost (mainly due to the reduction of the penalty cost). As cleanrooms have a high requirement of control reliability, the penalty cost is introduced as a visual expense to quantify the dissatisfaction of the service due to insufficient capacities. To adopt the proposed design method in real applications, identifying/quantifying the relations of penalty cost and dissatisfaction of the service according to the cleanliness level, function and type of cleanrooms is a key issue. In addition, the dissatisfaction of the service due to the unmet of indoor contamination level [43,44] should also be quantified and involved in design optimization.

In this study, the single objective optimization has been adopted to minimize the system life-cycle cost, which can provide the optimal solution directly for a given objective. For cleanroom air-conditioning systems, due to the strict requirements on indoor environment controls, multi-objective optimization is also needed to provide multiple design alternatives for designers to make better compromised decisions (e.g. compromising energy costs, unmet hours, etc.).

Besides appropriate design, another issue encountered in practice is to find an online control strategy that can provide a satisfactory indoor environment with high energy performance.[45,46] For instance, Wang et al. [47] found that the total energy use of a variable air volume (VAV) air-conditioning system can be reduced by 3.3% through online optimizing outdoor air ventilation. As indicated by Ren and Cao [48], the energy use of ventilation systems and air conditioning terminals could be reduced by up to 50% and 32% respectively by adopting a proper online control strategy. Therefore, to achieve energy conservations in cleanrooms, the online control strategy is required to be further developed for ensuring the actual operation of the air-conditioning systems, providing properly-design air-conditioning systems.

Conclusions

In this study, an uncertainty-based robust optimal design method is developed for cleanroom air-conditioning systems considering the life-cycle performance. Three sources of uncertainty, including uncertainties of design inputs, load diversities of multiple spaces and the component/equipment performance variations, were quantified using probabilistic methods. To provide systems with the robustness to operate at high energy efficiency and high reliability over its life cycle, the interaction between an optimal ventilation strategy and component performance variations were considered in the design optimization. Two maintenance modes were adopted to consider the flexibility of maintenance. The proposed method was tested and validated using an air-conditioning subsystem of an existing pharmaceutical building as a reference in Hong Kong. Based on the results and analysis of a case study, detailed conclusions are made as follows.

- The proposed robust optimal design method can offer cost-effective design alternatives for cleanroom air-conditioning systems. Compared with the conventional design method, the proposed method could provide preferable designs with over 54% life-cycle cost saving.
- The air-conditioning system designed from the conventional design method (without considering degradation and maintenance) would result in serious dissatisfaction of services due to the unmet cooling/heating demands. Significant annual unmet hour reduction can be achieved by implementing the proposed design method.
- Compared with the design by setting the same maintenance interval for the whole system

(Robust Design #1), better satisfaction of services of the system (i.e. reduction of 27 unmet hours annually on average) and slightly lower life-cycle costs (i.e. 0.2%) can be obtained by setting different maintenance intervals for different components (Robust Design #2).

- A higher frequency of maintenance could significantly reduce the unmet hours but increase the system maintenance cost. Finding the optimal maintenance interval by compromising between the satisfaction of services and life-cycle costs is a key issue.

Authors' contribution

Dr. Chaoqun Zhuang conducted the detailed development and validation of the methods presented. Prof. Shengwei Wang initialized this study and supervised the development.

Declaration of conflicting interests

The author(s) declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this paper.

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Appendix A The investment of components

The initial cost of the centrifugal fan, axial fan, duct, coil, and electric heater can be estimated by Eqs. (A.1) -(A.5) based on RSMeans Mechanical Cost Data [38].

$$C_{cen,f} = 1125.9V + 3375.1 \tag{A.1}$$

$$C_{axi,f} = 296.97V + 1406.4 \tag{A.2}$$

$$C_{duct} = (3.0V^3 - 29.2V^2 + 138.9V + 7.68) \times len_{duct} \tag{A.3}$$

$$C_{cc} = -1.3313CAP_{cc}^2 + 165.09CAP_{cc} + 1746.7 \tag{A.4}$$

$$C_{he} = 221.01CAP_{he} + 211.05 \tag{A.5}$$

Where, $C_{cen,f}$, $C_{axi,f,}$ C_{duct} , C_{cc} and C_{he} (USD) are the initial cost of centrifugal fan, axial fan, duct, cooling coil and electric heater. CAP_{cc} (kW), CAP_{he} (kW) and V (m^3/s) are the capacity of the cooling coil, electric heater and design airflow, respectively. len_{duct} is the length of the duct (m).

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