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Probabilistic Optimal Design of Cleanroom Air-conditioning Systems Facilitating Optimal Ventilation Control under Uncertainties

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Abstract: Buildings with cleanrooms and spaces requiring strict temperature and humidity controls, such as pharmaceutical cleanrooms and semiconductor/microchip factories, have been growing very quickly in terms of total floor area and energy consumption. In such buildings, much of the energy is unnecessarily wasted due to the incoordination of system design and operation/control, especially under "off-design" and ever-changing ambient and load conditions. This paper, therefore, proposes a probabilistic optimal design method for cleanroom air-conditioning systems facilitating optimal ventilation control strategies under uncertainties. To consider the effects of asynchronous loads in different zones/spaces with reduced computation demand, a probabilistic diversity factor method is proposed which is a simplified method to quantify the effects of uncertainties of space load diversities in multiple zones/spaces using diversity factors. The proposed design method is implemented and validated in the design optimization of air-conditioning systems for implementing four different ventilation control strategies considering possible and uncertain off-design conditions. The energy and economic performance as well as service satisfaction of the air-conditioning systems are also evaluated and compared. Results show that the proposed design method can obtain the optimal air-conditioning systems with minimum life-cycle cost and superior satisfaction of service.

Keywords: probabilistic optimal design, optimal ventilation strategy, design optimization, air-conditioning system, uncertainty

Nomenclature

ADV	Adaptive full-range decoupled ventilation
AHU	Air-handling unit
IC	Interactive control
DV	Dedicated outdoor air ventilation
MAU	Make-up air-handling unit
PAU	Primary air-handling unit
PD	Partially decoupled control
SHR	Sensible heat ratio
C_{OT}	Overall annualized total cost (USD)
C_C	Capital cost (USD)
C_M	Maintenance cost (USD)
C_O	Operation cost (USD)
C_P	Penalty cost (USD)
COP_c	Overall coefficient of performance of cooling system
COP_{he}	Overall coefficient of performance of heating system
CRF	Capital recovery factor
D_{sen}	Sensible cooling demand of zones (W/m^2)
D_{lat}	Latent cooling demand of zones (W/m^2)
E_{tot}	The total cost of electricity (USD)
h	Enthalpy of air (kJ/kg)
h_{fg}	Latent heat of vaporization (kJ/kg)
Δp	Total pressure rise (kPa)
Q_{sen}	Space sensible cooling load (W/m^2)
Q_{lat}	Space latent cooling load (W/m^2)
Q_{tot}	Space total cooling load (W/m^2)
$Q_{cc,MAU}$	Cooling coil thermal load of make-up air-handling unit (kW)
$Q_{cc,AHU}$	Cooling coil thermal load of supply air-handling unit (kW)
$Q_{he,AHU}$	Heating thermal load of supply air-handling unit (kW)
T	Temperature (°C)
w	Humidity ratio (kg/kg)
W_f	Fan power (kW)
i'	Real discount rate
i_d	Discount rate
i_e	Energy inflation rate
i_g	General inflation rate
i''	Effective discount rate
N	Lifetime (year)
V	Air volumetric flow rate (m^3/s)
Z_{sen}	Zone sensible cooling load (W/m^2)
Z_{lat}	Zone latent cooling load (W/m^2)

Greek letters

γ_{pen}	Penalty price ratio
β	Diversity factor
η_f	Fan efficiency
$£$	Price

Subscripts

ave	Average
cc	Cooling coil
ele	Electricity
f	Fan
he	Heating system
lat	Latent
pen	Penalty
sen	Sensible
t	Total

1. Introduction

Buildings with spaces requiring strict temperature and humidity controls, such as pharmaceutical cleanrooms, semiconductor/microchip factories and hospitals, have been growing very fast in terms of total floor area and energy consumption worldwide [1]. In the Pearl Delta Region (South China), a subtropical region, the increase is even faster due to the rapid increase of semiconductor fabrication [2]. The energy intensity of air-conditioning systems in such buildings is usually 10-100 times greater than the average energy intensity in commercial buildings [3].

Due to this high energy intensity as well as the complexity of system design and control, buildings for such applications consume high and rapidly increasing amount of energy. Much of the energy is unnecessarily wasted due to improper system design and control in engineering practice. For example, system retrofitting work in pharmaceutical factory buildings in Hong Kong achieved up to 42% of annual energy savings by optimizing/retrofitting the system control strategies only, without hardware modification [4]. This indicates that the energy saving potential of such air-conditioning systems is very high when strict and simultaneous temperature and humidity control is required. However, many problems need to be solved in order to realize this energy saving potential, due to the complexity of air-conditioning systems and their operation/control. The challenges in solving these problems are particularly associated with ever-changing working conditions and the uncertainties of information used for the air-conditioning system design. For cleanroom air-conditioning, selection of the system configuration is key to achieving high energy efficiency due to the required high recirculation airflow rate and high-pressure losses at filters [5]. For instance, a system configuration, with a make-up air-handling unit (MAU) integrating with local axial fans and dry cooling coils, is recommended by some design guides because of its low-pressure drop characteristics [6][7]. However, such a configuration is not widely used due to the high initial cost and system complexity (e.g., the need for dual-temperature chillers and additional duct installations) and the inconvenience of maintenance. The combined use of a MAU together with several air-handling units (AHUs) is still the mainstream configuration in real applications [8][9].

Although there are generic air-conditioning system design approaches as summarized by ASHRAE [10], very few studies have addressed the component design of cleanroom air-conditioning systems. Some researchers have developed optimal design methods to enhance the performance of the air-side components of cleanroom air-conditioning systems, such as cooling coils [11], MAU fans [12] and humidifiers [13]. Nevertheless, although these components may be well designed, their performance in practice often deviates significantly from expected performance due to the fact that *they cannot be adjusted to "off-design" and ever-changing ambient and load conditions*. Particularly, the mismatch between system design and operation/control still widely exists because *the coordination and interaction among these components/processes in different off-design conditions are not considered sufficiently*. For example, a cleanroom facility site study [7] shows that the actual cooling load of the MAU in operation was only about one-fourth of its design value. Improper system designs lead to improper controls and low energy efficiency in operation, which are often observed and well-understood by engineers today. At the design stage, the air-conditioning systems need to be designed with sufficient consideration on their coordination with certain properly selected optimal and energy-efficient ventilation strategy to facilitate the systems to be adaptive to different off-design conditions. However, such a design method coordinating the design effectively with certainly preferred ventilation strategy for cleanroom air-conditioning systems is not available.

Another challenge encountered in practice is due to the fact that even well-selected data/information used as design inputs can be rather different from that in real operation. Such inherent deviations are regarded as "uncertainties". In conventional design practice, the capacities of the air-conditioning components for a building is determined under the design condition which is certain and presumed in a climate region [14]. Due to the existence of uncertainty issues, the actual conditions of air-conditioning systems in operation often deviate significantly from those projected at the design stages. Without proper means to consider and handle these uncertainties, it is very difficult to ensure the actual operating performance of air-conditioning systems will be up to expectations. For the design of building air-conditioning systems, cooling load calculation considering uncertainties have been considered when conducting performance estimates or optimizing the design of building energy systems [15]. Accurate and reliable prediction of cooling/heating loads is very important for building energy system design [16], and uncertainties in predicting cooling/heating loads have been studied widely to solve the widely existed under-sizing and over-sizing problems in practical applications [17][18]. Domínguez et.al [19] quantified the uncertainties of building models and divided the input factors into three groups: certain factors, scenario elements, and uncertain factors. Sun et al. [20]

proposed a design method to size building energy systems considering uncertainties in weather conditions, building envelope and internal loads. The co-author of this paper also considered the impacts of the cooling load uncertainties on the design optimization of building central cooling plant systems in previous studies [21, 22]. Nevertheless, the cooling loads of different spaces in a zone could have large discrepancies at any moment and change with time [23]. The load diversities of multiple spaces (including sensible and latent loads), which are the key sources of uncertainty in the performance of air-conditioning systems [24-26], are usually neglected in system design. The diversity of cooling loads could greatly affect the cooling demands on the air-conditioning subsystems associated with a zone, and the component capacities needed eventually. However, the effective method to quantify the cooling/heating load uncertainties of multiple zones/spaces for design applications still cannot be found.

One more challenge is the need of an effective ventilation strategy that could achieve optimal and energy-efficient operation/control of the air-conditioning systems for cleanrooms/spaces requiring strict and simultaneous humidity and temperature controls under different off-design and ever-changing conditions. The very commonly-used ventilation strategy today is the "interactive control (IC)" [27][28], which employs cooling (or sub-cooling) and reheating processes to eliminate the coupling between temperature and humidity control loops while the counteraction of the sub-cooling and reheating processes causes a great amount of energy waste. The "dedicated outdoor air ventilation strategy" [9][29] fully decouples cooling and dehumidification to avoid sub-cooling and reheating processes. For a system adopting this ventilation strategy, the MAU handles all the latent heat and part of space sensible heat while the AHUs remove the rest of space sensible heat. However, to remove moisture produced by machines/processes/occupants, the necessary outdoor airflow rate may exceed, from time to time, the outdoor airflow rate required to maintain acceptable indoor air quality and/or positive pressure. Thus, a large MAU cooling capacity is usually required to meet the high outdoor air cooling demand [30]. A "partially-decoupled control strategy" [4] was proposed by the co-authors to overcome the drawbacks of the fully-decoupled ventilation strategy. It decouples the dehumidification/cooling processes while working at the required minimum outdoor airflow. However, this strategy is only applicable to systems serving spaces with relatively low internal latent loads due to the fact that simultaneous cooling and reheating would occur when the internal latent load is high.” To address this challenge, the authors of this paper have proposed and developed an “adaptive full-range decoupled ventilation strategy” (ADV strategy) [31] with very promising energy saving potentials and the strategy is applicable for the buildings and spaces requiring strict temperature and humidity controls. This strategy can identify the best operation mode with superior energy efficiency over the full range of internal load and weather conditions by compromising properly “inducing more outdoor air” and “sub-cooling and reheating process with minimum outdoor airflow”. For different ventilation strategies, the system sizing may be different due to the different cooling demands on air-conditioning components. However, air-conditioning systems of proper design are essential to achieve the goal of this strategy in practical applications.

This paper, therefore, proposes a probabilistic optimal design method for cleanroom air-conditioning systems facilitating optimal ventilation control strategies under uncertainties. The main focuses of this study include: 1) optimal design of air-conditioning systems (i.e., optimal component sizing) that fully fulfill the needs for implementing the ADV strategy. 2) developing a simplified method for the quantification of various uncertainties associated to the design of air-conditioning systems for multiple zones/spaces. To consider the effects of asynchronous loads in different zones/spaces with reduced computation demand, a probabilistic diversity factor method is proposed, which is a simplified method to quantify uncertain space load diversities by introducing two probabilistic diversity factors for sensible and latent loads respectively. The proposed design method is implemented and validated in the design optimization of air-conditioning systems for implementing four different ventilation control strategies (including ADV strategy) with full consideration of possible and uncertain off-design conditions. The cleanrooms in a pharmaceutical building (located in Hong Kong, a humid sub-tropical city), which requests strict indoor environment control, is selected for the validation case studies. The energy and economic performance as well as service satisfaction of the designed air-conditioning systems, facilitating different ventilation control strategies, are also evaluated and compared.

2. Optimal design of multi-zone air-conditioning systems concerning uncertainties

2.1 Outline of the proposed design method

Fig. 1 shows the typical configuration of the cleanroom air-conditioning systems concerned, which serve multiple spaces requiring strict temperature and humidity controls. It consists of a MAU and a few AHUs. Each AHU might serve a few spaces. The MAU consists of a cooling coil, a centrifugal fan and filters for conditioning make-up air. Each AHU contains a cooling coil, a heater, an axial fan, a humidifier and filters for conditioning the supply air. Due to the high supply air flowrate requirements of cleanrooms to meet the air cleanness, the cooling/heating demands can be met even under the lower-limit of supply air flowrate (i.e., 20 ACH for the Class ISO 8 cleanrooms [32]). The cleanroom air-conditioning systems of such configuration are usually designed as constant air volume (CAV) systems.

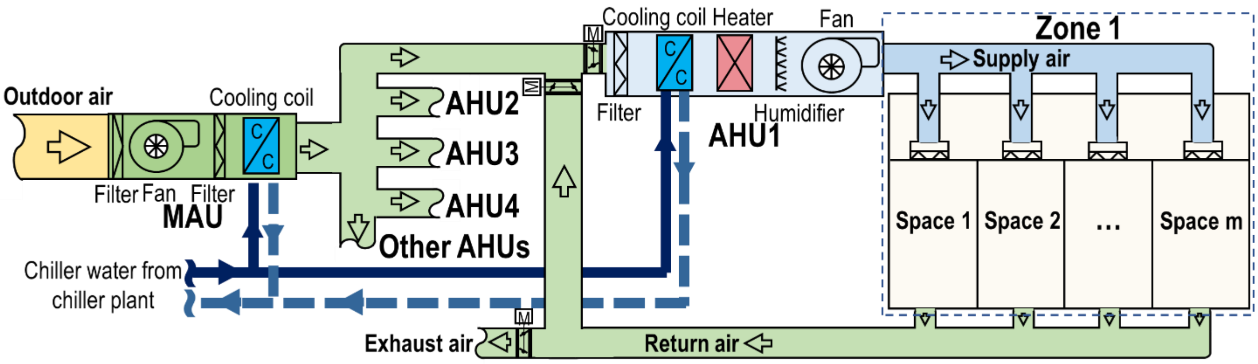

Fig. 1. System configuration of a typical multi-zone air-conditioning system

Fig. 2 presents the process and major steps of the proposed design method for multi-zone cleanroom air-conditioning systems. The objective of the design optimization is to minimize the life-cycle cost and provide systems with the robustness to operate at high energy efficiency under ever-changing dynamic working conditions. The main challenges to be addressed are associated with the impacts of: (1). Variation of working conditions due to changes of ambient and internal loads; (2). The diversities of space latent and sensible loads, particularly sensible heat ratios (SHRs), among different spaces; (3). The uncertainties of the ambient conditions and internal loads as well as their diversities.

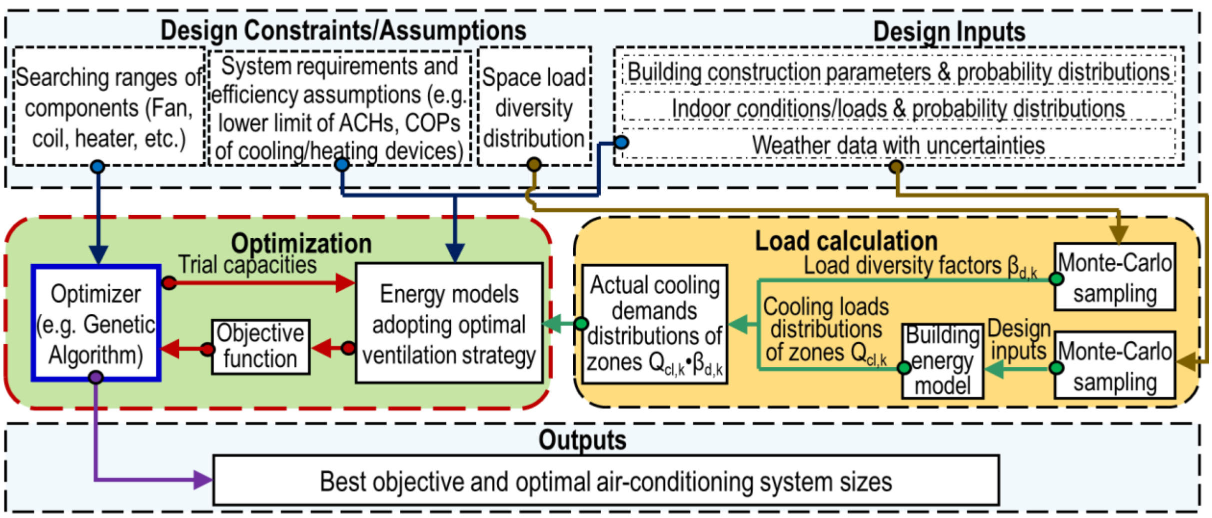

Fig. 2. Process and steps of proposed robust optimal design method using a probabilistic approach

The objective function for optimization is the overall annualized total cost ($C_{OT,a}$) (i.e., Eq. 1), which includes the annualized values of capital cost ($C_{C,a}$), maintenance cost ($C_{M,a}$), operation (or energy) cost ($C_{O,a}$) and penalty cost ($C_{P,a}$). The operation cost includes the total cost of electricity consumed by air-conditioning components (E_{tot}). The penalty cost is introduced to consider the impacts of insufficient cooling and dehumidification capacities to ensure the designed systems with a high level of service satisfaction. The system optimal design consists of three major steps involving quantification of these variations/diversities and their inherent uncertainties. *In the first step,* the design inputs (involving uncertainties) and design constraints are selected, including building envelope parameters, design indoor and weather conditions, assumed efficiency and air-conditioning system constraints as well as the search ranges for the system design parameters (i.e., component capacities) to be optimized. The purpose of this step is to obtain the required information for design optimization. *In the second step,* the annual overall probabilistic sensible/latent cooling demands of individual AHUs in each zone are obtained, which involve quantified uncertainties and diversities of spaces. The design input uncertainties (i.e., outdoor weather, building construction and indoor conditions) are considered in the overall zone cooling load calculation with different trials. The diversities of spaces in a zone are considered by adopting a simplified method (namely 'probabilistic diversity factor method'). Two probabilistic load diversity factors are introduced in this method. The probabilistic sensible and latent cooling demands (D_{sen}, D_{lat}) are then obtained by calculating the space sensible and latent load distributions within a zone (Z_{sen}, Z_{lat}) multiplied by the space sensible and latent load diversity factors (with quantified distributions), as shown in Eqs.2-3. The probabilistic diversity factors ($\beta_{d,sen}$, $\beta_{d,lat}$) represent the design input uncertainties during sensible and latent load calculations and their asynchrony in multiple spaces. The purpose of this step is to effectively quantify the design input uncertainties and the uncertainties due to the asynchronous behaviors of multiple spaces. *In the third step*, an "optimizer" determines the optimal component capacities by evaluating the overall system performance with various trials of component capacities within their search ranges. The purpose of this step is to find the optimal sizes for air-conditioning components based on the probabilistic cooling load profiles. A system energy model (Eq. 4), which is a function of dynamic cooling demands of zones (D_{sen}, D_{lat}), is used to estimate the energy consumption (E_{tot}) of the systems adopting a selected optimal ventilation control strategy (e.g. adaptive full-range decoupled ventilation strategy) [31]. Here COP_c and COP_{he} are the overall coefficients of performance for the central cooling and heating systems, respectively. In this paper, for the central cooling system, the overall coefficient of performance of the central cooling system (*COPc)* including the pumps and the chiller is assumed to be constant as 2.5 when calculating the overall electricity use [33][34]. COP of the heating system (*COPhe*) is assumed to be constant as 1.0 due to the heating energy is provided by the electric heaters. $W_{f,MAU}$ and $W_{f,AHU}$ are the fan powers of the MAU and AHUs, respectively. $Q_{cc,MAU}$ and $Q_{cc,AHU}$ are the MAU and AHU cooling loads, respectively. $Q_{he,AHU}$ is the AHU heating load. The detailed optimization process is shown in Fig. 2 and elaborated as follows.

$$C_{OT,a} = (C_{C,a} + C_{M,a} + C_{O,a}) + C_{P,a} \tag{1}$$

$$D_{sen} = Z_{sen} * \beta_{d,sen} \tag{2}$$

$$D_{lat} = Z_{lat} * \beta_{d,lat} \tag{3}$$

$$E_{tot} = \frac{Q_{cc,MAU}}{COP_c} + W_{f,MAU} + \sum_{i=1}^{k}\left(\frac{Q_{cc,AHU,i}}{COP_c} + \frac{Q_{he,AHU,i}}{COP_{he}} + W_{f,AHU,i}\right) = f(D_{sen,i}, D_{lat,i}) \tag{4}$$

For the retrofitting of existing buildings, the improper sizing problems can be easily addressed through the analysis of the operation data. However, for new buildings in the design phase, various inherent uncertainties exist which need to be considered for accurate load estimations. With the probabilistic estimates of cooling load distributions, the air-conditioning components are of higher probability to be properly designed, to avoid both under-sizing and over-sizing problems. Compared to current engineering practice involving detailed design calculation [19][20][35], no additional information is required at the design stage except the information or assumption on the load diversities among multiple zones/spaces. In the design stage, the model inputs required for design include the space control requirements, building layout, envelop parameters, historical weather, internal load conditions and possible distributions of concerned parameters, which are all the same as needed in current design practice when detailed design calculation is conducted. The users can obtain the information from the planning guide, local standards and regulations. However, for the multi-zone air-conditioning systems, each zone may contain several spaces. If the uncertainties in spaces were all considered individually, the calculation process would be very complicated. Therefore, to consider the effects of asynchronous loads in different zones/spaces with reduced computation demand, a probabilistic diversity factor method is proposed, which offers a simplified method to quantify the effects of uncertainties of space load diversities in multiple zones/spaces using diversity factors. More detailed descriptions are shown in Section 2.2 and 2.3.

2.2 Qualification of design input uncertainties in zone cooling load calculation

The uncertainties in design inputs are quantified by adopting the commonly-used Monte Carlo method [36][37]. Based on inputs ($x_1, x_2, \ldots, x_n$), the outputs Q (i.e., sensible/latent cooling loads of a space) are obtained as Eq. 5. The design inputs involving uncertainties (X) are generated by Monte Carlo simulation as Eq. 7, according to their probability distributions (G). The probabilistic cooling loads of a zone (Z), which are usually regarded as the sum of the cooling loads of the corresponding spaces, are then obtained using building energy simulation software.

$$Q = [q_1, q_2, \ldots, q_{8760}] = f(x_1, x_2, \ldots, x_n) \tag{5}$$

$$X = [X_1, X_2, \ldots, X_n] \tag{6}$$

$$X_i = [x_{j1}, x_{j2}, \ldots, x_{jm}]^T, X_i \sim G_i \;\; | \; j = 1,2, \ldots, n \tag{7}$$

$$Z = [Q_1, Q_2, \ldots, Q_m]^T = f(X_1, X_2, \ldots X_n) \tag{8}$$

Three groups of variables X, including outdoor weather, building construction and indoor conditions, are selected and quantified as the design inputs. For the outdoor weather, historical measurements of weather data in 38 years (i.e., 1979–2016) are used, which is proved to be a better way to account for the weather uncertainties [20]. For other variables, triangular distributions, normal distributions and uniform distributions are used respectively according to the characteristics of their variations. Latin Hypercube Sampling (LHS) method is used to improve the calculation efficiency [38]. By importing the samples into the cooling load calculation software, both the sensible and latent cooling load of the multiple spaces can be obtained.

2.3 Qualification of multi-space diversity effects concerning uncertainties

As a major task and challenge, the diversities of sensible and latent cooling loads of the multiple spaces in a zone are quantified to take their effects and uncertainties into account. To reduce the computation complexity, a probabilistic diversity factor method is proposed, which is a simplified method to quantify uncertain space load diversities by introducing two probabilistic diversity factors

($\beta_{d,sen}$, $\beta_{d,lat}$) for sensible and latent loads respectively. These diversity factors are defined as the ratio of actual sensible (or latent) cooling demand (due to the need for over-cooling) to the sum of the cooling loads of all spaces concerned (Eqs. 9-10). Probabilistic diversity factors are introduced to quantify the load diversity effects of multiple spaces under possible load profiles in a zone. Here AHU supply air temperature (t_s) and humidity (w_s) of a zone are determined according to the air state of the critical space (associated to the zone) in each time step (Eqs. 11-12). m_s is the supply airflow rate (kg/m^3). t_{space} is the actual space temperature (°*C*). t_{set} is the space temperature set-point (°*C*). w_{space} is the actual space humidity (kg/kg). w_{set} is the space humidity set-point (kg/kg). k is the number of a space in a zone. $Q_{sen,k}$ *and* $Q_{lat,k}$ *are* the sensible and latent cooling load of space k (*kW*), respectively. c_p is the air specific heat ratio (*kJ/(m^3•°C)*). h_{fg} is the latent heat of vaporization (*kJ/kg*).

$$\beta_{d,sen} = \frac{\sum m_{s,k}(t_{space,k} - t_s)}{\sum m_{s,k}(t_{set,k} - t_s)} = f_1(Q_{sen,k}) \quad | \ k = 1,2, \ldots, m \tag{9}$$

$$\beta_{d,lat} = \frac{\sum m_{s,k}(w_s - w_k)}{\sum m_{s,k}(w_s - w_{set,k})} = f_2(Q_{sen,k}, Q_{lat,k}) \quad | \ k = 1,2, \ldots, m \tag{10}$$

$$t_s = min\left(t_{space,k} - \frac{Q_{sen,k}}{c_p m_{s,k}}\right) \quad | \ k = 1,2, \ldots, m \tag{11}$$

$$w_s = min\left(w_{space,k} - \frac{Q_{lat,k}}{h_{fg} G_{s,k}}\right) \ | \ k = 1,2, \ldots, m \tag{12}$$

Both diversities and their probability distributions considering uncertainties among different spaces in a zone will be identified according to the main steps using the probabilistic diversity factor method shown in Fig. 3. Based on the sensible and latent cooling load profiles of multiple spaces (i.e., the uncertain load data generated by Monte Carlo simulation in this study) and design constraints, the parameters of two diversity factor models are identified by the "model identification" scheme involving four steps as follows. *In the first step*, the diversity factors of both sensible and latent loads (SLDF/LLDF) are calculated based on the individual space loads as shown in Eqs. 9-10. *In the second step*, the diversity factors are classified into different clusters using the k-means clustering algorithm [39]. *In the third step*, the correlations between the diversity factors and working conditions are identified using the decision-tree method [40], which is one of the most commonly-used data mining approaches. *In the fourth step*, the probability distributions of two diversity factors in each cluster are quantified by fitting the data using typical distribution functions. The detailed approaches for the qualification of load diversities of multiple spaces in a zone considering uncertainties are elaborated as follows.

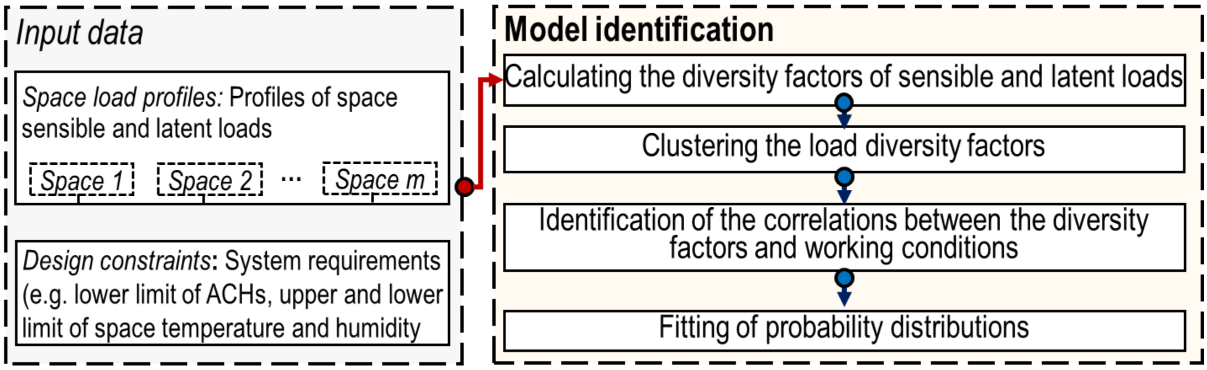

Fig. 3. The main steps of the proposed probabilistic diversity factor method

2.3.1 Clustering the load diversity factors

The task of this step is to categorize the data of the load diversity factors into proper clusters/subgroups, according to their magnitude and pattern. The k-means algorithm [39] is employed to ensure: (i) instances in the same cluster have high similarity and, (ii) instances in different clusters have low similarities. In the clustering process, the dissimilarity of the diversity factors is evaluated using the Euclidean distance [41] and the optimal number of clusters is evaluated by the Calinski-Harabasz (C-H) criterion [42].

2.3.2 Identification of the correlations between the diversity factors and working conditions

The task of this step is to create a decision tree model that predicts the value of *target variables* based on *predicted variable*s of the dataset. The target variables of the decision tree are the number of a cluster (i.e., Cluster 1, 2, …, n), which are identified in Section 2.3.1. The predicted variables are the weather and internal load conditions, including the mean outdoor air temperature (T_{avg}), humidity (W_{avg}) and sensible heat ratio (SHR_{sum}) during the operating period (i.e., 9:00-18:00) of a day. Here SHR_{sum} is the ratio of the total sensible cooling load to the total cooling loads of all spaces associated to an AHU, as shown in Eq. 13.

$$SHR_{sum} = \frac{\sum_{k=1}^{m} Q_{sen,k}}{\sum_{k=1}^{m} Q_{tot,k}} \tag{13}$$

The dataset (including predicted variables and target variables) is automatically and randomly split into two subsets, marked as "training set" (i.e., 3/5 of total data) and "testing set" (i.e., 2/5 of total data). The standard classification and regression trees (CART) algorithm [43] is employed to generate the decision tree using the training set. The decision tree is validated by cross-validation (using the test set) to estimate the statistical performance of the classification.

2.3.3 Fitting of the probability distribution for clusters

The task of this step is to fit the probability distributions for each cluster. For each cluster, the probability distributions of diversity factors (in each hour) are firstly fitted using four commonly-used probability density functions (PDFs): i.e., Normal distribution, Gamma distribution, Weibull distribution and Lognormal distribution [44]. The detailed functions can be found in Table A.1. The parameters defining these four PDFs are estimated based on the commonly-used the maximum likelihood method 45] while the Kolmogorov-Smirnov (K-S) test is introduced as the error metric to evaluate the fitness of each PDF [46]. The minimum K-S error of the four distributions is then selected as the target distribution function. Here 'K-S error' is the maximum absolute difference between the CDFs of the distributions of the two data vectors, as shown in Eq. 14.

$$K - S\ error = max\ (|\hat{F}_1(x) - \hat{F}_2(x)|) \tag{14}$$

2.4 Design optimization of air-conditioning systems adopting ADV strategy

Four energy models are developed in a preliminary study [31] to estimate the energy performance of the air-conditioning systems under different load and weather conditions, which have the configuration as shown in Fig.1 and are controlled ideally by the ventilation strategies concerned respectively. Optimal design of the system for implementing the "adaptive full-range decoupled ventilation strategy" (ADV strategy) is the focus of this study compared with that of the other three ventilation strategies. The ADV strategy is a recommended ventilation strategy for cleanrooms, which takes the interaction among different air-conditioning components/zones into account and provides systems with the robustness to operate at high energy efficiency under ever-changing dynamic working conditions. A Genetic Algorithm (GA) [47] is used to minimize the overall annualized total cost ($C_{OT,a}$) (i.e., the objective function: Eq.1). The capital cost (C_C) includes the investment (C_I) and installation cost (assumed as 30% of the investment cost as shown in Eq. 15 [48]). The investment cost (C_I) includes the costs of major components, such as fans, ducts, cooling coils, heaters, economizer, etc. The unit price of air-conditioning components in this study are presented in Appendix B. The annualized maintenance cost ($C_{M,a}$, Eq.16) is assumed as 20% of the annualized capital cost [49]. The operation or energy cost (annualized as shown in Eq.17) includes the cost of electricity consumed by the cooling/heating equipment and fans, calculated according to the air-handling processes of the selected ventilation strategy. The electricity cost is calculated using the local electricity price in Hong Kong, which takes the average price of 0.141 USD/kWh [50]. The penalty cost (C_P) is introduced as a "virtual expense" to quantify the service quality dissatisfaction due to insufficient cooling or heating capacity. It is quantified by the accumulation of unmet demand multiplied by a penalty price ($£_{pen}$) (Eq. 19), where *CRF* is the capital recovery factor, the weighting factor for calculating the present value of an annuity (a series of equal annual cash flows, Eq. 20). i' is the real discount rate (Eq. 21) accounting for the general inflation rate (i_g) and the discount rate (i_d). i'' is the effective discount rate adjusted for energy inflation (Eq. 22) accounting for the general inflation rate (i_g) and the energy inflation rate (i_e). i_d, i_g and i_e are set as typical values of 8%, 4% and 5% respectively [51]. *N* is the lifetime of air-conditioning systems, which is set as 20 years.

$$C_{C,a} = C_C \cdot CRF(i', N) = C_I(1 + 30\%) \cdot CRF(i', N) \tag{15}$$

$$C_{M,a} = C_{C,a} \cdot 20\% \tag{16}$$

$$C_{O,a} = C_O \cdot [\frac{CRF(i',N)}{CRF(i'',N)}] \tag{17}$$

$$C_{P,a} = C_P \cdot [\frac{CRF(i',N)}{CRF(i'',N)}] \tag{18}$$

$$C_P = £_{pen} \cdot \sum_{j=1}^{8760} max(0, D_{emand}(j) - C_{apacity}) \tag{19}$$

$$CRF(rate, year) = \frac{rate \cdot (1+rate)^{year}}{(1+rate)^{year}-1} \tag{20}$$

$$i' = \frac{i_d - i_g}{1+i_g} \tag{21}$$

$$i'' = \frac{i_d - i_e}{1+i_e} \tag{22}$$

2.4.1 An outline of the mechanisms and applications of ventilation strategies concerned

The preferred ADV strategy overcomes the limitations of the existing ventilation strategies, such as interactive control (IC), dedicated outdoor air ventilation (DV) and partially decoupled control (PD) [31]. The mechanisms and applications of all ventilation strategies concerned (including three other typical ventilation strategies for comparison) are highlighted in Table 1. The ADV strategy minimizes system energy consumption by avoiding sub-cooling and reheating as far as beneficial via the best use of MAU and economizer for cooling and dehumidification. As the ADV strategy offers superior energy performance compared with other strategies, the study focuses on the optimal design of the air-conditioning systems for implementing this strategy. In fact, the optimal design method concerning uncertainties is the same for the design of the air-conditioning system to adopt other ventilation strategies.

Table 1 Mechanisms and descriptions of four ventilation strategies [31]

Operational strategy	Mechanism	Description	Limitations/challenges
Interactive control (IC) [27][28]	Cooling (or sub-cooling) and reheating processes are adopted to eliminate the coupling between temperature and humidity control loops.	Outdoor air is treated to be close to the indoor enthalpy. Outdoor airflow is always set at the minimum.	Simultaneous cooling and reheating
Dedicated outdoor air ventilation (DV) [9][29]	MAU handles all the latent heat and part of space sensible heat while the AHUs remove the rest of space sensible heat.	Outdoor air is treated below the indoor air dew-point. Outdoor airflow can be set higher than the minimum.	High ventilation energy demand
Partially decoupled control (PD) [4]	MAU handles all the latent heat and part of space sensible heat while the AHUs remove the rest of space sensible heat under low internal load condition.	Outdoor air is treated below the indoor air dew-point. Outdoor airflow is always set at the minimum.	Simultaneous cooling and reheating under high internal latent load
Adaptive full-range decoupled ventilation [31]	The best operation mode is identified by comparing the energy performance of different control modes.	Outdoor air temperature and flowrate are reset according to the identified optimal operation mode.	Higher demands on system design and control

2.4.2 Procedure and main steps of optimization

Different from the ventilation strategies applied in general buildings, such as office buildings and commercial buildings, the ADV strategy is applicable for cleanrooms or spaces requiring strict humidity/temperature controls, such as pharmaceutical cleanrooms, semiconductor/microchip factories and hospitals. The key issue of the ADV strategy is to identify the optimal operation mode under different weather and internal load conditions. At the design stage, the optimal operation mode when adopting the ADV strategy can be identified based on the information of possible building cooling load profiles and weather conditions. For the design optimization of the air-conditioning systems facilitating the ADV strategy, an overall trade-off between the satisfaction of service and system costs is made as shown in Fig. 4. With the decrease of service satisfaction (or component capacities), the operation (energy) cost increases first due to the limited choice of operation modes (from optimum to suboptimum) and then decreases due to the insufficient capacities (i.e., under-provision). The overall total cost decreases first and then increases after it reaches the minimum at point "O", which is the target point indicating the optimal capacity. Since the performance robustness of air-conditioning systems is the main concern in the design of cleanrooms, a higher penalty price (i.e., greatly larger than local electricity price in Eq.19) is usually set to avoid insufficient air-conditioning component capacities. When the component capacities are relatively small (i.e., insufficient cooling/heating capacities), the penalty cost can be higher than the operation cost. The decrease in the total cost is mainly due to the decrease in the penalty cost. In contrast, when the component capacities become larger, the required cooling loads of MAU/AHU can be met at most of the operation period, and the penalty cost can be close to zero. The ADV strategy provides various operation modes and, in operation, the most economic mode will be selected in a particular working condition. The ADV strategy has lowest operation cost and superior energy performance compared with that of adopting other three existing ventilation strategies (i.e., IC, PD and DV) as presented by the previous research of the authors [31]. The optimal design method minimizes the overall annualized total life-cycle cost and therefore makes a proper compromise between the satisfaction of service and system life-cycle costs.

The method and procedure to estimate the penalty cost due to insufficient capacity are shown in Fig.5. The actually available choices of operation modes in a particular load/weather condition are subject to the provision of sufficient capacities of all components needed for the operation modes concerned. At each time step of performance evaluation, for the trial component capacities given by the optimizer, the feasibilities of utilizing optimal/suboptimal operation modes are assessed by verifying whether the required component capacities are satisfied and the best available mode is chosen as the actual operation mode. If required component capacities of all operation modes cannot be satisfied, the system fails to provide satisfactory performance, a penalty cost (C_p) would be given (that hour is also called as 'unmet hour' (Uh)). Due to the different control modes provided by the ADV strategy, the ADV strategy can choose the optimal mode that can satisfy the control requirements under the given capacities of air-conditioning components and working conditions. This indicates the ADV strategy can offer superior service satisfaction (less unmet hour) due to the operation mode switching compared with other ventilation strategies.

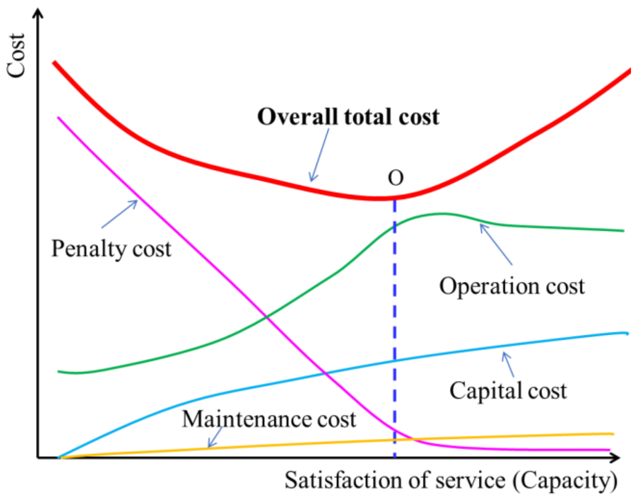

Fig. 4. Cost vs. capacity of air-conditioning systems facilitating ADV strategy

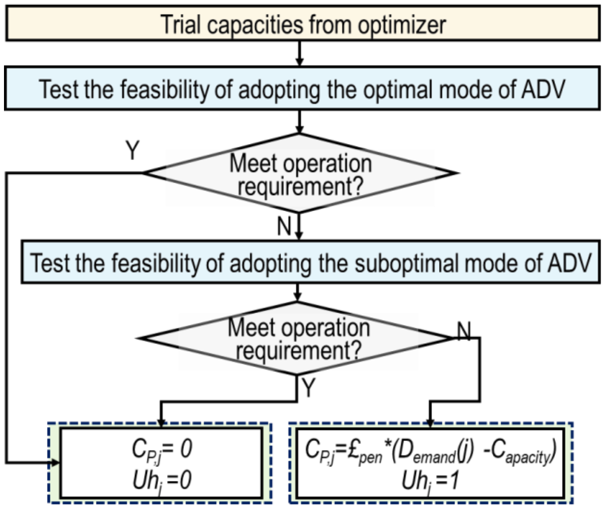

Fig. 5. The procedure to estimate the penalty cost /unmet hour facilitating ADV strategy

3. Building, air-conditioning system and energy models for design case study

3.1 Building/system description and load characteristics

A pharmaceutical factory building located in Tai Po district of Hong Kong is selected to demonstrate the use of the probabilistic optimal design method. It has five floors and the total cleanroom area is about 3620 m^2. All the production areas are designed as Class ISO 8 cleanrooms [32]. For the cleanrooms concerned, the configuration of a typical cleanroom air-conditioning sub-system is selected as shown in Table 2. In this sub-system, a MAU serves 3 AHUs, and each AHU serves several cleanrooms at 2nd floor with constant air flowrate (i.e., 20ACH). The system configuration of the selected system is similar to Fig. 1, while the difference is that the humidifier is not adopted due to the humid weather conditions in Hong Kong.

Table 2 Cleanroom subsystem configuration and control requirements

Floor area of the served zones	Zone 1: Total 100.5 m^2 (9 spaces served by AHU-1) Zone 2: Total 121 m^2 (8 spaces served by AHU-2) Zone 3: Total 151 m^2 (8 spaces served by AHU-3)	
Height of the served zones	2.8 m	
Operating period	9:00-18:00	
Installed fans specification	MAU fan (centrifugal) pressure (Pa)	1600
	AHU fan (axial) pressure (Pa)	1350
	Fan efficiency (%)	60
The overall coefficient of performance (COP) of systems	Cooling system (central cooling)	2.5 (constant)
	Heating system (electric heater)	1.0 (constant)
Space control requirements [32, 52, 53]	Temperature (°C)	20±3
	Relative Humidity (%)	55±10
	Supply airflow rate (ACH)	≥20
	Outdoor airflow rate (ACH)	≥2

TRNSYS 18 [54] is used to calculate the probabilistic sensible and latent cooling loads of the selected multi-zone cleanroom systems concerning weather, building and internal load uncertainties. Totally 950 (38×25) sets of samples are used to obtain the uncertain sensible and latent cooling loads for spaces in each zone. The weather uncertainty is introduced by using historical weather data of 38 years (1979 to 2016) instead of one typical year. Building parameter and internal load uncertainties are introduced by randomly sampling according to their distributions. Eventually, 25 sets of their samples are selected. The weather, building and load parameters and their uncertainties are shown in Table 3. It is worth noting that, the outdoor weather and building parameters are sampled and set as the same for all the spaces associated to a zone, while the internal loads are sampled independently for different spaces concerning their asynchronous behaviors.

Table 3 Weather, building and load parameters and their uncertainties for cooling load calculation

Group	Parameter	Uncertainty analysis	
		Distribution	Values
Outdoor weather	Outdoor dry-bulb air temperature (°C) Outdoor air relative Humidity (%) Global radiation (W/m^2) Diffuse radiation (W/m^2)	Actual data: 1979–2016	
Building parameter	Internal shading coefficient	Normal	$(0.5, 0.1^2)$
	External shading coefficient	Normal	$(0.2, 0.05^2)$
	Conductivity of window ($W/(m^2 \cdot K)$)	Uniform	(1.5,3)
Indoor condition	Occupant density (m^2/person)	Triangular	10*triangular (0.3, 1.2, 0.9)
	Lighting density (W/m^2)	Triangular	14*triangular (0.3,1.2, 0.9)
	Process sensible load (W/m^2)	Relative normal	45* normal $(1,0.06^2)$
	Process latent load (W/m^2)	Relative normal	15* normal $(1,0.06^2)$

Fig. 6 shows the cumulative distribution functions (CDFs) of space/zone loads served by three AHUs. Although the spaces in a zone have similar functions, the cooling load profiles are different. The cooling load (W/m^2) of a zone is the weighted average of the cooling loads of spaces in this zone. It can also be seen that the peak cooling load of a zone has a high probability to be lower than that of the simple sum of peak loads of individual spaces. In the air-conditioning design, the actual cooling/heating demands of the components (serve for a zone) are significantly influenced by the cooling load of the critical space particularly when both temperature and humidity are controlled. It is especially great for the cleanroom air-conditioning systems which have very high air flow rates and employ CAV systems [23]. This indicates if the total sensible and latent cooling loads of a zone are directly used for sizing the components, the systems are of high possibility to be undersized significantly. It confirms that the load diversity effects of multiple spaces should be taken into account in the system design.

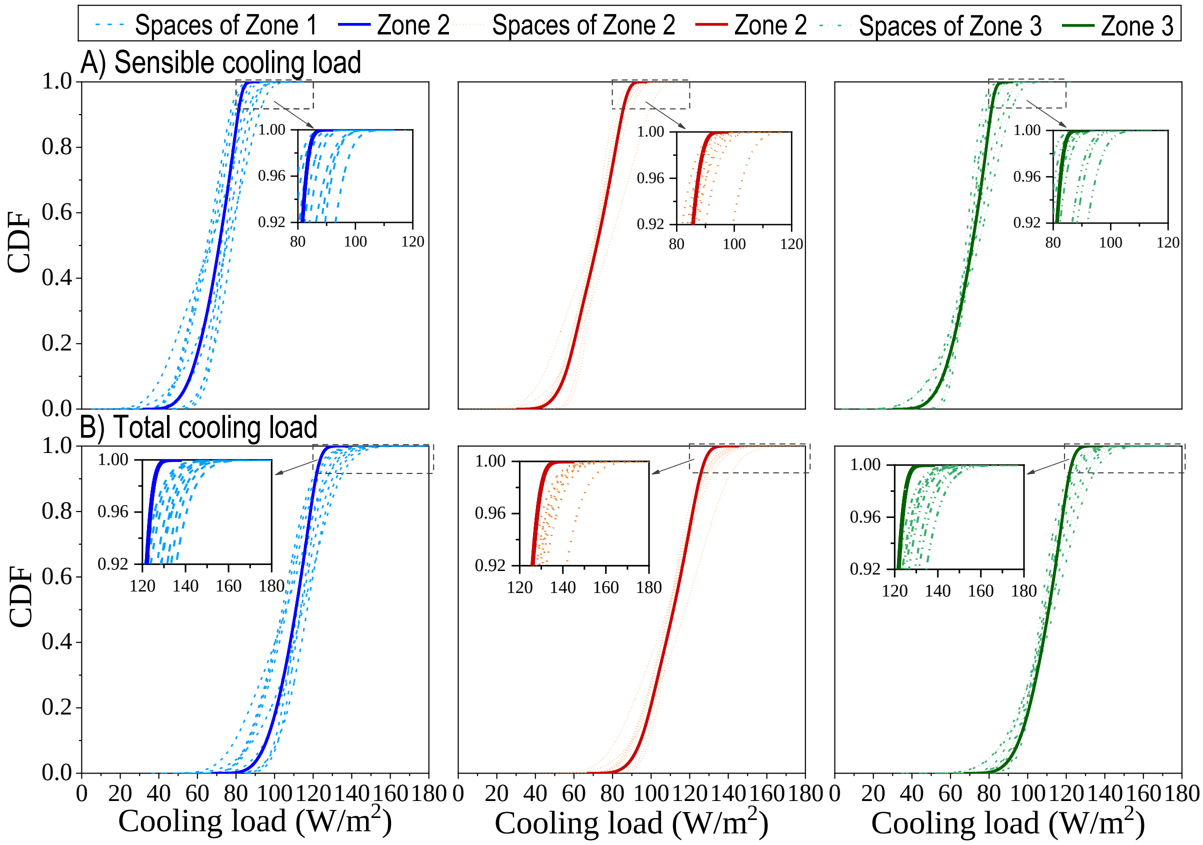

Fig. 6. Distribution of cooling loads in multiple spaces/zones

3.2 Air-conditioning subsystem energy models

As mentioned in Section 2, the thermal loads of the all air-side components are converted into the electrical load for the convenience of operation cost calculation, which are the functions of dynamic cooling demands of zones (D_{sen}, D_{lat}). The total electrical load can be calculated using Eq. 4, which includes the (equivalent) electrical load of the MAU/AHU cooling coils, AHU heaters, make-up air fan and supply air fans. Several simplified models are used to evaluate the electrical loads of these components shown as follows.

Fan model: The fan power of MAU/AHU fans is characterized by their volumetric flow rate, pressure rise and efficiency, as shown in Eq. 23. Here W_f is the total fan power (kW). V is the air volumetric flow rate (m^3/s). Δp is the total pressure rise (kPa). η_f is fan efficiency.

$$W_f = \frac{V\Delta p}{\eta_f} \tag{23}$$

System energy balance model: With the quantification of the cooling demands of zones, the supply air state of each zone is calculated using Eqs. 24-25. The cooling loads of the air-conditioning components are then determined based on the energy and mass balances, to process the air to the required supply air state. The equivalent electrical loads of cooling coils (Q_{cc}) and heaters (Q_{he}) are calculated according to their inlet and outlet air states and the cooling/heating system overall COPs using Eqs. 26-28. Here m_{fh} and m_s are the outdoor air mass flowrate (*kg/s*) and AHU supply air mass flowrate (*kg/s*), respectively. h_{in} and h_{out} are the enthalpy of the inlet and outlet air, respectively (*kJ/kg*). It is worth noting that the air flowrates and inlet/outlet air states at each time step are determined according to the air-handling processes of the adopted ventilation strategy as presented in Ref. [31].

$$t_s = t_{set} - \frac{D_{sen}}{m_s c_p} \tag{24}$$

$$w_s = w_{set} - \frac{D_{lat}}{m_s h_{fg}} \tag{25}$$

$$Q_{cc,MAU} = \frac{Q_{cc,MAU}}{COP_c} = \frac{m_{fh}(h_{out,cc,MAU} - h_{in,cc,MAU})}{COP_c} \tag{26}$$

$$Q_{cc,AHU} = \frac{Q_{cc,AHU}}{COP_c} = \frac{m_s(h_{out,cc,AHU} - h_{in,cc,AHU})}{COP_c} \tag{27}$$

$$Q_{he} = \frac{Q_{he}}{COP_{he}} = \frac{m_s(h_{out,he,AHU} - h_{in,he,AHU})}{COP_{he}} \tag{28}$$

4. The design case study, results and analysis

4.1 Training and validation of diversity factor models

In this study, the datasets (e.g. weather, sensible load ratio and space loads) of Zone 1 are used to quantify the diversity factors and train the diversity factor models, while the datasets of Zone 2 and Zone 3 are used to validate the models.

4.1.1 Model training

Clustering the load diversity factors: Fig. 7 shows the distributions of space load diversity factors of Zone 1 calculated by Eqs. 9-12, by fully considering constraints/interaction among multiple spaces and the cooling loads of the critical space. It can be seen that estimated kernel density estimation functions well match the histograms of both the diversity factors. 95% confidence interval of sensible/latent cooling load diversity factors are in the range of [1.06, 1.38] and [1.48, 2.89], respectively. This indicates that the actual cooling demands are significantly larger than the cooling loads of the corresponding zone. Fig. 8 shows the clustering performance evaluated by the Calinski-Harabasz criterion [55] using the Statistics and Machine Learning Toolbox™ in MATLAB.

Comparing the performance of clustering solutions containing two to six clusters, both the diversity factors of sensible cooling load and latent cooling load are grouped into two clusters/subgroups. Fig. 9 shows the results of categorizing the diversity factors into an optimal number of clusters, where the blue line is the centroid curve of diversity factors in a cluster.

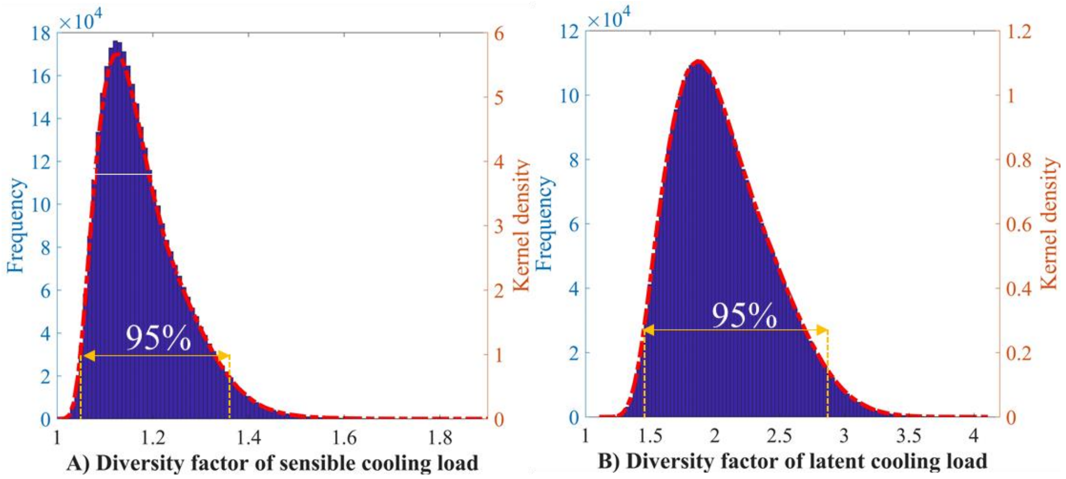

Fig. 7. Histograms and Kernel density estimation functions of diversity factors

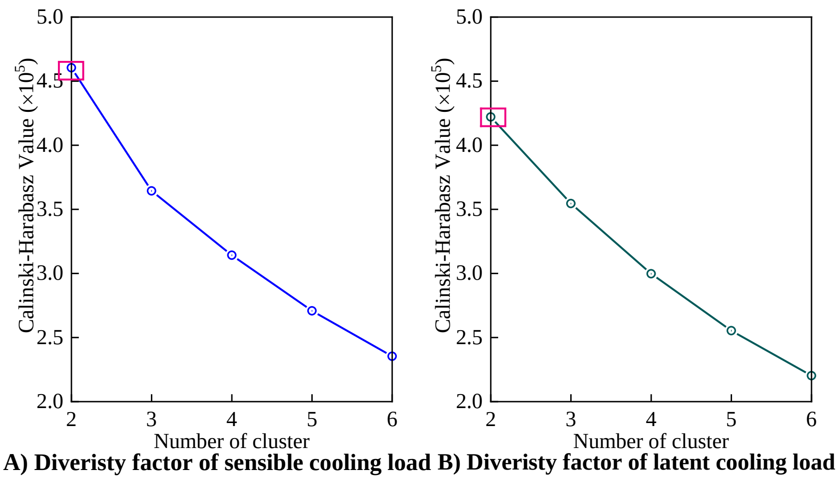

Fig. 8. Clustering performance for different numbers of clusters

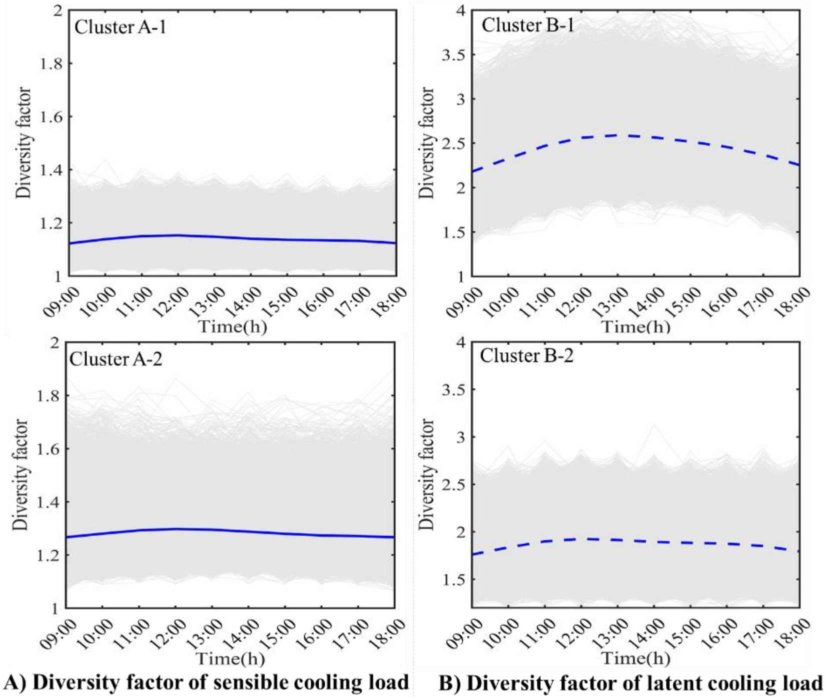

Fig. 9. Clustering results for each subgroup

<u>*Correlations between the diversity factors and working conditions*</u>: Based on predicted variables (i.e., SHR_{sum}, T_{avg} and W_{avg}), decision trees and decision rules can be utilized to predict target variables (i.e., the number of a cluster) as shown in Fig. 10. The accuracy of the decision trees should be evaluated before being applied to the datasets of other zones (i.e., Zone 2 and 3). Table 4 shows that 91.6% and 87.0% of all the training records are correctly classified for the target clusters of sensible cooling load diversity factor (SLDF) and latent cooling load diversity factor (LLDF), respectively. Accordingly, the obtained decision trees were applied to the testing sets and the results are also given in Table 4. The result shows that 91.0% and 86.0% of the testing records are correctly classified for the target clusters of SLDF and LLDF, respectively. This indicates a good accuracy of the decision tree models which can be further applied to a new dataset for classification and prediction.

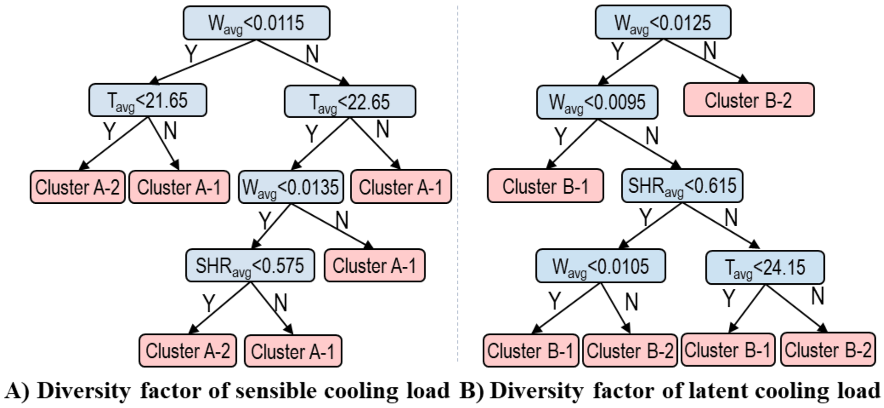

Fig. 10. Decision trees for prediction of target clusters

Table 4 Classification performance of the decision tree models

Dataset	Decision tree	Predicted cluster	Correct/total number	Accuracy
Training set	Decision tree for prediction of target clusters (SLDF)	Cluster A-1	141,919/151,046	91.6%
		Cluster A-2	48,757/57,004	
	Decision tree for prediction of target clusters (LLDF)	Cluster B-1	52,630/62,913	87.0%
		Cluster B-2	138,046/145,137	
Testing set	Decision tree for prediction of target clusters (SLDF)	Cluster A-1	111,783/119,762	91.0%
		Cluster A-2	35,737/42,325	
	Decision tree for prediction of target clusters (LLDF)	Cluster B-1	38,885/47,822	86.0%
		Cluster B-2	108,635/114,265	

The probability distribution for clusters/subgroups: The diversity factor in each cluster is then used to fit the probability distributions using the four alternative PDFs listed in Table A.1. By selecting the distributions with the minimum K-S error, the fitted PDFs and the identified parameter values of the diversity factors are listed in Table 5.

Table 5 Identified probability distribution functions and parameter values for the fitted probability density functions of the diversity factors

Time	Cluster A-1	Cluster A-2	Cluster B-1	Cluster B-2
	Distribution (Parameter)	Distribution (Parameter)	Distribution (Parameter)	Distribution (Parameter)
9:00	Logn (0.11,0.040)	Logn (0.23, 0.062)	Logn (0.77, 0.126)	Logn (0.56 0.114)
10:00	Logn (0.13,0.043)	Logn (0.25, 0.058)	Logn (0.84, 0.116)	Gam (69.55, 0.026)
11:00	Gam (497.7, 0.002)	Logn (0.25, 0.056)	Logn (0.90, 0.114)	Norm (1.92, 0.246)
12:00	Logn (0.14, 0.045)	Logn (0.26, 0.054)	Logn (0.93, 0.113)	Gam (60.67, 0.032)
13:00	Logn (0.14, 0.044)	Gam (359.1, 0.004)	Logn (0.95, 0.111)	Gam (62.79, 0.032)
14:00	Gam (561.9, 0.002)	Logn (0.25, 0.052)	Logn (0.94, 0.108)	Gam (62.79, 0.030)
15:00	Logn (0.13,0.040)	Logn (0.25, 0.052)	Logn (0.92, 0.105)	Gam (65.82, 0.029)
16:00	Logn (0.13,0.039)	Gam (358.5, 0.004)	Logn (0.89, 0.103)	Gam (68.79, 0.027)
17:00	Logn (0.12,0.039)	Logn (0.24, 0.055)	Logn (0.86, 0.110)	Gam (71.67, 0.026)
18:00	Logn (0.12,0.039)	Logn (0.23, 0.059)	Logn (0.80, 0.126)	Logn (0.58 0.119)

* Note: Logn, Gam, Norm represent Lognormal, Gamma and Normal distribution, respectively.

4.1.2 Model validation

The diversity factor models are validated using the datasets of Zones 2 and 3 (i.e., served by AHU-2 and AHU-3 respectively). Fig. 11 shows the CDFs of cooling loads and demands of the two zones. The predicted cooling demands refer to the cooling demands calculated using the proposed probabilistic diversity factor method. The actual cooling demands refer to the cooling demands calculated by Eqs. 9-12 when fully considering constraints/interaction among multiple spaces and the cooling loads of the critical space. It can be seen that the distributions of cooling demands of these two zones are very close, while the values of the cooling demands are significantly larger than that of the cooling loads. The index of agreement (*d*) [56] is used to evaluate the similarity of the predicted and actual cooling demands, as shown in Eq. 29. The range of *d* lies between 0 and 1, with higher values signifying good fit between the model and data. Here *A* and *P* are the actual and predicted values respectively, sorted in ascending order. The actual average value of the cooling demand is denoted by $\bar{A}$.

$$d = 1 - \frac{\sum_{i=1}^{n}(A_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{A}| + |A_i - \bar{A}|)^2} \tag{29}$$

By calculating the index of agreement of predicted and actual sensible/latent cooling demands, it is found that the four indexes of cooling demands of two zones (also shown in Fig. 11) are all higher than 0.95. This confirms that the proposed probabilistic diversity factor method is deemed satisfactory, which can be used to effectively quantify the diversity effects of multiple spaces.

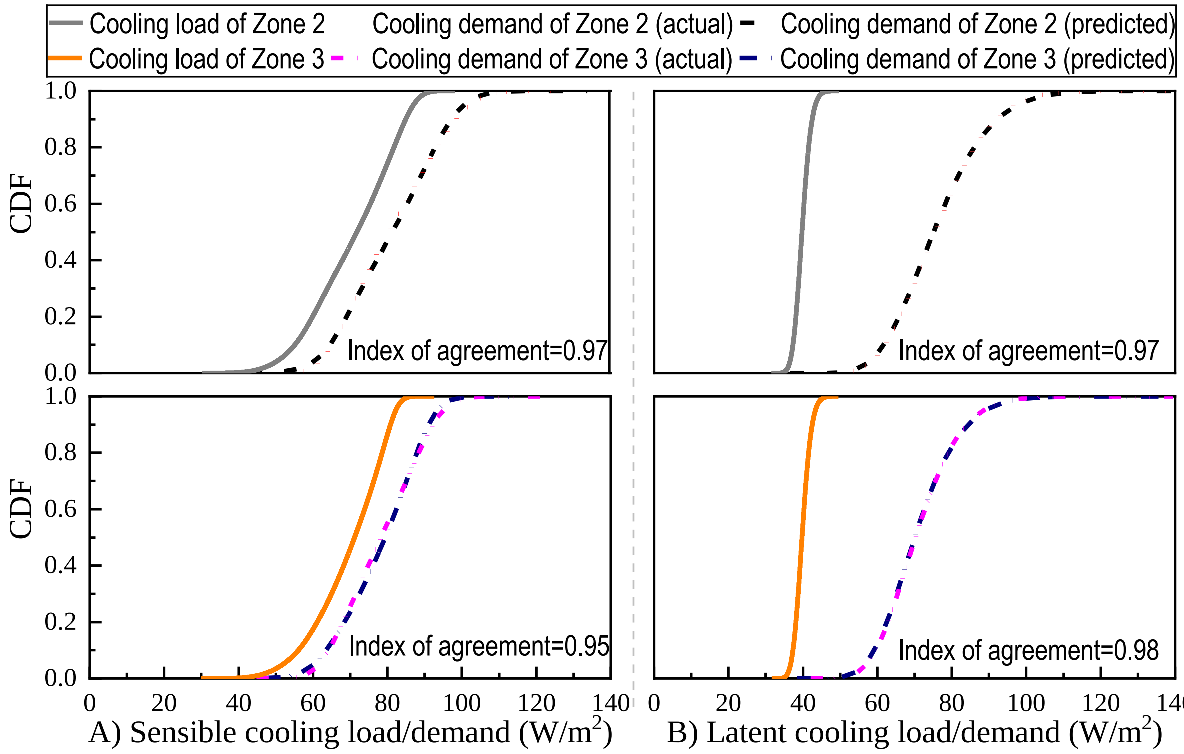

Fig. 11. The cumulative distribution functions (CDFs) of cooling loads and cooling demands

4.2 Performance of air-conditioning systems designed for different ventilation strategies

Referring the actual sizes of the air-conditioning systems and the actual energy consumption of the building, the search ranges for the cooling coil of MAU, the cooling coils of AHUs, the electric heaters of AHUs, and design outdoor air flowrate for different ventilation strategies are set between [0, 300] kW, [0,100] kW, [0, 50] kW and [0.58, 5.80] m^3/s, respectively.

As introduced in Section 2, the penalty price affects the design objective. Before a sensitivity study of the penalty price is conducted, the optimization based on a penalty price of 1.41 USD/kWh (i.e., penalty price ratio equals 10) is conducted first and the results are shown in Fig. 12. Here the "penalty price ratio" (γ_{pen}) is defined as a ratio of penalty price ($£_{pen}$) to the local electricity price ($£_{ele}$) as shown in Eq. 30.

$$\gamma_{pen} = \frac{£_{pen}}{£_{ele}} \tag{30}$$

Fig. 12(A) presents the required cooling/heating capacities of the air-conditioning system adopting four different ventilation strategies (ADV, DV, PD and IC). In general, the capacities of components adopting ADV strategy are in-between that of the other three ventilation strategies. The DV strategy requires the highest cooling capacity of MAU, which can be 2.4, 5.8 and 8.9 times that of the ADV, PD and IC strategy, respectively. The PD strategy requires the highest heating capacities while the IC strategy requires the highest cooling capacities of all three AHUs. Fig. 12 (B) shows the design outdoor air flowrate for different ventilation strategies. The IC strategy requires the largest design volume of outdoor airflow (i.e., 5.26 m^3/s or 18 ACH) due to the involving of the enthalpy-based economizer. The PD strategy requires the minimum (i.e., 0.58m^3/s or 2 ACH), while the design outdoor air flowrates for the ADV and DV strategy are 72.6% and 68.2% compared with that of IC strategy. The overall annualized mean total costs of adopting different ventilation strategies are shown in Fig. 12(C). It can be seen that the overall annualized mean total cost adopting ADV strategy is reduced by 18.2%, 13.6% and 6.5% compared with that of using the DV, PD and IC strategy respectively.

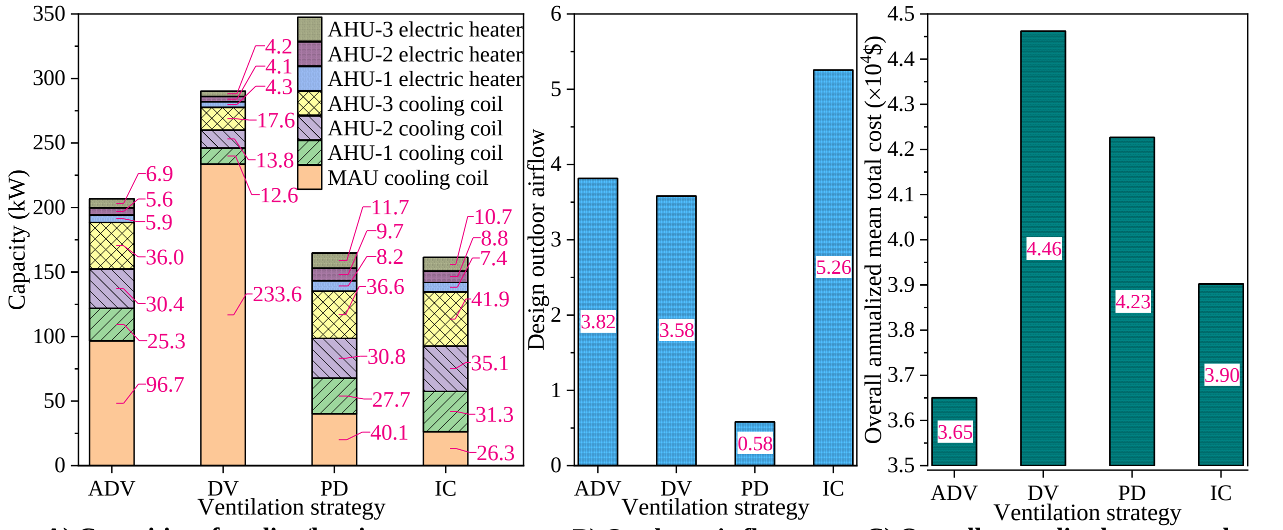

Fig. 12. Optimal air-conditioning sizes and objective value adopting different ventilation strategies

The optimal capacities of the air-conditioning system partially depend on the difference between the electricity price and the penalty price. Therefore, a sensitivity study is conducted to show the effect of the penalty price on the optimal capacities of the air-conditioning system adopting different strategies as shown in Fig. 13. It can be seen that with the increase of the penalty price ratio, the larger capacities of the components are required. However, when the penalty price ratio is larger than a certain value (i.e., 10), the capacities of air-side components adopting all ventilation strategies vary only with little difference. Under a certain penalty price ratio, the capacities of the components adopting ADV strategy are in-between that of the other three ventilation strategies.

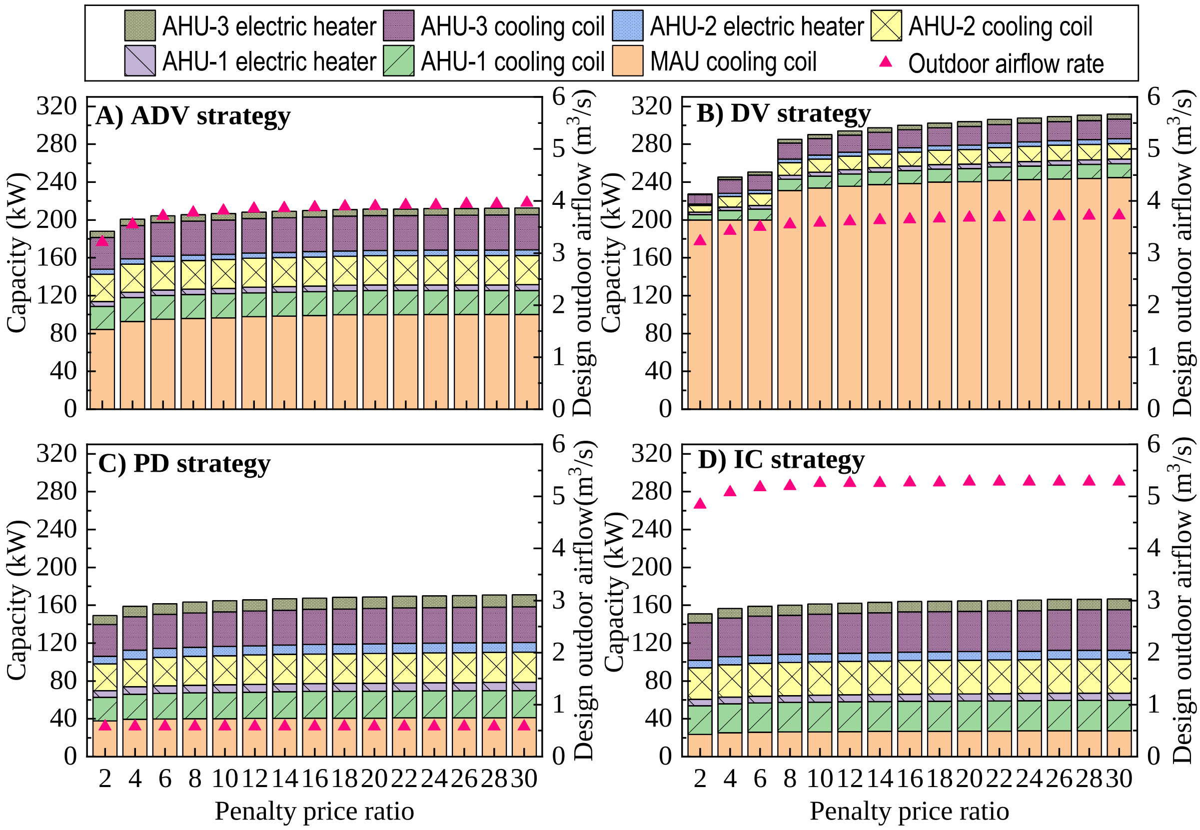

Fig. 13. Optimal sizes at different penalty price ratio adopting different ventilation strategy

In some practical cases, the number of hours when the cooling or heating capacity cannot meet the required demands (namely unmet hour) are also concerned by the designers to quantify the deficiency in the cooling or heating capacity (i.e., the dissatisfaction of service). It is worth noting that, in this study, the unmet hour is also affected by the ventilation strategy selected due to the coordination and interaction among these components/processes in different operation conditions. The overall annualized mean total cost (objective) and the corresponding annual mean unmet hour adopting the four ventilation strategies at different penalty price ratio are shown in Fig. 14. In general, the annual mean unmet hour decreases with the increase of the overall annualized mean total cost. However, both the overall annualized mean total cost and annual mean unmet hour of systems adopting ADV strategy are significantly lower than that of the other three strategies as shown in Fig. 14(A), especially for the cases with high penalty price ratios (i.e., larger than 2). This indicates the air-conditioning system, which is designed for the ADV strategy using the proposed design method, can offer superior energy and economic performance as well as the satisfaction of service (represented by the unmet hour) than other three ventilation strategies. It is also worth noting that a higher penalty price would ensure the air-conditioning system with a higher level of service satisfaction (more cooling/heating demands can be met and lower annual mean unmet hours). Under a low penalty price ratio (i.e., penalty price ratio =2), the annual mean unmet hour of the air-conditioning system adopting ADV strategy is about 468 h, slightly higher than that of adopting IC strategy (450 h), significantly lower than that adopting DV (1223 h) and PD strategies (856 h). When the penalty price ratio is larger than 10, the annual mean unmet hour is smaller than 35 h by adopting the ADV strategy, significantly lower than that associated to the other three ventilation strategies. This indicates that the penalty price ratio should be properly set especially for the cleanroom system requiring a high level of service satisfaction.

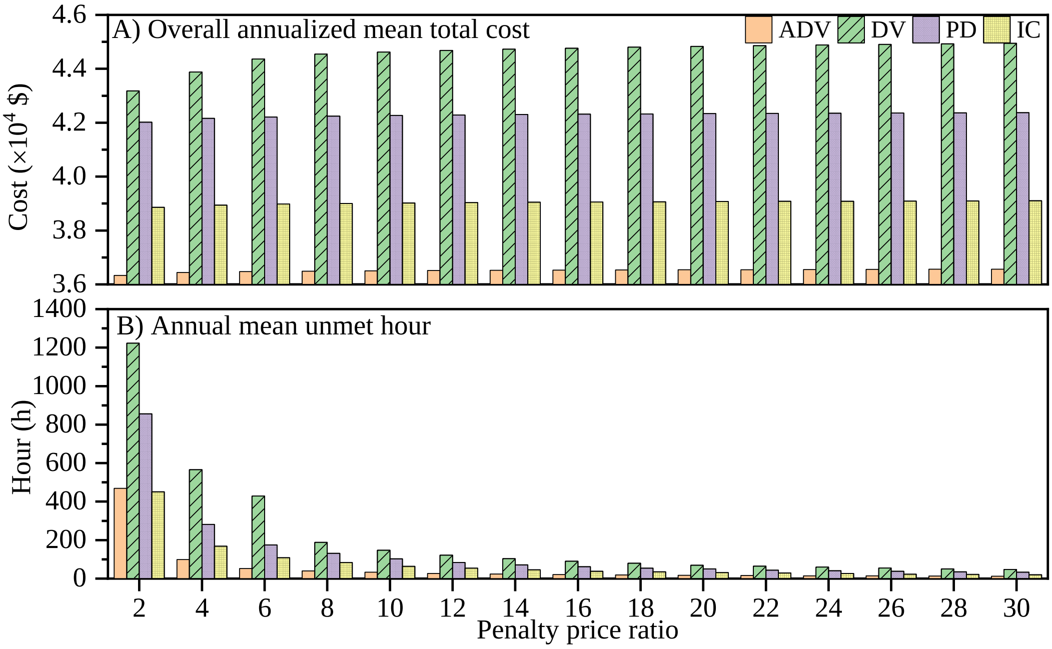

Fig. 14. Overall annualized mean total cost and annual mean unmet hour at different penalty price ratios

5. Conclusions and discussion

A probabilistic optimal design method of air-conditioning systems is developed for cleanrooms/spaces requiring strict temperature and humidity controls, which facilitates optimal ventilation control strategies to be implemented successfully under uncertainties. To consider the effects of asynchronous loads in different zones/spaces with reduced computation demand, a probabilistic diversity factor method is proposed, which is a simplified method to quantify the uncertainty of space load diversity in multiple zones/spaces using a diversity factor. The proposed design method is implemented and validated in the design optimization of air-conditioning systems for implementing four different ventilation control strategies with full consideration of possible and uncertain off-design conditions. Based on the results and analysis of a case study, detailed conclusions can be made as follows.

- The proposed probabilistic optimal design method offers optimal and energy-efficient alternatives for cleanroom air-conditioning system design, facilitating different ventilation control strategies.
- The air-conditioning system, which is designed for the "adaptive full-range decoupled ventilation strategy" (ADV strategy) using the proposed design method, offers the superior economic performance and satisfaction of service compared with systems designed for other ventilation strategies. The overall annualized mean total cost of the system designed for ADV strategy can be reduced by 18.2%, 13.6% and 6.5% compared with that of the systems designed for the DV, PD and IC strategy respectively in the selected case.
- The diverse behavior of multiple zones/spaces has significant effects on the cooling demand of components, and thus the sizing of optimal design. The design approach without considering the diverse behavior of multiple spaces will result in undersized problems for some components. It is recommended to conduct uncertainty quantification of load diversity when estimating the cooling loads of system and components at the design stage.
- The introduction of two probabilistic diversity factors using the proposed probabilistic diversity factor method is very effective to quantify the effects of load diversities in multiple zones/spaces.
- The optimal capacities of the components are affected significantly by penalty prices. The optimal component capacities become larger at higher prices. When the penalty price ratio is larger than 10, the optimal design capacities of air-side components vary only within a small range. The penalty price ratio needs to be properly set, in order to obtain a system with desirable life-cycle costs and satisfaction of service.

It is worth noting that the diversity factor models are trained using the building simulation tools and validated in specific cases in this study. To improve/ensure the accuracy of the diversity factor models in a particular application, operation or simulation data of typical representative working conditions relevant to the application case are needed for the model training. To obtain more generic models to extend their application scope, different types of building data, such as the number of spaces, zone orientation, space function, working schedules, etc., are also needed for training the models.

It is also worth noting that, in this study, the design optimization of the cleanroom air-conditioning systems is conducted under the condition that ideal controls are adopted to achieve the intended operation of specific ventilation strategies. For the ADV strategy, the required system configuration is the same as that of the existing ventilation strategies. However, the successful implementation of the ADV strategy requires the supervisory controller to identify the best operation mode. In actual applications, an online control strategy is needed to ensure the actual achievement of the ventilation strategy systems concerning measurement uncertainties and component degradation, which needs further investigations.

Acknowledgement

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Appendix A Descriptions of the four commonly-used probability distribution functions

The formula and detailed coefficient descriptions of each of the four commonly-used probability distribution functions are shown in Table A.1.

Table A.1 Detailed descriptions of the four commonly-used probability distribution functions

Distribution	Probability density function	Coefficient description
Normal	$f(x\|\mu,\delta)=\frac{1}{\delta\sqrt{2\pi}}e^{\frac{-(x-\mu)^2}{2\delta^2}}$	μ is the mean parameter, and σ is the standard deviation parameter.
Lognormal	$f(x\|\gamma,\emptyset)=\frac{1}{x\emptyset\sqrt{2\pi}}e^{\frac{-(lnx-\gamma)^2}{2\emptyset^2}}$	γ is the mean parameter of ln(x) and ∅ is the standard deviation parameter of ln(x)
Gamma	$f(x\|\alpha,\beta)=\frac{x^{\alpha-1}e^{(-\frac{x}{\beta})}}{\beta^\alpha\Gamma(\alpha)}$	α is a shape parameter, β is an inverse scale parameter, and Γ(α) is a complete Gamma function
Weibull	$f(x\|\lambda,k)=\frac{k}{\lambda}(\frac{x}{\lambda})^{k-1}e^{(-\frac{x}{\lambda})^k}$	λ is the scale parameter, and k is the shape parameter

Appendix B The investment of components

The investments of air-side components are the function of the corresponding component capacities in this study. The initial cost of the centrifugal fan, axial fan, duct, coil, and electric heater can be estimated by Eqs. A.1-5 based on RSMeans Mechanical Cost Data [57]. The initial cost of the economizer is estimated as 8 USD/m^2 of the floor area considering the installation of additional dampers, sensors and actuators [58].

$$IC_{cen,fan}=1125.9flow+3375.1 \qquad flow\in[0.5,6] \tag{A.1}$$

$$IC_{axi,fan}=296.97flow+1406.4 \qquad flow\in[0.5,6] \tag{A.2}$$

$$IC_{duct}=(3.0flow^3-29.2flow^2+138.9flow+7.68)\times length_{duct} \quad flow\in[0.5,6] \tag{A.3}$$

$$IC_{coil}=-1.3313CAP_{coil}^2+165.09CAP_{coil}+1746.7 \qquad CAP_{coil}\in[2,55] \tag{A.4}$$

$$IC_{ele,heater}=221.01CAP_{ele,heater}+211.05 \qquad CAP_{ele,heater}\in[0.5,20] \tag{A.5}$$

Here $IC_{cen,fan}$, $IC_{axi,fan}$, IC_{duct} , IC_{coil} and $IC_{ele,heater}$ (USD) are the initial cost of centrifugal fan, axial fan, duct, cooling coil and electric heater. CAP_{coil} (kW), $CAP_{ele,heater}$ (kW) and $flow$ (m^3/s) are the capacity of the cooling coil, electric heater and design outdoor airflow, respectively. $length_{duct}$ is the length of the MAU duct, set as 15 m. It should be noted that when the design capacities of the cooling coil and electric heater are larger than the upper limit of the ranges (i.e., 55 kW for cooling coil, and 20 kW for the electric heater), multiple same cooling coils and electric heaters would be selected. For example, if the design cooling coil capacity is 100 kW, the initial cost of the cooling coil is the sum of the initial costs of two cooling coils, each with the capacity of 50 kW.

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