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Coordinated robust optimal design of building envelope and energy systems for zero/low energy buildings considering uncertainties

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Abstract: Uncertainties exist throughout the life cycle of zero/low energy buildings, which may lead to low energy efficiency and even failure of achieving zero/low energy goal in operation. However, current design practice of the entire zero/low energy buildings, including building envelope and energy systems, seldom considers the uncertainties or roughly considers the uncertainties using safety factors in system sizing. Actually, the computing cost of optimal design of the entire zero/low energy buildings is high as numerous design options and parameters are involved. The consideration of uncertainties in the design would further increase the computing cost significantly, since each design option needs to be evaluated under a large number of uncertain scenarios. Thus, an efficient method is needed. In this study, a coordinated robust optimal design method is proposed to efficiently identify the global optimal design solutions for the entire zero/low energy buildings under uncertainties. The design process is divided into two stages, including robust design optimizations of building envelope and energy systems considering uncertainties. These two stages are coordinated to assure that the optimal design solution obtained is global optimal. Point estimate method is adopted for uncertainty quantification. A case study is performed to test and validate the proposed method using the zero carbon building in Hong Kong as the reference building. Results show that the proposed method is robust and efficient to identify the global optimal design solutions for the entire building under uncertainties. It can provide designs of better performance with reduced cost compared with current design methods.

Keywords: robust optimal design; uncertainty-based design; uncertainty analysis; design optimization; zero/low energy buildings.

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Nomenclature

COP	coefficient of performance of chiller
D	infeasible performance
D_{dis}	thermal discomfort index
E	energy (kWh)
$E(\cdot)$	weighted average
$\tilde{F}$	objective of robust design optimization
GII	grid impact index
IC	initial cost (USD)
M	total number of uncertain design inputs concerned
OC	operation cost (USD)
P	power (kW)
PMV	predicted mean vote value
$Prb(\cdot)$	probability of occurrence
Q	thermal load (kW)
RC	replacement cost (USD)
S	coordinating design variables
TC	total cost (USD)
X	vector of design variables
a	penalty ratio for infeasible building performance
a'	penalty ratio for infeasible system performance
c	unit price
f	performance indicator
$g(\cdot)$	equality design constraints
$h(\cdot)$	inequality design constraints
p	vector of design inputs
t	time
w	weight

Greek letters

γ	the coefficient of skewness
ξ	standard location
μ	mean
σ	standard deviation
Δt	time interval

Subscripts

CL	cooling load
D	infeasible performance
EL	electricity load
PV	photovoltaic
S	coordinating design variables
dem	demand
ele	electricity
env	envelope
ex	export
f	performance indicator
im	import
max	the maximum value
min	the minimum value
p	vector of design inputs
sys	system
umt	unmet

1. Introduction

Zero/low energy buildings are regarded as efficient means to address the critical energy and environmental issues. Many countries/regions have adopted policies or regulations to promote the development of zero/low energy buildings. For instance, in the USA, a zero-energy target is set for all commercial buildings by 2050 [1]. In Europe, a nearly zero-energy target is set from 2020 for all new buildings [2]. Optimal design plays a significant role in achieving the zero/low energy goal and high energy efficiency in zero/low energy buildings. The optimal design of the entire zero/low energy buildings, including both building envelope and energy systems, is therefore addressed in this study.

Optimal design of the entire zero/low energy buildings generally needs to consider and evaluate numerous design options to make sure that the optimal design solution identified is global optimal. This requires high computing cost especially when all of the design variables are optimized simultaneously, which in fact is a common practice in previous studies [3-5]. To provide optimal design solutions efficiently, some scholars proposed "multi-stage design optimization methods". These methods divide the whole design optimization task into several subtasks [6-8]. Hamdy et al. [6] developed a multi-stage design optimization method for zero energy buildings, which involves three stages in total. The building envelope & heat recovery unit, heating/cooling system and renewable energy system were optimized in individual stages. Rysanek and Choudhary [7] broke down the whole optimization task into three stages to efficiently search refurbishment options for low carbon/energy buildings.

The computing cost of these multi-stage design optimization methods is reduced significantly compared with the methods optimizing all the design variables simultaneously, since the combinations of building envelope and energy system designs which are obviously non-optimal are avoided [6]. But the optimal design solutions achieved may be "local optimal design solutions" of building envelope and energy systems separately, instead of "global optimal design solutions" given by considering design optimizations of building envelope and energy systems as a whole. This is because the interactions between design optimizations of building envelope and energy systems are ignored in these methods. The authors addressed this problem in a previous study [9]. A coordinated optimal design method was proposed on the basis of the multi-stage design optimization methods to efficiently identify global optimal design solutions, by coordinating design optimizations of building envelope and energy systems, for the entire zero/low energy buildings [9].

However, these design methods of the entire zero/low energy buildings, including the coordinated optimal design method proposed in Ref. [9], identify the optimal design solutions under presumed and fixed design conditions, which are uncertain and may be very different in actual working conditions. The building energy demand may be overestimated or underestimated and the energy systems may be oversized or undersized by ignoring or roughly considering the uncertain nature of the design inputs or conditions [10]. And these may further lead to low energy efficiency and even failure of achieving zero/low energy goal in operation. Zhou et al. [11] measured and analyzed the actual performance of a zero energy building in Tianjin. They found that the electricity generated by the PV system, which were designed to meet the simulated building energy demand after considering a safety factor of 1.2, could satisfy 29.5% of building energy demand only in operation. Therefore, it is necessary to consider the uncertainties in the design of the entire zero/low energy buildings.

In recent years, more and more studies considers the impacts of uncertainties [12-17], including the studies on optimal design of zero/low energy buildings [18-26]. Lu et al. [20] proposed a robust optimal design method for renewable energy systems in zero energy buildings considering uncertainties in weather condition. Shen and Sun [21] compared two approaches for system sizing in zero energy building clusters considering uncertainties. One approach is separated design which handles the system sizing in individual buildings separately considering uncertainties. The other approach is integrated design, which optimizes all the systems in the building cluster simultaneously considering uncertainties. Huang et al. [22] proposed a robust optimal design method for energy systems in zero energy buildings considering uncertainties and the degradation of energy systems in life-cycle. The design process is divided into two stages to reduce the computing time, including: sizing of renewable energy system and sizing of energy storage system. The authors proposed a robust optimal design method for building envelope of zero/low energy buildings considering uncertainties in a previous study [26]. It can be seen that previous studies on optimal design of zero/low energy buildings considering uncertainties focus on the optimal design of energy systems [20-25], while a few studies investigated the optimal design of building envelope [26]. No study has been found on optimal design of the entire zero/low energy buildings, including both building envelope and energy systems, considering uncertainties.

Compared with the optimal design of building envelope or building energy systems considering uncertainties for zero/low energy buildings, the optimal design of the entire zero/low energy buildings considering uncertainties faces more and larger challenges. One of the challenges is the much higher computing cost, since more design variables are involved and each design option needs to be evaluated under a large number of uncertain scenarios. Some methods are available to reduce the computing time of design optimization, such as multi-stage design optimization method introduced before [3-5], using surrogate model for performance simulation [9, 25, 26] and using Latin hypercube sampling (LHS) method instead of Monte Carol sampling method for uncertainty quantification [26-30]. However, the computing cost is still high since LHS method still requires the number of uncertain scenarios to be more than 20 times the number of uncertainty parameters concerned to fully represent the impacts of uncertainties concerned [26]. Bordbri et al. [31] proposed to use point estimate method for energy consumption analysis under uncertainties. They tested the accuracy of point estimate method in performance analysis by a case study. The results showed that the method caused a bit accuracy loss but reduced the simulation time by more than 97%. This method theoretically can significantly reduce the computing cost of design optimization under uncertainties, but it has not been used and validated for this application, especially for the application in robust design optimization of the entire zero/low energy buildings which pose more complexity and challenges for design.

In this study, a coordinated robust optimal design method is therefore proposed to efficiently identify global optimal design solutions for the entire zero/low energy buildings by considering uncertainties using point estimate method. The whole design optimization process is divided into two main stages, including robust design optimization of building envelope and energy systems considering uncertainties. These two stages are coordinated to assure that the optimal design solution achieved is the global optimum. Point estimate method is used to quantify the uncertainties in the cooling and electrical power loads. A case study is conducted to test and validate the proposed method using the zero carbon building (ZCB) in Hong Kong as the reference building. The point estimate method is validated for the use in design optimization under different climate conditions. This paper presents the procedure and method of the proposed coordinated robust design optimization, the design results of the case study and the validation of the methods. The major innovations of this study include: the optimal design of the entire zero/low energy buildings under uncertainties is investigated; a novel optimal design method is proposed to efficiently identify the global optimal design solutions for the entire zero/low energy buildings considering uncertainties; point estimate method is first adopted and validated for use in building robust design optimization.

2. Procedure and method of coordinated robust design optimization

2.1 Procedure of coordinated robust design optimization

The proposed coordinated robust optimal design method optimizes both building envelope and energy systems considering uncertainties. Three measures are adopted to reduce the high computing cost caused by assessment of numerous design options, performance simulation, and uncertainty analysis. First, the whole design task is divided into two subtasks, i.e., robust design optimization of building envelope and robust design optimization of energy systems. Second, an artificial neural network (ANN) model is used as the building performance model in robust design optimization of building envelope, since it requires much less time for performance simulation compared with building simulation software (e.g., EnergyPlus). Third, point estimate method [31] is adopted for the quantification of the uncertainties in cooling load and electrical power load to largely reduce the uncertain scenarios that need to be considered and thus to reduce computing time. Unlike the Monte Carlo simulation method and LHS method which require hundreds or even thousands of uncertain scenarios to represent the uncertainty impacts, a few uncertain scenarios (i.e., double of the number of uncertainty parameters concerned) are only needed using the point estimate method. In addition, the robust design optimizations of building envelope and energy systems are coordinated to consider the interactions between building envelope and energy systems to assure the achievement of robust global optimal design solutions under possible uncertainties.

Fig.1 shows the procedure of the coordinated robust design optimization method, which involves two main steps, i.e., the identification of coordinating design variables and the coordinated multi-stage robust design optimizations. The first step is to identify the coordinating design variables (S). They should be design variables of energy systems, which have influence on the design optimization of building envelope. These variables are presumed and considered at the stage of building envelope robust design optimization, and optimized at the stage of energy system robust design optimization.

The second step is to iteratively conduct the multi-stage robust design optimizations. The multi-stage robust design optimizations are coordinated using the coordinating design variables. Each multi-stage robust design optimization is taken as an optimization loop. Each loop involves two stages, including robust design optimization of building envelope and robust design optimization of energy systems. At the first stage, the coordinating design variables (S_i) are initialized and considered in the performance assessments of envelope design options to make a trade-off between the performance of building and energy systems in the robust design optimization of building envelope. Possible uncertain scenarios are generated using the point estimate method according to the probability density distributions of the uncertain design inputs concerned. The design variables of building envelope are optimized to identify the robust optimal envelope design, which has the minimum optimization objective value of building envelope under the uncertain scenarios. At the second stage, the profiles of the hourly cooling loads and electrical power loads (excluding that for cooling), associated to the identified robust optimal envelope design, are calculated under these uncertain scenarios using a building simulation software, and used for robust design optimization of building energy systems. The energy system design variables, including the coordinating design variables, are optimized by minimizing the optimization objective of energy systems while satisfying the building cooling and electricity demands associated to the robust optimal envelope design, to identify the robust optimal energy system design.

If the robust optimal coordinating design variables obtained in the robust design optimization of energy systems (S_i') deviate significantly from the values assumed in the robust design optimization of building envelope (S_i), a new trial of robust design optimization of building envelope will be performed by setting a new S_{i+1} on the basis of the S_i and S_i' at the last optimization loop. The new S_{i+1} can be set as the S_i' or the average of the S_i and S_i' to accelerate the convergence. The robust design optimizations of building envelope and energy systems are conducted again under the new setting. The optimization loop repeats until the deviation between S_i and $\mathrm{S_i'}$ in the same optimization loop is lower than a preset threshold, ε. In this study, ε is determined as 2% by assuming that the impacts on the performance of building and systems are negligible when the deviation is within 2%. The robust optimal envelope design and robust optimal energy system design, achieved eventually, is regarded as the robust optimal design solution for the entire building.

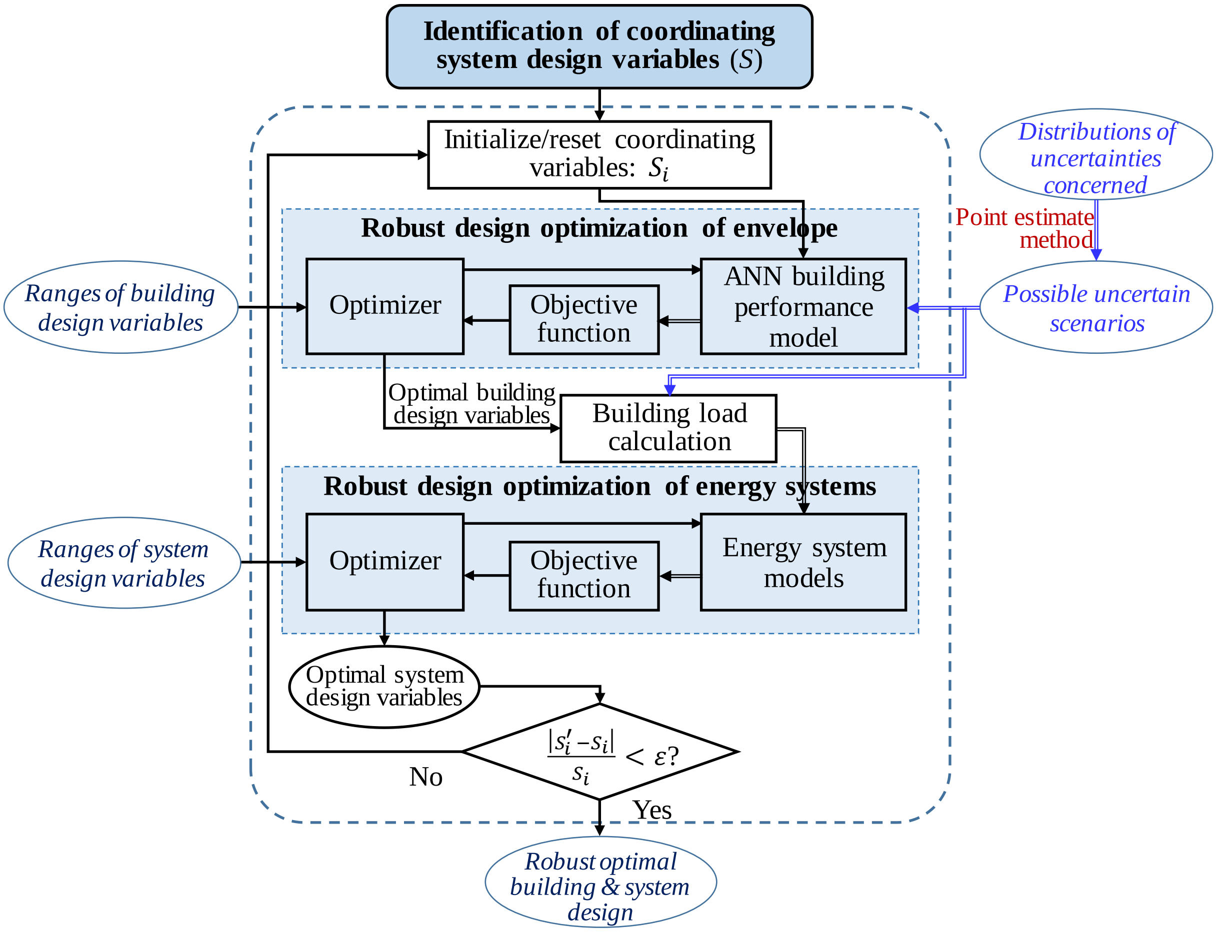


Fig.1. Procedure of the coordinated robust optimal design method

Compared with the coordinated optimal design method proposed in a previous study of the authors [9], a major improvement/innovation of the coordinated robust optimal design method proposed in this study is that uncertainties are quantified based on a probabilistic approach and considered in the design optimization. This enables maintaining good performance of the building and energy systems in operation even when the working condition is very different from the typical design condition. Compared with the previous studies on robust optimal design of zero/low energy buildings, the innovations of this study are that robust design optimizations of both building envelope and energy systems are addressed, and a more efficient uncertainty sampling method (i.e., point estimate method) is adopted to reduce the increased computing cost caused by the involvement of uncertainty analysis.

2.2 Formulation of the optimization problems

The robust design optimization problems of building envelope and energy systems can be formulated as Eq. (1) and Eq. (2) respectively, according to the proper objective function identified for robust design optimization in building energy field in a previous study of the authors [19]. The robust design optimization of building envelope minimizes the objective function involving the mean of building performance indicator, the mean of building infeasible performance penalty and the mean of performance of the energy systems associated with the coordinating design variables *S* under all uncertain scenarios. The robust design optimization of energy systems minimizes the objective function involving the mean of the system performance indicator, and the mean of the system infeasible performance penalty under all uncertain scenarios.

$$\begin{cases} \text{Minimize: } \tilde{F}_{env}(X_{env}, p_{env}, S) = \mu_{f_{env}} + a * \mu_{D_{env}} - \mu_{f_S} \\ \text{subject to: } X_{env,min} \leq X_{env} \leq X_{env,max} \end{cases} \quad (1)$$

$$\begin{cases} \text{Minimize: } \tilde{F}_{sys}\left(X_{sys}, p_{sys}\right) = \mu_{f_{sys}} + a' * \mu_{D_{sys}} \\ \text{subject to: } X_{sys,min} \leq X_{sys} \leq X_{sys,max} \\ g(X_{sys}, p_{sys}) = 0 \\ \mathrm{h}(X_{sys}, p_{sys}) \leq 0 \end{cases} \quad (2)$$

where, $\tilde{F}$ is the objective of robust design optimization. f is the performance indicator. D is the infeasible performance. μ is the mean. X is the vector of design variables. p is the vector of design inputs, which can be uncertain. The subscript "*env*" refers to building envelope, while the subscript "*sys*" refers to energy systems. a and a' are penalty ratios for building and system infeasible performance respectively.

2.3 Uncertainty sampling using point estimate method

The 2-point estimate method (2PEM), as a modified point estimate method, is adopted in this study to quantify the uncertainties in building cooling and electrical power loads. Based on the 2PEM method [31], the uncertainty in the ith uncertain design input (i.e., p_i, $\forall i = 1, 2, \ldots, M$) can be represented by two points (i.e., $p_{i,j}$, and $j = 1, 2.$), together with a weighting factor for each point (i.e., $w_{i,j}$). Each representing point and its weighting factor are calculated using Eqs. (3-6) and Eq. (7), respectively. All weighting factors are between 0 and 1, and the sum of the weighting factors for all the uncertain design inputs should be 1. In the end, the mean of performance under uncertain scenarios is calculated using Eqs. (8-9) by summing the performance under a representing point of an uncertain design input multiplied by its corresponding weighting factor, while setting the other uncertain design inputs as the mean of their distribution. Where, $\xi_{i,j}$ represents the standard location of the *j*th concentration of p_i. $\gamma_{i,3}$ represents the coefficient of skewness. *M* is the total number of uncertain design inputs concerned. $Prb(p_{i,j})$ is the probability of occurrence $p_{i,j}$ according to the probability distribution of the *i*th uncertain design input.

$$p_{i,j} = \mu_{p_i} + \xi_{i,j} * \sigma_{p_i} \tag{3}$$

$$\xi_{i,j} = \frac{\gamma_{i,3}}{2} + (-1)^{3-j}\sqrt{M + (\frac{\gamma_{i,3}}{2})^2} \tag{4}$$

$$\gamma_{i,3} = \frac{E[(p_i - \mu_{p_i})^3]}{(\sigma_{p_i})^3} \tag{5}$$

$$\mathrm{E}\left[\left(p_i - \mu_{p_i}\right)^3\right] = \sum_{j=1}^{2} prb(p_{i,j}) * (p_{i,j} - \mu_{p_i})^3 \tag{6}$$

$$w_{i,j} = \frac{1}{M}(-1)^j \frac{\xi_{i,3-j}}{2\sqrt{M+(\frac{\gamma_{i,3}}{2})^2}} \tag{7}$$

$$\mu_f \cong \sum_{i=1}^{M}\sum_{j=1}^{2} f(i,j) * w_{i,j} \tag{8}$$

$$f(i,j) = f(x, \mu_{p_1}, \mu_{p_2}, \cdots, p_{i,j}, \cdots, \mu_{p_M}) \tag{9}$$

3. The validation case, building performance model and energy system models

3.1 Overview of the validation case

A building, which is simplified on the basis of ZCB in Hong Kong [32], is considered as the reference building for the test and validation of the proposed design method. In the validation, the design variables of the building envelope and energy systems are optimized over the building life cycle in a subtropical climate using the proposed method. The layout of this building, the design parameters (excluding the design variables) of the building envelope and the configuration of the energy systems are assumed to be selected prior to the design optimization. The design variables, uncertain design inputs and building & system performance concerned in the design optimization are introduced in Sections 3.2-3.4. The building performance model and energy system models used in the design optimization are presented in the Sections 3.5 and Section 3.6, respectively.

The building layout considered in the validation case is shown in Fig. 2. The building is connected to the power grid. A typical configuration of energy systems in subtropical regions is considered as shown in Fig. 3 by referring to the energy systems used in Ref. [33] and Ref. [34]. The energy systems mainly include wind turbines, PV panels, co-generators, an electric battery, electric chillers, absorption chillers and associated cooling system components. The PV panels are installed and fixed on the slope roof of the building. Heating of the tap water is not considered. Cooling is considered only since there is no heating provision in most subtropical regions. It is provided in the office hours (8:00-19:00, except Wednesday).

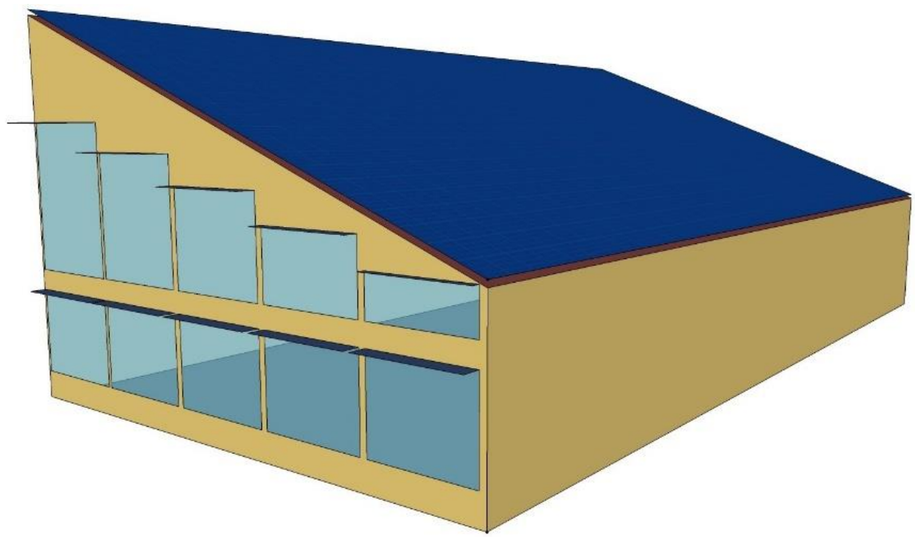


Fig. 2. Building architecture model for the validation case

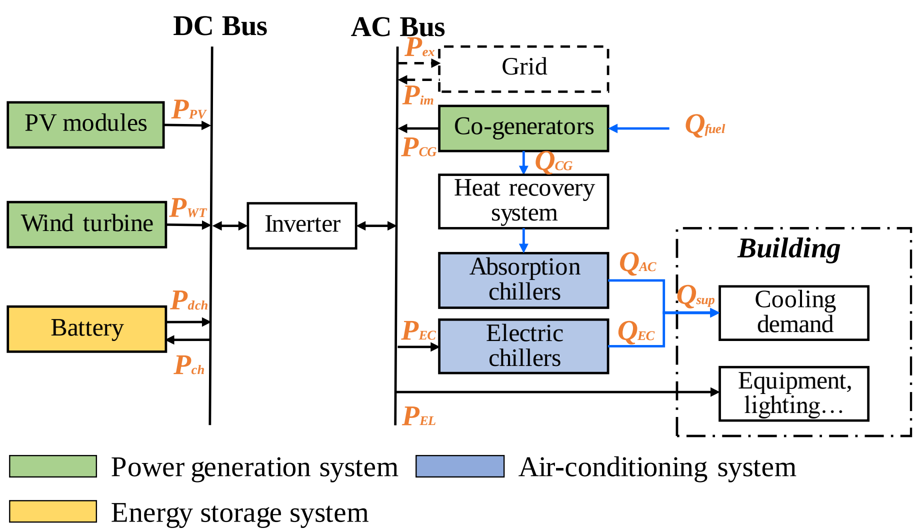


Fig. 3. Configuration of energy systems

3.2 Design variables concerned

Table 1 shows the design variables concerned in the case study and their searching ranges. There are 5 envelope design variables and 10 system design variables. The design variables of building envelope are identified according to the results of a sensitivity analysis in a previous study of the authors [35]. They are building orientation, window-to-wall ratio (WWR), overhang projection ratio, roof solar absorptance and wall solar absorptance. The design variables of energy systems concerned in this study are the sizes of the system components, including the component capacity and number. The lower limits of the searching ranges of the component capacities are set as the minimum capacities of available devices in the market. The upper limits of their searching ranges are determined according to the energy demand of the reference building. In the design optimization, the number of each system component is taken as discrete variable, while the design variables of building envelope and the capacity of each system component are taken as continuous variables.

Table 1. Design variables and their searching ranges

Category	**Design variable**	**Abbreviation**	**Searching range**	**Unit**
Building envelope	Building orientation	BO	[0,360]	°
	Roof solar absorptance	RSA	[0.1,0.9]	-
	Window-to-wall ratio	WWR	[0.2,0.6]	-
	Wall solar absorptance	WSA	[0.1,0.9]	-
	Overhang projection ratio	OPR	[0.05,0.5]	-
Building energy systems	PV area	A_{PV}	[100,1032]	m²
	Capacity of wind turbines	Cap_{WT}	[1,40]	kW
	Number of wind turbines	n_{WT}	{0,1,2,3}	-
	Capacity of co-generators	Cap_{CG}	[30,150]	kW
	Number of co-generators	n_{CG}	{1,2,3}	-
	Capacity of absorption chillers	Cap_{AC}	[20,200]	kW
	Number of absorption chillers	n_{AC}	{1,2,3,4,5}	-
	Capacity of electric chillers	Cap_{EC}	[20,200]	kW
	Number of electric chillers	n_{EC}	{1,2,3,4,5}	-
	Capacity of battery	Cap_{bat}	[10,100]	kWh

3.3 Main uncertainties concerned

In this study, uncertainties in the design inputs are only considered in the design optimization. The uncertainties in the models are not considered. Three main categories of uncertain design inputs are identified for the zero/low energy buildings in subtropical regions through a sensitivity analysis in a previous study of the authors [26], and considered in the validation case. They are weather condition, internal loads and infiltration. The uncertainties in theses design inputs are quantified using a probabilistic approach, as shown in Table 2. The uncertainty in the weather condition over the building life cycle is quantified using the historical weather data together with the uncertainty in future climate change trend (i.e., a linear increase/decrease in dry-bulb temperature), to consider both the stochastic variation of weather condition and the possible temperature increase in the future. 30 years of historical weather data from 1979 to 2008 in Hong Kong are used to quantify the stochastic variation. The uncertainty in future climate change trend follows a truncated normal distribution, which is derived from a normal distribution with a mean of 0.012 K/year and a standard deviation of 0.006 K/year by bounding it within the range between 0 and 0.024 K/year. The maximum value of this range is determined based on the dry bulb temperature increase (i.e., 0.012 K/year) from 1885 to 2017 in Hong Kong, reported by the Hong Kong Observatory, and by considering the urban island effect. The possible weather condition over building life cycle is generated by adding the possible climate change trend to the randomly-ordered historical weather data.

Table 2. Main uncertain design inputs considered

Category	**Uncertain design inputs**	**Unit**	**Distribution**
Weather condition	Dry bulb temperature	°C	Historical weather data: 1979-2008
	Relative humidity	%	
	Solar radiation	Wh/m^2	
	Wind speed	m/s	
	Wind direction	-	
	Climate change trend	K/year	$TN_{(0, 0.024)}$ (0.012, 0.006)
Internal loads	Occupant density	-	Factor: N(1, 0.1)
	Lighting load	-	
	Equipment load	-	
Infiltration	Infiltration air mass flow rate	kg/(s·m)	$TN_{(0.008, 0.04)}$(0.024, 0.008)

Note: N(μ, σ) refers to a normal distribution (μ and σ are the mean and standard deviation respectively).$TN_{(a, b)}(\mu, \sigma)$ *refers to a truncated normal distribution, which is derived from a normal distribution N(μ, σ) by bounding the variable within (a, b).*

The uncertainties in occupant density, lighting load and equipment load are quantified by assigning an uncertain factor to their design values, since they are all related to occupant behavior. The uncertain factor is assumed to follow a normal distribution with a mean of 1 and a standard deviation of 0.1. The uncertainty in infiltration is assumed to follow a truncated normal distribution, which is derived from a normal distribution with a mean of 0.024 kg/(s·m) and a standard deviation of 0.008 kg/(s·m) by bounding it within 0.008 and 0.04 kg/(s·m). Truncated normal distributions or normal distributions are used to quantify the uncertainties in this study, since they are reasonable and easy to implement when point estimate method is used for uncertainty sampling. The ranges of these uncertain design inputs are determined based on the best and worst cases that may occur in practice.

3.4 Building and system performance concerned

The performance indicator of building envelope concerned in this study is the energy cost in building life-cycle, which is calculated using Eq. (10). The accumulated thermal discomfort index (i.e., winter thermal discomfort) in building life cycle (as shown in Eq. (11)) is considered as the infeasibility performance of building envelope to avoid a severely cold indoor environment in the winter season in subtropical regions without heating provision. The hourly winter thermal discomfort is calculated using Eq. (12) [35]. The cost for selling the electricity generated by PV in building life cycle is taken as the system performance to be considered in envelope design optimization, since the PV area is identified as the only coordinating design variable for the reference building as introduced in a previous study of the authors [8]. It is calculated using Eq. (13). The penalty ratio for winter thermal discomfort is set as 15 in this study (i.e., *a*=15), which is the electricity cost for cooling supply in the reference building in a typical summer day. It is determined by assuming that the owner would like to pay the same amount of electricity cost used in summer to heat the building in winter when the indoor PMV reaches -3.

$$f_{env} = c_{ele} * \left(E_{EL} + \frac{E_{CL}}{COP}\right) \tag{10}$$

$$D_{env} = \sum D_{dis} \tag{11}$$

$$D_{dis} = \begin{cases} \frac{\text{-PMV-0.5}}{2.5} & \text{PMV}<\text{-0.5} \\ 0 & \text{PMV}\geq\text{-0.5} \end{cases} \tag{12}$$

$$f_S = c_{PV} * E_{PV} \tag{13}$$

where, c_{ele} is the unit price of buying electricity (USD/kWh). E_{EL} is the electricity load (excluding that for cooling) in building life cycle (kWh). E_{CL} is the total cooling load in building life cycle (kWh). *COP* is the overall coefficient of performance of chillers, which is set as 3 in the stage of envelope design optimization in this study. D_{dis} is the hourly thermal discomfort index. PMV is the hourly predicted mean vote value. c_{PV} is the unit price of selling electricity generated by PV (USD/kWh). E_{PV} is the total electricity generated by PV in building life cycle (kWh).

The performance indicator of building energy systems concerned in this study is the total cost (*TC*) in the building life cycle. It is the sum of initial cost (*IC*), operation cost (*OC*) and replacement cost (*RC*), as shown in Eq. (14). Two infeasible system performance are considered as shown in Eqs. (15-16). They are the accumulated unmet cooling load (Q_{umt}) over the building life cycle due to insufficient cooling capacity, and the accumulated monthly grid impact index (*GII*) over the building life cycle. The monthly grid impact index is calculated using Eq. (17) [9]. For standalone buildings, the accumulated unmet cooling and power loads are recommended as the infeasible performance. Different penalty ratios are set for these two infeasible performance. The penalty ratio for unmet cooling load is set as 3, and the penalty ratio for grid impact index is set as 240, according to a previous study of the authors [9]. Where, Δt is time interval, which is set as one hour in this study. P_{im} is the power imported from the power grid (kW). P_{ex} is the power exported to the power grid (kW). P_{dem} is the power demand (kW).

$$f_{sys} = TC = IC + OC + RC \tag{14}$$

$$D_{sys,1} = \sum Q_{umt} * \Delta t \tag{15}$$

$$D_{sys,2} = \sum GII \tag{16}$$

$$\mathrm{GII} = \mathrm{std}\left(\frac{P_{im,t} - P_{ex,t}}{\int_{t1}^{t2} P_{dem} dt}\right) \tag{17}$$

<u>*3.5 Building performance model*</u>

A building performance model is developed based on the ANN, and used for performance assessment in the robust design optimization of building envelope to reduce the computing time. The inputs of the ANN model are the design variables of building envelope listed in Table 1, the coordinating design variables and the main uncertain design inputs listed in Table 2. The outputs of the ANN model are the cooling load, electricity load (excluding that for cooling) and winter thermal discomfort in building life cycle (i.e., the concerned building performance introduced in Section 3.4). The input data for training/validation of ANN model are generated by sampling according to the searching ranges or probability density distributions of the model inputs using LHS method [36]. LHS method is used to generate more samples to cover more scenarios for ensuring high accuracy of building performance estimation. The output data is obtained by building simulation using EnergyPlus under the possible weather condition generated considering uncertainties. The detailed design assumptions (such as internal loads) in the reference building are introduced in a previous study of the authors [35].

3.6 Energy system models

Mathematical models are developed for energy system components to simulate their performance. A typical control strategy is implemented on the energy systems for system performance assessment. The renewable energy systems, including PV and wind turbines, have the highest priority for power supply, followed by battery, co-generators and power grid. When co-generators are in operation, absorption chillers are used for cooling supply. In this situation, electric chillers are activated only when the absorption chillers cannot satisfy the building cooling demand. When co-generators are not in operation, electric chillers are used only for cooling supply. The detailed energy system models, control strategy and model parameters are introduced in a previous study of the authors [9]. With the provision of hourly cooling & electrical power loads and the capacity of each energy system component, the energy generation and dispatch of the energy systems can be obtained and used to calculate the system performance introduced in Section 3.4.

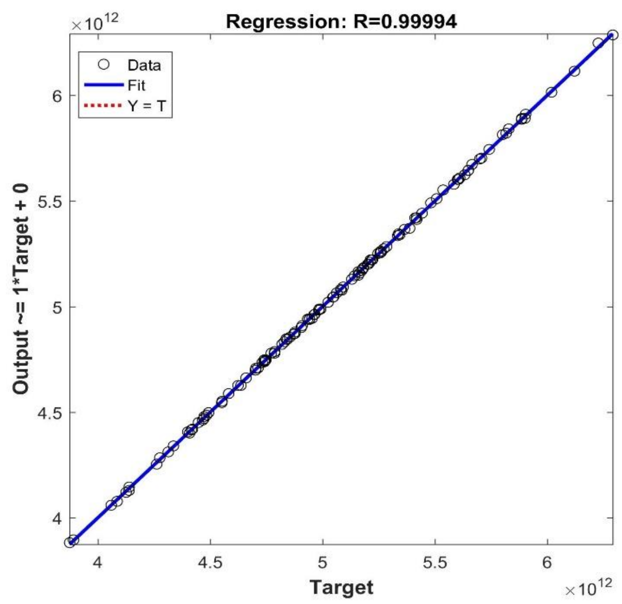
4. Design case study results and analysis

4.1 Training and validation of ANN building performance model

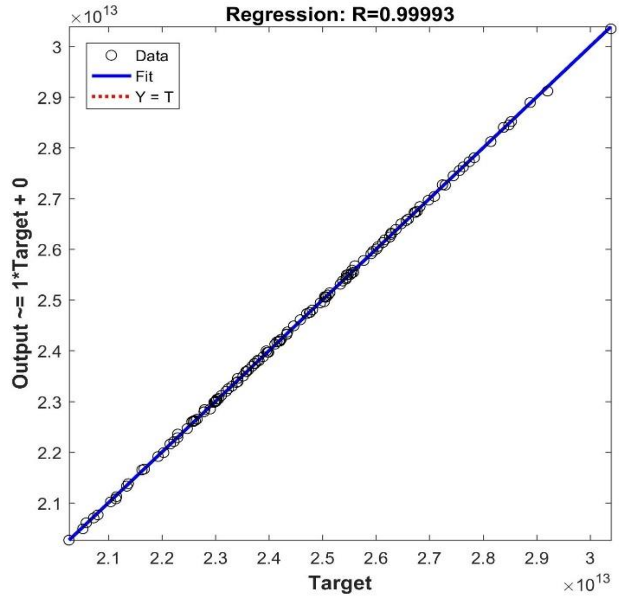
2,400 sets of training data and 120 sets of test data are prepared for the training and validation of the ANN model. Mean squared error (MSE) is selected and used for performance evaluation of ANN model. In the training, the model structure and parameters of the ANN model are optimized in two separate steps. In the validation, the consistency between the building performance given by ANN model and that given by EnergyPlus is tested.

At the first step of the training process, the ANN model structure is optimized using 10-fold cross-validation [37]. The model structure with the minimum average MSE in the cross-validation is identified as the optimal model structure. Different numbers of hidden layers (1-2 hidden layers) and different numbers of neurons in different hidden layers (1-27 neurons when using 1 hidden layer, 1-9 neurons for each layer when using 2 hidden layers) are tested. The training results show that the optimal structure of the ANN model in this study is one hidden layer with 27 neurons. Its average MSE is 1.19×10^{-4}.

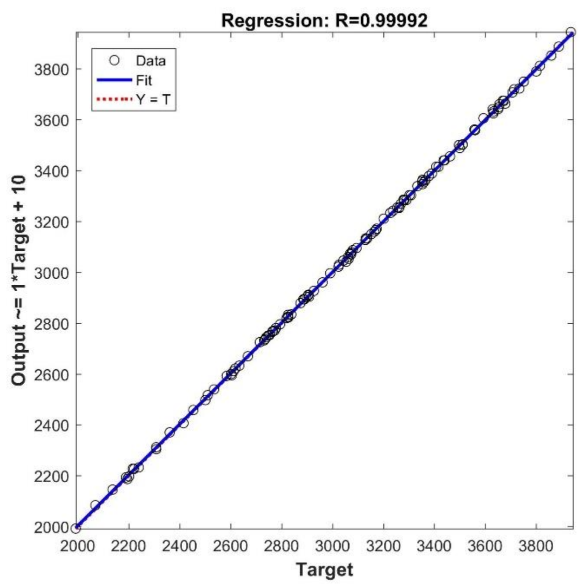
At the second step of the training process, the parameters of the ANN model with the optimal model structure are further optimized to obtain the optimal ANN model. Test data are used to validate the optimal ANN model obtained. It can be seen from Fig.4 that the outputs of the optimal ANN model well match the corresponding outputs of EnergyPlus. The coefficients of linear regression on electricity load, cooling load and winter thermal discomfort are all up to 0.999. The consistencies between the influence of design variables on the building performance estimated using the ANN model and EnergyPlus are also validated. The impact of building orientation is taken as an example. Fig.5 shows the outputs given by ANN model and EnergyPlus when the building orientation varies. It can be seen that the outputs given by ANN model and EnergyPlus match very well respectively. So the optimal ANN model has good accuracy in estimating building performance including the impacts of design variables.



(A) Electricity load in life cycle

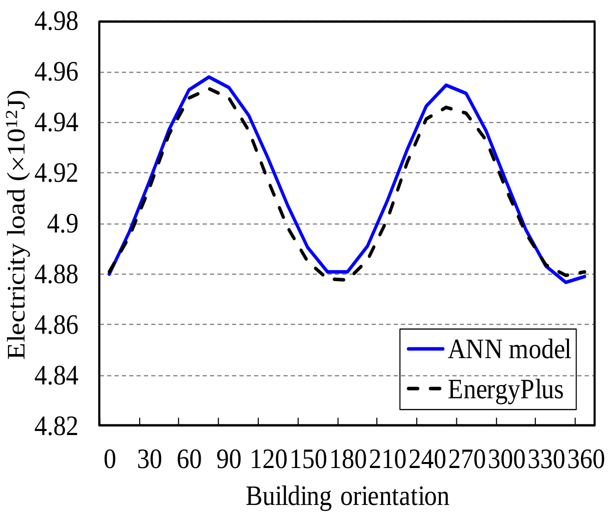


(B) Cooling load in life cycle

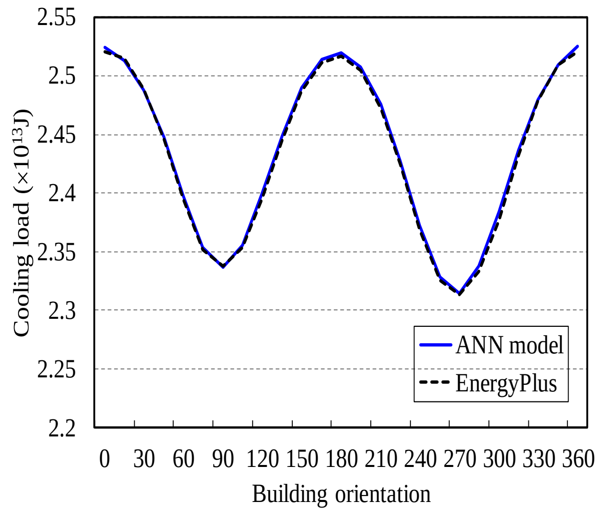


(C) Winter thermal discomfort in life cycle

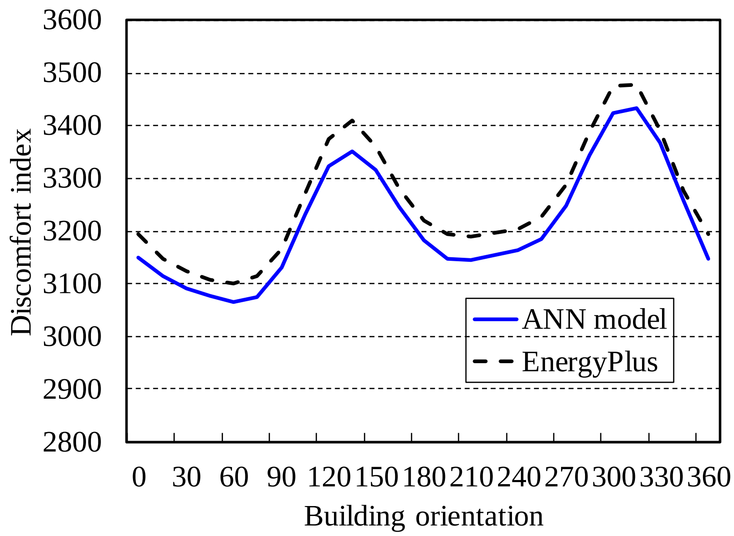
Fig.4. Outputs of optimal ANN model and their targets (i.e., EnergyPlus outputs) during model validation using test data



(A) Electricity load in life cycle



(B) Cooling load in life cycle

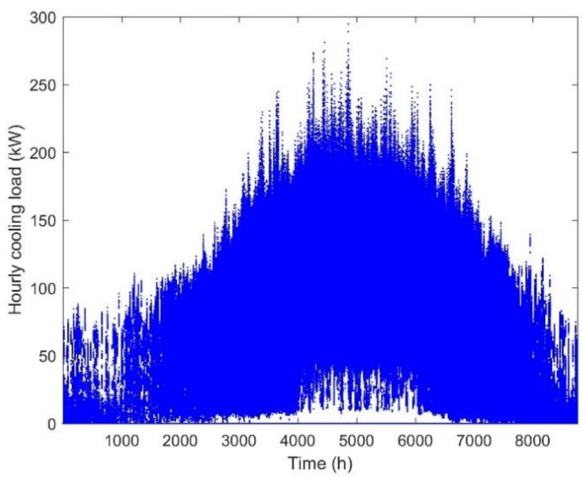


(C) Winter thermal discomfort in life cycle

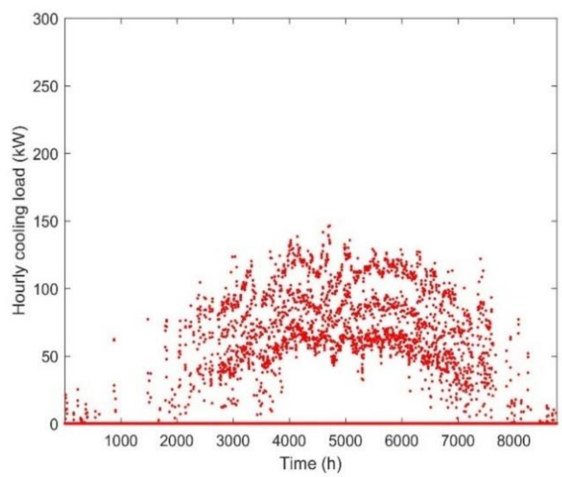
Fig.5. Outputs of optimal ANN model and EnergyPlus *vs.* building orientation

4.2 Cooling and electricity loads under uncertainties

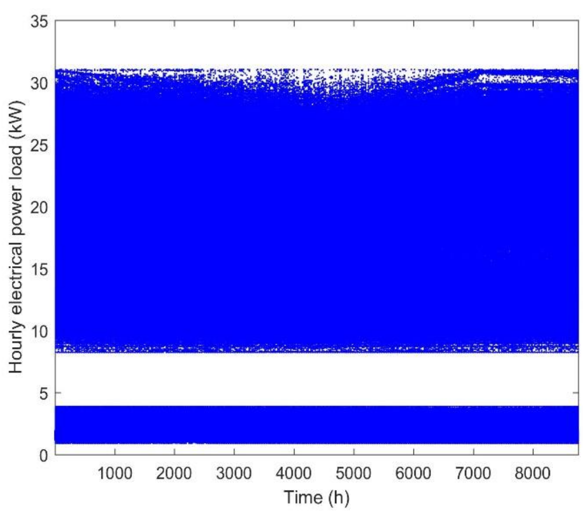
Fig.6 shows the hourly cooling and electrical power load profiles of the reference building in each year of the building life cycle, under uncertain scenarios (generated by LHS method) and the typical design scenario respectively. It can be seen that the hourly cooling load or electrical power load in operation may vary in a wider range than that estimated under the typical design scenario. The actual peak cooling load may be up to 2 times the peak cooling load estimated under the typical design scenario. The actual peak electrical power load in operation may be up to 1.2 times the peak electrical power load estimated under the typical design scenario. In addition, there may be a larger proportion of low cooling load (excluding the cases when the hourly cooling load is 0 kW) in actual operation compared with the estimation under the typical design scenario. This means that the energy systems optimized to satisfy the cooling and electrical power demands estimated under the typical design scenario are probably insufficient for energy supply (it is worth noticing that power supply is always sufficient in this case since the building is connected to the grid), and have higher probability of low load operation with low energy efficiency in operation. Therefore, it is necessary to consider uncertainties in the design of the entire zero/low energy buildings.



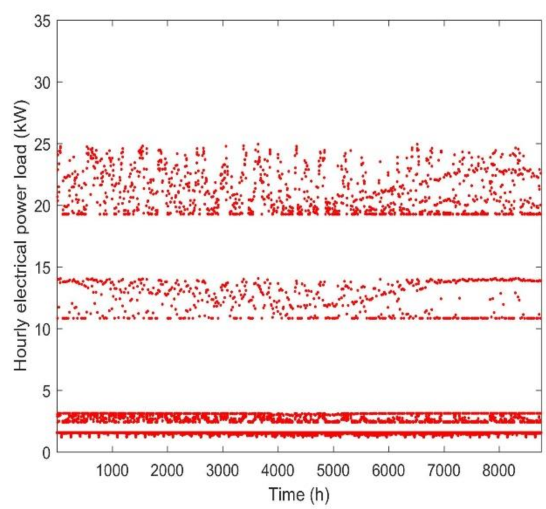
(A) Hourly cooling loads under uncertain scenarios



(B) Hourly cooling loads under the typical design scenario



(C) Hourly electrical power loads under uncertain scenarios



(D) Hourly electrical power loads under the typical design scenario

Fig.6. Hourly load profiles of the reference building under uncertain scenarios and the typical design scenario

4.3 Results of coordinated robust design optimization

The design variables of building envelope and energy systems in the reference building are optimized using the proposed method. Genetic algorithm is used as the optimization algorithm for the robust design optimizations of building envelope and energy systems. According to the analysis in the previous study of the authors [9], PV area (i.e., A_{PV}) is identified as the coordinating design variable since the optimal design of PV area has significant impacts on the design optimization of building envelope. The design results in each optimization loop are shown in Table 3. It can be seen that five optimization loops are needed to reach the convergence when the initial PV area for robust design optimization of building envelope is set as 1,032 m^2. When a PV area of 1,032 m^2 is assumed for the envelope design, the robust optimal PV area given by robust design optimization of energy systems is 458 m^2 only, which deviates significantly from the PV area assumed in robust design optimization of building envelope. Then a new optimization loop starts by setting the PV area as 458 m^2 for robust design optimization of building envelope. This design process is repeated until the PV area for envelope design is set as 419 m^2. The corresponding optimized PV area given by robust design optimization of energy systems is 416 m^2, which is within the convergence tolerance (2%). Therefore, the optimal design obtained in optimization loop 5 is eventually identified as the robust optimal design for the reference building.

Table 3. Optimization loops of the design case using coordinated robust optimal design method

Loop nos.	A_{PV}	Robust optimal envelope design					Robust optimal system design										
		BO	RSA	WWR	WSA	OPR	A'_{PV}	Cap_{WT}	n_{WT}	Cap_{CG}	n_{CG}	Cap_{AC}	n_{AC}	Cap_{EC}	n_{EC}	Cap_{bat}
1	1032	0	0.1	0.2	0.1001	0.3930	458	17	0	30	1	50	1	130	1	43
2	458	0.0006	0.1002	0.2001	0.1002	0.4119	430	10	0	30	1	50	1	129	1	58
3	444	0.0001	0.1	0.2	0.1	0.4118	419	27	0	30	1	50	1	128	1	67
4	432	0.0001	0.1	0.2	0.1	0.4122	419	35	0	30	1	50	1	128	1	67
5 (final)	***419***	***0***	***0.1***	***0.2***	***0.1001***	***0.4126***	***416***	***29***	***0***	***30***	***1***	***50***	***1***	***126***	***1***	***68***

** Note: The units of variables refer to that in Table 1.*

It can be seen, from Table 3, that the robust optimal envelope and energy system designs obtained under different settings of PV area in envelope design (i.e., A_{PV}) are different. When different PV areas (i.e., A_{PV}) are set in the robust design optimization of building envelope, the robust optimal overhang projection ratio (i.e. OPR) obtained changes while the robust optimal values of other envelope design parameters do not have any obvious changes. Though the robust optimal envelope design changes a little under different A_{PV}, the robust optimal envelope design obtained under smaller A_{PV} requires smaller PV area (i.e., A'_{PV}), smaller electric chiller capacity (i.e., Cap_{EC}) and larger battery capacity (i.e., Cap_{bat}) for energy systems. This is because it is more beneficial to reduce energy consumption demand than maximizing the PV power generation when smaller A_{PV} is set in envelope design. The robust optimal envelope design obtained when A_{PV} is set smaller has lower cooling load and higher electricity load (excluding that for cooling). Therefore, it is necessary to coordinate the robust design optimizations of building envelope and energy systems to make sure that the optimal design solution achieved is global optimum. A similar conclusion was also drawn on the effectiveness of coordinated design optimizations on the achievement of global optimal design solutions in a previous study of the authors [9].

4.4 Validation of point estimate method and its sensitivity to climate condition

Effectiveness of point estimate method compared with the commonly-used method

Fig. 7 shows the building performance (i.e., the annual average thermal discomfort index and annual average total electricity demand in building life cycle) of the robust optimal envelope design, identified in Section 4.3, under the uncertain scenarios generated using different uncertainty sampling methods. The uncertainty sampling methods include the LHS method widely-used in previous studies and the point estimate method adopted in this study. 60 uncertain scenarios (i.e., 20 times the number of uncertain design inputs concerned in this study) are generated by sampling according to the probability density distribution of uncertain design inputs using the LHS method. 6 uncertain scenarios (i.e., 2 times the number of uncertain design inputs concerned) are generated using the point estimate method.

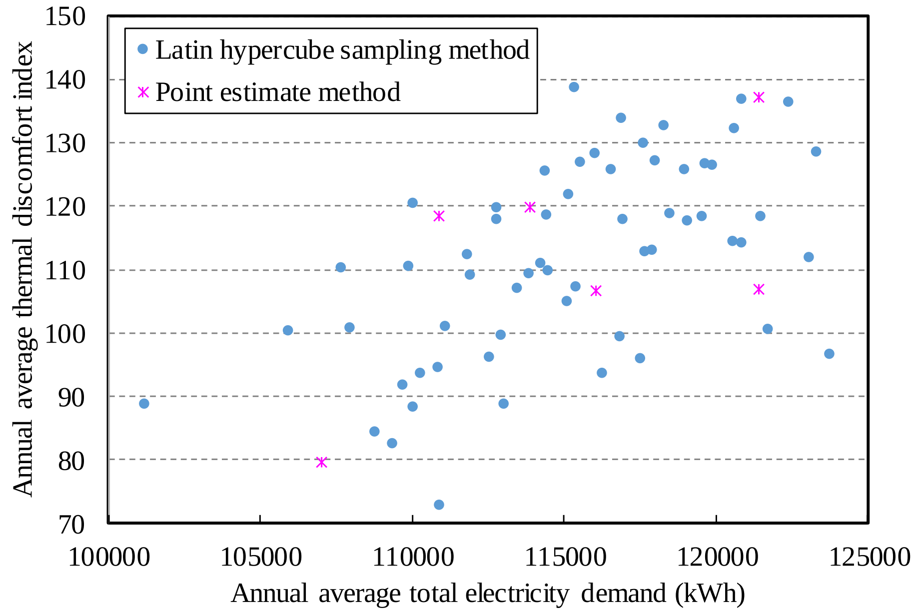


Fig.7. Building performance of robust optimal envelope design under scenarios generated using different methods

It can be seen from Fig. 7 that the building performance can be very different when the operation condition deviates from the typical design condition. If 60 scenarios generated using LHS method were considered as all possible conditions/scenarios which may exist in actual operation, the annual average thermal discomfort index of the reference building in the life cycle would vary between 73 and 139 in operation when designed according to the robust optimal design solution identified in Section 4.3. Its annual average total electricity demand in the life cycle would vary between 101,142 and 123,710 kWh in operation. The building performance under the 6 scenarios generated using point estimate method distribute evenly within the ranges covered by the building performance under the 60 scenarios generated using LHS method, as shown in Fig. 7. The annual average thermal discomfort index in life cycle of the robust optimal envelope design, identified in Section 4.3, varies between 79 and 137 under the 6 scenarios. Its annual average total electricity demand in the life cycle varies between 107,039 and 121,416 kWh. The maximum annual average thermal discomfort index in the life cycle under the 6 scenarios is only 1.4% less than that under 60 scenarios. Its maximum annual average total electricity demand in the life cycle is only 1.9% less than that under 60 scenarios. The mean of the annual average thermal discomfort index in building life cycle under the 6 scenarios is 114.0, which is the same as that under the 60 scenarios. The mean of the annual average total electricity consumption in building life cycle under the 6 scenarios is 115,114 kWh, which is 0.05% smaller than that under 60 scenarios. This means that the uncertain scenarios generated using point estimate method can well represent the impacts of all the uncertain design inputs concerned.

The robust optimal envelope and system designs obtained under these two different sets of scenarios are also compared, as shown in Table 4. The robust optimal envelope designs obtained under the two different sets of scenarios are the same. The robust optimal PV area and electric chiller capacity obtained under the 6 scenarios generated using point estimate method are slightly smaller (i.e., reduced by 2.6% and 5.3% respectively) than that obtained under the 60 scenarios generated using LHS method. The robust optimal capacity of battery obtained under the 6 scenarios generated using point estimate method is slightly higher (i.e., increased by 9.7%) than that obtained under the 60 scenarios generated using LHS method. When evaluated under the 60 scenarios, the system optimization objective value of the robust optimal system design obtained under the 6 scenarios generated using point estimate method is only 1.96% higher than that obtained under the 60 scenarios generated using LHS method. When evaluated under the 6 scenarios, the system optimization objective value of the robust optimal system design obtained under scenarios generated using point estimate method is only 0.3% less than that obtained under the scenarios generated using LHS method. It can be seen that the deviation of the system performance of the robust optimal system designs obtained under these two sets of scenarios is negligible. This indicates that point estimate method is effective in uncertainty sampling for robust design optimization.

Table 4. Optimal design solutions given by robust design optimizations under scenarios generated using different methods and their computing time

(A) Robust optimal envelope design

Uncertainty sampling method	Nos. of scenarios	A_{PV}	Robust optimal envelope design					Computing time (min)
			BO	RSA	WWR	WSA	OPR	
Latin hypercube sampling method	60	419	0.0	0.10	0.20	0.10	0.41	56.2 (-)
Point estimate method	6	419	0.0	0.10	0.20	0.10	0.41	6.8 (*-87.9%*)

(B) Robust optimal system design

		Robust optimal system design			

Uncertainty sampling method	Nos. of scenarios	A'_{PV}	Cap_{WT}	n_{WT}	Cap_{CG}	n_{CG}	Cap_{AC}	n_{AC}	Cap_{EC}	n_{EC}	Cap_{bat}	$\tilde{F}_{sys}$ under the 60 scenarios	$\tilde{F}_{sys}$ under the 6 scenarios	Computing time (h)
Latin hypercube sampling method	60	427 (-)	22	0	30	1	50	1	133 (-)	1	62 (-)	578,385 (-)	575,436 (-)	53.1 (-)
Point estimate method	6	416 (*-2.6%*)	29	0	30	1	50	1	126 (*-5.3%*)	1	68 (*+9.7%*)	589,710 (*+1.96%*)	573,764 (*-0.3%*)	4.1 (*-92.3%*)

Sensitivity analysis on point estimate method under different climate conditions

To evaluate the adaptability of the point estimate method, its effectiveness under different climate conditions is also assessed by comparing the building performance under scenarios given by 2PEM method and LHS method. The sensitivity to climate condition is chosen to be analyzed, since one of the major difference among different applications of building robust design optimization is the climate condition (the uncertainty sources of building load profiles are similar). Five typical cities in the USA are selected for convenience as their weather data are easily accessed in the EnergyPlus database. These cities are from 5 different climate zones (i.e., cold, mixed-humid, hot-dry, hot-humid and marine). The parameters of building envelope at different climate conditions are set according to the envelope requirements in the International Energy Conversation Code [38]. The total electricity demand considers the electricity for heating and the thermal discomfort index considers the summer discomfort (i.e., PMV $\geq$ 0.5), when heating provision is needed.

The results of the sensitivity analysis are shown in Table 5. It can be seen from Table 5 that the differences between the mean of annual average total electricity demand or thermal discomfort index under scenarios given by 2PEM method and LHS method are very small at different climate conditions, which can be negligible. The differences between the maximum annual average thermal discomfort index under scenarios given by 2PEM method and LHS method are mostly less than 2% except in Miami. The differences between the maximum annual average thermal discomfort index under scenarios given by 2PEM method and LHS method are less than 2% except in three cities, including New York, Los Angeles and San Francisco. But the differences are within 5.5%. If the accuracy is not acceptable to the decision-makers, it can be further improved by using more concentration points in point estimate method, e.g., 3 points, which still requires much less computing time than the LHS method. It can be, therefore, concluded that the point estimate method is effective for uncertainty quantification under different climate conditions and for the application of robust design optimization.

Table 5. Differences between building performance indicators under scenarios given by 2PEM and LHS at different climate conditions

City	Climate zone	Building performance indicators			
		Mean of annual average total electricity demand	Mean of annual average thermal discomfort index	Maximum annual average total electricity demand	Maximum annual average thermal discomfort index
Miami	Cold	-0.051%	-0.824%	-1.653%	-2.830%
New York	Mixed-humid	0.046%	-0.459%	-4.534%	-0.547%
Los Angeles	Hot-dry	0.058%	-0.624%	-5.208%	-1.764%
Houston	Hot-humid	-0.020%	-0.739%	-1.828%	-1.216%
San Francisco	Marine	0.038%	-0.760%	-5.321%	-1.009%

4.5 Robustness of the coordinated robust optimal design method

The design variables of building envelope and energy systems in the reference building are also optimized using the coordinated optimal design method proposed in a previous study of the authors [9] and the existing multi-stage optimal design method (i.e., the uncoordinated optimal design method in the rest of this paper) respectively. The impacts of uncertainties are not considered in these two methods. The optimization results are shown in Table 6. It can be seen that the optimal building orientation given by the coordinated robust optimal design method is closer to north and the optimal overhang projection ratio is rather large, compared with those given by the other two design methods. The optimal building design given by the coordinated robust optimal design method requires larger absorption chiller, electric chiller and battery, compared with that given by the other two design methods. Its optimal PV area is larger than that given by the coordinated optimal design method, but is smaller than that given by the uncoordinated optimal design method. This is due to more cooling and electrical power loads are required considering possible uncertainties compared with considering a typical and fixed design condition as illustrated in Section 4.2.

Table 6. Optimal building designs given by different optimal design methods

Design method	Optimal envelope design					Optimal system design									
	BO	RSA	WWR	WSA	OPR	A'_{PV}	Cap_{WT}	n_{WT}	Cap_{CG}	n_{CG}	Cap_{AC}	n_{AC}	Cap_{EC}	n_{EC}	Cap_{bat}
Coordinated robust optimal design	0.0	0.10	0.20	0.10	0.41	416	29	0	30	1	50	1	126	1	68
Coordinated optimal design	8.7	0.10	0.20	0.10	0.45	395	9	0	32	1	42	1	90	1	50
Uncoordinated optimal design	83.8	0.10	0.29	0.10	0.20	498	14	0	32	1	42	1	92	1	54

The system performance of the optimal system design solutions given by these three design methods are calculated and compared under the 60 scenarios generated using LHS method as shown in Fig.8. It can be seen that the optimal design given by the coordinated optimal design method has averagely 31.91 times (i.e., 111,625 kWh) more accumulated unmet cooling load and 54.2% (i.e., 320,081 USD) more energy system design objective value in life cycle under the 60 scenarios compared with that given by the coordinated robust optimal design method. Its total cost in life cycle is averagely 2.6% lower (i.e., 14,102 USD) and its accumulated grid impact index is averagely 1.7% (i.e., 3) less. The optimal design given by the uncoordinated optimal design method has averagely 35.94 times (i.e., 125,740 kWh) more accumulated unmet cooling load, 3.5% (i.e., 6) more accumulated grid impact index and 62.6% (i.e., 369,239 USD) more energy system design objective value over the life cycle under the 60 scenarios compared with that given by the coordinated robust optimal design method. Its total cost in the life cycle is averagely 1.7% (i.e., 9,406 USD) less.

The system performance of the optimal system design, obtained by assigning a safety factor of 1.1 to the optimal system design given by the uncoordinated optimal design method, is also calculated under the 60 scenarios as shown in Fig. 8. Its total cost in life cycle is increased by 2.3% (i.e., 12,258 USD) in average under the scenarios, compared with the coordinated robust optimal design method. The unmet cooling load in life cycle is much reduced compared with uncoordinated optimal design, but is still 15.43 times (i.e., 53,979 kWh) of that given by coordinated robust optimal design. The grid impact index in life cycle is 9.0% (i.e., 15) higher and the energy system design objective value is 30.1% (i.e., 177,816 USD) larger than that given by the coordinated robust optimal design method. It can be seen that the coordinated robust optimal design method using a probabilistic approach to quantify the impacts of uncertainties can provide better services (i.e., cooling supply) with higher energy efficiency and less "cost" (i.e., the objective value in this study) under uncertainties, compared with the design methods ignoring uncertainties or quantifying uncertainties roughly using safety factors.

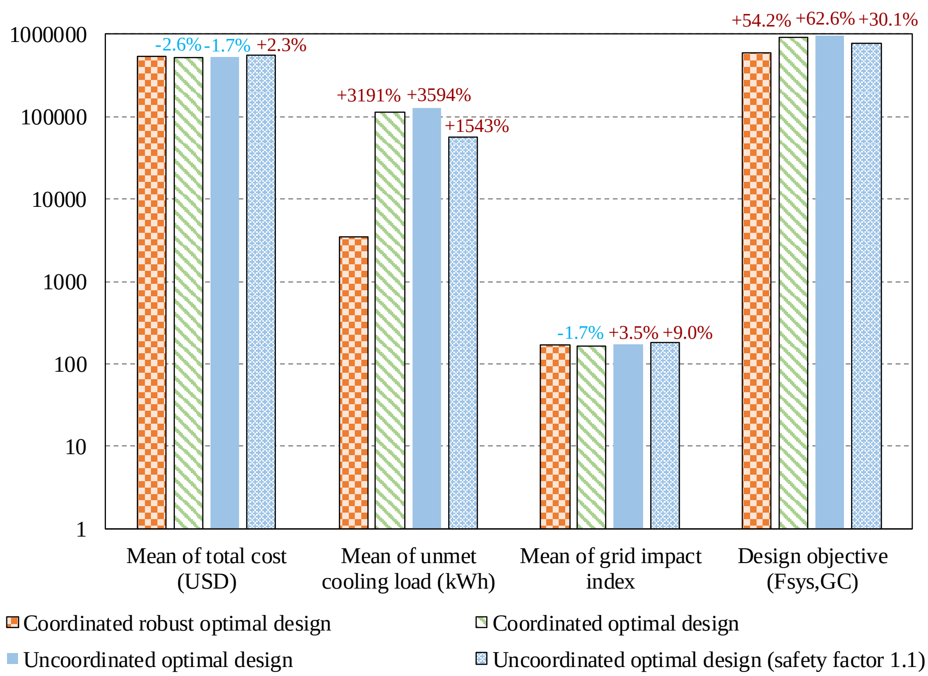


Fig.8. System performance of the optimal design solutions given by different design methods under the 60 scenarios generated using LHS method

The unmet cooling loads in building life cycle of the optimal building designs, given by these three different design methods, under each scenario generated using LHS method are further investigated. The results are shown in Fig. 9. It can be seen that the unmet cooling loads in building life cycle of the optimal building design given by the coordinated robust optimal design method are much less than that given by the coordinated optimal design method and the uncoordinated optimal design method under all the scenarios. The unmet cooling loads in building life cycle of the optimal design given by the coordinated optimal design method are equal to or less than that given by the uncoordinated optimal design method under uncertain scenarios. Even though a safety factor of 1.1 or 1.2 is considered in system sizing, the unmet cooling load in building life cycle of the optimal design given by the uncoordinated optimal design method is still much higher than that given by the coordinated robust optimal design method. It can be seen that the coordinated robust optimal design using a probabilistic approach to quantify the impacts of uncertainties is the most robust, among the three optimal design methods, to provide sufficient services under possible uncertainties.

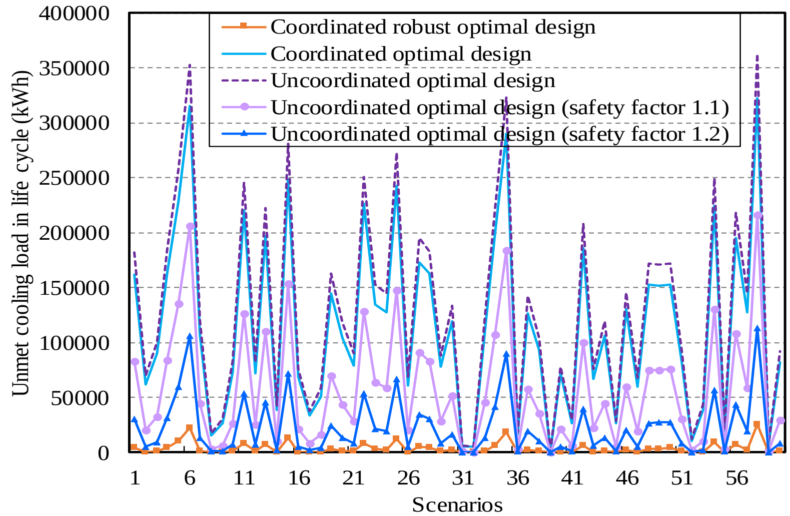


Fig.9. Unmet cooling loads in building life cycle of optimal building designs given by different design methods under the 60 uncertain scenarios

4.6 Efficiency of the coordinated robust optimal design method and point estimate method

The computing time of the coordinated robust optimal design method is also compared with the conventional robust optimal design method to validate its optimization efficiency. The conventional robust optimal design method optimizes building envelope and energy systems simultaneously based on GA. EnergyPlus is used for building performance simulation and LHS is used for uncertainty sampling. Its computation time is estimated to be about 15,000 hours, if assuming the same evaluation times (i.e. 10,000 times = 100 generations x 100 populations, for the energy system optimization in the above case study) are needed. The actual computation time could be much longer as it would actually need much more evaluation times as 15 design variables (instead of 10 design variables for system design optimization) are involved. The computing time of the proposed coordinated robust design method (i.e., 21 hours on a regular PC in this case) is reduced by 99.86% compared with this estimated minimum computation time of conventional simultaneous robust design optimization. It can be seen that the proposed coordinated robust design method is very efficient to identify the global optimal design solutions for the entire zero/low energy buildings.

The computing time reduced by using point estimate method is also investigated, as shown in Table 4. It can be seen that the computing time of robust design optimization of building envelope and energy systems using point estimate method for uncertainty sampling is significantly reduced compared with that using LHS method, since much less scenarios need to be considered in performance evaluation. The computing time of robust design optimization of building envelope using point estimate method for uncertainty sampling is 6.8 minutes, which is reduced by 87.9% compared with that using LHS method (i.e., 56.2 minutes). The computing time of robust design optimization of building energy systems using point estimate method for uncertainty sampling is 4.1 hours, which is reduced by 92.3% compared with that using LHS method (i.e., 53.1 hours). It can be seen that point estimate method is much more efficient for uncertainty sampling in robust design optimization compared with LHS method, and can help to significantly reduce computing time for robust design optimization considering uncertainties. This is particularly important and meaningful for the robust design optimization of buildings.

5. Conclusions

In this study, a coordinated robust optimal design method is proposed to efficiently identify the global optimal design solutions for the entire zero/low energy buildings under uncertainties. The whole design process is divided into two coordinated stages, including design optimizations of building envelope and energy systems. Point estimate method is used to quantify the uncertainties in the cooling and electrical power loads. A case study is conducted to test and validate the point estimate method and the proposed design method. Based on the results of the case study, conclusions can be made as follows.

Point estimate method is effective and efficient to quantify the impacts of uncertainties for robust design optimization under different climate conditions. The computing time of robust design optimization using the point estimate method for uncertainty sampling is reduced by around 90% in the case study compared with that using LHS method (e.g., reduced from 53.1 hours to 4.1 hours for system design).

The coordinated robust optimal design method is more robust to provide services (e.g., sufficient cooling) compared with the coordinated optimal design method and the existing multi-stage design optimization method (even a safety factor is considered in the system sizing). It can provide better services with higher energy efficiency and less cost compared with the optimal design methods which ignore uncertainties or consider uncertainties blindly using a safety factor. In the validation case, the optimal designs given by the design methods ignoring uncertainties have over 31.91 times more accumulated unmet cooling load and over 54% more energy system objective value in average under the uncertain scenarios, compared with the proposed method.

The coordinated robust optimal design method is very efficient to identify the global optimal design solutions under uncertainties. The computing time of coordinated robust design optimization is reduced by 99.86% (i.e., reduced from 15,000 hours to 21 hours), compared with the simultaneous robust optimal design method using LHS for uncertainty sampling.

Acknowledgement

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