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Robust Optimal Design of Renewable Energy System in Nearly/Net Zero Energy Buildings under Uncertainties

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Abstract: It is acknowledged that the conventional design methods can easily lead to oversized system or unsatisfactory performance for different design conditions. Most existing studies on design optimization of net zero energy building (nZEB) are conducted based on deterministic data/information. However, the question is: How is the actual performance of a design nZEB in different years considering uncertainties? This study, therefore, proposed a robust design method for sizing renewable energy systems in nZEB concerning uncertainties in renewable resources and demand load. The proposed robust design method is applied to the planning of renewable energy system for the Hong Kong Zero Carbon Building. The annual performance of nZEB under the optimal design options are systematically investigated and compared using the proposed robust design method and the deterministic method. It is meaningful to obtain a fitting formula to identify the relationship between the probability of achieving annual zero energy balance and the design mismatch ratio. On the basis of Monte Carlo uncertainty propagation methods, the uncertainty of nZEB performance is quantified which provides flexibility for designers in selecting appropriate design options according to the required probability of achieving nZEB during the design stage.

Keywords: Net zero energy building, robust design, Monte Carlo simulation, mismatch ratio

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1. Introduction

With an increasing requirement and heavily dependency on energy, much pressure has been put on conventional energy resources (such as coal, oil and nature gas). However, the limited reserves of conventional energy resources are too expensive and too environmentally damaging to retrieve. Renewable and distributed power generations, such as wind turbine, solar PV, diesel engine and so on, have been recognized as efficient, reliable and environment-friendly options for buildings to achieve sustainable and low-carbon development [1-3]. The idea of nearly/net zero energy building (nZEB), which generates the same amount of energy as they consume over a specific period (e.g. a year), has been proposed to address the issue of energy and environment problems [4-6]. Policies and regulations are promoted greatly for the development of nZEB as the future buildings such as the "EU Directive on Energy Performance of Buildings" and the "Building Technology Program" of the US Department of Energy. However, there is still no exact approach for designing and realizing nZEB at present [7-8]. How to design nZEB is therefore of great challenge mainly due to the complex interplay of the passive & active climate control & energy-generation systems and it may also interact with the smart grid.

Optimal design of nZEB has been widely investigated in term of passive design and/or energy efficiency system design and/or energy-generation system design [8-22]. Most existing studies on system design of nZEB have been performed based on deterministic method without any regard to the uncertainties in energy demand, renewable resources, etc. Sun [6] proposed an exhaustive search approach for the design of renewable energy system and storage system in a nZEB to minimize the overall initial investment. Lu et al. [8] presented a study of optimal designing the renewable energy systems for low/zero energy buildings to minimize the total cost, CO_2 emissions and the stress on the power grid. Two design optimization methods, i.e. single objective optimization using GA and multi-objectives optimization using Non-dominated Sorting Genetic Algorithm (NSGA-II), were applied in this study. Thalfeldt et al. [13] presented an investigation on cost optimal solutions for nearly zero energy buildings in terms of building facade solutions (e.g. window properties, external wall insulation, shading and the ratio of window-to-wall). Baglivo et al. [14] carried out a multi-objective analysis to obtain several types of high energetic efficiency external walls for zero energy buildings through the combination of various materials. Hamdy et al. [15] introduced a multi-stage simulation-based optimization method to find the cost-optimal design solutions for nZEB in Finland. The design options involve the building-envelope parameters, heat-recovery units, heating/cooling systems and sizes of thermal/ photovoltaic solar systems. The application of energy-generation systems (e.g. combined cooling and/or heat and power, photovoltaic panel, wind turbine) is another essential step for buildings to achieve the target of annual energy balance [16-18]. Fong and Lee investigated the design of renewable energy systems for low/zero energy buildings in hot and humid climate. In [19], they conducted a case study on feasibility of net zero energy target in three-storey houses and it reveals a possible direction towards realizing the target: PV panels and BIPV with nominal efficiencies of more than 13% as well as good human behaviors involved. In [20], they proposed a hybrid renewable cooling system (HRCS) for office building application and it demonstrates the metric of hybrid system by utilizing the solar energy and ground source, and the strategy of renewable cooling is robust for green building and sustainable air-condoning design in hot and humid climate.

The conventional design methods, based on deterministic data, usually lead to oversized problems. Many efforts have been made on uncertainty analysis of renewable energy system design [23-25]. Sreeraj et al [23] proposed a novel method combining the advantage of both deterministic and probabilistic approach (taking uncertainty of resource into account) to size standalone hybrid systems. Based on the GA algorithm and Monte Carlo method, Zhou et al. [24] proposed a two-stage stochastic programming model to optimally size the distributed energy systems. A small difference was found by comparing the optimal solutions obtained using the deterministic and the stochastic approach. Lujano-Rojas [25] presented a mathematical model for stochastic simulation and design optimization of small wind energy systems considering the uncertainties in the load profile and battery bank lifetime. Maheri [26] proposed a robustness design methodology for a standalone wind/PV/diesel hybrid system considering uncertainties in cost and reliability measures. The aim is to find the most reliable system subject to a constraint on the cost and/or most cost-effective system subject to constraints on reliability measures. Sun et al. [2] proposed a multi-criteria system design optimization method to size the air condition system and renewable energy system for gird-connected nZEBs under uncertainties. In [27], two system sizing approaches for net energy building clusters under uncertainties were investigated, in which the conventional separated design and the integrated design were applied to provide services for individual buildings and all buildings respectively.

Uncertainties must be taken into consideration for designing the type of sensitive buildings such as nZEB. However, not fully understanding its performance discrepancy at the two stages (i.e. design stage and operation stage), designers may not be able to select the right approach for achieving net zero energy in practice. This study, thus, aims to quantify the uncertainties of nZEB performance and to identify the relationship between the probability to achieve annual zero energy balance and the design mismatch ratio when the uncertainties in energy demand, renewable resources are concerned. The deterministic approach and stochastic approach, applied in sizing renewable energy system for nZEB respectively, are investigated and compared. This paper is structured as follows: The idea and methodology of sizing renewable energy system for nZEB are presented in Section 2. Then the proposed method is applied for a developed building based on Hong Kong Zero Carbon Building. Basic information of the building and energy system models are introduced in Section 3. Application of the proposed method in case study is evaluated and discussed in Section 4. Conclusion is given in Section 5.

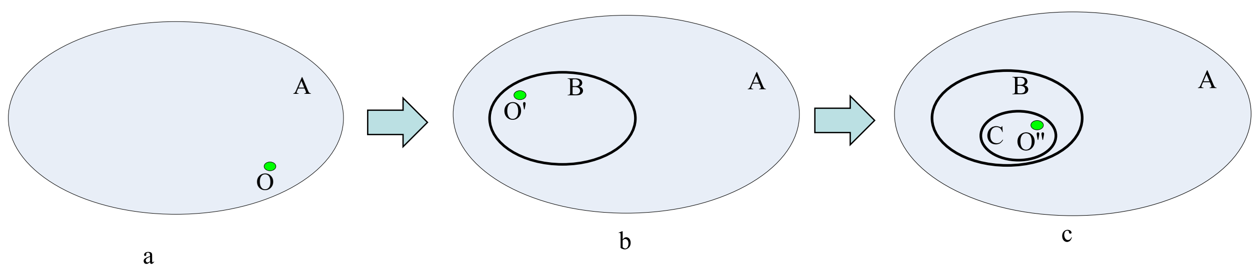
2. Methodology

2.1 The idea of optimal sizing renewable energy system for buildings

Fig 1 shows the basic idea of optimal sizing renewable energy system for buildings. Three categories are classified to meet the requirement of different buildings. For the design of renewable energy systems in conventional buildings (No constraint on the mismatch between energy generation and energy consumption), the optimal design option (Point *O*) can be easily found within all the design options (Area of *A*) using searching methods, as shown in Fig 1a.

In terms of optimal sizing renewable energy systems for nZEBs using deterministic approach, annual energy balance must be achieved for the design year. The optimal design option (point *O′*) could be found within a few design options (Area of *B*). *B* represents all the design options that are satisfying for nZEB in the design year, as shown in Fig 1b.

Regarding optimal sizing renewable energy systems for nZEB considering uncertainties, a narrowed area of *C* is identified using stochastic approach. *C* represents all the design options that are satisfying for nZEB in different years. Finally, the optimal design option (point *O″*) could be found among the narrowed area of *C*, as shown in Fig 1c. This study proposes a robust design method, which aims to investigate the influence of uncertainties on system design and identify the relationship between the probability of achieving annual zero energy balance and the design mismatch ratio..



Remarks: *A*: all design options; *B*: design options for nZEB based on deterministic condition; *C*: design options for nZEB under uncertainties; *O*/*O′*/*O″*: optimal design option.

Figure 1 Optimal design option under different requirements

2.2 Steps of design optimization

This study focuses on design optimization of RES for nZEB considering uncertainties (Fig 1c). The steps of design optimization procedure are shown in Fig. 2. It can be further explained as follows:

- In the first step, the uncertainties of input parameters (e.g. solar radiation, wind velocity, cooling load and other load) are identified in a sample file generated by Monte Carlo simulation. In this study, each sample represents the corresponding parameters in the typical meteorological year. Therefore, the sample file stores the input parameters of n years.

- In the second step, the size ranges of RES are set for simulation and the total number (N) of design options is determined. In order to simulate the electricity generation and electricity consumption of the building, the RES model and building energy system model are developed in MATLAB while building cooling load model is built in TRNSYS. The typical meteorological year in Hong Kong (i.e. 1987) is selected as the deterministic condition for design. Using Monte Carlo simulation, n years' samples are generated and stored in a sample file, which provides the samples for these models to calculate the building electricity generation and consumption.
- In the third step, the mismatch ratio between electricity generation and electricity consumption in each year can be computed under the current design option. If the mismatch ratio is equal or above 0, then this year is labeled and stored as a positive year; else it is labeled and stored as a negative year. Therefore, the average performance (objective function) of each design option in n years can be calculated using exhaustive searching methods.
- Finally, the performance of all the design options in n years are evaluated and compared. Thus the optimal design option can be identified by ranking their performance.

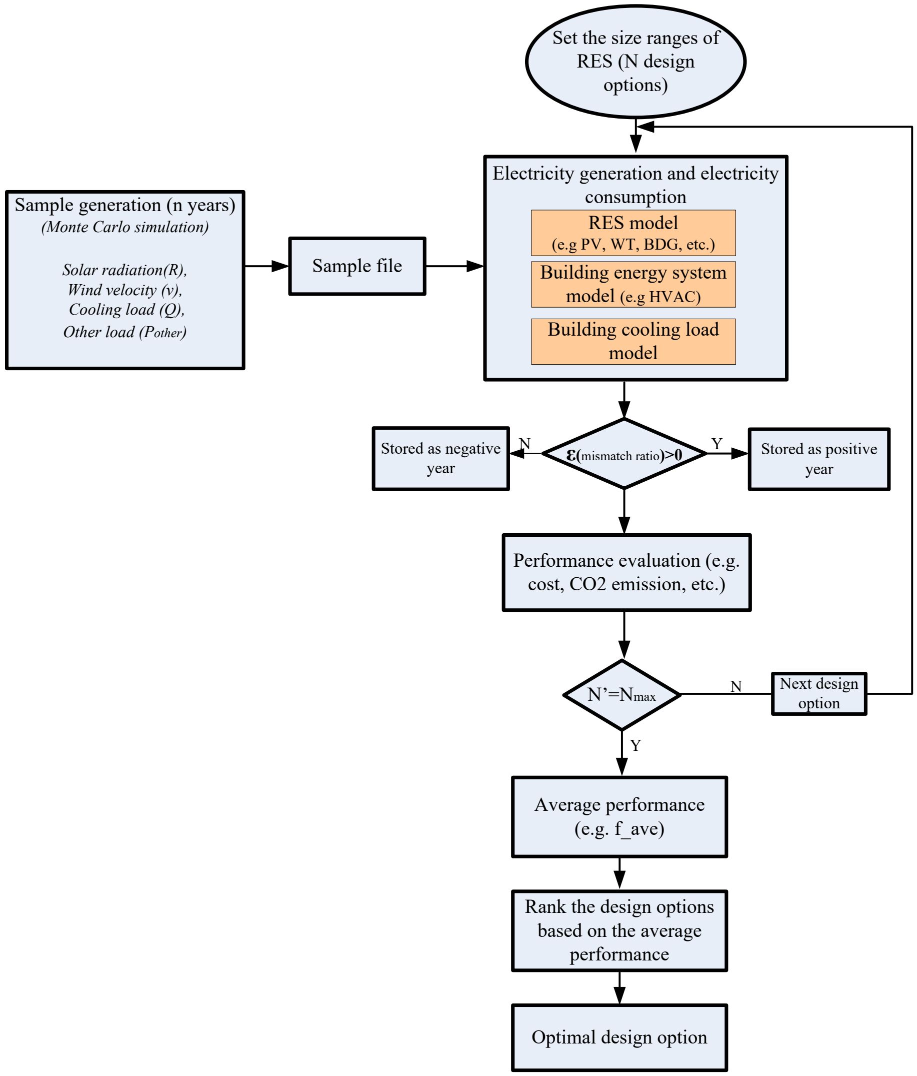


Figure 2 Steps of design optimization of RES for ZEB under uncertainties

3. Case study

3.1 Building description

The proposed methodology is tested in the design of renewable energy systems for Hong Kong Zero Carbon Building. The building is oriented south-east to receive the site prevailing wind as natural ventilation operation, and it covers a total land area of 14,700 m^2 with air conditioned area of 995 m^2. Fig. 3 shows the aerial view of Zero Carbon Building in Hong Kong. The three-story building includes two exhibition rooms, two eco-offices, two meeting rooms, one multi-purpose room and one eco-home. The indoor temperature is set to 24◦C, and the relative humidity is set to 60%. The design peak cooling load of the building is 163 kW. Three electric chillers combining with one absorption chiller are used to undertake the building cooling load. The main parameters of the building and its energy systems are listed in Table 1.

Figure 3 Aerial view of Zero Carbon Building in Hong Kong

Table 1 Specifications of the building and its energy systems

Types	Feature	specification
Passive design	Orientation	south-east
	Building air conditioning area	995 m^2
	Window-to-wall ratio	<10-40%
	Shading	45° angle
	Wall U value and absorption	<1.0W/m^2/K & <0.4
	Roof U value and absorption	<1.0W/m^2/K & <0.3
	Peak cooling load designed	163 kW
Energy systems	PV	1015 m^2
	Bio-diesel generator	Rated power=100 kW
	Electrical chiller	70 kW×3, COP_N=4.2
	Adsorption chiller	70 kW×1
	Heat recovery system efficiency	0.8
	Bio-diesel generator efficiency	0.3
	Coefficient of performance of absorption chiller	0.7
	Unit price of bio-diesel generator	205.53 USD/kW
	Unit price for photovoltaic	378.17 USD/m^2
	Unit price for wind turbine	714.29 USD/kW
	Lifetime for bio-diesel generator	40,000h
	Lifetime for photovoltaic	20 years
	Lifetime for wind turbine	20 years
Others (i.e. price and emission factors)	Oil price	1.3 USD/l [28]
	Emission factors of electricity from the grid	0.608 [29]
	Emission factors of bio-diesel combustion	0.552 [29]
	Delivered electricity price	0.13 USD/kWh [8]
	Exported electricity price	0.065 USD/kWh [8]

3.2 Energy system model

To determine the optimal size of renewable energy systems for the building that can achieve the target of annual zero energy, energy system models are developed to obtain cooling load and electricity generation/consumption in the building. In this study, TRNSYS and Matlab are applied to simulate the cooling load and electricity generation/consumption of the building. Three types of renewable energy systems including photovoltaic (PV), wind turbine (WT) and bio-diesel generator (BDG) are assumed to be installed in the building. The thermal/electricity balance and simplified models of energy systems are described as follows.

Thermal balance

There is no heating load of the building under the weather condition in Hong Kong, the cooling load of the building (Q_c) in summer is undertook by absorption chiller (Q_{ac}) and electric chillers (Q_{ec}) as shown in Eq-1. The operation strategy is like this: When the building cooling load is larger than the capacity of absorption chiller, the absorption chiller will work on its full capacity and the rest of the cooling load will be met by the electric chillers. Otherwise, the absorption chiller undertakes the total cooling load.

$$Q_c^t = Q_{ec}^t + Q_{ac}^t \tag{1}$$

Electricity demand and supply

The electrical demand (W_{demand}) in the building comes from the electric chillers (W_{ec}), pumps (W_{pump}), cooling tower fans (W_{ct}), AHU (air handling unit) fans (W_{fan}) and other appliances (W_{other}) including power consumed by lighting, socket outlet, fuse spur, etc.. The electricity demand, as shown in Eq-2, is satisfied by the PV (W_{PV}), wind turbine (W_{WT}) and bio-diesel generator (W_{BDG}) while the power grid (W_{grid}) is assumed as the energy storage to store surplus electricity and to cover the power shortage.

$$W_{demand}^t = W_{ec}^t + W_{pump}^t + W_{ct}^t + W_{fan}^t + W_{other}^t \tag{2}$$

$$W_{supply}^t = W_{PV}^t + W_{WT}^t + W_{BDG}^t + W_{grid}^t \tag{3}$$

Mismatch ratio (ε) is defined in this study as the ratio of the difference between electricity generation and building electricity demand to the building electricity demand in one year, Eq-4. In zero energy buildings, the value of the design mismatch ratio is not less than 0 because it is required that electricity generation on site should be not less than building electricity demand, represented in Eq-5.

$$\varepsilon = \frac{\sum_{t=1}^{8760}(W_{PV}^t + W_{WT}^t + W_{BDG}^t - W_{ec}^t - W_{pump}^t - W_{ct}^t - W_{fan}^t - W_{other}^t)}{\sum_{t=1}^{8760}(W_{ec}^t + W_{pump}^t + W_{ct}^t + W_{fan}^t + W_{other}^t)} \tag{4}$$

$$\sum_{t=1}^{8760}(W_{PV}^{t} + W_{WT}^{t} + W_{BDG}^{t}) \geq \sum_{t=1}^{8760}(W_{ec}^{t} + W_{pump}^{t} + W_{ct}^{t} + W_{fan}^{t} + W_{other}^{t}) \quad (5)$$

Electric chiller model:

The chilled water system consists of three numbers of 70 kW scroll type water-cooled chiller, using environmental friendly refrigerant R407c. The electricity consumption of the electric chiller (Eq-6) is calculated based on its cooling load and COP_{ec}. Where, the COP_{ec} of electric chiller is obtained using an empirical model as shown in Eq-7 [8]. *a*=-1.6757, *b*=0.3083, *c*=3.5093, *d*=0.853, and these parameters are obtained by fitting the models with the measured data of chillers in the building (Fig 4).

$$W_{ec} = \frac{Q_{ec}}{COP_{ec}} \quad (6)$$

$$COP_{ec} = COP_{N} \times \frac{T_{eva,out}}{T_{con,in} - T_{eva,out}} \times (a \times PLR^{3} + b \times PLR^{2} + c \times PLR + d) \quad (7)$$

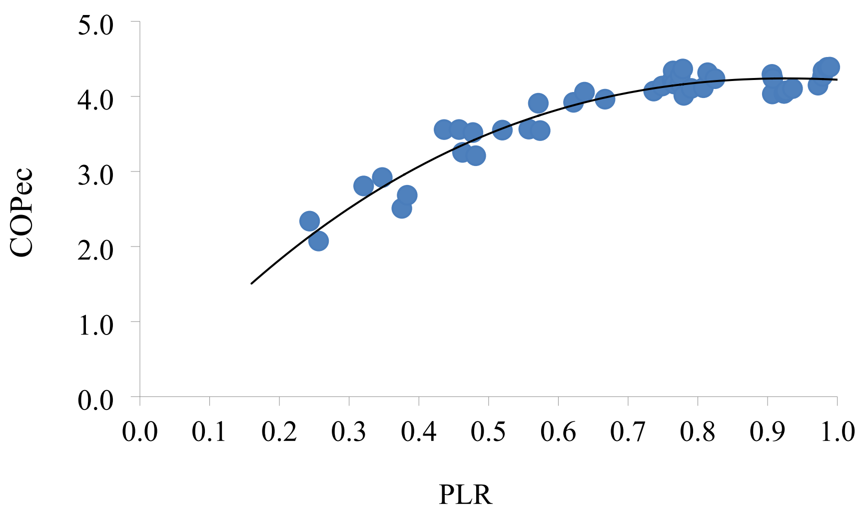


Figure 4 The actual chiller COP varied with PLR

Pump models:

The cooling water pumps are constant speed pumps that are assumed to work at rated power. The chiller water pumps are variable speed pumps. Their electricity consumption depends on the pressure drop (Δp_{cwp}), the water flow rate (m_w) and pump efficiency (η_{cwp}) as shown by Eq-8. It is finally reformulated as Eq-9 and the parameters are identified by using the on-site data in ZCB.

$$W_{cwp} = \frac{\Delta p_{cwp} \times m_w}{\eta_{cwp}} \tag{8}$$

$$W_{cwp} = 10 \times \frac{m_w}{m_{w,design}} - 1 \times \left(\frac{m_w}{m_{w,design}}\right)^2 \tag{9}$$

Cooling tower model:

The relationship between the fan power consumption and the corresponding air flow rate can be represented by Eq-10. Where, A and k are constant parameters depending on the tower size. The cooling capacity of the cooling tower (Q_{ct}) varies proximately in direct proportion to the fan speed, thus is proximately proportional to the air flow rate (m_a). The energy consumption of cooling tower fan is finally obtained using Eq-11.

$$W_{ct} = A \times {m_a}^k \tag{10}$$

$$W_{ct} = W_{ct,design} \times \left(\frac{Q_{ct}}{Q_{ct,design}}\right)^{1.5} \tag{11}$$

AHU fan model:

The power consumed by a fan (W_{fan}) is calculated based on the pressure head of the fan (Δp_{fan}), the air flow rate (v_a) and the fan efficiency (η_{fan}) as shown in Eq-12. Based on a simple empirical relation between total air flow rate of all AHUs and the building cooling load and the operation parameters at the design condition, an empirical fan power model is finally obtained as Eq-13. The parameters are identified by using the on-site data in ZCB.

$$W_{fan} = \frac{\Delta p_{fan} \times v_a}{\eta_{fan}} \tag{12}$$

$$W_{fan} = 8 \times \frac{v_a}{v_{a,design}} + 12 \times \left(\frac{v_a}{v_{a,design}}\right)^3 \tag{13}$$

PV model: The PV power generation can be computed by Eq-14 [30-31]. Where, A_{des} is the total area of PV (m^2). η_m is the PV module efficiency. P_f is the packing factor. η_{PC} is the power conditioning efficiency. I is the hourly irradiance (kWh/m^2).

$$W_{PV} = A_{des} \times \eta_m \times P_f \times \eta_{PC} \times I \tag{14}$$

Wind turbine model: Power generation from the wind turbine can be computed by Eq-15 [31-32]. Where, ρ_a is the air density (kg/m^3), $c_{p,w}$ is the coefficient of the wind turbine performance, η_{WT} is the combined efficiency of the generator and wind turbine, A_{WT} is the area of blade, v_{wind} is the wind velocity.

$$W_{WT} = 0.5 \times \rho_a \times A_{WT} \times v_{wind}^3 \times c_{p,w} \times \eta_{WT} \tag{15}$$

Bio-diesel generator model: The fuel consumption of the bio-diesel generator in operation is estimated by Eq-16 [33]. In this study, the power generation is depending on the building cooling demand, as shown by Eq-17 [34]. Where, W_{BDG} and $W_{rated,BDG}$ are the actual power output and the rated power of the BDG respectively. The values of A_G and B_G are given in Table 1. In this study, the efficiency of the bio-diesel generator (η_{BDG}) is considered as its rated efficiency of 0.3.

$$F_{bio} = A_G \times W_{BDG} + B_G \times W_{rated,BDG} \tag{16}$$

$$W_{BDG} = \frac{Q_r}{(1-\eta_{BDG}) \times \eta_{hrs}} \times \eta_{BDG} \tag{17}$$

3.3 Formulation of objective function

In order to find the optimal size of renewable energy system, the average value of objective (*f_ave*), concerning three objectives including annual total cost ($f_{1,i}$), CO_2 emission ($f_{2,i}$) and grid interaction index ($f_{3,i}$), is used to evaluate the performance of the building energy systems in n years. Where, X is a vector of design variables at the design stage, the set U is a form of uncertainty set representing uncertain parameters in the operation stage. It should be mentioned here, $f_{1,i}$, $f_{2,i}$ and $f_{3,i}$ are the normalized total cost, normalized carbon dioxide emission and normalized grid interaction index in the *i* year.

$$\text{Min } f\_ave = \sum_{i=1}^{n} (w_1 \times f_{1,i}(X,U) + w_2 \times f_{2,i}(X,U) + w_3 \times f_{3,i}(X,U))/n, \; i=1,2\ldots n \tag{18}$$

$$\text{s.t.} \quad AX \le a \tag{19}$$

$$g_1(X,U) \ge 0 \tag{20}$$

$$g_2(X,U) = 0 \tag{21}$$

In this study, the fluctuations of predicted solar radiation, wind velocity, cooling load and other load are considered as the uncertain parameters in the set U. These uncertain parameters are assumed to follow the uniform distribution (Table 2).

$$U = [I^{t,i};v_{wind}^{t,i};Q^{t,i};W_{other}^{t,i}] \quad (22)$$

$$I^{t,i} \in [I^t - \delta_I \times I^t, I^t + \delta_I \times I^t]$$

$$v_{wind}^{t,i} \in [v_{wind}^t - \delta_{v_{wind}} \times v_{wind}^t, v_{wind}^t + \delta_{WT} \times v_{wind}^t]$$

$$Q^{t,i} \in [Q^t - \delta_Q \times Q^t, Q^t + \delta_Q \times Q^t]$$

$$W_{other}^{t,i} \in [W_{other}^t - \delta_{W_{other}} \times W_{other}^t, W_{other}^t + \delta_{W_{other}} \times W_{other}^t]$$

In order to satisfy the requirement of nZEB, deterministic design method simply applies the typical year parameters for optimal designing the RES. However, parameter fluctuations in different years may cause unsatisfactory requirement under the design system. Therefore, an indicator (Eq-23), the ratio between the number of year satisfying nZEB requirement and total number of simulation year, is defined to evaluate the probability of achieving the design target (annual zero energy balance). γ =1 represents that the design option can satisfy nZEB requirement in all simulation year, and γ =0 represents that the design option cannot even meet the requirement in one year among these simulation years. It is obviouly that a higher value of γ is prefered for a nZEB.

$$\gamma = \frac{n'(the\ number\ of\ year\ satisfying\ nZEB\ requirement)}{n(total\ number\ of simulation\ year)} \times 100\% \quad (23)$$

3.4 Description of uncertain parameters

The basic information for design optimization of renewable energy systems under uncertainties is shown in Table 2. The size ranges for WT, BDG are between 0 and 40, between 0 and 60, each with an interval of 5. The size ranges for PV is between 0 and 2000 with an interval of 100. Therefore, the total design options are 2457. The three weighting factors are treated equally in this study. In fact, different weighting factors may be preferred for different designers, and the results are usually different under different weighting factors. In this study, the weighting factors are assumed equally to evaluate the effect of uncertain parameters on the optimal design options. The uncertain parameters, i.e. solar radiation, wind velocity, cooling load and other load, are all assumed to be independent and following uniform distributions. The hourly renewable energy resources and building energy load in a representative day are shown in Fig. 5.

Under the deterministic design, exhaustive search is applied to find the optimal size combination of RES in the typical year (e.g. 1987). By contrast, exhaustive search combined with Monte Carlo simulation (500 samples) is applied for robust design.

Table 2 Basic information for design optimization of renewable energy systems under uncertainties

	Parameters	Conditions	Remarks
Search ranges of design variables	WT (kW)	0:5:40	Total design options (N):9*13*21=2457
	BDG(kW)	0:5:60	
	PV(m^2)	0:100:2000	
Weighting factor	w_1(Cost)	1/3	Constraint: $w_1+w_2+w_3=1$
	w_2(CDE)	1/3	
	w_3(GII)	1/3	
Uncertain parameters and corresponding distribution	Solar radiation (I_{irra})	Uniform (δ_I=±0.2)	Assumption: the four parameters are independent
	Wind velocity (v_{wind})	Uniform ($\delta_{v_{wind}}$=±0.1)	
	Cooling load (Q_c)	Uniform (δ_Q=±0.3)	
	Other load (W_{other})	Uniform (δ_{Other}=±0.15)	
Design method	Deterministic design	1987	Exhaustive search
	Robust design	n=500 years	Monte Carlo simulation & Exhaustive search

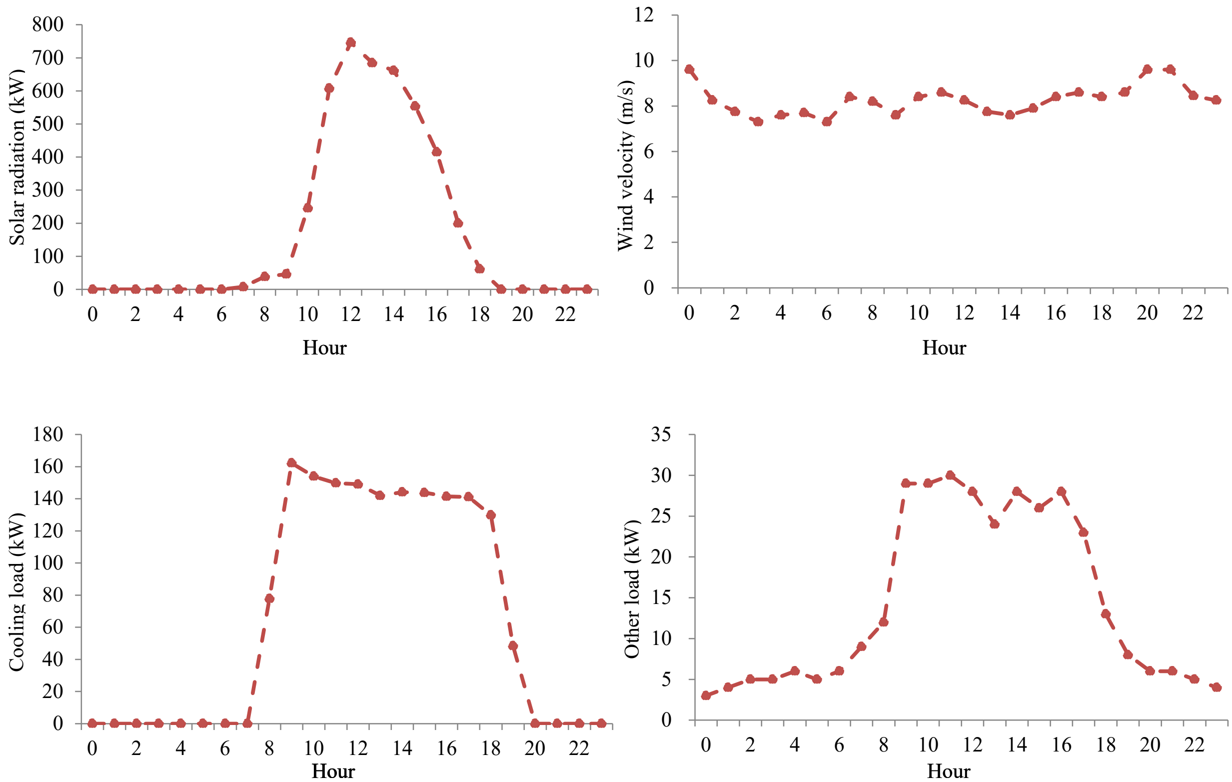


Figure 5 Renewable energy resources and energy load in a representative day

4. Results and discussions

4.1 Overall performance evaluation

Based on the optimization method and simulation model described in Section 2 and 3, robust design method is applied to seek the optimal planning of the renewable energy system for ZCB in Hong Kong. Exhaustive search is applied to evaluate all the design options (2457), the overall performance evaluation in 500 years are shown in Fig. 6. It can be observed that the mismatch ratios are between -100% and 100%, which has covered reasonable ranges of design options in regular cases. In general, the overall performance is reduced firstly and then increased with the increase of mismatch ratio. The probability to be nZEB is 0 when the mismatch ratio is less than -20%, indicating that it is impossible to realize annual zero energy target in these design options. However, the probability can be achieved to 1 when the mismatch ratio is more than 30%, indicating that the building can realize annual zero energy target in different years in these design options.

When designing RES for conventional buildings without the requirement to be nZEB, the optimal design option, i.e. WT of 40 kW, BDG of 25 kW and PV of 700 m^2, is found at the point *O* (*f_ave* =0.691, ε=-14.75%, γ =0.042) within the area *A*. In terms of optimal designing of RES for a nZEB with the probability γ above 0.5, the optimal design option, i.e. WT of 40 kW, BDG of 30 kW and PV of 900 m^2, is found at the point *O′* (*f_ave* =0.706, ε=1.46%, γ =0.544) within the area *B*. It is interesting to find that the point *O′* is also the optimal design options for buildings to achieve annual zero energy balance using deterministic approach. Regarding the probability to be 1 for achieving NZEB, the optimal design option, i.e. WT of 40 kW, BDG of 30 kW and PV of 1400 m^2, is found at the point *O″* (*f_ave* =0.772, ε=25.77%, γ =1) within the area *C*.

It is interesting to observe the optimal design option *O′*, obtained using deterministic approach, has a probability of 54.4% for the building to achieve annual zero balance. By contrast, the optimal design option *O″* obtained by the robust design method has a probability of 100% for the building to achieve annual zero balance in 500 years.

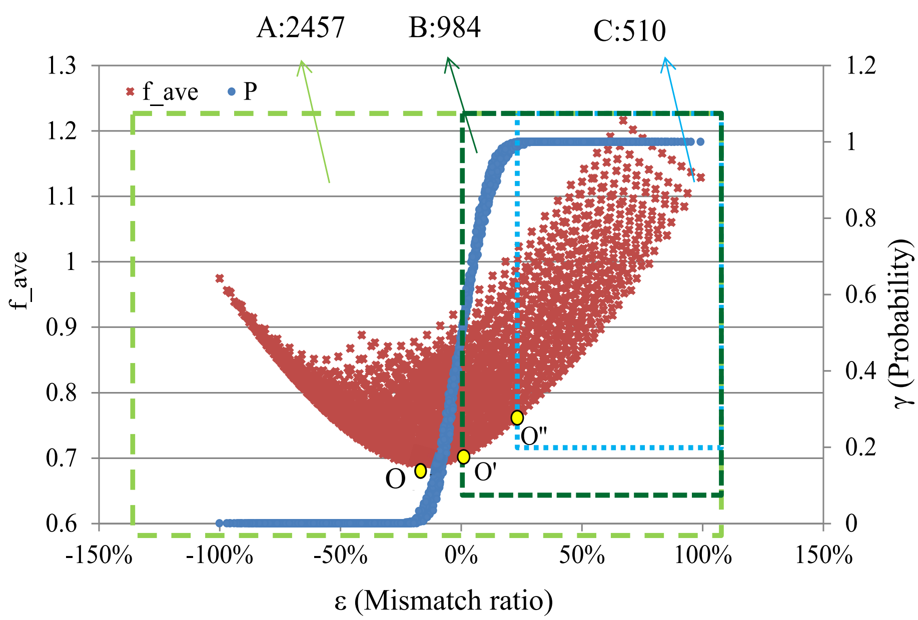


Figure 6 *f_ave* and probability **VS** mismatch ratio

The results of optimal RES sizes and the corresponding performance under different requirements are shown in Table 3. The size of WT keeps at the maximum value (40 kW) under different requirements. Meanwhile, the size of BDG and PV vary between 25 kW and 35 kW and between 700 m^2 and 1400 m^2 respectively under different conditions. A higher probability may require the design option with a poor overall performance and a larger mismatch ratio (ε), as shown in Fig. 7. Designers could select appropriate design option according to the probability required to be nZEB during the design stage.

Table 3 Optimal size and corresponding performance under robust design

Requirement: γ >p	Optimal design option			Performance			Remark
p	WT (kW)	BDG (kW)	PV (m^2)	f_ave	ε	γ	
0	40	25	700	0.691	-14.75%	0.042	*O*
0.1	40	25	800	0.692	-10.00%	0.124	
0.2	40	25	900	0.696	-5.25%	0.27	
0.3	40	30	800	0.699	-3.40%	0.346	
0.4	40	25	1000	0.703	-0.50%	0.462	
0.5	40	30	900	0.706	1.46%	0.544	*O′*
0.6	40	25	1100	0.712	4.26%	0.64	
0.7	40	30	1000	0.716	6.32%	0.72	
0.8	40	25	1200	0.723	9.01%	0.82	
0.9	40	35	1000	0.735	13.03%	0.92	
1	40	30	1400	0.772	25.77%	1	*O″*

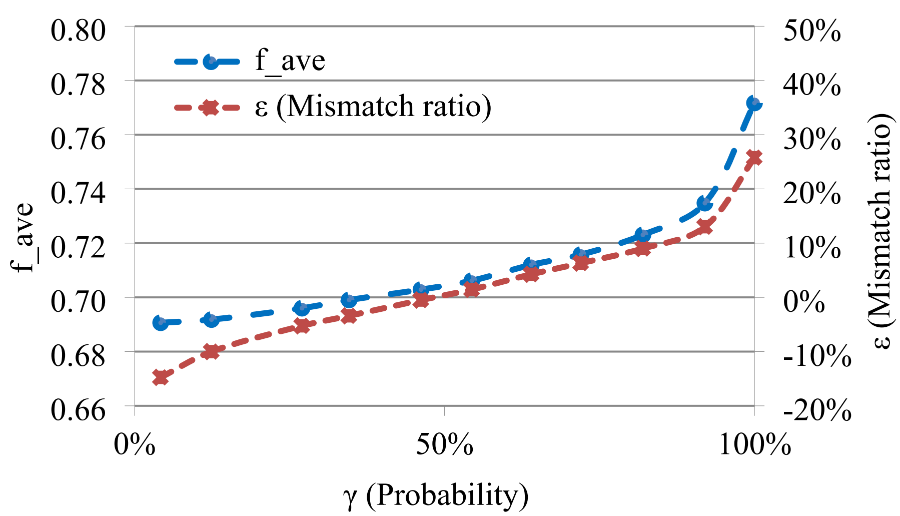


Figure 7 *f_ave* and mismatch ratio **VS** probability under robust design

It is generally acknowledged that the probability for a building to achieve nZEB is largely depending on the selected design options. The design mismatch ratio can be used to classify different types of design options. Fig. 8 shows the relationship between the probability and the design mismatch ratio, the red points represent different design options. It is interesting to find that the probability is highly depending on mismatch ratio. The probability keeps at the minimum value (0) when the design mismatch ratio is less than -20% and it keeps at the maximum value (1) when the mismatch ratio is more than 30%, and a fitting formula, i.e. $y=-999.75x^6+483.69x^5+80.297x^4-64.531x^3-1.3263x^2+4.2483x+0.4828$, is obtained to describe an appropriate relationship between the probability and mismatch ratio within -20% to 30%. Therefore, the probability of nZEB can be evaluated by the mismatch ratio of different design options during the design stage.

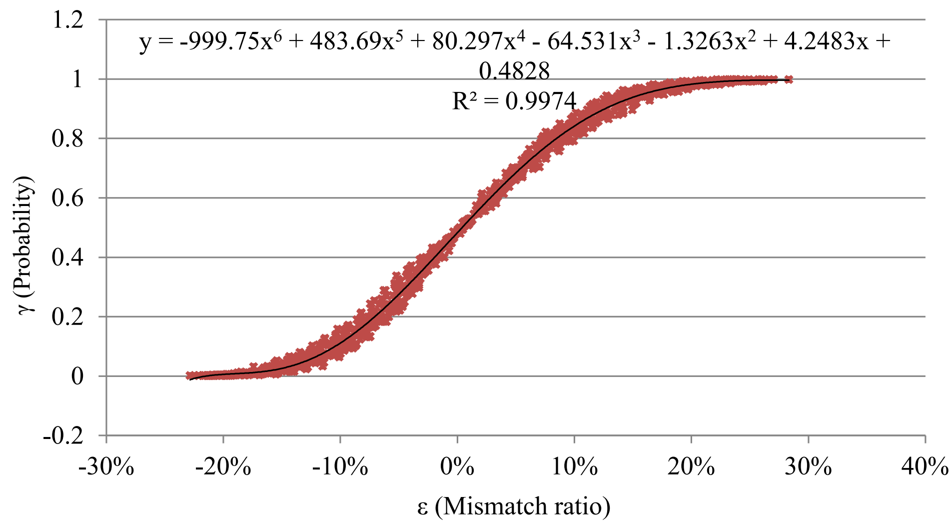


Figure 8 Relationship between probabilities and mismatch ratio

4.2 Estimating performance uncertainty of optimal design options (O' and O'')

The performance of nZEB under the optimal design options (O' and O''), obtained by deterministic method and the proposed robust design method, are evaluated for 500 years respectively. The frequencies of the overall performance and mismatch ratio of the two design options are shown in Fig. 9 and Fig. 10 respectively. For the design option O', the overall performance fluctuates between 0.654 and 0.778 with the highest frequency at around 0.69. The mismatch ratio fluctuates between -18.1% and 32.1% with the highest frequency at around 0%. For the design option *O''*, the overall performance fluctuates between 0.743 and 0.816 with the highest frequency at around 0.758, the mismatch ratio fluctuates between 0.3% and 63.6% with the highest frequency at around 20%.

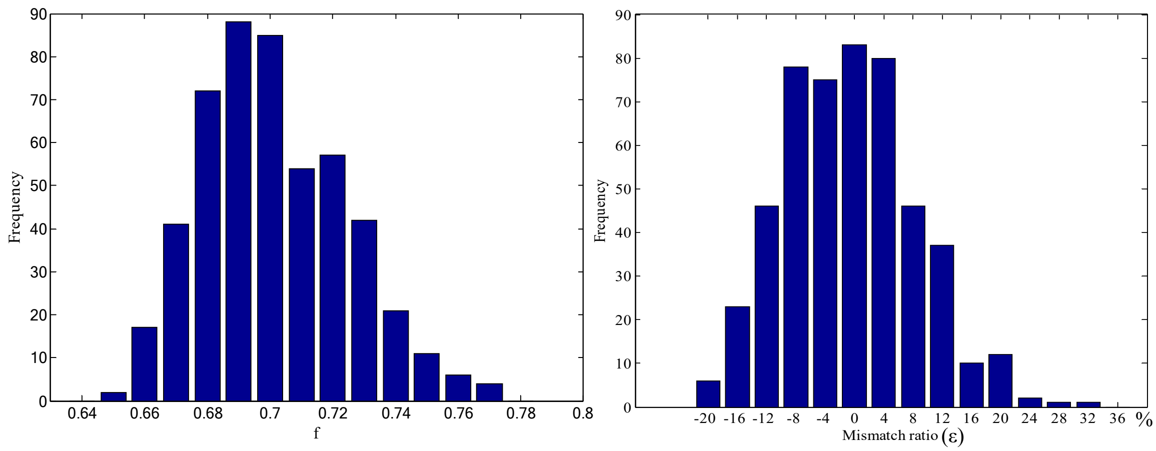


Figure 9 Frequencies of overall performance and mismatch ratio of *O'* in 500 years

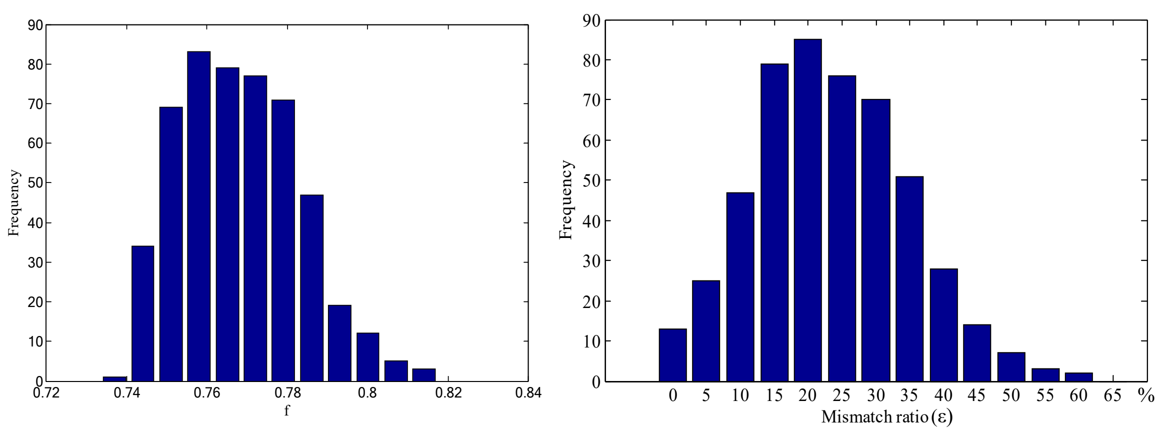


Figure 10 Frequencies of overall performance and mismatch ratio of *O''* in 500 years

Table 4 shows the uncertainties of overall performance and mismatch ratio at the two design options respectively. For the design option *O'*, the cumulative probability is 5% and 95% at the overall performance of 0.672 and 0.748 respectively. And it is 55.0% at the mean overall performance (0.706). The cumulative probability is 5% and 95% at mismatch ratio of -12.7% and 16.4% respectively. And it is 51.6% at the mean mismatch ratio (1.46%). For the design option O'', the cumulative probability of the overall performance is 5% and 95% at overall performance of 0.75 and 0.797 respectively. And it is 53.3% at the mean overall performance (0.772). The cumulative probability is 5% and 95% at mismatch ratio of 8.2% and 45.1% respectively. And it is 52.1% at the mean mismatch ratio (25.77%). The uncertainty ranges of the overall performance and mismatch ratio at the two design options are shown in Fig. 11 and Fig. 12 respectively.

Table 4 Uncertainties of overall performance and mismatch ratio (samples=500 years)

Performance	Mean	Lower 5th confidence level	Upper 95th confidence level
Overall performance of O'	0.706	0.672	0.748
Overall performance of O''	0.772	0.75	0.797
Mismatch ratio of O'	1.46%	-12.70%	16.40%
Mismatch ratio of O''	25.77%	8.20%	45.10%

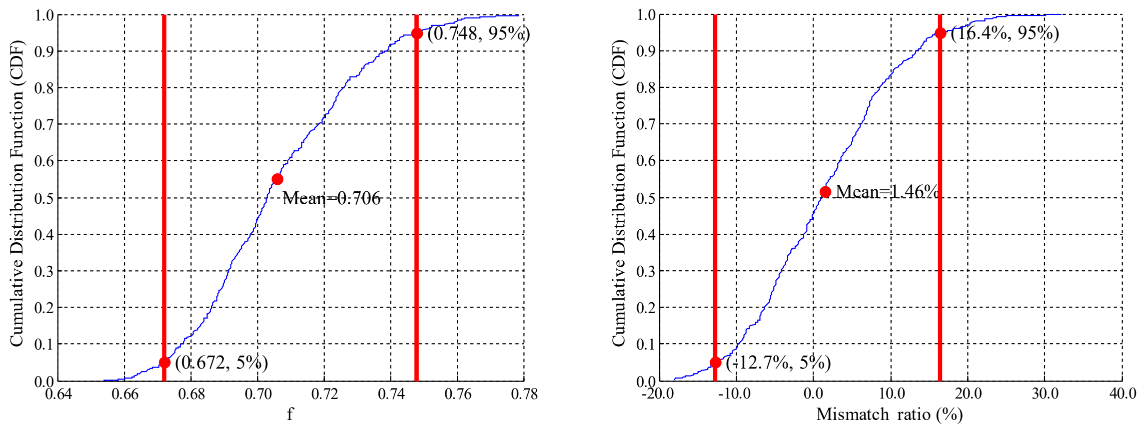


Figure 11 Uncertainty analysis of overall performance and mismatch ratio of O'

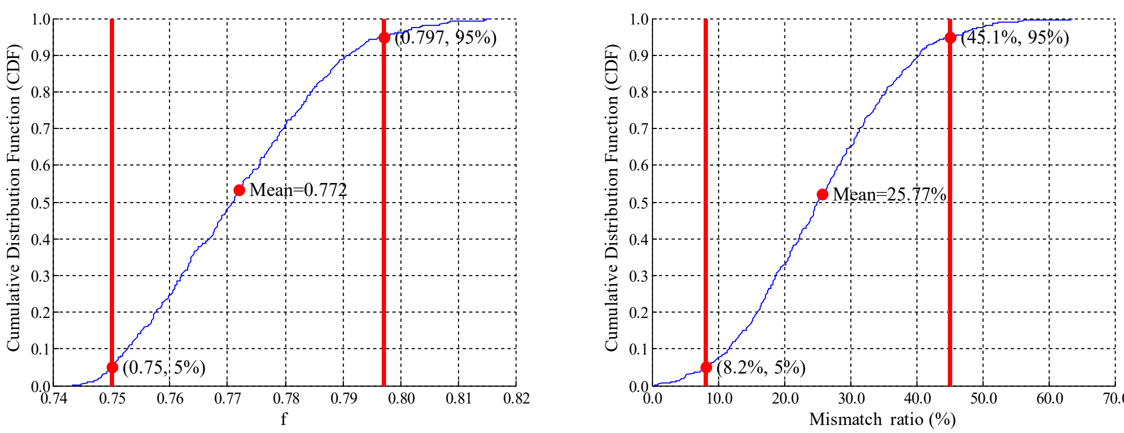


Figure 12 Uncertainty analysis of overall performance and mismatch ratio of O''

5. Conclusion

This study proposes a method to optimal sizing renewable energy system for nZEB considering uncertainties. In order to evaluate the proposed robust design method, a case study is conducted to investigate and compare the optimal design options which are obtained using two different methods (i.e. the proposed robust method and the deterministic method). Based on the result, several conclusions can be drawn:

(1) The optimal design option (O'), i.e. WT of 40 kW, BDG of 30 kW and PV of 900 m^2 obtained by deterministic method, shows that the probability that the building achieves annual zero balance in different years is 54.4%. A higher probability may require a design option with larger mismatch ratio and higher investment..

(2) The optimal design option (O''), i.e. WT of 40 kW, BDG of 30 kW and PV of 1400 m^2 obtained by robust design method, shows that the probability that the building achieves annual zero balance in 500 years is 100%..

(3) A fitting formula, i.e. y=-999.75x^6+483.69x^5+80.297x^4-64.531x^3-1.3263x^2+4.2483x+0.4828, is obtained in this study, which can be used to describe the relationship between the probability of achieving nZEB and the design mismatch ratio within -20% to 30% during the design stage.

The proposed method provides an effective way to identify the effect of the design mismatch ratio on the building performance and its target to achieve annual zero energy balance when the uncertainties in energy demand, renewable resources are concerned. In addition, it also provides flexibility to designers in selecting different design options based on their requirements and the quantification of the uncertainties in design parameters.

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