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Impacts of renewable energy system design inputs on the performance robustness of net zero energy buildings

Yuehong Lu, Shengwei Wang*, Chengchu Yan, Kui Shan

Department of Building Services Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong

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ABSTRACT

Due to the intermittent and uncontrollable nature of renewable energy resources, the performance of nZEB (net zero energy buildings) may suffer a great degree of uncertainties. In this study, a GA (genetic algorithm) optimization approach is employed to search optimal sizes of four design options for a net zero energy building. Then, sensitivity analysis is conducted on an optimized system (photovoltaic/wind turbine/bio-diesel generator) to investigate the impacts of the design input variations on the building performance (i.e. operation cost, CO_2 emission, impact on grid). The results show that, with 20% variations in the four variables, the maximum change of the combined objective is 26.2%. In addition, wind velocity is the key factor concerning mismatch ratio, the cost and CDE (CO_2 emissions), while the building loads should be considered with high priority concerning the comprehensive performance (combined objective) of the building. The performance of the energy system, integrating photovoltaic and bio-diesel generator, is not the best. But, compared with the other three design options, the variations of operation variables have least effects on its performance (i.e. most robust performance). The results also provide the quantitative assessment on the impact of active energy generation systems on enhancing the performance robustness of net zero energy buildings.

1. Introduction

Uncertainty and variability are inherent features of any process or system especially in system design and operations [1]. In order to overcome the uncertainty and variation of the world, one needs to take appropriate management action to respond to the changing environment. Sensitivity analysis is a valuable tool for decision-makers to explore the impacts of the changes in input variables on model outputs. In recent years, the use of sensitivity techniques has been popularized for applications in different fields, such as environmental modeling and assessment applications [2–4], investment projects in business [5,6], engineering projects [7–11] and other applications [12–14]. Buildings consume approximately 40% of the total energy utilization [15] and this percentage for the building sector in Hong Kong is even much higher (over 90% of electricity [16]). Sensitivity analysis has been used to identify the key factors affecting building energy/thermal performance from both observational study and energy simulation models. The objectives include the exploration of the characteristics of building energy/thermal performance in different applications, such as building retrofit [11,17], building stock [18,19] and impacts of climate change on buildings [20,21].

Many efforts have been made in the areas of sensitivity analysis on design parameters in traditional building energy systems [22–26]. Most of these efforts focused on identifying the key parameters that affect peak loads, energy consumption/cost and thermal comfort. Lam and Hui [22] conducted a sensitivity study on the building system design parameters of an office building in Hong Kong. The most significant design parameters in that study were identified and analyzed in terms of peak design loads, building load profile and building annual energy consumption. Similarly, Heiselberg et al. [23] applied sensitivity analysis to identify the important design parameters affecting building performance in order to reduce the primary energy consumption. Wang [24] studied uncertainties in energy consumption due to building operational practices and the actual weather, based on the simulation of a medium-size office building. The results show that poor operations may cause an increase of 49–79% in energy use across the selected cities, while good practice reduces energy use by 15–29%. The energy use may vary from −4% to 6% due to the year-

* Corresponding author. Tel.: +852 27665858; fax: +852 27657198.
E-mail address: beswwang@polyu.edu.hk (S. Wang).

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to-year weather fluctuation. In a study on the building energy consumption data collected in a city in China, Lu et al. [25] conducted a quantitative uncertainty and sensitivity analysis. The main sources of uncertainties affecting the total energy consumption were identified and effective means to reduce the uncertainty of the provision of energy were proposed for decision-makers. Tian [26] pointed out that sensitivity analysis plays an important role in building energy analysis. He reviewed the sensitivity analysis methods and the implementation of sensitivity analysis in building performance evaluation.

Unlike traditional buildings, the energy generation systems installed in low/zero energy buildings mainly depend on the renewable energy resources of intermittent and uncontrollable nature (e.g. solar radiation, wind). The application of energy storage systems in buildings could assist to enhance the load match of the building through the reduction of the dependence of the building on the uncertainty of renewable systems generation [27–30]. Guarino et al. [27] analyzed the performance of PCMs (phase chang materials)PCMs in residential housing for different climates through an experimental study. In another study [28], the minimum size of the energy storage was identified to improve energy load match between energy generation and energy consumption. Lu et al. [29] adopted the MPC method based on mixed-integer nonlinear programming to optimize the operation of integrated energy systems in low energy buildings under day-ahead electricity price. A few studies have been conducted on the uncertainty/sensitivity analysis in the design of renewable energy systems in buildings. Maheri [31] studied the uncertainties in renewable resources, demand load and power modeling in the optimal design of a standalone wind-PV-diesel hybrid system. Ren et al. [32] studied the optimal design of a grid-connected PV (photovoltaic) system considering the uncertainties in the efficiency and cost of PV systems. The sensitivity of levelized cost and simple payback period to various economic and technical circumstances were also analyzed. Zhou [33] proposed a two-stage stochastic programming model for the optimal design of distributed energy systems. The impacts of demand and supply uncertainties on the design optimization were investigated and compared with the deterministic optimal design. The results indicate that the negative impacts of energy demand and supply uncertainties can be reduced by introducing grid connection and energy storage. Ashouri [34] investigated the design of building energy systems taking into account the uncertainties of boundary conditions such as weather conditions and user demands. The results of sensitivity analysis indicate that, when the robustness of the energy systems designed was concerned, the equipment sizes might vary up to 100% compared with the system designed using the traditional method. Similar studies could also be found in other studies [35–40].

Over the last decades, studies on nZEB (net zero energy buildings) can be categorized into several subject areas, including different definitions and evaluation methods [41,42], system design and configurations [43–45], case study/demonstration projects [46–48] and management optimization of energy systems [29,30]. Very few studies can be found concerning the sensitivity analysis on system design parameters of nZEB as stated by Sun [44]. He, therefore, proposed a dynamic simulation platform to study the impacts of each building parameters (i.e. wall thickness, window to wall ratio, infiltration rate etc.) on the sizes of main energy systems in net zero energy buildings. Bucking et al. [49] proposed a methodology to identify the influential variations on the building performance metric, which helps to understand possible discrepancies between predicted and realized building performance. However, the sensitivity of the energy system performance of net zero energy buildings to the discrepancies between the real and design operation conditions (e.g. weather condition and demand load) are not yet clear based on the above studies.

This paper therefore presents a sensitivity analysis on the impacts of the major inputs for renewable energy system design and the study on the performance robustness of different design options for a net zero energy building. This paper is structured as follows. Section 2 presents an outline and the framework of sensitivity analysis method. In Section 3, the building studied and the performance measures used in design optimization are introduced. Section 4 presents the results of the sensitivity analysis on a system combining PV (photovoltaic), WT (wind turbine) and BDG (bio-diesel generator) and the comparison on the performance robustness of different design options. Conclusions are given in Section 5.

2. Outline of methodology

Fig. 1 shows the approach and steps of the sensitivity analysis to evaluate the performance of buildings with different energy system design options. At the first step (Step I), an optimization software tool based on GA (genetic algorithm) is implemented to obtain the optimal sizes of renewable energy systems and the corresponding building performance. The genetic algorithm is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each trial, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution [50]. GA is now one of the most preferable and widespread searching algorithms for optimization problems. It is easy to be transferred in existing simulations and models. The values of weather data and occupancy/equipment schedules, the parameters of energy systems and renewable energy systems are set as the inputs and parameters for building model and the energy system models. TRNSYS (a complete and extensible software environment for the transient simulation of systems) [51] building model is used to calculate the cooling load. The models of energy and renewable energy systems are developed and implemented in Matlab (2006). The size ranges of renewable energy systems are set as the constraints for the GA optimizer (included in Matlab 2006). The objective function, combining the TC (total annualized cost), CDE (CO_2 emissions) and the GII (grid interaction index) using weighting factors shown in Eq. (1), is evaluated and minimized by the GA optimizer based on trial values of renewable energy system sizes.

At the second step (Step II), the comprehensive performance of the building, when the input variables vary over certain arranges, is computed using the objective function and the same building energy and renewable energy system models. Four most important input variables representing the working condition of buildings are selected and each of them is assigned with a variation range. In this study, the input variables concerned include wind velocity, solar radiation, building cooling load and building electric load. The solar radiation and wind velocity in the typical year (1987) are added with variations of a given range (20%). The building cooling load refers to the total cooling needed from the chiller plant. It is calculated using the TRNSYS building model as explained above. The building electric load refers to the total building electric load of all electricity appliances in the building except the air-conditioning system. The typical cooling load and building electric load are also assigned with variations in a given range (20%).

At the third step (Step III), based on the optimal system size determined at Step I and the input variables associated with their variation distributions determined at Step II, the one-way

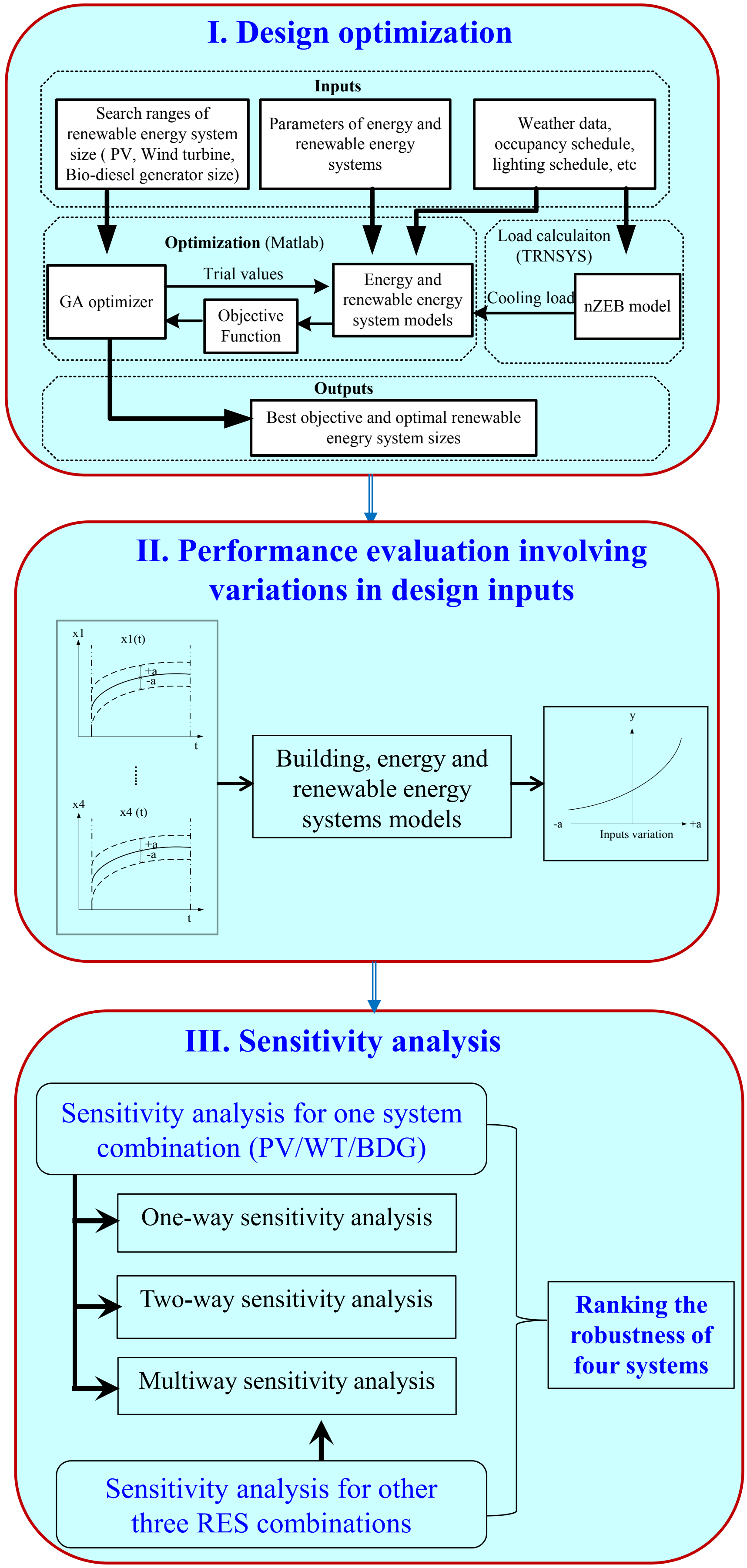

Fig. 1. Approach and steps of sensitivity analysis.

sensitivity analysis, two-way sensitivity analysis and multi-way sensitivity analysis are performed on the optimized PV/WT/BDG system. The input variables that have significant impacts on the building performance are identified. Multiway sensitivity analysis is also performed on the other three renewable energy systems design options. By comparing the performances of the four design options with variations in input variables, the performance robustness of the four design options are assessed and ranked.

In this study, the renewable energy systems concerned are PV, WT and BDG. Four most commonly used system combinations or design options (i.e., PV/WT/BDG, PV/WT, PV/BDG and WT/BDG) are considered. The typical meteorological year in Hong Kong (i.e. 1987) is selected as the weather condition for building energy systems simulation. It is usually selected as the representative year for building load simulation in the building professions in Hong Kong as it is regarded to represent the Hong Kong weather condition the best among the weather data of last few decades. Detailed energy system models used can be found in the previous paper of the authors on design optimization [45].

3. Building description and system optimization

3.1. Building and energy system description

A nZEB is commonly regards as a building in which the annual electricity consumption equals to its annual electricity generation [44,45]. The nZEB under study is based on the Hong Kong ZCB (zero carbon building). This building adopts photovoltaic panels and a bio-diesel generator to generate electricity from renewable energy sources, which can achieve zero net carbon emissions on an annual basis [52]. The total net floor area of ZCB is 1520 m^2, and the designed peak cooling load is about 160 kW. Three electric chillers and one adsorption chiller, each with rated power of 70 kW, are employed to provide the chilled water for the building air-conditioning system. Photovoltaic panel of 1015 m^2 in total and a bio-diesel generator with peak capacity of 100 kW are installed to provide the electricity for ZCB. The bio-diesel generator is controlled following the thermal load. A heat recovery system is used to collect the exhaust heat from bio-diesel generator to drive the absorption chiller. When the cooling provided by the absorption chiller is not sufficient, the extra cooling load is provided by the electric chillers. As shown in Fig. 2, wind turbine/photovoltaic/bio-diesel generator is assumed as three available energy generation systems on-site providing electricity for the building. The basic information of the building and parameters used for the design optimization of renewable energy systems are listed in Table 1.

Fig. 3 shows the solar radiation and wind velocity, building cooling load and building electric load. The daily peak values of solar radiation and wind velocity, building cooling load in the typical year are shown in Fig. 3A and B respectively. Their highest values in the year are 1017 W/m^2, 15 m/s and 170 kW respectively. The building electric load, shown in Fig. 3C, is obtained from the on-site monitoring in ZCB, which is assumed to be same throughout the year.

Table 1
Basic data and energy system parameters.

Parameters	Value
Total net floor area (m^2)	1520
Designed peak cooling load (kW)	160
Average electricity demand by equipment except HVAC (kW)	14
Rated capacity of absorption chiller (kW)	70 × 1
Rated capacity of electric chiller (kW)	70 × 3
Initial costs of BDG (USD/kW)	205.53
Initial costs for PV (USD/m^2)	378.17
Initial costs for WT (USD/kW)	288.86
Oil price (USD/l)	1.3
Delivered electricity price (USD/kWh)	0.13
Exported electricity price (USD/kWh)	0.065
Lifetime for BDG (h)	15,000
Lifetime for PV (a)	20
Lifetime for WT (a)	20
Heat recovery system efficiency	0.8
BDG efficiency	0.3
Coefficient of performance of absorption chiller	0.7
PV module efficiency	0.13
Emission factors of electricity from the grid	0.608
Emission factors of bio-diesel combustion	0.552

3.2. Objective function

In order to conduct a comprehensive evaluation on the building performance, a combined objective (f) is used. It considers the performance indices of the TC (total annualized cost), CDE (CO_2 emissions) and GII (the grid interaction index) using weighting factors as shown in Eq. (1). Where, TC_n, CDE_n and GII_n are the dimensionless values of the above three indices, which are the values of the three indices divided by their corresponding indices of the benchmark building. As a net zero energy building, it is required that the energy generated is equal to the building energy demand over a year. x_1, x_2, x_3 stand for the sizes of PV, WT and BDG respectively that are to be optimized during the design optimization. w_1, w_2, w_3 are assigned to indicate the relative importance of the three objectives (i.e. TC_n, CDE_n and GII_n). The sum of weighting factors w_1, w_2 and w_3 is 1. They can be tuned according to the preferences of the decision makers. In this study, the three objectives are assumed to be equally important, that is $w_1 = w_2 = w_3 = 1/3$. The benchmark building refers to the ZCB after

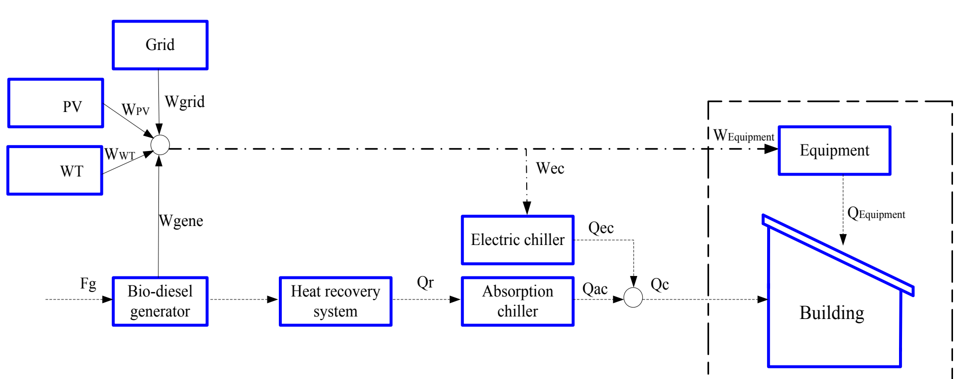

Fig. 2. Energy flows among the energy systems.

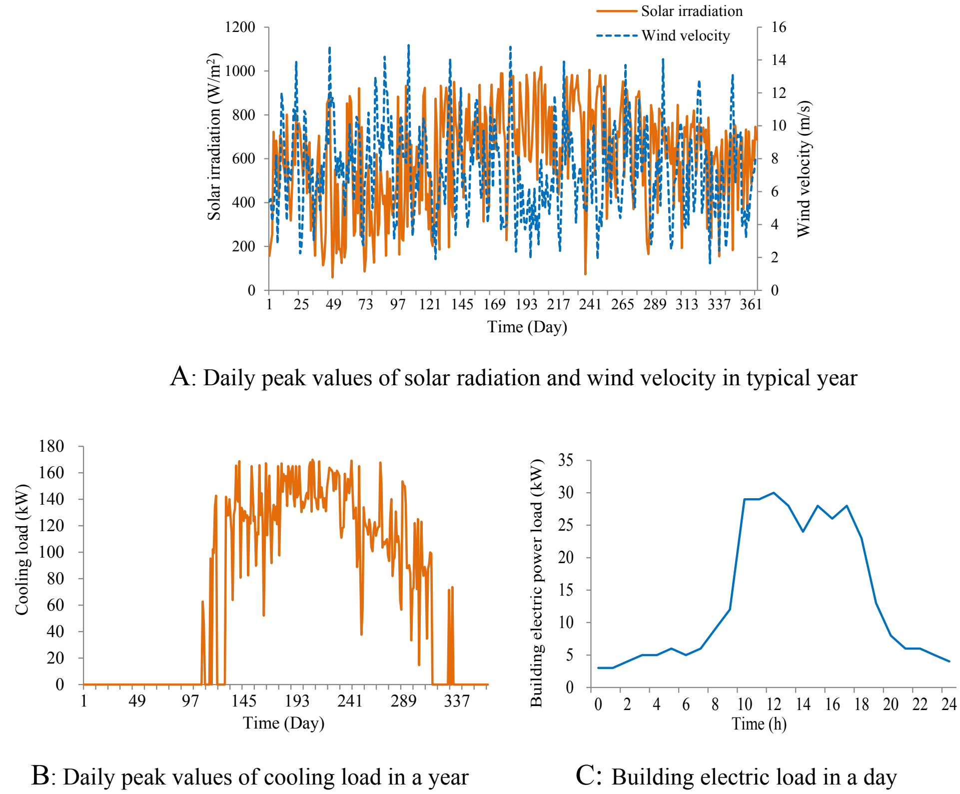

Fig. 3. Weather data and building loads.

deleting all renewable energy systems. Eq. (1a), from Refs. [31], is used to estimate the total annualized cost. The CO_2 emissions come from electricity generation (CDE_{ele}) and bio-diesel generator (CDE_{BDG}) as shown in Eq. (1b) [45]. The grid interaction index, as shown in Eq. (1c), is used to estimate the average stress of a building on the grid. It is defined as the standard deviation of the building-grid interaction ($f_{grid,i,T}$) over a year. A smaller combined objective represents a better performance of the building system design option and is therefore preferred.

$$\begin{aligned} &\min f = w_1 \times TC_n + w_2 \times CDE_n + w_3 \times GII_n \\ &\text{s.t. } \varphi(x_1, x_2, x_3) = 0 \end{aligned} \tag{1}$$

$$TC = C_t \times UCRF \tag{1a}$$

$$CDE = CDE_{ele} + CDE_{BDG} \tag{1b}$$

$$GII = STD\left(f_{gird,i,T}\right) \tag{1c}$$

where, C_t and $UCRF$ are the total life-span cost and uniform capital recovery factor respectively. C_t, $UCRF$, CDE_{ele}, CDE_{BDG} and $f_{grid,i,T}$ can be calculated using Eqs. (2)–(6) respectively. C_j is the cost including capital cost, operation cost and maintenance cost in the year, j. The parameter d represents the annual discount rate and N_s is the life-span of the energy system in years. F_{bio} is the amount of bio-diesel consumed. W_{ex}, W_{im} are the exported energy, imported energy respectively, and E_i represents the average energy demand of the building during a given period. It should be noted, the designed net zero energy building may have deviation on zero energy balance during the actual operation. The mismatch ratio, defined by Eq. (7), is therefore used to investigate the effect of input variables on the target of annual energy balance.

$$C_t = \sum_{j=0}^{N_s} \frac{C_j}{(1+d)^j} \tag{2}$$

$$UCRF = \frac{d \times (1+d)^{N_s}}{(1+d)^{N_s} - 1} \tag{3}$$

$$CDE_{ele} = (W_{im} - W_{ex}) \times cde_{ele} \tag{4}$$

$$CDE_{BDG} = F_{bio} \times cde_{bio} \tag{5}$$

$$f_{gird,i,T} = \frac{W_{ex,i} - W_{im,i}}{\int_{t1}^{t2} E_i \, dt / T} \tag{6}$$

$$Mismatch\ ratio = \frac{W_{gene} - W_{cons}}{W_{cons}} \tag{7}$$

3.3. Optimization results

Based on the GA optimization method as explained earlier in Section 2, the sizes of equipment in the four design options, i.e. PV/WT/BDG, PV/WT, PV/BDG and WT/BDG, are determined as shown in Table 2. The settings for GA optimization are as following: crossover fraction = 0.8, migration fraction = 0.2, population size = 50, Stall-GenLimit = 200, function tolerance = 1.0×10^{-10}. The combined objective of the BB (benchmark building) is equal to 1 according to the definition of the objective function in this study. It is observed that the combined objectives of the building under three design options are less than 1, including PV/WT/BDG ($f = 0.91$), PV/WT ($f = 0.85$) and WT/BDG ($f = 0.93$). This means that

Table 2
Optimal sizes of renewable energy systems and corresponding building performances.

Design options	PV (m^2)	WT (kW)	BDG (kW)	f	TC (USD)	CDE (kg/kWh)	GII
- (BB)	0.0	0.0	0.0	1.00	30,893.6	144,487.2	1.13
PV/WT/BDG (nZEB)	256.4	50.0	49.5	0.91	62,149.2	18,486.8	0.68
PV/WT (nZEB)	762.3	100.0	0.0	0.85	43,827.4	14.4	1.28
PV/BDG (nZEB)	767.5	0.0	60.2	1.26	92,274.5	22,011.0	0.74
WT/BDG (nZEB)	0.0	50.0	61.8	0.93	61,023.2	22,516.9	0.74

PV: photovoltaic; WT: wind turbine; BDG: bio-diesel generator; TC: total annualized cost; CDE: carbon dioxide emission; GII: grid interaction index; BB: benchmark building; nZEB: net zero energy building; f: combined objective.

the comprehensive performances of these three design options are better than that of the benchmark building. However, the comprehensive performance of the building with PV/BDG system ($f = 1.26$) is worse than that of the benchmark building.

4. Sensitivity analysis and evaluation of system performance robustness

4.1. Input variables and their impacts on building performance

In practical operation, the weather conditions and building loads usually deviate from that used at the design stage. In this study, four design input variables considered (i.e. wind velocity, building electric load, cooling load and solar radiation) and the maximum ranges of their variations are all assigned to be ±20%. In order to evaluate the impact of the four input variables on the building performances collectively, the minimum and maximum values of the combined objective (comprehensive performance) associated to different magnitudes of variations in the four variables are presented in Fig. 4. As the impact of variations in input variables may reduce or increase the combined objective, both the minimum and maximum values of the combined objective are presented to show the maximum impacts on the combined objective in two different directions (extremes). The minimum and maximum values of the combined objective are 0.852 and 1.09 respectively. With 20% variations in the four input variables, the maximum variation of the combined objective is about 26.2%. It is important to notice that the variations in the four variables have different impacts on the combined objective in terms of direction and the magnitude, as shown in Fig. 4. Each point on the curve represents a case when the combination of signs of the variations results in the lowest (left side) or highest (right side) combined objective at certain magnitude (X-axis) of variations in all input variables. It is also worth noticing that the combined objective of the PV/WT/BDG system without introducing variations to the input variables is 0.91 (also see Table 2).

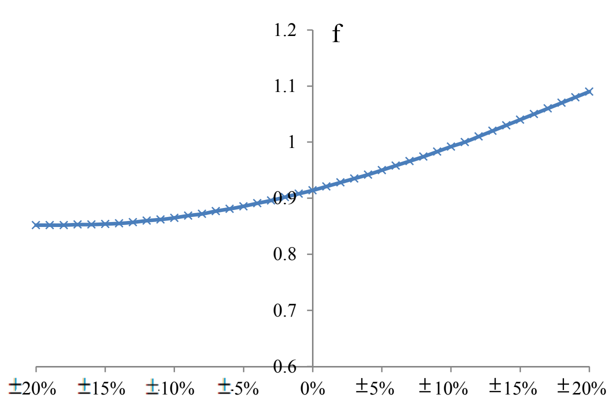

Fig. 4. Maximum impact of variations in input variables on the combined objective.

4.2. One-way sensitivity analysis of PV/WT/BDG system

One-way sensitivity analysis allows a user to assess the impacts of changes in certain input parameters on the conclusions of a model [53]. For each change of a variable, the impact on the outputs of the model could be recorded while all the other variables are kept at their baseline values. The sensitivity analysis results of the PV/WT/BDG system are shown in Tables 3–7. The low and high values of the operation cost, CO_2 emissions, grid interaction index and combined objective, their swing values and the corresponding input values are shown in these tables. Where, the swing is simply the varying range (=High−Low) of an output for a given variation in input. A "% variance" ($=\text{Swing}^2/\sum\text{Swing}^2$) is defined and used to assess the performance robustness [54].

From the one-way analysis, it can be seen that, for mismatch ratio and the outputs except the combined objective, the input variable associated with largest % variance of outputs is the wind velocity, followed by the building electric load and cooling load. The variation of the solar radiation has a weak impact on these outputs (about 1%). It is due to the fact that the impact of the solar radiation on PV generation is considered only and variation of the cooling load is considered separately. As the PV size is small, the impact of the solar radiation on PV generation has lowest % variance. With respect to the operation cost (Table 4), CO_2 emissions (Table 5) and the grid interaction index (Table 6), the % variances caused by the variation of the wind velocity account for 49.8%, 71% and 93.13% respectively. It is followed by the building electric load, with the % variances of 25.08%, 19.54%, and 4.97% respectively. It could be concluded that wind velocity is the most influential input variable to the above three outputs, which is due to that the wind power is proportional to the cube of the wind velocity and thus the variation of the wind velocity could affect the power generation significantly. Meantime, there is only very low energy demand in the building during the night, thus the variation of wind generation during this period will increase the interaction between the building and grid greatly. For solar radiation, the time of PV generation is exactly the time when the electricity is used in the building resulting nearly no impact on grid.

However, it is interesting to note that the combined objective (Table 7) is not most sensitive to the wind velocity, but to the building electric load (% variance = 44.4%) and cooling load (% variance = 34.2%). This is because that the operation cost, CO_2 emissions and the grid interaction index are all most sensitive to the wind velocity, but the directions of their impacts are not the same. In other words, the increase of the wind velocity could greatly reduce the operation cost and CO_2 emissions, but has a dramatically negative effect on the grid interaction index. Therefore the combined objective concerning the three outputs equally is not influenced greatly by the wind velocity. The results indicate that when the operation cost (or total annualized cost) and/or CO_2 emissions are concerned, the accuracy of the wind velocity prediction should be the priority to be concerned during the design stage. While the accuracy of building loads prediction should be paid more attention regarding the comprehensive objective.

Table 3
Mismatch ratio of PV/WT/BDG system – single-factor sensitivity analysis.

Variable	Mismatch ratio				Corresponding input variable	
	Low	High	Swing	% Variance	Low output	High output
Wind velocity	−18.58%	27.83%	46.40%	71.06%	0.8*V_d	1.2*V_d
Building electric load	−10.81%	13.91%	24.72%	20.17%	1.2*W_d	0.8*W_d
Cooling load	−7.64%	7.77%	15.41%	7.83%	1.2*Q_d	0.8*Q_d
Solar radiation	−2.61%	2.71%	5.30%	0.93%	0.8*R_d	1.2*W_d

Table 4
Operation cost of PV/WT/BDG system – single-factor sensitivity analysis.

Variable	Output – operation cost				Corresponding input variable	
	Low (USD)	High (USD)	Swing (USD)	% Variance	Low output	High output
Wind velocity	42,291.6	49,873.1	7581.5	49.83%	1.2*V_d	0.8*V_d
Building electric load	44,016.0	49,394.7	5378.7	25.08%	0.8*W_d	1.2*W_d
Cooling load	44,063.2	49,327.9	5264.7	24.03%	0.8*Q_d	1.2*Q_d
Solar radiation	46,098.3	47,203.1	1104.8	1.06%	1.2*R_d	0.8*W_d

Table 5
CO_2 emissions of PV/WT/BDG system – single-factor sensitivity analysis.

Variable	Output - CO_2 emissions (CDE)				Corresponding input variable	
	Low (kg/kWh)	High (kg/kWh)	Swing (kg/kWh)	% Variance	Low output	High output
Wind velocity	−16,208.2	41,656.0	57,864.2	71.00%	1.2*V_d	0.8*V_d
Building electric load	3254.9	33,613.5	30,358.7	19.54%	0.8*W_d	1.2*W_d
Cooling load	9177.9	29,229.0	20,051.1	8.53%	0.8*Q_d	1.2*Q_d
Solar radiation	15,117.5	21,750.9	6633.4	0.93%	1.2*R_d	0.8*W_d

Table 6
Grid interaction index of PV/WT/BDG system – single-factor sensitivity analysis.

Variable	Output–grid interaction index (GII)				Corresponding input variable	
	Low	High	Swing	% Variance	Low output	High output
Wind velocity	0.492	1.024	0.532	93.13%	0.8*V_d	1.2*V_d
Building electric load	0.630	0.753	0.123	4.97%	1.2*W_d	0.8*W_d
Cooling load	0.665	0.741	0.076	1.90%	1.2*Q_d	0.8*Q_d
Solar radiation	0.678	0.682	0.004	0.00%	0.8*R_d	1.2*W_d

Table 7
Combined objective of PV/WT/BDG system – single-factor sensitivity analysis.

Variable	Output – combined objective (f)				Corresponding input variable	
	Low	High	Swing	% Variance	Low output	High output
Wind velocity	0.889	0.947	0.058	17.8%	1.2*V_d	0.8*V_d
Building electric load	0.873	0.964	0.092	44.4%	0.8*W_d	1.2*W_d
Cooling load	0.883	0.964	0.081	34.2%	0.8*Q_d	1.2*Q_d
Solar radiation	0.902	0.928	0.026	3.6%	1.2*R_d	0.8*W_d

For the variation of wind velocity, the lowest outputs of operation cost (42,291.6 USD) and CO_2 emissions (−16,208.2 kg/kWh) occurred at the maximum wind velocity (1.2*V_d). It is obvious that an increase in wind velocity could result in a lower electricity demand from grid thus a lower operation cost and CO_2 emissions will be achieved. However, a low grid interaction index (0.492) is obtained at the minimum wind velocity (0.8*V_d).

A more complete view on the relationships between each input variable and the performance is provided in Fig. 5. It shows how a model output is affected by the percentage of change in each of the input variables. The *x*-axis is the change range of input variables represented as the percentage of their corresponding baseline values, while *y*-axis is the associated model output. The center of the plot is the output obtained when all the input variables are set at their baseline values. Near-linear relationships can be observed for the operation cost *vs* the input variables except the wind velocity. The CO_2 emissions are linear with the solar radiation and the building electric load only. However, the grid interaction index is nonlinear with all the input variables except the solar radiation. The combined objective is near-linear with solar radiation, nonlinear with wind velocity, building electric load and cooling load. The results also reveal that the increase of wind velocity has strong positive effect on both operation cost saving and CO_2 emissions reduction. While both the increases of building electric load and cooling load have negative effects on the two outputs. However, the increase of wind velocity has a notably negative effect on the grid interaction index. Thus, the effect of wind velocity on the combined objective is alleviated because the directions of its effects on the

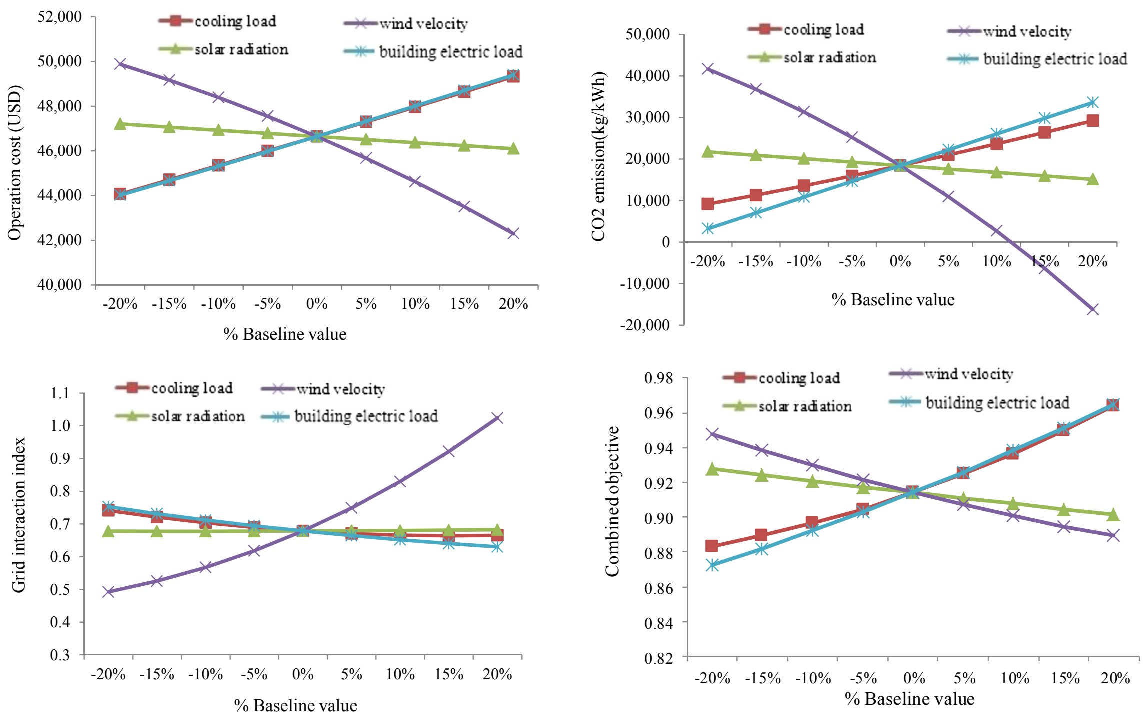

Fig. 5. Outputs (performances) *vs* design input variables (operation variables).

three outputs are different. In addition, a noticeable positive effect on the combined objective is obtained by reducing the building electric load or building cooling load.

4.3. Two-way sensitivity analysis of PV/WT/BDG system

The effects of simultaneous changes in any two input variables on the outputs are also studied. Since there are four input variables, six pairs (i.e., $4 \times (4-1)/2$) should be evaluated to investigate the impact of each possible combination. The outputs are calculated for each pair when the variables of the pair are changed to their low/high extreme values simultaneously and other input variables are kept at their baseline values.

The results of two-factor sensitivity analysis concerning each output are shown in Tables 8–12, which list the low and high output values, the swing and % variance values as well as the corresponding input variables. The maximum range of mismatch ratio is between 35.52% and 2.87%. The maximum ranges of performance outputs under the variation of wind velocity & building electric load, are between 39,842.7 and 52,792.9 USD for the operation cost, between −31,387.5 and 56,825.4 kg/kWh for CO_2 emissions, between 0.476 and 1.156 for the grid interaction index, respectively. The variations of other two pairs, i.e. solar radiation & building electric load and cooling load & solar radiation, have less effects on the above outputs with the % variances of less than 10%.

Regarding the combined objective, the most significant pair is cooling load & building electric load (% variance = 27.82%). The maximum range of the combined objective is between 0.853 and 1.019. Wind velocity & building electric load (% variance = 20.43%), cooling load & wind velocity (% variance = 19.26%) are also two important influential pairs.

The sensitivity order for the operation cost is: wind velocity & building electric load > cooling load & wind velocity > cooling load & building electric load > solar radiation & wind velocity > solar radiation & building electric load > cooling load & solar radiation. The sensitivity orders for the other two outputs are the same (but slightly different from that for the operation cost): wind velocity & building electric load > cooling load & wind velocity > solar radiation & wind velocity > cooling load & building electric load > solar radiation & building electric load > cooling load & solar radiation. Regarding the combined objective, the sensitivity order is: cooling load & building electric load > wind velocity & building electric load > cooling load & wind velocity > solar radiation & building electric load > cooling load & solar radiation > solar radiation & wind velocity.

4.4. Multiway sensitivity analysis of PV/WT/BDG system

The multiway sensitivity analysis is conducted to assess the extreme cases when all of the input variables varied simultaneously to their 'best' and 'worst' values. Fig. 6 shows the multiway

Table 8
Mismatch ratio of PV/WT/BDG system — two-factor sensitivity analysis.

Variable	Mismatch ratio				Corresponding input variable	
	Low	High	Swing	% Variance	Low output	High output
Wind velocity & building electric load	−27.41%	45.54%	0.730	35.52%	0.8^*V_d, 1.2^*W_d	1.2^*V_d, 0.8^*W_d
Cooling load & wind velocity	−24.64%	38.21%	0.629	26.36%	1.2^*Q_d, 0.8^*V_d	0.8^*Q_d, 1.2^*V_d
Solar radiation & wind velocity	−21.24%	30.49%	0.517	17.85%	0.8^*R_d, 0.8^*V_d	1.2^*R_d, 1.2^*V_d
Cooling load & building electric load	−16.88%	24.36%	0.412	11.34%	1.2^*Q_d, 1.2^*W_d	0.8^*Q_d, 0.8^*W_d
Solar radiation & building electric load	−13.18%	16.94%	0.301	6.05%	0.8^*R_d, 1.2^*W_d	1.2^*R_d, 0.8^*W_d
Cooling load & Solar radiation	−10.07%	10.68%	0.208	2.87%	1.2^*Q_d, 0.8^*R_d	0.8^*Q_d, 1.2^*R_d

Table 9
Operation cost of PV/WT/BDG system — two-factor sensitivity analysis.

Variable	Output - operation cost				Corresponding input variable	
	Low (USD)	High (USD)	Swing (USD)	% Variance	Low output	High output
Wind velocity& building electric load	39,842.7	52,792.9	12,950.3	27.83%	1.2^*V_d, 0.8^*W_d	0.8^*V_d, 1.2^*W_d
Cooling load & wind velocity	39,796.7	52,648.4	12,851.7	27.40%	0.8^*Q_d, 1.2^*V_d	1.2^*Q_d, 0.8^*V_d
Cooling load & building electric load	41,574.6	52,158.2	10,583.6	18.59%	0.8^*Q_d, 0.8^*W_d	1.2^*Q_d, 1.2^*W_d
Solar radiation & wind velocity	41,781.0	50,469.3	8688.3	12.52%	1.2^*R_d, 1.2^*W_d	0.8^*R_d, 0.8^*W_d
Solar radiation & building electric load	43,517.0	49,990.7	6473.7	6.95%	1.2^*R_d, 0.8^*W_d	0.8^*R_d, 1.2^*W_d
Cooling load & solar radiation	43,567.0	49,924.0	6357.1	6.71%	0.8^*Q_d, 1.2^*R_d	1.2^*Q_d, 0.8^*R_d

Table 10
CO_2 emissions of PV/WT/BDG system — two-factor sensitivity analysis.

Variable	Output - CO_2 emissions				Corresponding input variable	
	Low (kg/kWh)	High (kg/kWh)	Swing (kg/kWh)	% Variance	Low output	High output
Wind velocity & building electric load	−31,387.5	56,835.4	88,222.9	34.39%	1.2^*V_d, 0.8^*W_d	0.8^*V_d, 1.2^*W_d
Cooling load & wind velocity	−25,464.5	52,450.8	77,915.3	26.82%	0.8^*Q_d, 1.2^*V_d	1.2^*Q_d, 0.8^*V_d
Solar radiation & wind velocity	−19,524.9	44,972.7	64,497.6	18.38%	1.2^*R_d, 1.2^*V_d	0.8^*R_d, 0.8^*V_d
Cooling load & building electric load	−6001.5	44,408.3	50,409.8	11.23%	1.2^*R_d, 0.8^*W_d	0.8^*R_d, 1.2^*W_d
Solar radiation & building electric load	−61.8	36,930.2	36,992.1	6.05%	1.2^*R_d, 0.8^*W_d	0.8^*R_d, 1.2^*W_d
Cooling load & solar radiation	5861.2	32,545.7	26,684.5	3.15%	0.8^*Q_d, 1.2^*R_d	1.2^*Q_d, 0.8^*R_d

Table 11
Grid interaction index of PV/WT/BDG system — two-factor sensitivity analysis.

Variable	Output—grid interaction index				Corresponding input variable	
	Low	High	Swing	% Variance	Low output	High output
Wind velocity & building electric load	0.476	1.156	0.680	38.84%	0.8^*V_d, 0.8^*W_d	1.2^*V_d, 1.2^*W_d
Cooling load & wind velocity	0.513	1.123	0.610	31.25%	0.8^*Q_d, 0.8^*V_d	1.2^*Q_d, 1.2^*V_d
Solar radiation & wind velocity	0.494	1.028	0.534	23.96%	1.2^*R_d, 0.8^*V_d	0.8^*R_d, 1.2^*V_d
Cooling load & building electric load	0.630	0.848	0.218	4.00%	0.8^*Q_d, 0.8^*W_d	1.2^*Q_d, 1.2^*W_d
Solar radiation & building electric load	0.633	0.762	0.129	1.39%	1.2^*R_d, 0.8^*W_d	0.8^*R_d, 1.2^*W_d
Cooling load & solar radiation	0.670	0.751	0.081	0.55%	0.8^*Q_d, 1.2^*R_d	1.2^*Q_d, 0.8^*R_d

Table 12
Combined objective of PV/WT/BDG system — two-factor sensitivity analysis.

Variable	Output — Combined objective				Corresponding input variable	
	Low	High	Swing	% Variance	Low output	High output
Wind velocity & building electric load	0.867	1.009	0.142	20.43%	1.2^*V_d, 0.8^*W_d	0.8^*V_d, 1.2^*W_d
Cooling load & wind velocity	0.870	1.008	0.138	19.26%	0.8^*Q_d, 1.2^*V_d	1.2^*Q_d, 0.8^*V_d
Solar radiation & wind velocity	0.877	0.962	0.085	7.23%	1.2^*R_d, 1.2^*V_d	0.8^*R_d, 0.8^*V_d
Cooling load & building electric load	0.853	1.019	0.166	27.82%	0.8^*Q_d, 0.8^*W_d	1.2^*Q_d, 1.2^*W_d
Solar radiation & building electric load	0.862	0.979	0.117	13.86%	1.2^*R_d, 0.8^*W_d	0.8^*R_d, 1.2^*W_d
Cooling load & solar radiation	0.873	0.980	0.106	11.39%	0.8^*Q_d, 1.2^*R_d	1.2^*Q_d, 0.8^*R_d

sensitivity analysis tornado charts for the outputs of the PV/WT/BDG system, arranged downward according to the % variances. The swings of outputs corresponding to the single-factor and two-factor, which have the most significant impacts on the outputs, are also presented in the figure for comparison. With respect to the combined objective, the ranges of the output are between 0.85 and 1.09 when all of the input variables varied simultaneously, between 0.87 and 0.96 when two input variables varied simultaneously, and between 0.85 and 1.02 when only one input variable varied at a time.

4.5. Multiway sensitivity analysis for different design options

Multiway sensitivity analysis for four design options is performed to investigate the performance robustness of the building with the four design options under extreme conditions. The results are presented in Tables 13–15, which list the low/high output values (in the form of the percentages of their corresponding baseline values), swings and % variances. Fig. 7 presents a comparison between performance robustness of four design options, represented by the swings of outputs to variation of input variables. Concerning the sensitivities of the performance index except the grid interaction index, the order is: PV/WT > PV/WT/BDG > WT/BDG > PV/BDG. For the PV/WT system, the swing range of the dimensionless operation cost could reach between −226.3% and 210.4% when all the input variables vary simultaneously and their impacts are at the same directions, indicating that the building integrated with PV/WT system may have poor performance robustness (in terms of the operation cost) compared with the buildings adopting other three design options. Furthermore, the swing of the dimensionless CO_2 emissions is infinite for the PV/WT system. This is because CO_2 emissions of NZEBs are zero at baseline design values and even a small variation in the outputs will cause an infinite variation of the dimensionless CO_2 emissions.

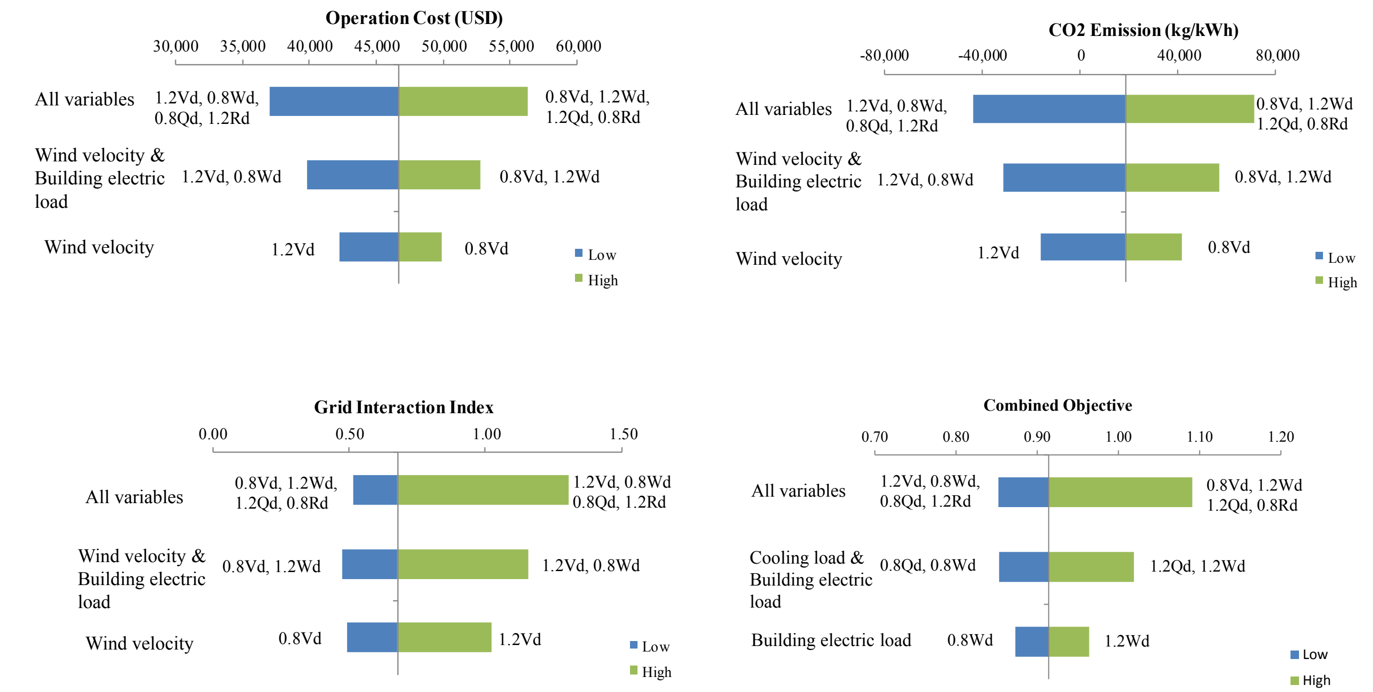

Fig. 6. Comparison of outputs variation for PV/WT/BDG system.

Table 13
Comparison of mismatch ratio of four design options.

System	Dimensionless mismatch ratio			
	Low	High	Swing	% Variance
PV/WT	−48.7%	90.0%	138.7%	47.9%
PV/WT/BDG	−34.4%	62.8%	97.2%	23.5%
WT/BDG	−32.4%	58.6%	91.0%	20.6%
PV/BDG	−23.4%	33.0%	56.4%	7.9%

The results indicate that the PV/WT system is the most sensitive system concerning the variations in the input variables while the performance of PV/BDG system is the most robustness in terms of mismatch ratio, the operation cost, CO_2 emissions and combined objective. It is noticing that the swing of mismatch ratio under PV/WT system achieves more than 100%. It is also observed that the performance of the renewable energy system integrated with active energy generation systems, e.g. BDG, is less sensitive to the variations of input variables. It is most likely due to that active energy generation systems can be controlled according to the changes of operation conditions, which may alleviate fluctuations in the outputs to some extent. Similar observation can be found also in the work of Zhou [33]. He pointed out that the negative impacts of energy load and generation uncertainties are reduced after introducing the energy storage and/or grid connection for a building. In this study, the BDG is operated following the thermal load and therefore the variation of cooling load could be undertaken by the BDG to some extent. When only passive renewable energy systems, especially the wind turbine, are used for building energy generation, the building may have a high risk of poor performance robustness under the variations of operation conditions. However, it is not the case for the grid interaction index since its

Table 14
Comparison of operation cost/CO_2 emissions of four design options.

System	Dimensionless operation cost				Dimensionless CO_2 emissions			
	Low	High	Swing	% Variance	Low	High	Swing	% Variance
PV/WT	−226.3%	210.4%	436.7%	98.2%	"$-\infty$"	"∞"	"∞"	–
PV/WT/BDG	−20.6%	20.7%	41.3%	0.9%	−338.5%	284.9%	623.3%	55.5%
WT/BDG	−17.4%	16.2%	33.6%	0.6%	−252.0%	214.3%	466.3%	31.1%
PV/BDG	−11.8%	12.1%	23.9%	0.3%	−147.3%	159.5%	306.8%	13.4%

Table 15
Comparison of grid interaction index/combined objective of four design options.

System	Dimensionless grid interaction index				Dimensionless combined objective			
	Low	High	Swing	% Variance	Low	High	Swing	% Variance
PV/WT	−21.61%	71.15%	92.76%	18.97%	−15.37%	30.2%	45.5%	63.9%
PV/WT/BDG	−24.14%	92.84%	116.98%	30.17%	−6.73%	19.3%	26.1%	21.0%
WT/BDG	−28.62%	85.22%	113.83%	28.57%	−5.38%	15.9%	21.2%	13.9%
PV/BDG	−34.65%	65.9%	100.5%	22.3%	−0.10%	6.1%	6.2%	1.2%

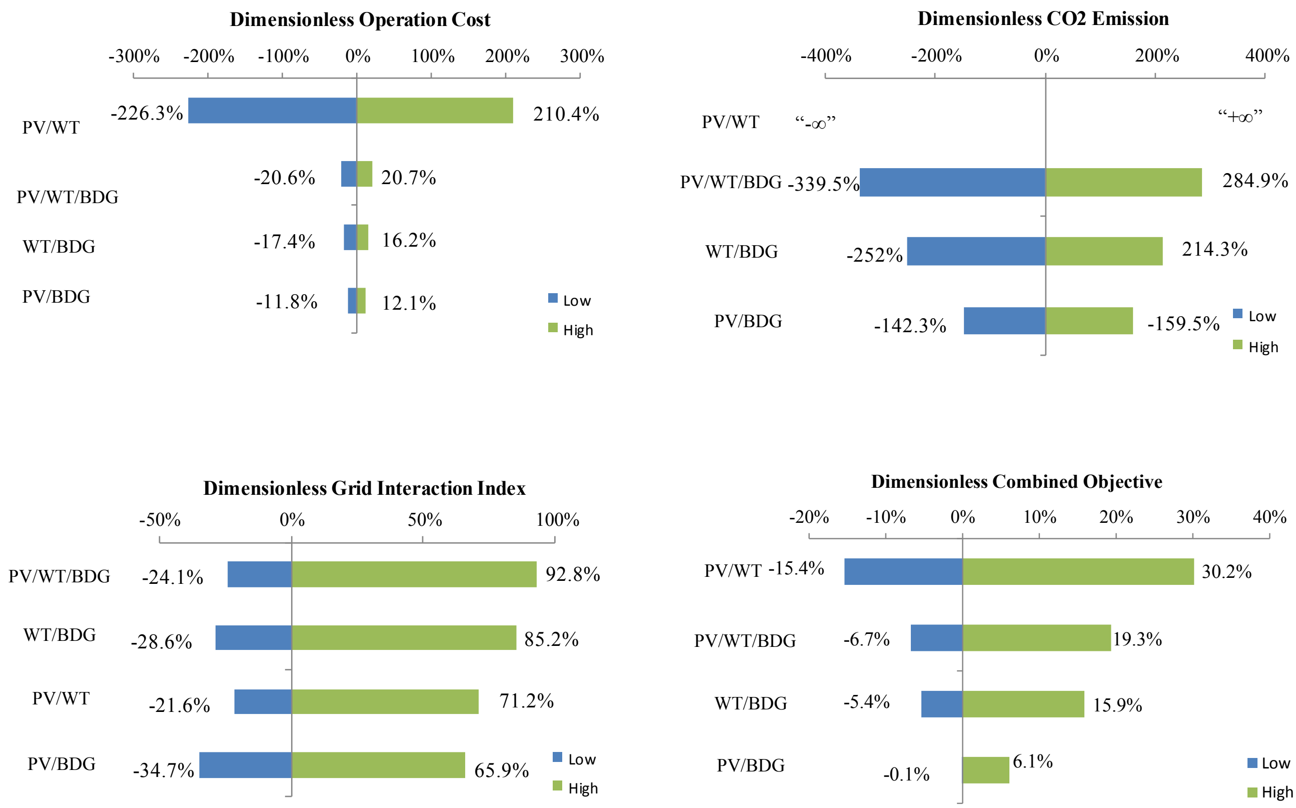

Fig. 7. Comparison between performance robustness of four design options.

swings and % variances do not change significantly under different design options.

5. Conclusions

In this study, four renewable energy system combinations for a grid-connected net zero energy building are studied. One-way sensitivity analysis, two-way sensitivity analysis and multiway sensitivity analysis are performed for the typical design option, i.e. PV/WT/BDG, to identify the most significant factor that affects the building performance.

With the inputs variations of 20%, the maximum change of the comprehensive performance (i.e. combined objective) is 26.2%. The results of the one-way sensitivity analysis show that wind velocity is the key factor that significantly affects annual energy balance (mismatch ratio) and the three outputs (operation cost, CO_2 emissions and grid interaction index), with the % variances of more than 50%. It is followed by building electric load and building cooling load. The % variances of the outputs caused by the variation of solar radiation are very small (less than 1%), showing that the effect of the variation in solar radiation is negligible. In contrast, the comprehensive performance is most sensitive to building electric load rather than wind velocity, followed by cooling load. This is because the increase of wind velocity results in reduced operation cost and CO_2 emissions, but a dramatically increased grid interaction index. Thus the effect of wind velocity variation on the comprehensive performance is not significant due to compensation effects. The results of two-way sensitivity analysis further indicate that cooling load & building electric load, wind velocity & building electric load, cooling load & wind velocity are the three major pairs which affect the comprehensive performance significantly. In summary, more attention should be paid on the accuracy of wind velocity prediction regarding the total cost/operation cost and/or CO_2 emissions. But the accuracy of building loads prediction should be the priority to be concerned during the design stage concerning the robustness of the comprehensive performance.

The results of multiway sensitivity analysis on four design options indicate that the PV/BDG system may have a worse comprehensive performance under the design condition, but its performance in the real operation is most robustness. In addition, the introduction of active energy generation systems in buildings could increase the performance robustness of the building energy systems.

Sensitivity analysis at the early stage of the design process could provide important information to identify the design/operation inputs/parameters on which designers should paid more attention in the next phases. Sensitivity analysis also provides designers additional but important information on the performance robustness of different design options for making design decisions.

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