https://doi.org/10.1016/j.jclepro.2017.03.191

Developing a robust assessment system for the passive design approach in the green building rating scheme of Hong Kong

Xi Chen [a*], Hongxing Yang [a], and Tao Wang [b]

[a] Renewable Energy Research Group (RERG), Department of Building Services Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong, China

[b] Department of Sustainable Development & Environment, WSP | Parsons Brinckerhoff, Kowloon Bay, Hong Kong, China

Abstract

Building environmental assessment method (BEAM) has been practiced by local architects and engineers in Hong Kong as a reference for green building design over the last 20 years. The current version of BEAM Plus has introduced the passive design concept to make the rating scheme in line with the state-of-art energy efficient design in the world. However, the introduced passive design approach is criticized for its arguable criteria allocation, unjustified weighting system and incompatibility with the existing whole building energy simulation approach. In view of these flaws, a new assessment system based on robust energy end-use statistics, different global sensitivity analysis methods, modelling experiments and a green building case study is proposed in this article. The developed system is only applied to cooling and lighting related criteria, which is mainly influenced by specified passive design strategies. After a preliminary definition of the assessment framework and total available credits, the priorities of different sub-criteria are derived from sensitivity analyses of a generic building model with screening-based, variance-based and regression methods. Adjustment of assessment criteria is also performed according to significant tests and post optimization analyses. Furthermore, performance and grading scales are formulated with baseline requirements, optimization results and local sensitivity analyses. Eventually, the FAST (Fourier Amplitude Sensitivity Test) method is proved to generate the most appropriate weighting system considering the consistent credit prediction with the traditional whole building simulation approach. Findings from this research can guide decision-makers in the construction industry to obtain an optimized preliminary design by properly allocating resources and investments starting from the early planning stage. The research design can also be applied to determine the assessment system for other

* Corresponding author: Tel.:+852-2766 4726, Fax: 2765 7198, E-mail: climber027@gmail.com

performance-based criteria in a green building assessment scheme.

Keywords: Green building; BEAM; Passive design; Sensitivity analysis; Weighting; Assessment

1. Introduction

Hong Kong is a densely populated metropolis characterized by high energy use intensities where building sectors alone accounts for more than 90% of the total electricity consumption according to the statistics of the Electrical and Mechanical Services Department (EMSD). To cope with this situation, the Building Environmental Assessment Method (BEAM) emerged in 1990s as a guidance of sustainable building designs to encourage energy conservation and environment protection. BEAM initially introduced its rating system from BREEAM, which is the earliest green building rating scheme in the world. Accompanied by further development of the green building industry, new elements from major assessment schemes over the world including but not limited to LEED, GBL, and CASBEE gradually enriched the framework of BEAM. All these assessment tools intend to improve the building design and reduce its life cycle impacts from site selection, material use, water use, energy efficiency and indoor environment quality aspects. Credits or points are awarded to encourage good building practices according to improved performance or deployed features as specified by detailed assessment criteria. A scale of weighting is then applied to each criterion or aspect before summarizing attained credits. The weighting system acts as an important way to re-allocate credits among various assessment criteria. It can be embodied as different available points for each criterion or presented as weighting coefficients for different criteria only categories of criteria.

In spite of the importance of the weighting, there is by far not a satisfactory well-recognized weighting assignment method for assessment schemes. Lee et al proposed a scientific approach where the weighting was determined by the cost-effectiveness of adopted technologies (Lee et al., 2002). Corresponding credits are awarded when a certain performance level is achieved by the building project. The formulated crediting scale proportionally awards more credits to compensate for the loss of economic returns and is targeted at attracting profit-maximizing investors. However, this weighting design was only applied to the energy assessment framework and not suitable for other performance-based criteria. In order to reach a consensus between stakeholders in the whole green construction process, a multi-level fuzzy evaluation method is commonly used. The weight of each design factor is classified to a couple of grades by the analytic hierarchy process (AHP), which can assist decision-makers in prioritizing their preferable solutions from multiple design alternatives (Shi, 2009). Such evaluation methods were also applied to other green building assessment studies to formulate indicating systems in regard of environmental loads, building qualities and investment returns (Xia and Liu, 2013; Xue and Qiu, 2012; Yu et al., 2015). With reference to popular global green building rating tools, a unique assessment tool was designed to suit developing regions like Jordan, where the AHP process involves pair-wise comparisons of alternatives, criteria and categories (Ali and Al Nsairat, 2009). AHP was also used to evaluate the index weight for first-class indicators of green residential buildings in China through well-designed questionnaires (Pan and Liu, 2011). In the newest version of BEAM, assessment categories are also weighted by the AHP method with an expert team of stakeholders. They identified the difficulty in actualizing the variable importance for every index based on a comparison of the structure of major rating tools, and designed a weighting system for categories only to avoid an over complicated scheme in CASBEE (Lee, 2013).

From the above brief introduction, it can be summarized that most existing green building rating schemes adopt subjective weighting system reflecting preference of selected stakeholders, whereas little research focuses on constructing an objective weighting system for performance-based criteria. Such a weighting system can be derived from a comprehensive global sensitivity analyses which require massive computation modelling experiments and validations with case studies. This paper intends to develop a weighting system for the passive design route in the energy assessment category of BEAM Plus. It can not only generate assessment results consistent with the traditional whole building simulation approach, but also have application potential in other performance-based criteria of the whole rating scheme.

2. Overview of passive design approach in BEAM Plus

BEAM Plus for new buildings version 1.2 is the most updated local green building guidance to evaluate the overall sustainability of the building design and construction in Hong Kong. According to Fig.1, final building assessment grades are classified to four levels and determined by the weighted subtotal score together with attained scores in key categories including the material, energy, indoor environment quality and a bonus section of the innovation and additions. At the current stage, weighting coefficients for the five categories are allocated according to their perceived environmental impacts, while no specific weighting is assigned to sub-criteria enclosed in the passive design approach. Among five categories, the energy use is assigned with the highest weighting factor of 35%, which reflects its significant environmental, social and economic impact.

Within the energy category, 47.7% of maximum available credits in this category (i.e. 22 credits), are assigned to the passive design approach as an alternative to the annual energy use assessment. The passive design approach is further broken down to sub-criteria including the site planning, building orientation, building envelope (i.e. Overall Thermal Transfer Value), natural ventilation, daylight (i.e. vertical daylight factor), and active building system (i.e. HVAC, lighting and vertical transportation). Among these sub-criteria, the active building system should first be excluded from the general classification of passive designs, while others have to be adjusted in both assigned credits (i.e. weightings) and types of design strategies. The site planning and building orientation indeed greatly impact the building performance by addressing the peripheral shading, ventilation and daylight access condition, whereas it can cause inconsistency with the traditional whole building simulation because the modelling usually excludes any architectural structures outside the site boundary. The Overall Thermal Transfer Value (OTTV) is also a controversial performance index as suggested by many researchers, as its calculation involves inputs of more elementary design factors which might overlap with other criteria (Yik and Wan, 2005). Similarly, the natural ventilation and daylight performance are attributed to more basic architectural designs which even involve trade-offs in an optimization process as suggested by previous research (Chen et al., 2016). According to another study conducted by the authors, the passive design parameters can be divided into the building layout, envelope thermophysics, building geometry and infiltration and air-tightness (Chen et al., 2015a).

3. Research design and methodology

This study focuses on developing a validated passive design assessment approach in BEAM Plus as an equivalent alternative to the traditional whole building simulation. The coverage of passive designs is first refined according to local building energy statistics and comprehensive literature reviews. Consequently, weighting coefficients are determined based on the contribution of different design strategies to the variation of building performance, where the global sensitivity analysis (SA) is applied to a generic building model developed from a prototype of the public rental housing (PRH) in Hong Kong. As defined by Tian Wei (Tian, 2013), the global SA consists of the regression (or sampling-based), screening-based and variance-based approach, while representative methods from each approach including the standardized rank regression coefficient (SRRC), Morris, Sobol and FAST, are adopted for this research. These statistics can then be interpreted as weightings for each design input (i.e. assessment criterion). After the weighting is determined, baseline and optimum building performance levels for output and input parameters are obtained from the energy simulation requirement by BEAM Plus and NSGA-II (Non-dominated Sorting Genetic Algorithm II) based optimization process. The grading coefficient is finally determined with reasonable assumptions and the corresponding assessment results are validated by multiple modelling samples as well as a selected green building rating case. The overall framework of the research design is summarized in Fig. 2.

3.1.Define criteria coverage and total credits

As mentioned in Section 2, the scope of the existing passive design approach is obscure and inconsistent with the traditional annual energy use criterion. It is more similar to a descriptive approach to substitute for the performance-based estimation, because both building services systems and architectural features are allocated with certain credits. Based on different building energy saving levels, the annual energy use criterion grants a subtotal of 15 credits, which is less than the 22 credits of the existing passive design alternative. Therefore, to avoid the situation that project teams deliberately choose passive routes to take advantage of the unbalanced rating system, the total credits should be equal. Furthermore, in a strict passive route, all active system related credits should be excluded from the framework, and the remaining passive features should be only related to cooling and lighting performance (Chen et al., 2016). According to recent official statistics, the space conditioning, lighting, hot water, cooking, refrigeration, equipment and others respectively account for 31%, 10%, 9%, 10%, 14%, 16% and 10% of the total residential energy end use (as shown in Fig. 3) (EMSD). Total available credits for the passive design can then be obtained by multiplying its related proportion (i.e. 41%) with subtotal credits (i.e. 15 credits) of the traditional route. As a result, the subtotal credits for the new passive design route should be 6.15.

Apart from total available credits, the coverage of the passive approach should also be modified to include all basic architectural design elements which can influence future building energy performance in terms of cooling and lighting. These design elements, including the external obstruction angle (EOA), building orientation (BO), wall thermal resistance (WTR), wall specific heat (WSH), window U-values (WU), solar heat gain coefficient (SHGC), visible light transmittance (VLT), window to ground ratio (WGR), overhang projection fraction (OPF) and infiltration air mass flowrate coefficient (IAMFC), were all proved to be independent from each other with sufficient Monte Carlo sampling analyses (Chen et al., 2015b). Especially, the window light to solar gain ratio (i.e. VLT/SHGC) is fixed to one to simplify window property cases and the length of external obstructions is set to 100 m to represent the common street canyon scenario in Hong Kong (Allegrini et al., 2016; Niachou et al., 2005; Strømann-Andersen and Sattrup, 2011). In addition to above listed design inputs which are uniformly sampled in their normal distribution ranges, building surface properties (e.g. solar absorptance and reflectance of external and internal building surfaces) are assumed with a reasonable value and excluded from sensitivity analyses because their information can only be confirmed in final construction stages (Al-Obaidi et al., 2014; Li et al., 2006; Ozel, 2012).

3.2.Sensitivity analysis and transformation to weighting coefficient

The global sensitivity analysis is a valid and commonly used method to qualify and quantify the relative importance (i.e. Factor Prioritization) between different inputs for concerned outputs of a building model (A. Saltelli, 2008). It can also be used to prune the problem space for a subsequent optimization process by identifying insignificant inputs (i.e. Factor Fixing). In this study, the selected design variables in the passive approach are inputs to the building model, while the energy and indoor environment performance indices related to cooling and lighting are modelled as outputs. The generic building model is a two-habitant hypothetic space with a single-sided window opening on a heat transfer wall surrounded by adiabatic surfaces to represent the worst-case scenario for the daylight and ventilation access in a modularly designed high-rise residential building. Daily building operation schedules suggested by BEAM Plus cover the whole cooling period in the hot and humid weather conditions of Hong Kong (See Fig. 4), where the adaptive thermal comfort model (i.e. ASHRAE55 90% acceptability) is adopted to modulate the indoor operative temperature and the "continuous/off dimming" control is applied to the daylight reference point in the center of the proxy room. The modelling process is conducted by interlinked daylight, thermal balance and airflow network sub-modules in EnergyPlus, whose parameter settings are referenced to benchmarks in the BEAM Plus guidebook and EnergyPlus manuals (ENERGYPLUS™, 2013; Schulze and Eicker, 2013; Zhai et al., 2011).

After the generic building model and the input variation are constructed and specified as per Table 1 and 2 (Chen and Yang, 2015; Chen et al., 2015b), the sensitivity analysis is conducted with the Monte Carlo method, whereby an input-output dataset with an appropriate sample size is formulated as the following equation (Kim et al., 2011; Loutzenhiser et al., 2007):

$$\vec{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} f(x_{11}, x_{12}, \cdots, x_{1k}) \\ f(x_{21}, x_{22}, \cdots, x_{2k}) \\ \vdots \\ f(x_{N1}, x_{N2}, \cdots, x_{Nk}) \end{bmatrix} \tag{1}$$

where N is the sample size; k is the number of input factors; x is the input variable; and y is the output variable.

3.2.1. Regression method

The multiple linear regression is one of the most popularly adopted methods in building sensitivity analyses, from which the Standardized Rank Regression Coefficient (SRRC) is derived when the input-output matrix for the Standardized Regression Coefficient (SRC) has been rank transformed (Naji et al., 2016). Unlike SRC, which is suitable for linear regression only, SRRC can be applied to non-linear but monotonic correlations (Tian, 2013). The absolute value and sign of the SRRC indicate the relative importance of different inputs and the changing direction of the output against the input. In addition, an efficient sampling method – Latin Hypercube Sampling (LHS) is performed in advance to generate a well stratified input matrix (Calleja Rodríguez et al., 2013). A common multiple linear regression analysis of the responses/outputs (y_i) and the inputs/predictors (x_j) takes the form of Eq. (2):

$$\hat{y}_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_j \tag{2}$$

where $\hat{y}_i$ is the predicted y_i by the model; and β_j is the regression coefficient determined by minimizing Eq. (3):

$$\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{N} \left[y_i - \left(\beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} \right) \right]^2 \tag{3}$$

The sensitivity coefficient of each predictor in the regression model (i.e. SRC) can be calculated by:

$$SRC_j = \frac{\beta_j \sigma_x}{\sigma_y} \tag{4}$$

$$\sigma_x = \left[\sum_{i=1}^{N} \frac{(x_{ij} - \bar{x}_{ij})^2}{N-1} \right]^{1/2} \tag{5}$$

$$\sigma_y = \left[\sum_{i=1}^{N} \frac{(\mathrm{y}_i - \bar{y}_j)^2}{N-1} \right]^{1/2} \tag{6}$$

where $\bar{x}_{ij}$ and $\bar{y}_j$ are the averaged input and output respectively. The coefficient of determination (i.e. R^2 value) is further calculated by Eq. (7) to assess the correlation between the input and output.

$$R^2 = \frac{\sum_{i=1}^{N} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{7}$$

3.2.2. Variance-based method

Different from the regression method, the variance-based method is not limited by the model format and can be applicable to either non-linear or non-additive models. The non-additive assumption means that the effect of changing one predictor (i.e. input) on the variation of the model response (i.e. output) is not independent of other predictors (James et al., 2013). The total variance of the output $V(Y)$ is decomposed into conditional variances of increasing dimensionality as shown in Eq. (8) (Giap and Kosuke, 2014).

$$V(Y) = \sum_{i=1}^{k} V_i + \sum_{j>i}^{k} V_{ij} \cdots + V_{12\cdots k} \tag{8}$$

where $\sum_{i}^{k} V_i$ is the sum of conditional variances for the main effect of each input parameter; $\sum_{j>i}^{k} V_{ij}$ includes all conditional variances of the interaction between two input parameters; and $V_{12\cdots k}$ stands for the conditional variance including the interaction of all inputs.

If the above equation is divided by $V(Y)$, the relationship between different orders of sensitivity indices can be obtained:

$$1 = \sum_{i=1}^{k} S_i + \sum_{j>i}^{k} S_{ij} + \cdots + S_{12\cdots k} \tag{9}$$

where the S_i is called the first-order sensitivity index, which stands for the impact of solely changing

X_i on the variance of output Y. It is defined to be the average conditional variance left when X is frozen to all possible values in the distribution range (See Eq. (10)) (A. Saltelli, 2008).

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(\mathrm{Y} \mid \mathrm{X}_i))}{V(Y)} \tag{10}$$

Apart from the main effect of each input expressed by S_i, S_{ij} stands for the part of responses of Y to the change of X_i and X_j which cannot be explained by the superposition of S_i and S_j. This interaction effect between X_i and X_j is called the second-order sensitivity index. Similarly, there might be a fraction of output impact which cannot be explained by the summary of all lower order indices, taking the form of the higher-order index $S_{12\cdots k}$ (Mechri et al., 2010).

Among different orders of indices, the first-order index is usually linked to "Factor Prioritization", where the input with the highest S_i is considered to be the most influential factor. It can be approximated by the square of SRC in the regression model if the size of Monte Carlo sampling is large enough. However, it is not judicious to exclude an input parameter from further analyses just based on its zero first-order index, because the input might be involved with nonzero higher-order effects. Therefore, in order to identify a truly non-influential factor, a total sensitivity index S_{Ti} summarizing the first-order index of the target input and all higher-order indices involving it, should be calculated as below:

$$S_{Ti} = S_i + \sum_{j \neq i}^{k} S_{ij} + \cdots + S_{i \cdots j \cdots k} \tag{11}$$

This index accounts for all impacts on Y caused by X_i, so that the input can be fixed at any value in its possible distribution range without causing significant changes in the output if S_{Ti} is zero (Mara and Tarantola, 2008). Therefore, the total sensitivity index can be used for "Factor Fixing" to prune the model input space. Both the total and first order sensitivity indices are calculated in this study to comply with a synthetic SA pattern.

FAST and Sobol are two commonly used Analysis of Variance (ANOVA) methods adopted in this research to determine the relative importance between different passive strategies. Although the traditional FAST method only calculate first-order indices, the Extended FAST model is selected here to address interactions and works more computationally efficient than the Sobol model (Qian, 2013).

On the other side, Sobol can avoid the disadvantage of altering the original model as conducted by FAST (Saltelli et al., 2004).

3.2.3. Screening-based method

The Morris method is the most commonly used screening-based sensitivity approach to perform "Factor Fixing" from a large number of input variables. It qualifies the influence from each input through numerical experiments based on the concept of the Elementary Effect. For a given value of *X*, the elementary effect of the i^{th} input is defined as (Saltelli et al., 2004):

$$EE_i(x) = \frac{\left[y(x_1, x_2, \cdots x_{i-1}, x_i + \Delta, \cdots x_k) - y(x)\right]}{\Delta} \tag{12}$$

Where $x=(x_1, x_2, \cdots x_k)$ is any selected value in Ω so that the transformed point ($x+e_i\Delta$) is still in Ω for each index $i=1,2,...,k$; e_i is a vector of zeros with but one in the i^{th} component; Δ is a value in {1/(*p*-1),…1-1/(*p*-1)}.

Two sensitivity measures proposed by Morris are the mean μ and standard deviation σ of the distribution of the Elementary Effect F_i, as defined by Eq. (13) and (14):

$$\mu = \sum_{i=1}^{r} EE_i / r \tag{13}$$

$$\sigma = \sqrt{\sum_{i=1}^{r} (EE_i - \mu)^2 / r} \tag{14}$$

The mean value μ is to qualify the main effect of each input factor as a good proxy for S_{Ti}, while the standard deviation σ estimates the non-linearity and interactions between inputs. Although Morris sensitivity indices cannot quantify the exact influence of each input on the variation of outputs, it is still wildly used in building performance analysis as a convenient and efficient way to validate findings from other SAs (Silva et al.; Struck, 2012).

Due to the different indices derived from the above three SA methods, their transformation to the weighting coefficient has be unified. Referring to existing green building schemes, the subtotal of all weighting coefficients for different criteria in any category should be equal to one, whereas none of abovementioned original sensitivity coefficients can strictly comply with this requirement. With respect to the variance-based method, the summary of first-order sensitivity indices will always be less than one if the model is non-additive, while total-order indices can add up to a value higher than one. Squared SRRCs are equivalent to first-order variance-based indices, but the subtotal of their original values could still be higher than one. Morris indices, in their original form can add up to a value much higher than one depending on the scale of output and input variables. As a result, the weighting coefficient in the following study is presented as the ratio of each sensitivity index to total indices.

3.3.Determine performance and grading scale

The framework of a performance scale for energy efficiency usually consists of the baseline and optimal benchmarks (i.e. lower and upper benchmarks) as well as intervals of different energy reduction levels. In this study, the interval scales are not fixed so that any percentage of the performance improvement can lead to a prorate credit award.

The baseline energy use is simulated with input parameters referenced to the BEAM Plus scheme, where the building physical conditions and operation schedules are established from extensive energy audits of local buildings as illustrated in Table 2. The optimal energy use, however, is not calculated by assuming that all passive design strategies are applied in their best performance levels as indicated by an earlier paper (Chen et al., 2015b). Instead, the non-dominated sorting genetic algorithm II (NSGA-II) is used to derive the maximum energy reduction level based on screened out input variables for passive design criteria. NSGA-II is chosen for its universal application as well as smooth integration with jEPlus, a building parametric simulation tool developed by Yi Zhang to simultaneously explore large quantities of design variables by operating EnergyPlus models (Delgarm et al., 2016; Zhang). It is characterized by the higher computation efficiency, enhanced probability to create better solutions, and maintenance of population diversity by the crowding comparison (Wu, 2012).

To be in line with performance scales, grading scales also exclude fixed intermediate levels. The attainable credits for each selected passive strategies are derived from the product of subtotal credits in the whole approach (i.e. 6.15), the corresponding weighting coefficient of the sub-criterion and a grading coefficient. The grading coefficient is determined by the ratio of the reduction from the baseline energy use solely contributed by adjusting a specific design variable to the reduction of optimum performance. For instance, if the design variable has a positive linear effect on the building energy reduction, and the baseline and optimal value in its possible distribution range (a, b) are c and d respectively, the grading coefficient is then formulated by Eq. (15):

$$C_i = \begin{cases} 0, & if\,(a < x < c) \\ \dfrac{x-c}{d-c}, & if\,(c < x < d) \\ 1, & if\,(d < x < b) \end{cases} \tag{15}$$

And the total anticipated credits G for all passive design criteria should be presented as:

$$G = 6.15\sum_{i=1}^{k} C_i W_i \tag{16}$$

where W_i is the weighting coefficient for each sub-criterion.

3.4.Validation of assessment system and case study

The validation of the assessment system is first carried out by its application to randomly sampled cases generated by EnergyPlus. The obtained credits based on the whole building simulation and passive design approach are then correlated in scatterplots to observe their convergence through the coefficient of determination (i.e. R^2).

Furthermore, crediting results by the proposed assessment system, traditional building simulation and current passive design approach are compared in a local green building project registered to the BEAM Plus scheme. The case building belongs to one of the Hong Kong Housing Authority's PRHs which provide residence for about 31% of the local population. The site has totally three modularly designed blocks surrounded by existing architectural structures and hills below the average height of project buildings. The 3D model and layout plan of the case building are illustrated in Fig. 4 and Fig. 5.

4. Results and discussions

This research proposed a novel assessment system with robust weighting coefficients and grading scales for the passive design approach in the BEAM Plus rating scheme. Selected design variables are subject to extensive numerical experiments through different sensitivity analysis methods. Obtained sensitivity indices are then transformed to weighting coefficients and incorporated with performance and grading scales to formulate the whole assessing framework. Finally, the developed system was validated by both modelling and practical case studies. Major findings and discussions with reference to existing studies are presented in this section.

4.1.Sensitivity analysis and transformation to weighting coefficients

4.1.1. Regression analysis

The regression analysis here is an extension of the former work presented in an earlier paper (Chen et al., 2016), where nine selected building design parameters are modelled against the weighted sum (i.e. Weighted Unmet Time) of the Daylight Unsatisfied Time (DUT) and Thermal Discomfort Time (TDT) through 1000 Monte Carlo samples. Among the selected inputs, the external obstruction angle is defined as the angle between the horizontal line at the window sill level and the line connected with the highest point of the obstruction faced by the building (Li et al., 2006). It is intrinsically a combination of two more elementary variables including the external obstruction distance (EOD) and external obstruction height (EOH) (Mavromatidis et al., 2014). With the breakdown of EOA, the relative importance (i.e. absolute SRRC values) of all inputs is compared in Fig. 6. Based on a statistical summary of the above sensitivity study, the variation of the Weighted Unmet Time (WUT) cannot be well explained by nine or ten input variables with a low R^2 of 0.288 and 0.296 respectively. As a result, the validity of above sensitivity coefficients has to be improved by choosing alternative model outputs.

Given the indirect relationship between WUT and the actually building energy use, hybrid ventilation (i.e. mixed-mode ventilation) based on the indoor-outdoor air temperature difference and the adaptive thermal comfort model is modelled to obtain the total lighting and cooling energy consumption. Fig. 7 summarizes the variation of sensitivity coefficients under different ventilation models. SRRCs of the building orientation (BO) and infiltration air mass flow coefficient (IAMFC) both remained constant irrespective of the change of ventilation modes and they are also identified as insignificant input variables because of low SRRCs and higher Sig. indices than 0.05. The influence of wall thermal properties including the wall thermal resistance (WTR) and specific heat (WSH) as well as the window to ground ratio (WGR) all dropped dramatically, where WSH also became insignificant as suggested by its Sig. index. On the contrary, SRRCs of the window solar and light transmittance (SHGC/VLT), overhang project fraction (OPF) and external obstructions (EOH and EOD) all achieved great increments. In addition to the change of SRRCs, R^2 of the regression model was improved to 0.809, indicating an acceptable linear correlation between inputs and outputs. It can be clearly seen that the hybrid ventilation model with energy consumption outputs generated more reliable regression analysis results, so the following regression analyses are all based on the assumption of hybrid ventilation.

Furthermore, distribution ranges of three input parameters are subject to adjustment to observe its impact on the sensitivity indices. The original input distribution is referenced to local building practices and engineering experiences as shown in Table 1, but some of the upper or lower limitations might not reflect the strictest or most up-to-date building design in the world. After the adjustment of input distributions according to Fig. 8, the three inputs showed increasing SRRCs to varying degrees, while SRRCs of remaining important design parameters dropped correspondingly, leading to an exchanged ranking of WGR and WTR (See Fig. 9). In view of the influence of input uncertainties, the following studies are based on changed distribution ranges to acquire more robust SA results.

4.1.2. Variance-based analysis

The Analysis of Variance (ANOVA) with the Sobol method is then used to decompose the uncertainty of the total energy consumption (i.e. cooling and lighting) according to the ten input design parameters with adjusted distribution ranges suggested by above regression studies. This analysis totally involved 5632 simulations, which cost dramatically more computation time compared with the regression analysis. By comparing Fig. 10 with Fig. 9, the inconsistency between the variance-based and regression analyses might result from non-additive building model, which can be further validated by the fact that subtotals of SRRC^2 and S_i (0.804 and 0.670) are less than one. Therefore, around 33% of uncertainties in the output, as shown in the pie chart, is attributed to interactions between different design factors.

Subsequently, total-order sensitivity indices were calculated and compared to first-order indices in Table 3. Most total-order indices are larger than their first-order counterparts, while their ranking orders generally agrees well except that WGR exceeds BO, OPF and EOH becoming the third influential factor among all inputs. These changes demonstrated the interactions between design variables. The sum of total-order indices is 1.343, indicating that all variance in the total energy consumption can be explained by selected passive strategies.

The same number of simulations were also conducted for the FAST analysis and presented in Fig. 11, where contribution of interactions was reduced to 24.3%. Table 4 presents the comparison of first and total order FAST indices, where an increasing tendency similar to Table 3 can be observed. Nevertheless, WTR, WSH and IAMFC showed weak influences over the variance of total energy consumption as indicated by their non-zero total-order indices.

4.1.3. Screening-based analysis

The screening-based analysis (i.e. Morris analysis) only required 110 simulations to complete a qualitative interpret of the relative importance for each input (See Fig. 12). Compared with results from the former two analysis methods, SHGC/VLT is constantly the most influential design input, while IAMFC and WSH remain statistically insignificant. The ranking of WGR ascended to the third place, while BO ranked after OPF and WU. Input variables with higher main effects, are also identified with greater non-linearity and interactions, where WGR tops all other design variables.

4.1.4. Adjust criteria coverage and transformation to weighting coefficient

Based on initial sensitivity analyses, although ranking orders vary to some extent with analysis methods, IAMFC and WSH remain to be the least influential factors among the original ten inputs. In addition, regression and Sobol analyses identified them as insignificant factors that can be excluded from the passive design route. Furthermore, according to a previous study (Méndez Echenagucia et al., 2015), there is an opportunity to reduce the number of design variables on top of sensitivity analyses and significance tests by performing a post-optimization analysis. In this case, the optimization result is summarized in Table 5, where the value of WU (i.e. 5.83) for the optimum solution is quite close to the baseline benchmark (i.e. 5.69) specified in Table 2. This situation leaves little room for improvement for WU and make it another excludable input for the assessment system. Apart from above three excludable parameters, external obstruction inputs (i.e. EOH and EOD) are further removed from the assessment because the whole building simulation can exclude peripheral buildings from the modelling process as recommended in BEAM Plus and LEED. Consequently, the final assessment framework is made up of the remaining five design variables (i.e. SHGC/VLT, WGR, OPF, BO, and WTR) with reduced distribution ranges according to the baseline benchmarks. Weighting coefficients are then calculated as the ratio of each sensitivity index to the sum of all sensitivity indices. The comparison of weighting coefficients obtained from different SA methods is presented in Fig. 13, where the most suitable weighting system for the passive design approach is still depending on the verification in later sections.

4.2. Determine performance and grading scale

The formulation of performance scales starts with setting the lower and upper benchmarks. Since the lower benchmark (i.e. the baseline) has been stipulated in BEAM Plus. The upper limit is derived from a NSGA-II based optimization process as introduced in Section 3. The convergence progress of the objective function (i.e. the total lighting and cooling energy consumption) and solution distributions are then summarized in Fig. 14. The optimal solution was found to be 38.86 kWh/m^2, which is also taken as the upper benchmark of the performance scale.

The grading coefficient, as introduced in Section 3, can be calculated by Eq. (15) if each design input is linearly related to the model output when other inputs are fixed to their baseline benchmarks.

With the method of changing one input at a time (i.e. local sensitivity analysis), the independent effect of moving each input away from the baseline benchmark can be observed in Fig. 15. SHGC/VLT, OPF and WGR are all approximately linearly correlated with the total energy consumption and can therefore be applicable to Eq. (15). However, WTR and BO are only linearly correlated to the model output in some sections of the whole distribution range. In regard of WTR, the total energy consumption only varied with WTR below 0.66 m^2 K/W. Once exceeding this threshold, WTR had no more apparent impacts on the energy reduction. Consequently, the best-performance scale (i.e. the optimal value) for WTR in Eq. (15) is set to be 0.66. In terms of BO, total energy consumption varies periodically with the input, and the original distribution range can be discretized to four sessions, each of which displays an approximate linear relationship. The four sessions are then determined to be (0, 90), (90, 180), (180, 270), (270, 360) respectively, with the best-performance scale at 0° / 360°.

4.3. Validation of assessment system and case study

Succeeding to weighting coefficients and grading scales obtained from above sections, it is still essential to determine the most suitable weighting system by comparing the prediction accuracy through modelling experiments. Predicted credits through six differently weighted passive design assessment systems and the traditional whole building simulation are compared in Fig. 16. Among weighting systems by variance-based methods, the one transformed from first-order FAST indices leads to the best grading prediction by generating consistent rounded-up credits with the traditional assessment route in 73.3% of sampled cases. Furthermore, if the comparison is relaxed to include cases with credit differences no more than one, the prediction accuracy can be improved to 99.9%.

The optimal assessment system determined by the above comparative analyses is then applied to the case study of a registered BEAM Plus project in Hong Kong. Performance of the proposed assessment system is compared to the current passive design approach with reference to the traditional whole building simulation approach. The comparison is confined to the five passive design sub-criteria based on the credit achievement ratio.

The first criterion – site permeability is in essence a measure of the building separation which divides the subtotal of a minimum of 2/3 qualified Intervening Space (IS) and a maximum of 1/3 Permeable Element (PE) by the total assessment area as defined in the PNAP APP-152 standard. IS should be provided between the edge of a projected façade and the common building line (or the central line of adjacent streets), while PE is any inter-building space with a clear width and height over 3 m. For the case building, the site can provide a permeability of 35.173% and 35.538% for the low-zone and middle/high zone respectively, and obtain 2 credits with a permeability more than 33%. The second criterion - building orientation, grants 1 credit if the accumulated average solar irradiation on all building facades is less than 316 kWh/m^2 from April to October. By evaluating the building with multiple façade orientations, an average solar irradiation of 242 kWh/m^2 contributed another credit to the assessment. The third criterion – building envelope, grants up to five credits according to different levels of OTTV reduction. By summarizing the heat gain through the glazing and opaque wall, OTTV is calculated to be 19.03 W/m^2 and 5 more credits can thus be obtained. In the fourth criterion – natural ventilation, the total area that meets the single-sided ventilation requirements is calculated to be 24.3%, leading to the award of 1 more credit. The fifth criterion – daylight, grants one credit if 80% of kitchens and habitable rooms are accessible to natural lighting with a VDF no less than 6% and 12% respectively. According to a detailed daylight simulation, the total area in compliance with the standard is close to 100% and thus one more credit is attained. In summary, the total attainable credits under the current passive design system add up to 10, equivalent to 66.7% of maximum available credits by the whole building simulation approach.

The new passive design assessment system is also applied to the case building with design parameters and detailed calculations concluded in Table 6 and Table 7. The case building has four groups of flat designs with differences in the window orientation and window to wall ratio. Attainable credits under each passive criterion is calculated by multiplying weighted grading coefficients with area ratios of different flat designs. Total obtained credits from the new approach is rounded up to 2.00, which is 32.5% of maximum available credits by the traditional approach. Meanwhile, the simulated energy consumption of the assessed building is 65.11 kWh/m^2, also leading to accreditation of two rounded up credits based on the 32.5% energy reduction from the baseline. In contrast with the 66.7% attainable credits under the current passive design assessment system, the proposed new assessment system apparently achieved better consistency with the traditional route. The overestimated credit awarding by the currently passive approach can mislead the project team and impair practical energy efficiency in future building operations. Although the proposed assessment system is not perfect in predicting building energy use, it can surely be treated as a more robust substitute for the current system.

5. Conclusions

A new passive design assessment system as an alternative to traditional building energy simulation was developed in this study. Critical problems of the current passive design approach were first identified and the coverage of sub-criteria was preliminarily defined. Extensive global sensitivity analyses were then conducted on a generic building model representing a typical type of residential buildings in Hong Kong. The criteria coverage was adjusted and weighting coefficients were transformed from six sensitivity indices. The performance and grading scales are thereafter derived from an assumption of continuous linear variation between the baseline and optimal energy performance benchmarks. Finally, the proposed weighting and grading system are subject to validations from both modelling experiments and a green building case study. Preliminary conclusions can be drawn as below:

1) Sensitivity indices from regression analyses were proved to be influenced by the number of input variables, input distribution ranges, building control strategies and output performance indices. Because the non-linearity and non-additivity in the building model greatly impaired the validity and robustness of regression sensitivity indices, variance-based and screening-based analyses were also conducted. By detailed analyses of different SA indices, five design variables including SHGC/VLT, WGR, BO, OPF and WTR were selected to compose the assessment framework of the new passive design approach.
2) By varying selected design variables of the generic building model, the baseline benchmark of energy performance was simulated to be 77.64 kWh/m^2, while the optimal performance was derived from a NSGA-II based optimization process, in which convergence was achieved by a consolidated setting of the population size, number of generations, crossover rate and mutation probability. The optimal benchmark is consequently set to be 38.86 kWh/m^2 according to the optimization result. With the defined upper and lower benchmarks, the grading coefficient is determined by a local sensitivity analysis, which leads to a pro-rata credit awarding system without fixed interval levels.
3) Weighting systems transformed from different sensitivity indices were validated through

extensive modelling experiments. The assessment system based on FAST first-order indices can accurately predict 73.3% of test cases simultaneously assessed by the traditional whole building simulation approach. Rounded up credits showed an even higher consistency of 99.9%, when the allowable prediction uncertainty is relaxed to one credit. The derived optimum assessment system was also applied to a registered green building project in Hong Kong for further examination. The case building obtained 32.5% of maximum available credits under new passive design assessment system and the traditional building simulation approach, whereas obtained credits under the current passive design approach were overestimated to be 66.7% of total available credits.

4) This new passive design assessment system can replace the current system as an equivalent alternative to address energy efficient building designs. It can guide all stakeholders in a building project by appropriately allocating resources and investments to each design strategy based on a consolidated weighting. The systematic approach detailed in this study can also be expanded to develop alternative approaches for all performance-based criteria in a green building rating scheme.

Acknowledgment

The work described in this paper was supported by the Hong Kong PhD Fellowship Scheme, the Construction Industry Council of Hong Kong and the Research Institute for Sustainable Urban Development (RISUD) of The Hong Kong Polytechnic University. Appreciation is also given to the Housing Authority of the Hong Kong SAR Government and the Shenzhen Peacock Plan (KQTD2015071616442225) for supporting our research projects.

References

A. Saltelli, M.R., Terry Andres, Francesca Campolongo, Jessica Cariboni, Debora Gatelli, Michaela Saisana, Stefano Tarantola, 2008. Global Sensitivity Analysis: The Primer. John Wiley & Sons Ltd.

Al-Obaidi, K.M., Ismail, M., Abdul Rahman, A.M., 2014. Passive cooling techniques through reflective and radiative roofs in tropical houses in Southeast Asia: A literature review. Frontiers of Architectural Research 3, 283-297.

Ali, H.H., Al Nsairat, S.F., 2009. Developing a green building assessment tool for developing countries – Case of Jordan. Building and Environment 44, 1053-1064.

Allegrini, J., Dorer, V., Carmeliet, J., 2016. Impact of radiation exchange between buildings in urban street canyons on space cooling demands of buildings. Energy and Buildings 127, 1074-1084.

Calleja Rodríguez, G., Carrillo Andrés, A., Domínguez Muñoz, F., Cejudo López, J.M., Zhang, Y., 2013. Uncertainties and sensitivity analysis in building energy simulation using macroparameters. Energy and Buildings 67, 79-87.

Chen, X., Yang, H., 2015. Combined thermal and daylight analysis of a typical public rental housing development to fulfil green building guidance in Hong Kong. Energy and Buildings 108, 420-432.

Chen, X., Yang, H., Lu, L., 2015a. A comprehensive review on passive design approaches in green building rating tools. Renewable and Sustainable Energy Reviews 50, 1425-1436.

Chen, X., Yang, H., Sun, K., 2016. A holistic passive design approach to optimize indoor environmental quality of a typical residential building in Hong Kong. Energy 113, 267-281.

Chen, X., Yang, H., Zhang, W., 2015b. A comprehensive sensitivity study of major passive design parameters for the public rental housing development in Hong Kong. Energy 93, 1804-1818.

Delgarm, N., Sajadi, B., Kowsary, F., Delgarm, S., 2016. Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO). Applied Energy 170, 293-303.

EMSD, Hong Kong Energy End-use Data 2015. Electrical & Mechanical Services Department. http://www.emsd.gov.hk.

ENERGYPLUS™, 2013. EnergyPlus Engineering Reference - The Reference to EnergyPlus Calculations. US Department of Energy.

Giap, G.E., Kosuke, N., 2014. Sensitivity Analysis Using Sobol 'Variance-Based Method on the Haverkamp Constitutive Funtions Implemented in Richards' Water Flow Equation. Malaysian Journal of Soil Science 18, 19-33.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. An Introduction to Statistical Learning with Application in R. Springer.

Kim, K., von Spakovsky, M.R., Wang, M., Nelson, D.J., 2011. A hybrid multi-level optimization approach for the dynamic synthesis/design and operation/control under uncertainty of a fuel cell system. Energy 36, 3933-3943.

Lee, W.L., 2013. A comprehensive review of metrics of building environmental assessment schemes. Energy and Buildings 62, 403-413.

Lee, W.L., Chau, C.K., Yik, F.W.H., Burnett, J., Tse, M.S., 2002. On the study of the credit-weighting scale in a building environmental assessment scheme. Building and Environment 37, 1385-1396.

Li, D.H.W., Wong, S.L., Tsang, C.L., Cheung, G.H.W., 2006. A study of the daylighting performance and energy use in heavily obstructed residential buildings via computer simulation techniques, Energy and Buildings, pp. 1343-1348.

Loutzenhiser, P.G., Maxwell, G.M., Manz, H., 2007. An empirical validation of the daylighting algorithms and associated interactions in building energy simulation programs using various shading devices and windows. Energy 32, 1855-1870.

Mara, T.A., Tarantola, S., 2008. Application of global sensitivity analysis of model output to building thermal simulations. Building Simulation 1, 290-302.

Mavromatidis, L.E., Marsault, X., Lequay, H., 2014. Daylight factor estimation at an early design stage to reduce buildings' energy consumption due to artificial lighting: A numerical approach based on Doehlert and Box–Behnken designs. Energy 65, 488-502.

Mechri, H.E., Capozzoli, A., Corrado, V., 2010. USE of the ANOVA approach for sensitive building energy design. Applied Energy 87, 3073-3083.

Méndez Echenagucia, T., Capozzoli, A., Cascone, Y., Sassone, M., 2015. The early design stage of a building envelope: Multi-objective search through heating, cooling and lighting energy performance analysis. Applied Energy 154, 577-591.

Naji, S., Keivani, A., Shamshirband, S., Alengaram, U.J., Jumaat, M.Z., Mansor, Z., Lee, M., 2016. Estimating building energy consumption using extreme learning machine method. Energy 97, 506-516.

Niachou, K., Hassid, S., Santamouris, M., Livada, I., 2005. Comparative monitoring of natural, hybrid and mechanical ventilation systems in urban canyons. Energy and Buildings 37, 503-513.

Ozel, M., 2012. The influence of exterior surface solar absorptivity on thermal characteristics and optimum insulation thickness. Renewable Energy 39, 347-355.

Pan, B.Y., Liu, J.P., 2011. Building the Assessment and Evaluation System of Green Residential Area. Applied Mechanics and Materials 71-78, 134.

Qian, J., 2013. Towards a Whole-life Value Optimisation Model for Facade Design. University of Cambridge.

Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models. Wiley.

Schulze, T., Eicker, U., 2013. Controlled natural ventilation for energy efficient buildings. Energy and Buildings 56, 221-232.

Shi, H., 2009. Theoretical Study on Comprehensive Assessment of Green Building, Intelligent Information Technology Application, 2009. IITA 2009. Third International Symposium on, pp. 614-617.

Silva, A.S., Almeida, L.S.S., Ghisi, E., DECISION-MAKING PROCESS FOR IMPROVING THERMAL AND ENERGY PERFORMANCE OF RESIDENTIAL BUILDINGS: A CASE STUDY OF CONSTRUCTIVE SYSTEMS IN BRAZIL. Energy and Buildings.

Strømann-Andersen, J., Sattrup, P.A., 2011. The urban canyon and building energy use: Urban density versus daylight and passive solar gains. Energy and Buildings 43, 2011-2020.

Struck, C., 2012. Uncertainty propagation and sensitivity analysis techniques in building performance simulation to support conceptual building and system design. Eindhoven University of Technology.

Tian, W., 2013. A review of sensitivity analysis methods in building energy analysis. Renewable and Sustainable Energy Reviews 20, 411-419.

Wu, H., 2012. A multi-objective optimization model for green building design, HKU Theses Online (HKUTO). The University of Hong Kong (Pokfulam, Hong Kong).

Xia, L.M., Liu, J.J., 2013. Research on Green Building Assessment System Based on Bp Neural Network and Life Cycle Assessment (LCA). Applied Mechanics and Materials 357-360, 508.

Xue, Y., Qiu, N., 2012. Research on the methods of Green Building in China, 2012 International Conference on Innovation and Information Management, Singopore.

Yik, F.W.H., Wan, K.S.Y., 2005. An evaluation of the appropriateness of using overall thermal transfer value (OTTV) to regulate envelope energy performance of air-conditioned buildings. Energy 30, 41-71.

Yu, W., Li, B.Z., Yang, X.C., Wang, Q.Q., 2015. A development of a rating method and weighting system for green store buildings in China. Renewable Energy 73, 123-129.

Zhai, Z., Johnson, M.-H., Krarti, M., 2011. Assessment of natural and hybrid ventilation models in whole-building energy simulations. Energy and Buildings 43, 2251-2261.

Zhang, Y., Use jEPlus as an efficient building design optimization tool, CIBSE ASHRAE Technical Symposium, Imperial College, London UK – 18 and 19 April, 2012, London.

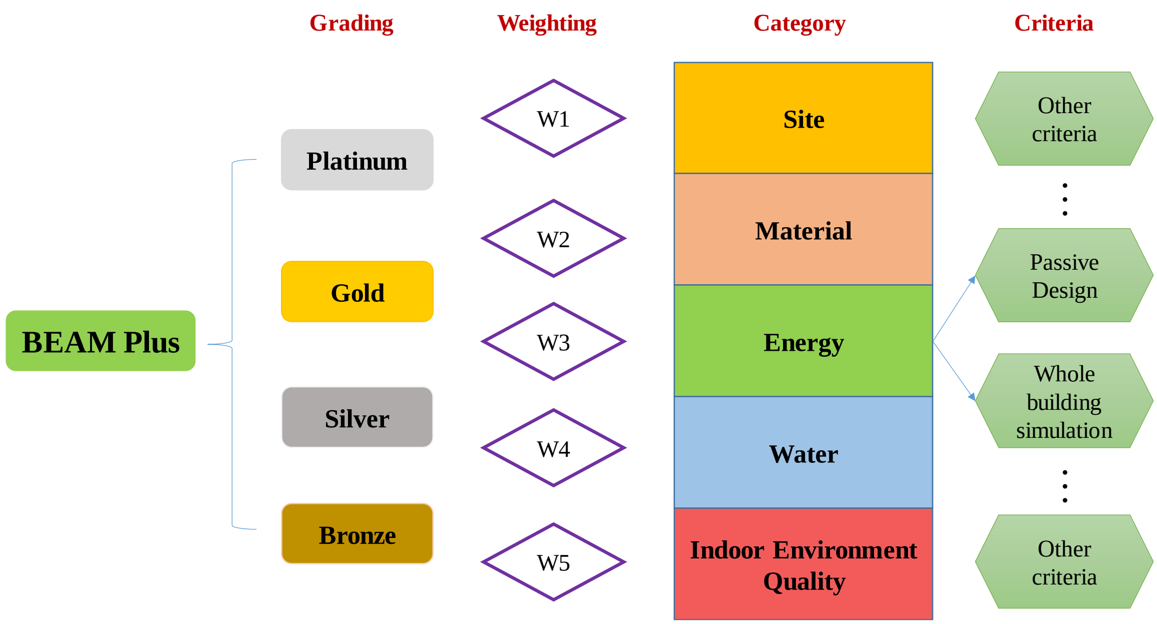


Fig. 1 Framework of BEAM Plus assessment scheme

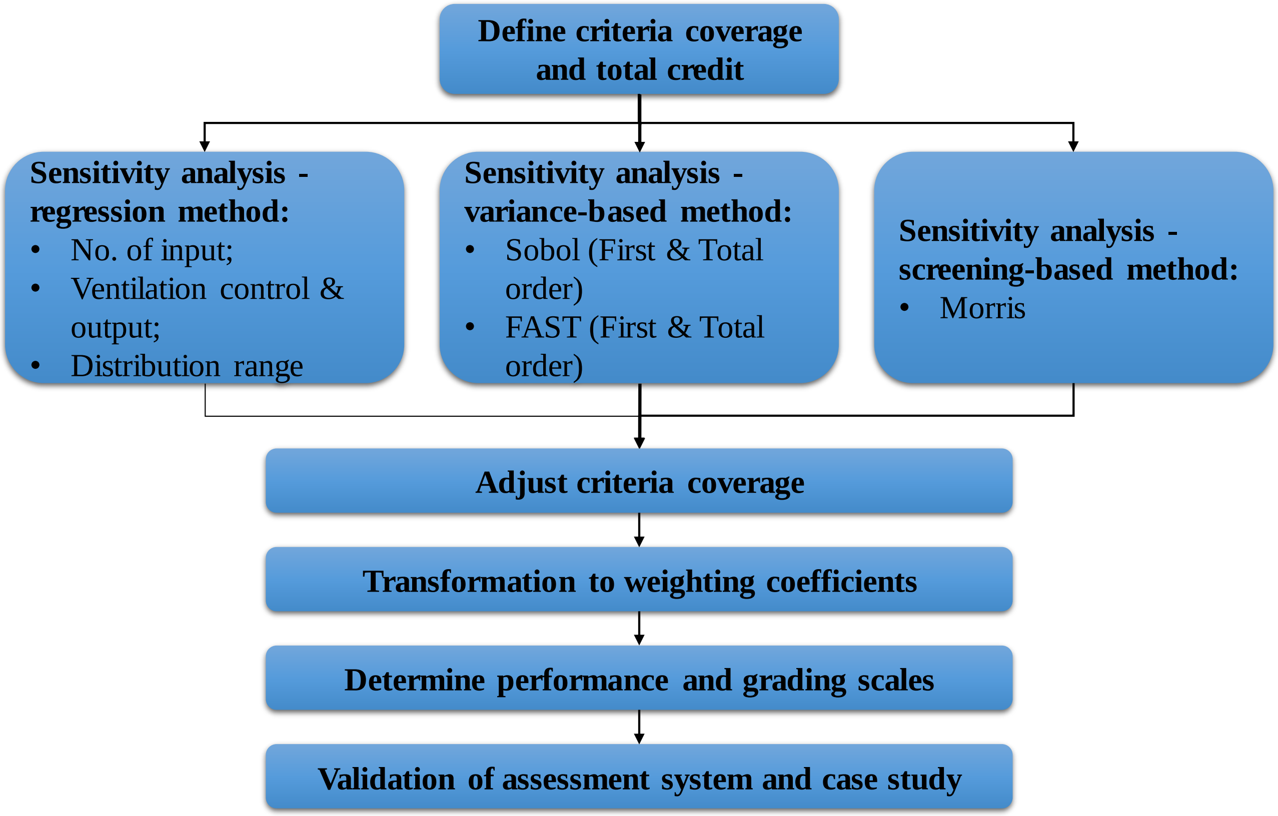


Fig. 2 Proposed flowchart of research methodology

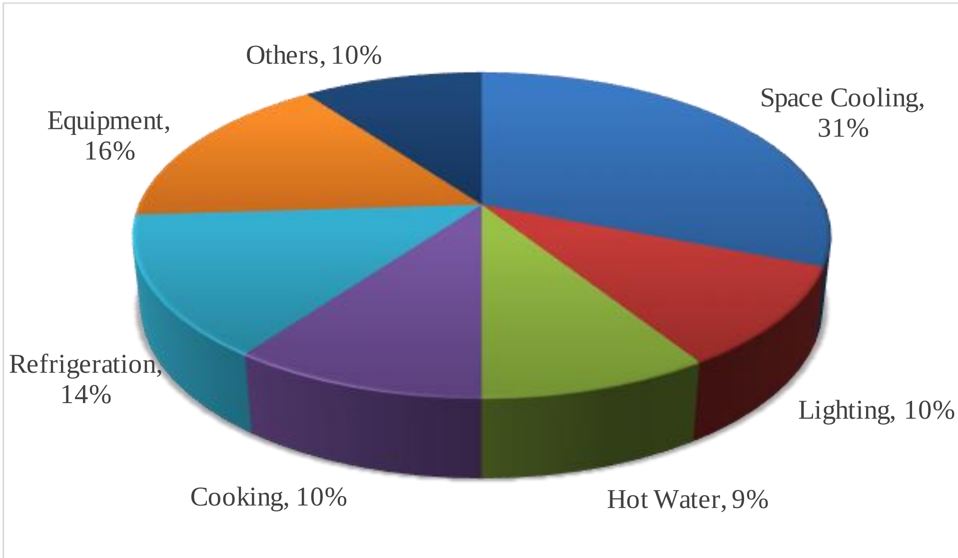


Fig. 3 Energy end use statistics of residential buildings in Hong Kong (by EMSD)

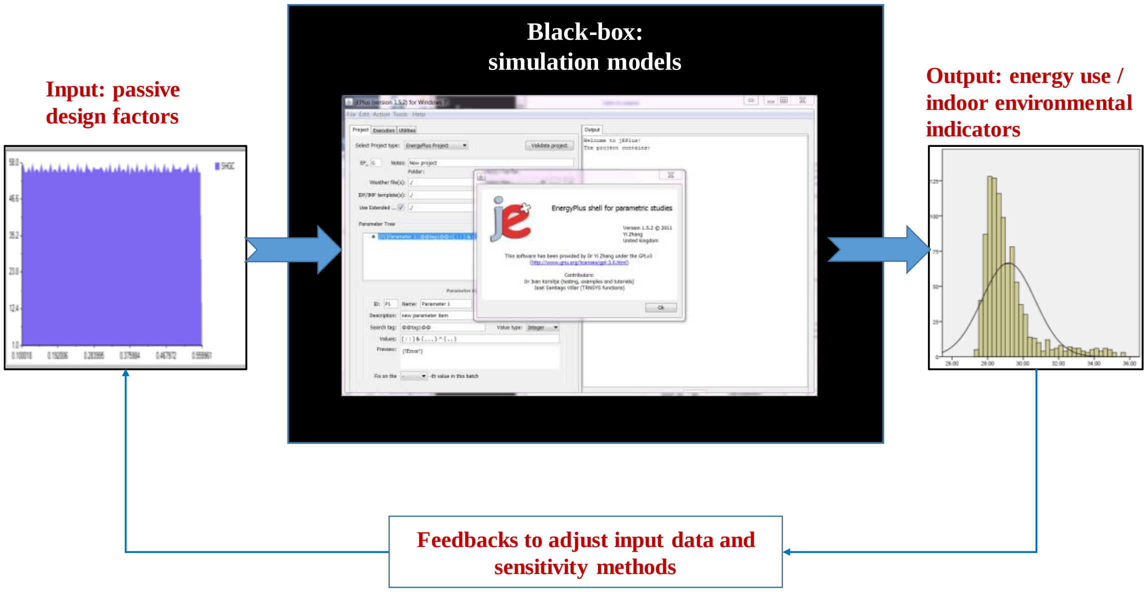


Fig. 4 Schematic of the sensitivity analysis framework

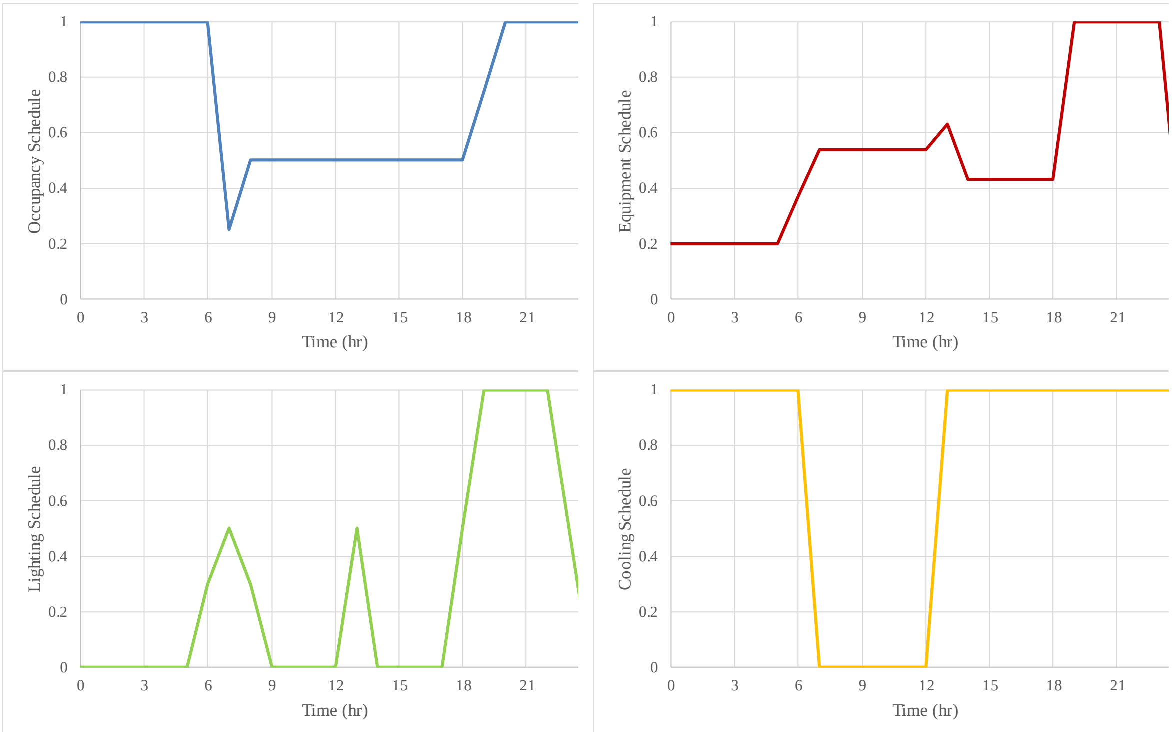


Fig. 5 Building operation schedules

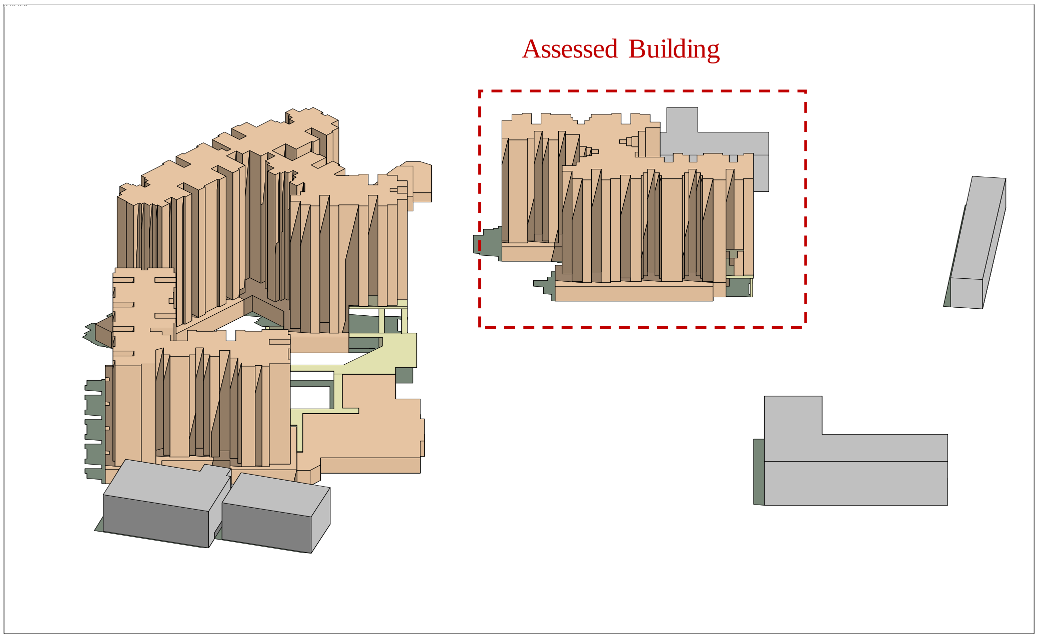


Fig.6 Site layout plan and assessed building in 3D modelling

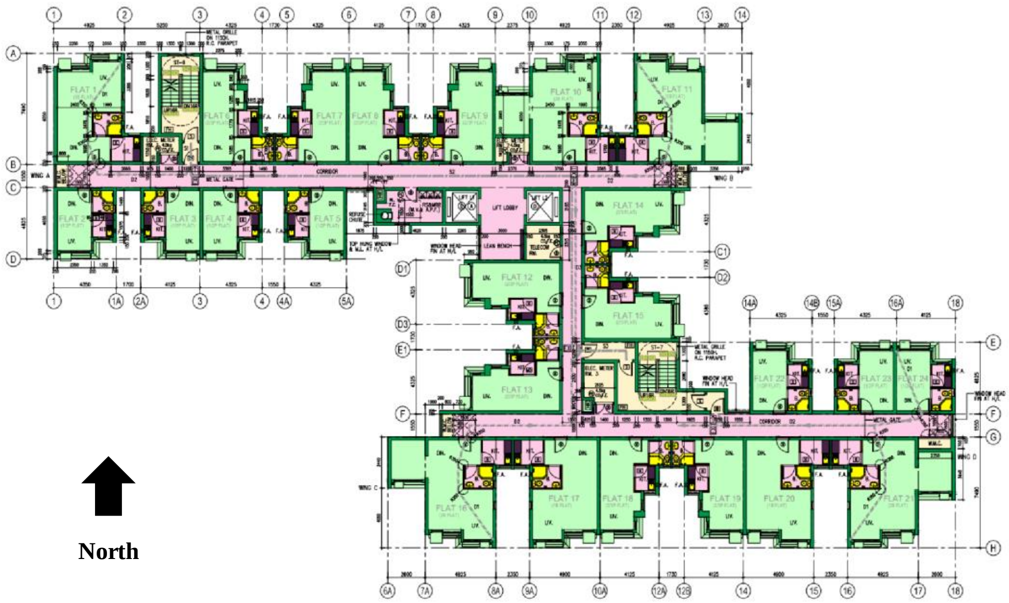


Fig. 7 Typical floor layout plan

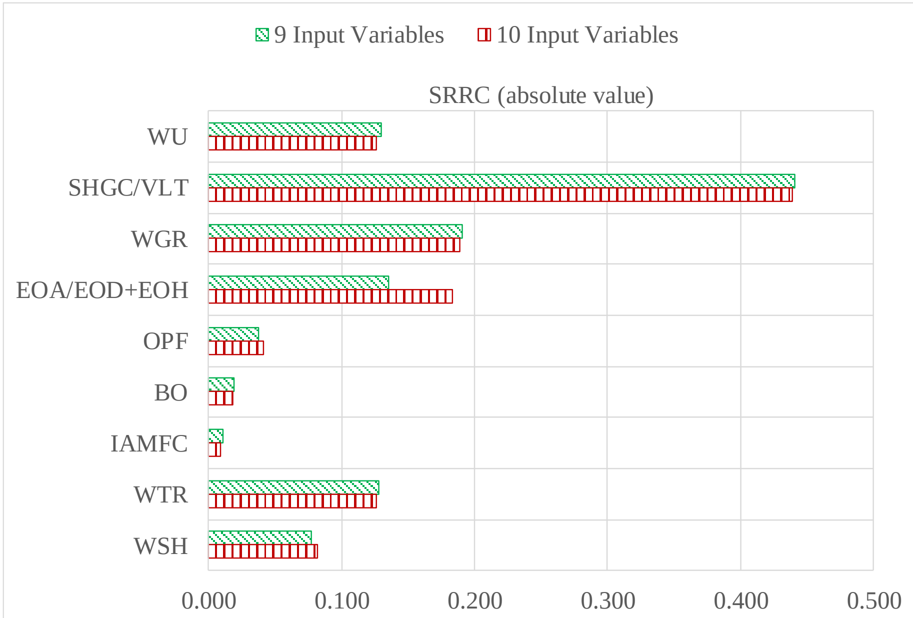


Fig. 8 Comparison of sensitivity results for different number of input variables

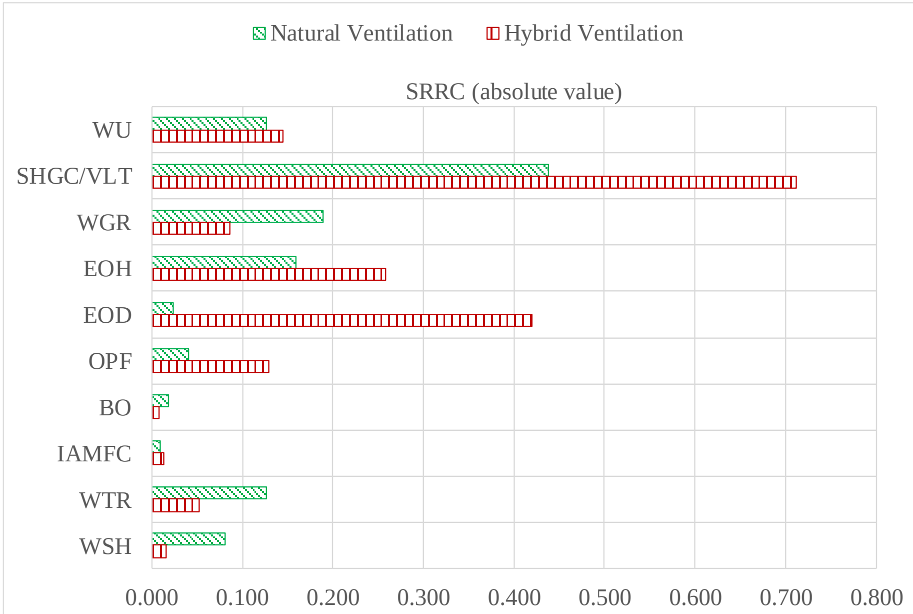


Fig. 9 Comparison of sensitivity results for different ventilation mode and output indices

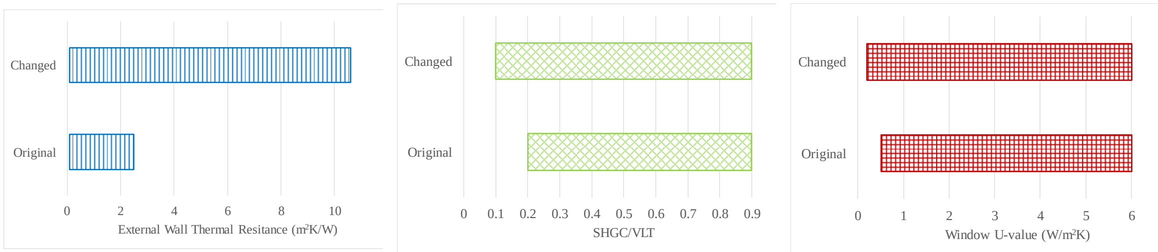


Fig. 10 Distribution range adjustment for three input variables

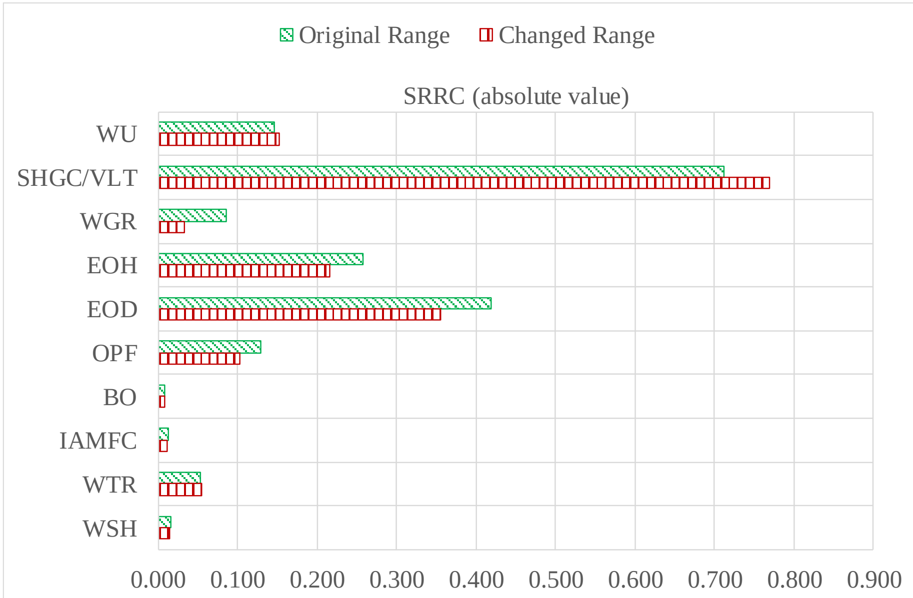


Fig. 11 Influence of input distribution ranges on sensitivity indices

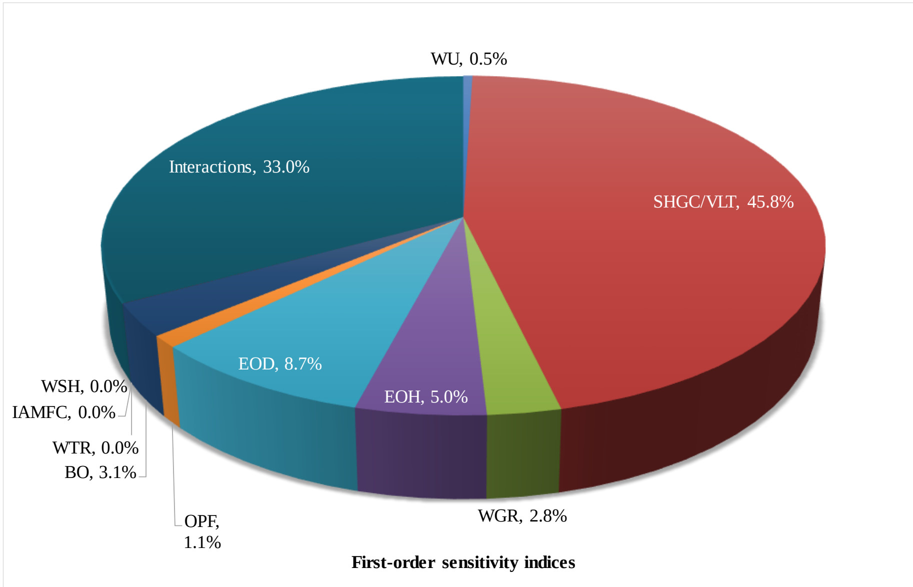


Fig. 12 First order sensitivity indices by the Sobol method

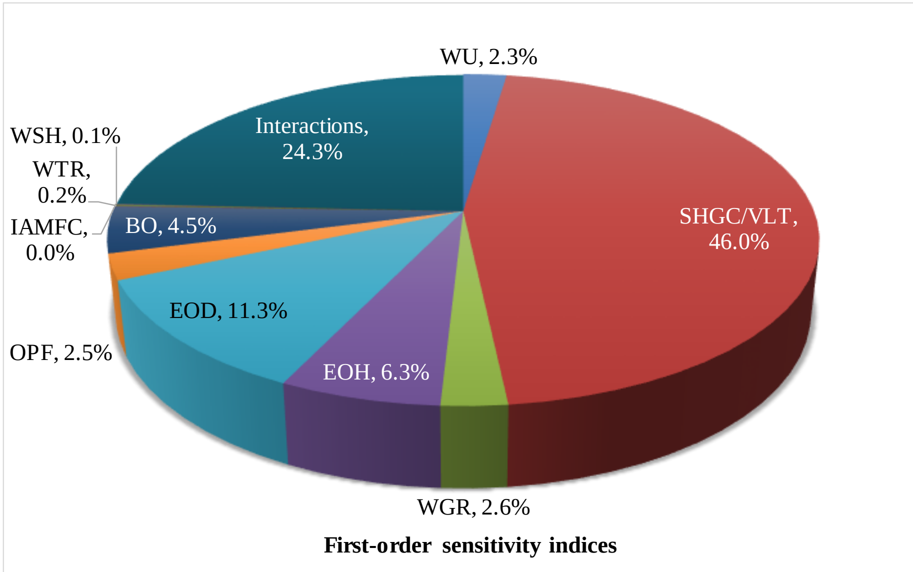


Fig. 13 First order sensitivity indices by the FAST method

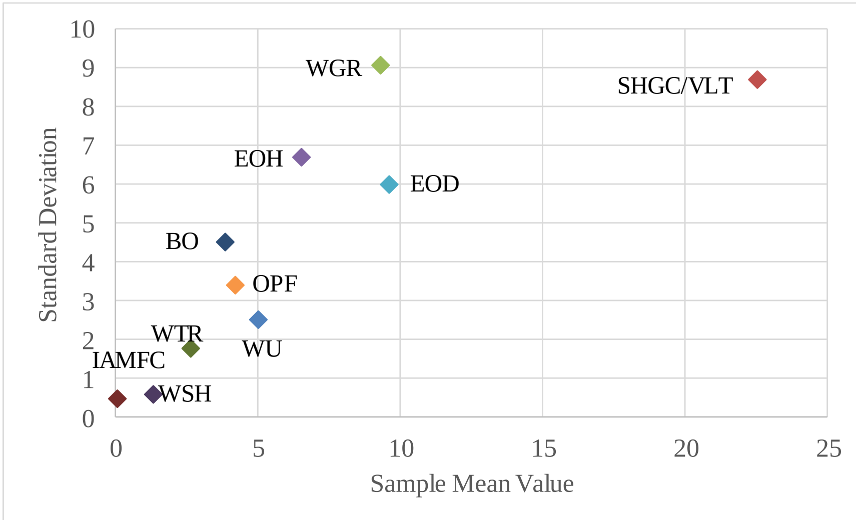


Fig. 14 Sensitivity indices by the Morris method

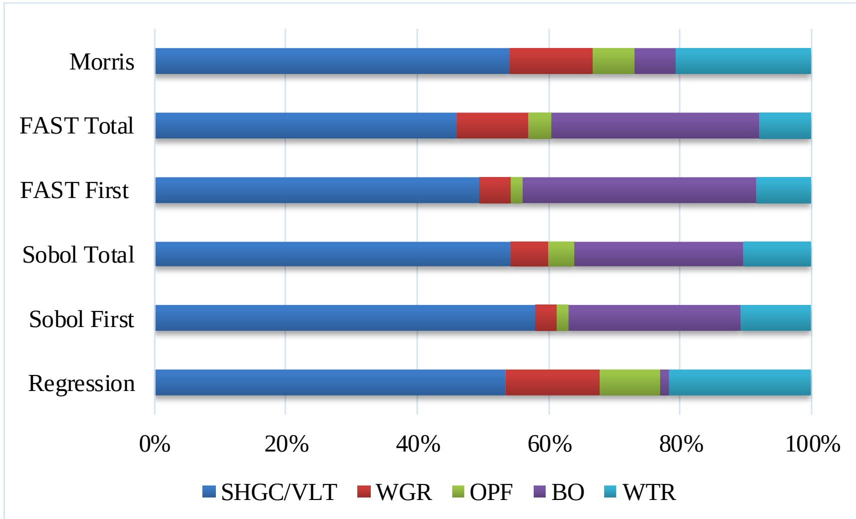


Fig. 15 Comparison of weighting coefficients from six sensitivity indices

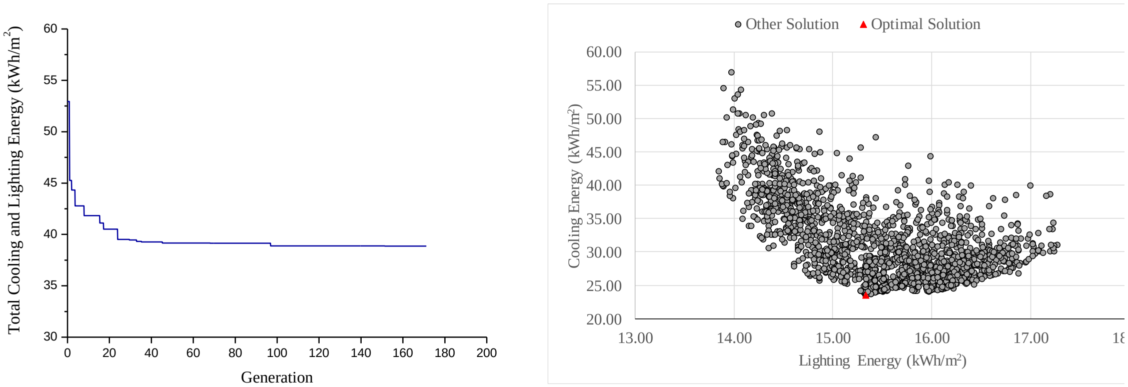


Fig. 16 Progress of NSGA-II based optimization and solution distribution

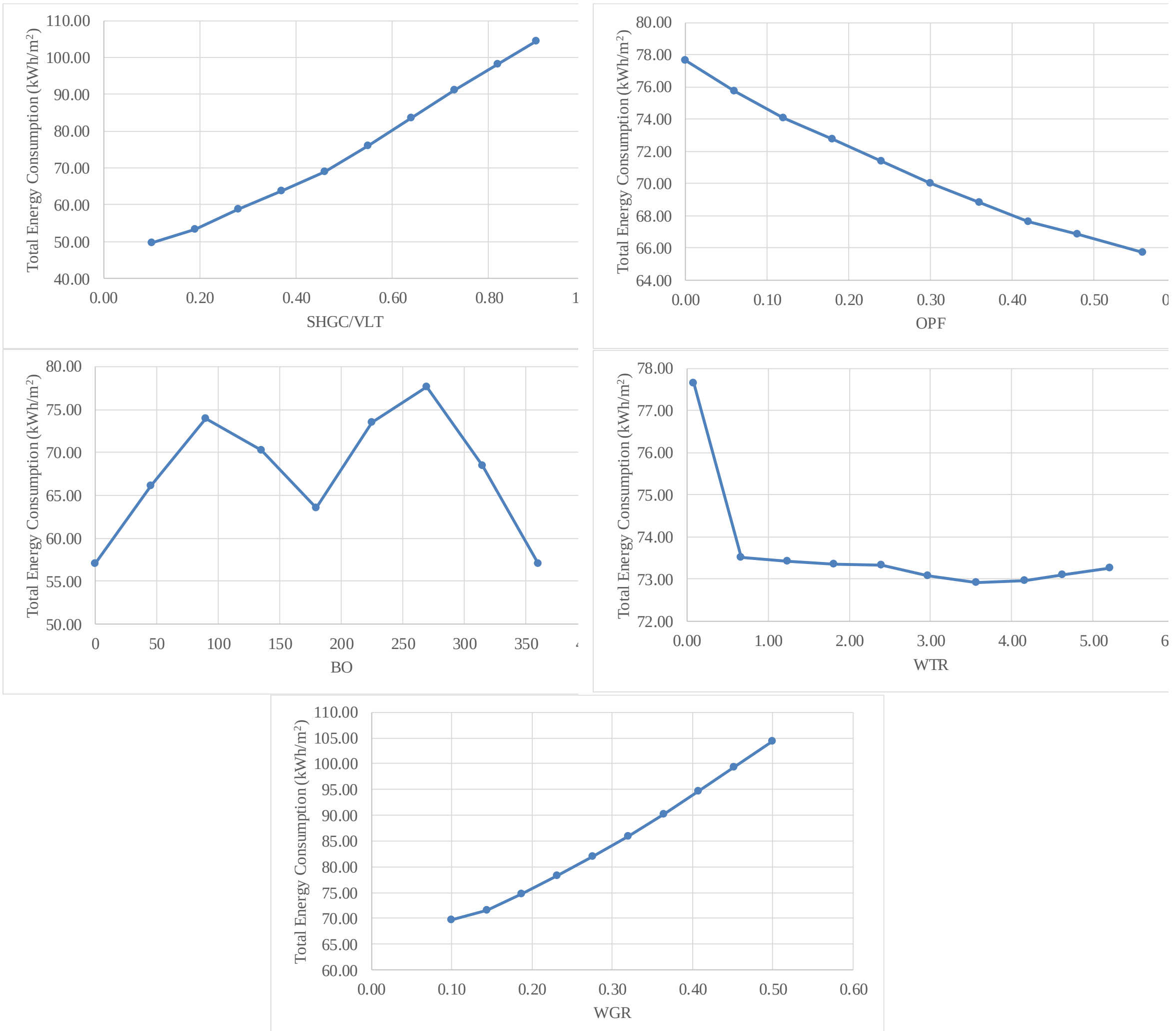


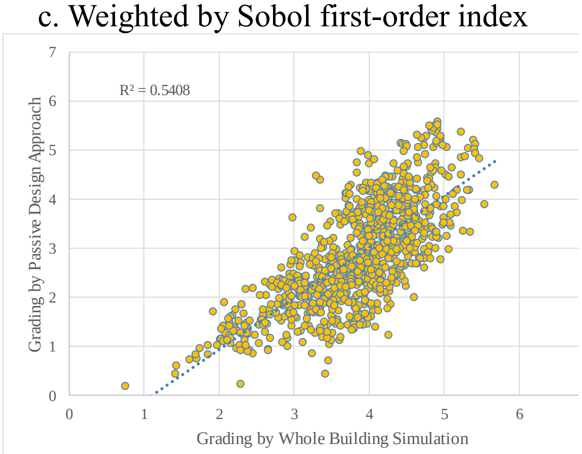
Fig. 17 Local sensitivity analysis with reference to the base case building

a. Weighted by FAST first-order index

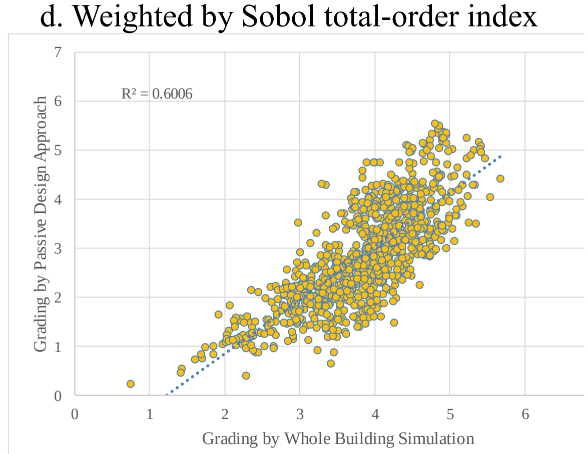
b. Weighted by FAST total-order index

c. Weighted by Sobol first-order index

d. Weighted by Sobol total-order index



e. Weighted by SRRC index



f. Weighted by Morris index

Fig. 18 The relation between predicted and simulated results under different weighting systems

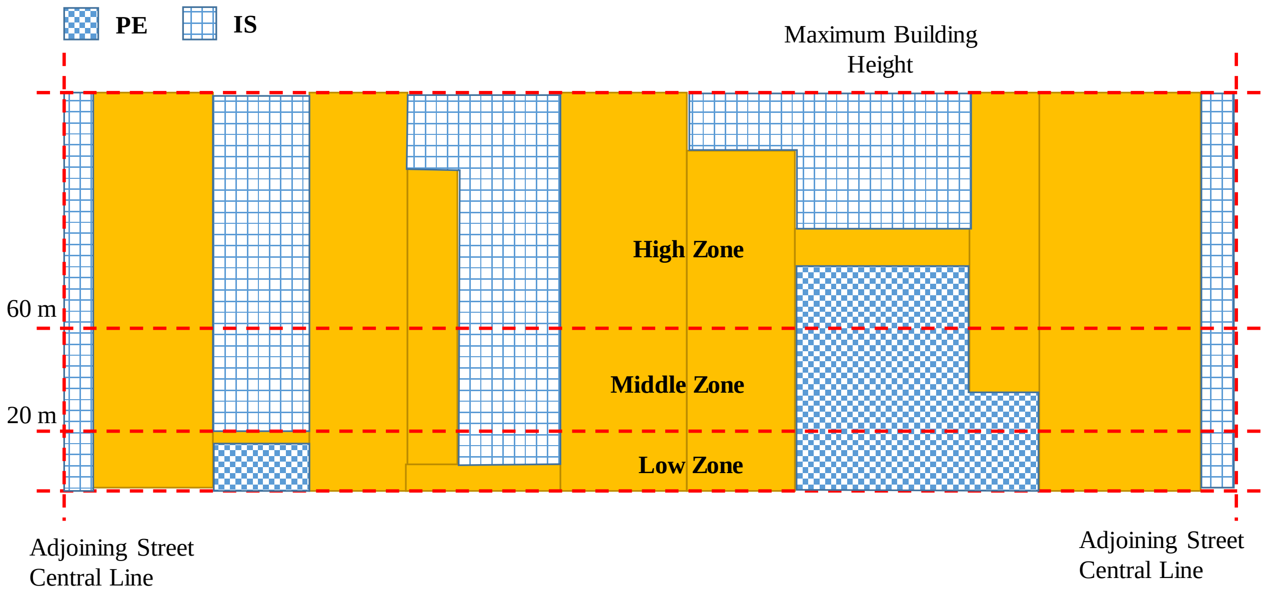


Fig. 19 Definition of Intervening Space and Permeable Element by PNAP APP-152

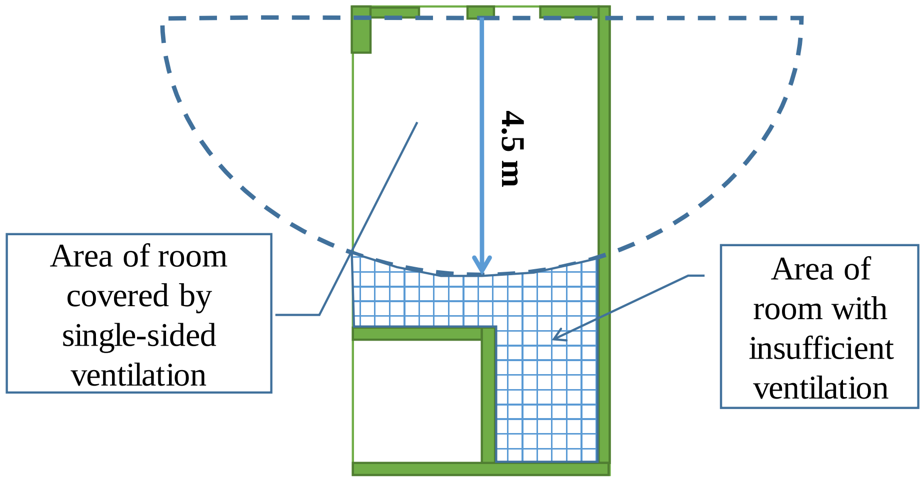


Fig. 20 The qualified area to achieve sufficient single-sided ventilation

Table 1 Input variables and their distributions

Input variables	Unit	Probability	Range
Building orientation (BO)	°	Continuous Uniform	0 - 360
External obstruction angle (EOA)	°	Continuous Uniform	0 - 87
External wall thermal resistance (WTR)	m^2 K/W	Continuous Uniform	0.09 – 10.56
External wall specific heat (WSH)	J/kg K	Continuous Uniform	800 - 2000
Window solar heat gain coefficient (SHGC)	-	Continuous Uniform	0.2 - 0.9
Window U-value (WU)	W/m^2 K	Continuous Uniform	0.5 - 6.0
Window to ground ratio (WGR)	-	Continuous Uniform	0.1 - 0.5
Overhang projection fraction (OPF)	-	Continuous Uniform	0.00 – 0.56
Infiltration air mass flow coefficient (IAMFC)	kg/s	Continuous Uniform	0.00 – 0.03

Table 2 Building physics of the generic model

Parameter		Unit	Value
Building Layout	Floor Area	m^2	23.2 (4.8×4.8)
	Height	m	2.7
	Orientation	-	West
Obstruction/Shading	Obstruction Angle	°	0
	Overhang Projection fraction	-	0
External Wall	Thermal Resistance	m^2 K/W	0.09
	Specific Heat	J/kg K	840
	Solar Absorptance	-	0.60
Fenestration/Window	U-Value	W/m^2 K	5.69
	Solar Heat Gain Coefficient	-	0.57
	Window to Wall Ratio	-	0.40

Table 3 Monthly cooling control temperature setting

Month	Monthly outdoor mean air temperature (℃)	90% acceptability upper limits (℃)	90% acceptability lower limits (℃)
May	26.1	27.3	22.3
Jun	27.9	28.4	23.4
Jul	28.9	28.9	23.9
Aug	28.4	29.2	24.2
Sep	27.5	29.1	24.1
Oct	25.3	28.8	23.8

Table 4 Summary of sensitivity indices by the Sobol method

	First-order indices	Total-order indices
WU	0.005	0.005
SHGC/VLT	0.458	0.660
WGR	0.028	0.172
EOH	0.050	0.110
EOD	0.087	0.247
OPF	0.011	0.045
BO	0.031	0.099
IAMFC	0.000	0.000
WTR	0.000	0.006
WSH	0.000	0.000

Table 5 Summary of sensitivity indices by the FAST method

	First-order indices	Total-order indices
WU	0.023	0.043
SHGC/VLT	0.460	0.633
WGR	0.026	0.157
EOH	0.063	0.142
EOD	0.113	0.199
OPF	0.025	0.075
BO	0.045	0.099
IAMFC	0.000	0.021
WTR	0.002	0.022
WSH	0.001	0.009

Table 6 Optimization results based on changed input ranges

Input parameter	Variation range	Optimal solution
WU (W/m^2 K)	0.2 - 6.0	5.83
SHGC/VLT	0.1 - 0.9	0.11
WGR	0.1 - 0.5	0.49
EOH (m)	0 - 100	12.38
EOD (m)	5 - 100	76.57
OPF	0.00 - 0.56	0.11
BO (°)	0 - 360	358.00
IAMFC (kg/s)	0.01 (fixed)	0.01
WTR (m^2 K/W)	0.09 – 10.56	0.16
WSH (J/kg K)	840.00 (fixed)	840.00
Total Energy Consumption (kWh/m^2)	35.74 - 135.66	35.74

Table 7 Passive design parameters for the case building

	Flat Design 1	Flat Design 2	Flat Design 3	Flat Design 4
Area weighting	0.422	0.422	0.078	0.078
SHGC/VLT	0.844	0.844	0.844	0.844
WGR	0.151	0.143	0.109	0.109
OPF	0.208	0.208	0.208	0.208
BO (°)	180	0	90	270
WTR (m^2 K/W)	0.278	0.278	0.278	0.278

Table 8 Assessment calculations under proposed passive design approach

	Grading coefficient for flat design 1	Grading coefficient for flat design 2	Grading coefficient for flat design 3	Grading coefficient for flat design 4	Weighting coefficient	Total grade
SHGC/VLT	0.000	0.000	0.000	0.000	54.9%	0.00
WGR	0.592	0.656	0.928	0.928	2.7%	0.11
OPF	0.371	0.371	0.371	0.371	1.4%	0.03
BO	0.686	1.000	0.180	0.000	30.2%	1.35
WTR	0.331	0.331	0.331	0.331	10.8%	0.22
Passive design approach						1.71