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Simulation-based approach to optimize passively designed buildings: a case study on a typical architectural form in hot and humid climates

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Abstract

Passive design strategies are important for achieving building sustainability given their proved influences over the building performance in both energy and indoor environmental aspects. The building layout, envelope thermophysics, building geometry and infiltration & air-tightness are major passive architectural parameters to improve the building energy efficiency. In this paper, a comprehensive literature review on simulation-based approaches to optimize passively designed buildings is conducted and corresponding research gaps are identified. Based on existing research methods, modelling experiments on a generic building are conducted to integrate robust variance-based sensitivity analyses with an early-stage design optimization process. Proposed mixed-mode ventilation and lighting dimming control algorithms are applied to the EnergyPlus model to simulate the total lighting and cooling energy demands by incorporating the related design criteria in a local green building assessment scheme. The non-dominated sorting genetic algorithm (NSGA-II) is then coupled with the modelling experiment to obtain the Pareto frontier as well as the final optimum solution. Different settings of NSGA-II are also investigated to improve the computational efficiency without jeopardizing the optimization productivity. Furthermore, the sensitivity of optimum design solutions to external environmental parameters in hot and humid areas are explored. Findings from this study will guide decision-makers through a holistic optimization process to fulfill energy-saving targets in a passively designed green building.

Keywords: Passive design; green building; Optimization; Sensitivity analysis; NSGA-II

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Contents

1. Introduction

Building sectors account for approximately 60% of the total energy use in Hong Kong according to official statistics conducted by the local government [1]. Driven by the urge to reduce the building energy demand and minimize its environmental impacts, local building design codes (i.e. BEC 2015) and green building rating schemes (BEAM Plus Version 2.0) have been launched recently to enhance the sustainable development of local communities. Among multiple building design guidelines and assessment criteria, passive design is recently under the spotlight owing to its proved effectiveness on improving the cooling and lighting performance of buildings [2, 3]. Because space cooling and lighting account for 41% of the total residential energy demand based on statistics of the Electrical and Mechanical Services Department (EMSD) (as shown in Fig. 1) [4], passive design features including the building layout, envelope thermophysics, building geometry and infiltration & air-tightness can make great contributions to low energy or near zero energy building designs [5]. Utilizing above passive strategies requires not only investigating their individual impacts as presented in some existing research [6-8], but also incorporating a holistic approach with deliberate consideration of interactive effects [9]. It is essential for architects and engineers to understand the relative importance of each strategy and deploy them appropriately at the first opportunity. Therefore, simulation-based optimization processes combined with in-depth and exhaustive sensitivity analyses (SA) are thoroughly reviewed in this study and an exemplary application of a proposed holistic design approach to a prototype high rise residential building in hot and humid areas will be analyzed and discussed in detail.

2. Review of simulation-based passive design approach

2.1.Sensitivity analyses to identify important design factors

Multiples building design factors can be subject to extensive and systematic examinations by different SA approaches using building simulation tools. According to Tian et al. [10], SA can be categorized as the local sensitivity analysis and global sensitivity analysis. The local SA is used to examine the impact of a certain input variable by independently changing its values while keeping other variables fixed [11]. A commercial building in Hong Kong was subject to the local SA with DOE-2 [12]. This study focused on the whole building design including the building structure, geometry, occupancy, load condition and HVAC system. Important input factors for the building annual energy use, peak load and load profile were identified respectively. A similar study was conducted to explore optimal energy-saving solutions for high-rise residential building in Netherland, where building envelope parameters such as the glazing type, window-to-wall ratio, sun shading and roof strategies contributed to a total energy saving of 42% [13]. Samuelson at al. performed a simple sensitivity analysis on the energy use intensity of case buildings in three urban contexts, where the window to wall ratio, glazing type and building orientation are determined to be the top three influential design factors [14]. Apart from investigating whole-building design inputs, passive design was specifically examined to decide their importance for five major climatic zones in China where retrofitting measures to improve the indoor thermal comfort and energy-saving performance for each zone were identified respectively [15]. The window opening size was also individually correlated with the peak load and annual energy consumption to provide concise design charts for early planning stages [16]. In addition, a few similar studies looked into the thermal load reduction efficiency by adjusting a single design variable such as the shape coefficient, envelope thermal resistance or occupant behavior pattern [17, 18]. Instead of modulating one design factor at a time in building simulations, the global SA can study building performances with the regression (i.e. sampling-based), screening-based or variance-based methods [19, 20]. The uncertainty and sensitivity of the indoor thermal comfort condition in a passively cooled office were examined by regression analyses [21]. According to the findings, the indoor weighted temperature excess hours (WTE) was most sensitive to the single-sided ventilation. Yildiz and Arsan estimated the impact of design parameters of low-rise apartment buildings in hot and humid climates using regression analyses coupled with the Latin Hypercube Sampling (LHS) and Monte Carlo approach [22], where the window size, U-value and solar heat gain coefficient (SHGC) were proved to have the greatest impact on heating and cooling loads of different floors. The Morris method (i.e. a popular screening-based method), which enables a qualitative assessment of the influence from each design variable, was integrated into a multi-criteria decision-making process for minimizing energy consumption and degree-hours of residential buildings in Brazil [23]. The most influential envelope feature in each climate zone was filtered out as further inputs to the performance evaluation of construction systems. The Analysis of Variance method (i.e. variance-based) was deployed in an uncertainty and sensitivity prediction of available solar irradiation on exterior building surfaces with shading devices [24]. The building latitude, orientation and width of overhang fins were proved to have more influence over calculated solar fractions and the uncertainty quantification process was identified as a crucial prerequisite for maintaining the building energy balance.

2.2.Optimization approach to improve building performance

Based on identified influential design variables from sensitivity analyses, a design optimization can be further conducted to improve the life-cycle cost effectiveness, energy efficiency and indoor environment qualities of buildings. Optimization studies can usually be classified to the mono-objective optimization and multi-objective optimization, where the latter is more common in building research area considering the requirements from multi-criteria design guidelines and assessment schemes [25-27]. Carlucci et al. carried out a four-objective optimization of a detached zero-carbon house in Italy and discussed trade-offs between the thermal and visual discomfort [28]. Futrell et al. performed both the pattern search and meta-heuristic optimization with GenOpt to simultaneously minimize the cooling, heating and lighting energy demand [29]. The target building was optimized respectively for each orientation and conflicts between thermal and daylight objectives were observed. In a similar work, energy performance optimization with the Multi-island Genetic Algorithm (GA) was performed on a software platform developed with the QT language and OpenGL interface [30]. When miscellaneous daylight illuminance indices were treated as optimization objectives, the window characteristics, building orientation and wall reflectance were thoroughly explored by evolutionary algorithms to search for an optimum interior design [31]. Final solutions were determined by their appearance frequencies in 6 sets of Pareto frontiers together with their mean distances to utopia points. As a holistic building design approach in early stages, multi-objective optimizations were also conducted with the energy use, thermal comfort and capital cost as objectives [32-34]. On top of abovementioned optimization objectives, Zhang et al. investigated trade-offs between the obtained solar radiation, space efficiency and shape coefficient of free-form buildings by changing building geometry inputs with Rhinoceros and Grasshopper [35]. In addition, the multi-objective particle swarm optimization (MOPSO) algorithm was exploited instead of GA methods to search for Pareto optimal solutions for a generic room model under different weather conditions of Iran [36]. Ruiz et al. proposed a methodology to accurately perform the automated building envelope calibration under the International Performance Measurement and Verification Protocol (IPMVP). A reliable energy simulation model was obtained from the Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Furthermore, building orientations and window characteristics were optimized by comparing the performance of the Hooke-Jeeves Algorithm, Multi-objective Genetic Algorithm-II and Multi-objective Particle Swarm Optimization Algorithm in terms of the stability, robustness, validity, speed, coverage and locality [37].

According to the above brief introduction and in-depth literature review (summarized in Table 2), it can be recognized that there is little research in combined sensitivity and optimization analyses of passively designed buildings in hot and humid climates under hybrid ventilation conditions. This paper mainly focuses on the energy demand minimization of a generic building model with selected significant input design variables based on a comprehensive sensitivity analysis. Simulation models with designed mix-mode ventilation and light dimming control strategies were coupled with NSGA-II to obtain the Pareto frontier as well as the final optimum solution under different algorithm settings and weather conditions. The originality of this article lies in the following points: (1) This optimization study is incorporated with sensitivity analyses to screen out the most significant influential factors and is therefore capable of improving the efficiency of optimization algorithm; (2) In most existing studies, only limited types of windows or walls are investigated, whereas this research thoroughly explores the whole feasible range of various thermal and lighting properties of passive design elements with a robust global sensitivity analysis; (3) External obstructions are usually overlooked by reviewed studies, which are proved to be a significant design factor and crucial in green building assessment with at least five relevant criteria specified in BEAM Plus; (4) The holistic design approach in this study is highly incorporated with the existing green building rating scheme, and the synergy of energy and indoor environment aspects are carefully considered in the decision making process; (5) Thermal comfort performance no longer contradicts with energy saving targets as observed in many existing multi-objective optimizations because of the application of adaptive thermal comfort model in the building performance simulation and assessment; (6) Monthly variation of sensitivity indices is investigated instead of short-term (i.e. daily or hourly) uncertainty profiles as presented in existing literatures and most suitable optimization settings specific to the proposed optimization problem is obtained; (7) The sensitivity analysis of optimization settings provided a more precise algorithm configuration compared with using empirical values suggested by existing literatures.

3. Research design and methodology

This study focuses on a simulation-based approach to optimize the energy efficiency of passive designed buildings under hybrid ventilation and lighting dimming conditions by deliberately considering the daylight and thermal comfort requirements in local green building guidelines (i.e. BEAM Plus). Based on previous statistical modeling studies [38, 39], a generic building model has been developed with determined probability distributions of architectural design parameters. Control algorithms of the hybrid ventilation, daylight and thermal comfort are designed and specified referring to local or international building standards. With a sufficient number of modelling samples, the variance-based sensitivity analysis is performed to address the interaction and non-linearity of input variables. The obtained sensitivity indices and their seasonal profiles can help refine the problem space for the consequent optimization process by identifying high impact design factors. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is then adopted to simultaneously minimize the cooling and lighting energy demand and obtain the Pareto frontier, where the final optimum solution was derived from the weighted sum approach. Optimization control parameters were also adjusted to improve the computation efficiency while maintaining the productivity of the algorithm. The whole research process is summarized in Fig. 2.

3.1.Selection of weather profiles

Meteorological data in hot and humid subtropical or tropical climatic zones are selected as weather inputs for building performance assessment during the cooling period, and Hong Kong (22.3 Nº, 114.17 Eº) is therefore chosen as a benchmark for the case study. The TMY2 data of Hong Kong is presented in Fig. 3 [38], which is considered a good approach to conduct building simulations. The annual average dry bulb temperature and relative humidity of Hong Kong are 23.1 ℃ and 78.1 %, and the use of air-conditioning usually lasts from April to October based on recommendations from BEAM Plus [40]. However, April is excluded from the simulation when the ASHRAE55 adaptive comfort model with 90% acceptability is used to assess thermal comfort conditions based on recommendations in previous research [41-43].

Apart from Hong Kong, four large metropolises characterized by high temperature and relative humidity as well as rich solar and wind resources are selected to exam the sensitivity of optimal solutions to external environmental parameters. Their climatic and geographic situations are briefly summarized in Table 1. Bangkok (BKK) has the highest seasonal average temperature (29.12 ℃) and solar radiation (147.77 kWh/m^2) but the lowest mean relative humidity (74.43%) in the whole cooling season. Hong Kong (HK), Guangzhou (GZ) and Taipei (TPE) are all influenced by the adjacent mainland and thus exhibit similar trends in the temperature and relative humidity. The solar-wind conditions of TPE and HK are subject to impacts of strong tropical cyclones where the highest monthly wind speed occurs at the end of the cooling season. The average radiation level of GZ (103.17 kWh/m^2) was the lowest in five cities because of the slightly higher latitude. Above climate indices in Singapore (SGP) are however comparatively stable with the lowest average wind speed of 1.92 m/s and the highest average relatively humidity of 82.63%. Overall, all five cities have great potential for the application of passive design strategies, which can significantly reduce the building energy demand.

3.2. Determination of input variation and constraints

3.2.1. Building Layout

The building layout includes the external obstruction angle (EOA) and building orientation (BO). BO is altered in the modelling experiment from 0 to 360 degrees to assess its influence when windows are only located on a single facade of the building. EOA measures the external shading effects from a street canyon which is a common situation in large metropolis with high population densities. The length of external obstruction is fixed to 100 meters as suggested in existing literatures [44-46]. The distance and height of external obstructions are basic elements for calculating EOA, which is defined as the angle between the horizontal line at the window sill level and the line connected with the highest point of the external obstruction [40, 47, 48]. The EOA should vary between 0° (i.e. unobstructed condition) to 87° with the assumption that the average obstruction height is 100 m and the minimum separation from the obstruction (i.e. road width) is 5 m [49].

3.2.2. Envelope thermophysics

The envelope thermophysics is referring to the external wall thermal resistance (WTR), specific heat (WSH), window U-values (WU) and solar heat gain coefficient (SHGC). The wall thermal resistance changes from a baseline equivalent thermal resistance of 0.09 m^2 K/W (0.005 m mosaic tiles + 0.01 m cement/sand plastering + 0.1 m heavy concrete + 0.01 m gypsum plastering [50]) to a highly insulated one of 10.56 m^2 K/W as suggested by the 2009 ASHRAE Handbook-Fundamentals. The wall specific heat changes from 800 to 2000 J/kg K as default limit values in EnergyPlus modelling guidelines [51, 52]. The window thermal properties changes from a triple-vacuum low emissive glazing (i.e. SHGC=0.1 and U-value=0.2 W/m^2 K [53]) to a clear single glazing (i.e. SHGC=0.9 and U-value=6.0 W/m^2 K). The window light to solar gain ratio is fixed to one in the modelling experiments to represent a traditional low-e glazing. The covariation of the visible light transmittance (VLT) and SHGC might cause conflicts between daylight and thermal performances.

3.2.3. Building geometry

The building geometry involves the window to ground ratio (WGR) and overhang projection fraction (OPF). The window to ground ratio changes between 10% and 50% based on the limitation of external wall areas as well as mandatory window opening requirements in the local building ordinance. On the other side, the overhang project ratio is subject to an upper limitation of 0.56 so that the total overhang length would not exceed 1.5 m so that its projection area will be exempted from the plot ratio and site coverage calculation.

3.2.4. Infiltration & air-tightness

The infiltration & air-tightness is evaluated by the infiltration air mass flowrate coefficient (IAMFC) of the crack on the external wall surface. IAMFC stands for the air mass flow rate under reference test conditions and varies between 0.01 and 0.03 kg/s in the simulation. The upper limit prevents the air change rate from exceeding 1.5 ACH which should be a level of induced natural ventilation rather than uncontrolled infiltration. The lower limit is a typical value of infiltration for the room to reach an air change rate around 0.5 ACH as specified in the Building Energy Code.

The abovementioned input variables are uniformly sampled as non-informative distributions to evaluate their relative impacts on the building energy efficiency [54]. In addition, building surface properties (e.g. the solar absorptance and reflectance of external and internal building surfaces) are preset with reasonable assumptions and excluded from sensitivity analyses because their information can only be confirmed in later construction stages [48, 55, 56].

3.3.Definition of modelling algorithm and control setting

3.3.1. Description of the building modelling

A generic building model is prototyped to represent a typical high-rise building (usually 30 to 40 floors) developed by the Hong Kong Housing Authority which accommodates over 30% of the local population [57]. These buildings are modularly designed with a standard floor layout plan as shown in Fig. 4 [58]. A two-habitant hypothetic generic model in the center of the typical floor with window openings on a single heat transfer facade surrounded by adiabatic surfaces is constructed to represent the worst-case scenario for the daylight and ventilation access [38]. The space is assumed to be occupied by two people with average activity levels of 100 W/person (between seated and sleeping). The lighting and equipment load are set to be 15 W/m^2 and 142 W/Room referring to the BEAM Plus guideline and Building Energy Code, based on which building operation schedules including the cooling, lighting, equipment and occupancy are specified in Fig. 5, to represent a combination of space functions of living room and bedroom [50].

The cooling and lighting energy demand is derived from interlinked sub-modules in EnergyPlus, which has been extensively recognized, calibrated and validated in building performance analyses [59, 60].

The daylight illuminance level on the specified indoor reference point is first derived from the external available solar illuminance, window transmittance, room geometry and surface properties [52]. Consequently, the artificial lighting is modelled to meet the a threshold of 150 Lux as recommended by CIBSE Code of Lighting at the reference point [61]. The required factional lighting output with respect to its full load occasion is calculated according to the "continuous/off dimming control" method [62].

The airflow network (AFN) model calculates multi-zone airflows driven by the outdoor wind pressure and stack effect through cracks and window openings. It is used to simulate the single-sided mixed-mode ventilation with the HVAC system as the supplementary solution. In an AFN model, the airflow is induced by the pressure difference between air paths and zones. The model further derives node temperatures and humidity ratios from the airflow rate and decide zone thermal loads, where air balance equations are applied and corresponding zone air conditions are obtained [43].

The IdealLoadsAirSystem is chosen to maintain the indoor thermal comfort condition when natural ventilation alone cannot meet the requirement. The module is a simplified HVAC component to calculate the cooling energy demand without handling too much details of the whole system design. The module can emulate an ideal unit which mixes air at the zone exhaust condition and removes the cooling load at 100% efficiency. The single cooling setpoint controller is used as the HVAC system thermostat to comply with the upper limit of the ASHRAE55 adaptive comfort model, which varies monthly with the prevailing outdoor air temperature [63].

The whole simulation model under naturally ventilated unoccupied conditions has been partially validated by an on-site measurement of selected flats in a local Public Rental Housing development, where the indoor temperature, relative humidity, air change rate and daylight factor showed reasonable trends [40].

3.3.2. Hybrid ventilation control and comfort index

Control of hybrid ventilation is proposed in this research to maximize the benefit of deploying passive design strategies. Silva et al. adopted a hybrid ventilation control method by allowing natural ventilation only during daytime while set on the air-conditioners at night [23]. However, a previous study performed by the authors consolidated that a full-day ventilation can lead to better building performance compared with daytime or nighttime ventilation approaches [40]. Therefore, the hybrid ventilation is allowable throughout the whole cooling period in this simulation. Although an existing study claims that EnergyPlus does not permit the co-operation of HVAC and Airflow Network (AFN) modules and the integration has to be realized by programming with Energy Management System (EMS) [64], yet the hybrid ventilation is actually feasible by introducing the Hybrid Ventilation Availability Manager.

The hybrid ventilation availability manager is applicable to spaces void of HVAC air loops. The controller serves as a preventer of simultaneous natural ventilation and mechanical cooling and is aimed to reduce the space cooling load by examining various strategies to maximize natural ventilation. The controller starts operating at the beginning of each timestep and can override local controls of both HVAC and AFN. It first checks the outdoor dry-bulb temperature when the "Temperature" mode is selected for the ventilation mode control schedule. If the temperature is within the preset upper and lower limits, the natural ventilation is possible. Then the indoor operative temperature is compared with the 90% acceptability upper limits of the adaptive comfort model which depend on the changing monthly mean outdoor temperature (calculated as 28.4, 28.9, 29.1, 28.8 and 28.1 °C from May to October as shown in Fig. 6) [65]. Assessing thermal comfort in naturally ventilated or mix-mode buildings with adaptive model is appropriate and viable because of the existence of occupant control and the psychological shift of expectations which cannot be addressed by traditional heat-balance based models [66-68]. Once the indoor operative temperature is lower than the calculated upper limits for each month, the natural ventilation will be executed whenever the outdoor temperature is lower. Otherwise the window should be closed and the HVAC system is then operated according to the availability status indicated by the cooling schedule. The above control circuit is summarized in Fig. 7.

3.4.Variance-based sensitivity analysis

The variance-based method is chosen to conduct the initial sensitivity analysis for the subsequent optimization because it is not limited by the model format and suitable for either non-linear or non-additive models [69]. The total variance of the output $V(Y)$ is decomposed into conditional variances of increasing dimensionality as shown in Eq. (1) [70].

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

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:

$$1 = \sum_{i=1}^{k} S_i + \sum_{j>i}^{k} S_{ij} + \cdots + S_{12\cdots k} \tag{2}$$

where the S_i is called the first-order sensitivity index, which stands for the independent impact of X_i on the variance of Y. It is defined to be the average conditional variance left when X is frozen to all possible values in the probability density function (See Eq. (3)) [71].

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(\mathrm{Y} \mid \mathrm{X}_i))}{V(Y)} \tag{3}$$

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 $S_{12\cdots k}$ [54].

Among different orders of indices, the first-order index is usually linked to "Factor Prioritization", where the input with the highest S_i is deemed as the most influential factor. However, an input parameter should not be excluded from further analyses solely based on its first-order index, because the input might be involved in a relation of higher orders. Therefore, Eq. (4) calculates a total sensitivity index S_{Ti} summarizing the all orders of indices to identify an insignificant factor. If S_{Ti} is zero, then the input can be fixed at any possible value [72]. In this regard, the total sensitivity index can be used for "Factor Fixing" to prune the model input space for optimization problems. The Extended FAST model is used as the Analysis of Variance (ANOVA) method in this research to screen out influential passive strategies given its higher computation efficiency than the Sobol model [73].

$$S_{Ti} = S_i + \sum_{j \neq i}^{k} S_{ij} + \cdots + S_{i \cdots j \cdots k} \tag{4}$$

3.5.Multi-objective optimization and decision-making

As mentioned in previous sections, the lighting and cooling energy demand are chosen to compose optimization objectives which can indicate the influence of efficient passive designs. In order to solve the multi-objective optimization problem, the non-dominated sorting genetic algorithm II (NSGA-II), which is characterized by the higher computation efficiency, enhanced probability to create better solutions, and maintained population diversity by the crowding comparison, is applied to crucial design factors identified by the initial SA study [74]. The NSGA-II is chosen for this research because of its wide application and smooth integration with EnergyPlus [36, 75]. The algorithm introduced the concept of elitism which combines a parent population and a child population to reproduce the next parent generation based on the non-domination ranking method. If the number of non-dominated solutions exceeds the preset population size, it will be decreased according to the crowding distance measure [76].

In general, the population size, number of generations, crossover and mutation probability are required to setup an optimization process. The population size is suggested to be twice the number of input variables, and up to 1800 evaluations are usually necessary to enable the convergence [76]. Furthermore, the crossover and mutation probability are preset to 0.9 and 0.355 respectively with reference to a statistical analysis of 68 optimization studies [28]. However, these settings are subject to an adaptive variation in this study to find the most suitable configuration.

When the NSGA-II program converges within the preset generations, non-dominated solutions are sorted out as the Pareto frontiers, where one solution has equal prevalence over all the others [77]. In order to obtain a single optimal solution, the weighted sum method is adopted to turn the partial order into a total order on the objective space [78]. In this case, weightings for both lighting and cooling energy demands are equal, making the total energy demand an ultimate optimization target.

4. Case study on a prototype building

A typical high-rise residential building in Hong Kong was used to perform the case study in this simulation-based optimization approach. Initial sensitivity analyses with time-series results helped exclude insignificant design factors to improve the optimization efficiency, while NSGA-II was performed to obtain the final optimum solution in the early design stage under different algorithm settings and weather conditions in hot and humid areas. Major findings and discussions with reference to existing studies are presented in this section.

4.1. Initial sensitivity analysis

The Analysis of Variance (ANOVA) with the FAST method managed to decompose the uncertainty of the annual energy demand (i.e. cooling and lighting) in response to the defined variation of design factors. This analysis totally involved 5632 simulations, which cost dramatically more computation time compared with a previous regression-based approach [38]. Fig. 8 shows that the window transmittance (SHGC/VLT) is the most prioritized input in all passive design strategies, behind which the external obstruction height (EOH) and external obstruction distance (EOD) are ranked in view of their influences over the total energy demand. This result also echoes with findings by regression analyses in previous works [62, 79]. However, BO, whose impact was almost ignorable judged by its regression coefficient, is ranked fourth in this analysis. WTR, WSH and IAMFC all make no unique contribution to the output with zero first-order indices. The inconsistency between the variance-based and regression analyses might result from the non-additive building model as indicated by the subtotal of first-order indices (i.e. 0.670) less than one. The remaining 33% of uncertainties in the output is then attributed to interactions between different design factors.

Subsequently, total-order sensitivity indices are calculated and compared to first-order indices in Fig. 9. Most total-order indices are larger than their first-order counterparts due to additive interactions of different orders. Their rankings generally agree well with first-order counterparts except that the window to ground ratio (WGR) becomes the third influential factor among all inputs, surpassing the building orientation (BO), overhang projection ratio (OPF) and EOH. The sum of total-order indices is 1.343, which can explain all variances in the total energy demand. In addition, sensitivity indices of the infiltration air mass flow coefficient (IAMFC) and wall specific heat (WSH) still equal zero and are consequently excluded from the optimization problem space. Although WTR has no unique contribution to the output, yet it is proved to have a certain interactive impact with other inputs and thus included for further optimization studies.

Furthermore, monthly variance-based sensitivity indices are shown in Fig. 10 to illustrate the seasonal variation of design impacts. This information is important to estimate the interference of outdoor ambient conditions, but is only available for short time periods in existing SA studies [24, 72]. Kristensen et al. conducted a time series estimation for elementary effects of envelope factors and air-conditioning setpoints, whereas their simulation results cannot clearly present the variation of Morris sensitivity indices [80]. In this regard, Fig. 10 gives a detailed illustration of monthly sensitivities of the cooling, lighting and total energy output to each passive design strategy.

As shown in the sensitivity variation for the lighting output, there is a noticeable increasing trend of SHGC/VLT and EOD starting from August, companied by corresponding decreases of other influential design factors such as EOH. This time series variation can be explained by the available solar radiation. In Hong Kong, the solar radiation level peaks in July, while the solar altitude starts to drop after the summer solstice. Consequently, the solar irradiance in lower angles can bypass the overhang projection and fall on the window surface. This condition has made the lighting energy demand more sensitive to the window transmittance and obstruction distance. The same reason caused the dramatically increased sensitivity index of BO, when the difference between the available solar radiation on north and south facing building facades grows with the subsolar point moving towards the southern hemisphere.

On the other side, the variation of sensitivity indices for the cooling energy output follows the trend of outdoor dry bulb temperature as presented in Fig. 3. However, the substantial increment of the sensitivity index of BO in October can also be attributed to the increased availability of the solar radiation on building facades. In addition, the seasonal change of sensitivity indices for the total energy demand is more similar to that for the cooling energy output, because cooling accounts for larger building energy demand than lighting.

4.2.Preliminary optimization

From the above sensitivity analysis, eight design factors are selected to compose the parametric problem space by a uniform sampling from their distribution ranges. Based on the simulation setting specified in Section 3, totally 3124 evaluations were made before the optimization engine reached the convergence.

As a result, 108 sets of Pareto optimal solutions are identified from the design problem space as highlighted in Fig. 11. The Pareto Frontier conspicuously exhibits a trade-off conflict where the cooling energy demand increased as the lighting energy demand decreased. The annual lighting energy varies slightly from 13.30 kWh/m^2 to 14.70 kWh/m^2, while the cooling energy changes dramatically from 21.04 kWh/m^2 to 77.60 kWh/m^2. In this simulation, minimizing the cooling energy is equivalent to maximizing the thermal comfort, as the cooling thermostat setting is based on temperature fluctuation ranges within the comfort zone. It is an approach different from most existing optimization research where the thermal comfort and air-conditioning energy objectives conflict with each other [33, 81]. Part of the conflict between minimizing the cooling and lighting energy demand is attributed to the fixed light to solar gain ratio, where less solar heat gain incurs less daylight access. If a selective window film, which filters thermal radiation while keeps high transparency, is included in the passive design, the conflict can be alleviated to a certain extent. Nonetheless, WGR, OPF and EOA still cause the converse effect on cooling and lighting energy outputs. Since the Pareto optimization only imposes a partial order on solution candidates, a total-order based fitness assignment can be suitable for external decision-making to obtain the final single solution [78]. The weighted sum method is a linear aggregation of objective functions multiplied by importance indicators or weightings, which are set to be equal in this study. The bi-objective problem is then reduced to a mono-objective one which can be solved by NSGA-II with the same setting. The ultimate solution was found to be 35.73 kWh/m^2, with a breakdown of 14.66 kWh/m^2 electric lighting and 21.07 kWh/m^2 mechanical cooling demand. The optimum solution is attributed to a high window U-value and window to ground ratio of 5.81 and 0.49 W/m^2 K, a low window transmittance and wall thermal resistance of 0.11 and 0.26 m^2 K/W, as well as a small shading projection ratio of 0.15. All glazing of the optimum design is facing north and less shaded by surroundings with an EOA of 14.00°. The solution is different from previously conducted optimization of the same building in natural ventilation conditions [38]. Such difference can be caused by the adopted hybrid control algorithm and building operation schedules.

4.3.Influence of different optimization settings

As per previous introduction, settings for the above preliminary optimization referred to statistical analyses of existing building optimization research. As a rule of thumb, the crossover probability usually assumes a higher value to allow swift exploration of the entire search space, while the mutation rate is kept lower to control the convergence speed within a reasonable range [82, 83]. These general guides are obtained from empirical studies, whereas the most appropriate setting of NSGA-II might depend on practical scenarios, so that the previous optimization setting is subject to examination in this section to consolidate its viability in terms of the solution quality and computation efficiency. Below modelling cases are all conducted to achieve a weighted single objective (i.e. the total building energy demand).

Fig. 12 illustrates the change of optimization progress when the population size is reduced from 32 to 4, which explored a broader range compared to a related optimization study on residential buildings [84]. All optimization tests managed to achieve convergence within 100 generations, when the total number of evaluations dropped from 2955 to 361. However, the minimum total energy demand of 35.50kWh/m^2 can only be obtained when the population size is equal or larger than 16, which can provide required number of evaluations indicated in existing literatures [76]. Therefore, the following parametric tests on the crossover and mutation probability are based on a reduced population size of 16 instead of 32 used for preliminary analyses.

Crossover is a reproduction method in genetic algorithms to create new individuals for the next-generation population. It is a recombination of genes from parental generations and thus recognized as a binary search operation. When the crossover rate is tuned down from 1.0 to 0.0, Fig. 13 showed that the required generations for arriving at a global optimal solution decreased from 98 to 50. Despite the increased convergence speed, the optimum solution can only be attainable when the probability is no less than 0.8 compared with the preliminary optimization analysis. Although conducting search operations with fewer crossovers can greatly save computation efforts, yet the search engine can be stuck with local optimal solutions without exploring the whole design problem space.

Mutation in the genetic algorithm is referring to the small and random variation in the genotype [78]. It is another method of reproduction in optimization search operations. As presented in Fig. 14, the convergence cannot be researched within the specified 100 generations when the mutation rate is 1.0. The convergence can be achieved and the optimum solution was approached gradually as the mutation rate descends from 1.0 to 0.4. Nevertheless, if the mutation rate is zero, the optimization prematurely ended at the 46th generation without exploring the whole search space. Thus, the mutation probability is recommended to be higher than zero but lower than 0.4 for acquiring a global optimal solution in this case study.

4.4. Optimum design configuration under different weather conditions

The selected five cities are all located in hot and humid tropical or subtropical areas with high population densities, where the high-rise residential building format in Hong Kong has a great application potential. As per the comparison conducted in Section 3.1, these cities share common climatic characteristics but differs with each other in terms of average levels and trends of the temperatures, humidity, solar radiation and wind velocity. For the above reason, the optimum design for each city features the following similarities and differences (See Table 3).

To minimize the total building energy demand, all optimal solutions are characterized by low window transmittances (close to the lower input limit 0.10), high window U-values (close to the upper input limit 6.00) and high window to ground ratios (close to the upper input limit 0.50). The high window to ground ratio and window U-value help to make full use of natural ventilation and release the heat to the outside environment whenever available. External walls, however, have a broader thermal insulation distribution range from 0.09 to 0.61 m^2 K/W, which is most sensitive to weather conditions. For instance, the relatively higher thermal resistance for optimum design in BKK might correspond to its highest annual temperature and solar radiation. The major building façade of most optimum designs are oriented to north (between 0 to 14° relative to north) to minimize direct solar radiation. This orientation preference fit in with the findings by Bre et al [84]. However, the optimal building orientation for SGP is determined as south because of its special geological location close to the equator. Both external and local shadings are not preferred by optimized designs with a low EOA between 8.91° and 14.00° and OPF between 0.04 and 0.05. Less shadings and obstructions offer better daylight and ventilation access whereas increase solar irradiation on building surfaces. In general, the optimum design under each weather condition shares a similar configuration of passive design strategies. For the corresponding energy demands of optimized design solutions, the electric lighting energy varied little across different cites from 14.12 kWh/m^2 to 15.25 kWh/m^2, while the cooling energy fluctuated in a wider range between 18.15 kWh/m^2 and 38.72 kWh/m^2. This result indicates that weather conditions have non-negligible influences over the optimized passive design configuration especially on building thermal insulation levels. More detailed analyses of the sensitivity to weather conditions will be presented as an independent research topic in future works.

5. Conclusions

A holistic design-optimization approach is applied to a passively designed generic building with the mixed-mode ventilation and lighting dimming control in hot and humid areas. Variance-based sensitivity analyses were conducted ahead of the optimization to reduce the search space of the evolutionary algorithm by removing insignificant factors. Time series sensitivity indices for the lighting and cooling energy outputs were presented to reveal their correlations with outdoor thermal and solar radiation conditions. Furthermore, passive architectural parameters were explored by NSGA-II under different optimization settings and weather conditions. The most suitable setting and optimum design for each weather profile were presented and discussed. Main conclusions can be drawn as below:

1) The variance-based initial sensitivity analysis thoroughly investigated the whole possible distribution ranges of selected major passive design parameters. The obtained first-order and total-order indices were used to exclude the external wall specific heat and infiltration air mass flow coefficient from the problem space of the subsequent optimization of building energy demands. Among these design strategies, window transmittance properties and external

obstruction levels were proved to have greater impact on building energy demands, and therefore should be given the increased weighting in any green building design or assessment guidelines. Correlations between sensitivity indices and external weather conditions can also be identified from the monthly variation of sensitivity indices. Furthermore, these sensitivity indices can also help stakeholders in a building project to prioritize the resource allocation to most influential design factors at the earliest opportunity.

2) The NSGA-II based optimization was initially conducted with a benchmarking setting of the population size, crossover rate and mutation probability. The Pareto frontier was obtained within the maximum allowable evaluations and a trade-off was identified between the lighting and cooling energy demand. Among Pareto optimal solutions, the lighting energy demand varies slightly from 13.30 kWh/m^2 to 14.70 kWh/m^2 whereas the cooling energy demand changes dramatically from 21.04 kWh/m^2 to 77.60 kWh/m^2. Conflicts between two objectives were attributed to the fixed light to solar gain ratio as well as the converse effects from the window to ground ratio, overhang projection ratio and external obstructions. The ultimate optimal solution based on equally weighted objectives achieved a low energy demand of 35.73 kWh/m^2 in Hong Kong. This integrated sensitivity analysis and optimization process can be used to incorporate the passive design approach into green building assessment to determine the optimum performance level for grading scales.

3) To find the most appropriate setting of NSGA-II to improve the computation efficiency while keep the optimization productivity, different population sizes, crossover probabilities and mutation rates were examined. A population size of 16, a crossover rate between 0.8 and 1.0, as well as a mutation probability between 0.0 and 0.4 were recommended for this optimization study under the specific control and operation modes. This approach offered a more precise algorithm setting compared with using empirical values suggested by existing literatures.

4) In addition, this simulation-based optimization process was applied to four other cities with similar climatic characteristics. As a result, the optimum design under all weather conditions showed similar architectural features of low obstruction levels and window transmittances while high window heat transfer coefficients and solar transmittances. But wall insulation levels showed more diverse distribution due to the difference in outdoor temperature and solar

radiation conditions. However, for the limitation of this work, extending the current simulation approach to more diverse climatic zones and detailed building design stages involving additional input variables and evaluation objectives will be carried out in the future.

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Nomenclatures

Abbreviation

AFN	airflow network
ANOVA	analysis of variance
BEAM	building environment assessment method
BO	building orientation
EMSD	electrical and mechanical services department
EOA	external obstruction angle
EOD	external obstruction distance
EOH	external obstruction height
FAST	Fourier amplitude sensitivity test
HVAC	heating ventilation and air conditioning
IAMFC	infiltration air mass flow coefficient
LHS	Latin hypercube sampling
NSGA-II	non-dominated sorting genetic algorithm II
OPF	overhang projection fraction
PRH	public rental housing
SA	sensitivity analysis
SHGC	solar heat gain coefficient
SRC	standardized regression coefficient
SRRC	standardized rank regression coefficient

VLT	visible light transmittance
WGR	window to ground ratio
WSH	wall specific heat
WTR	wall thermal resistance
WU	window U-values

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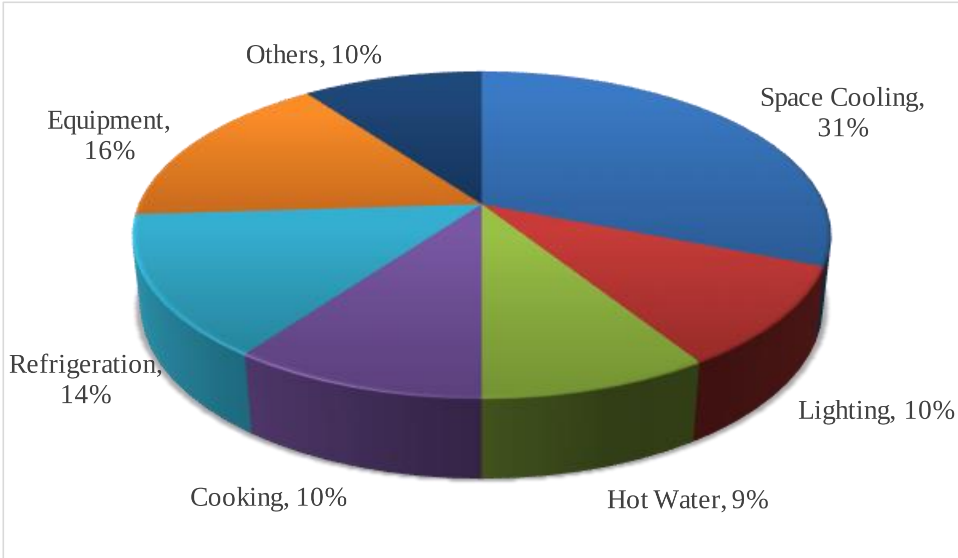


Fig. 1 Energy end use statistics of residential buildings in Hong Kong (by EMSD)

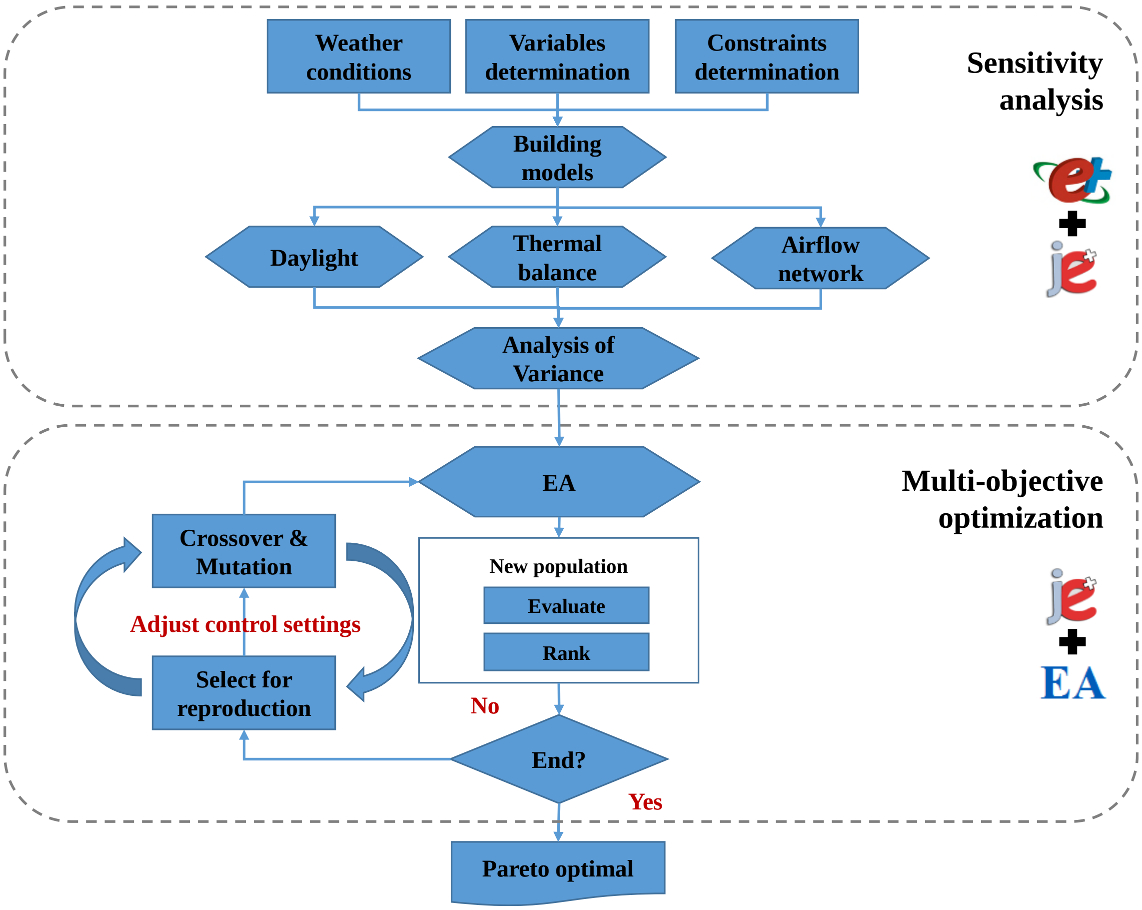
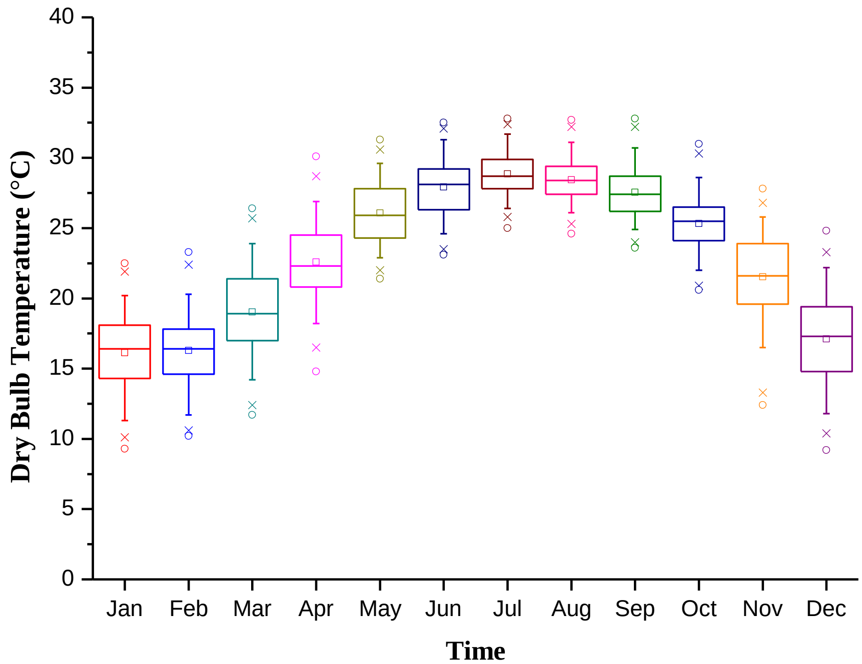
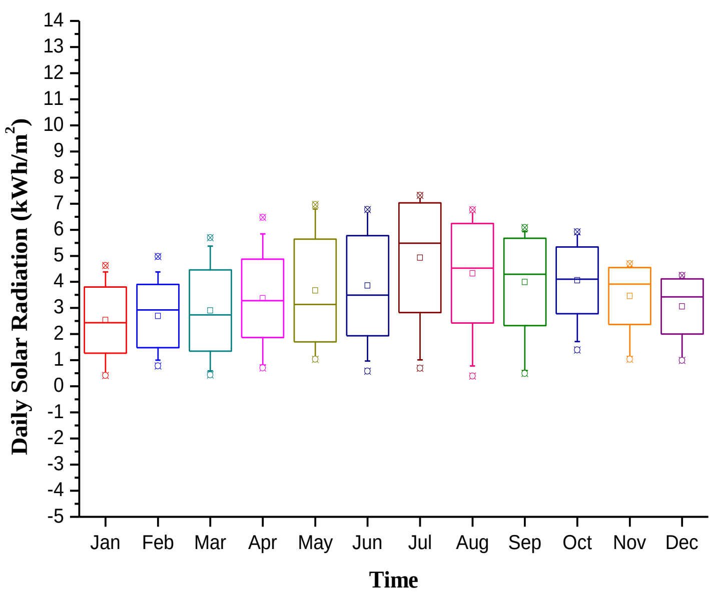


Fig. 2 Proposed flowchart of research methodology



a. Hourly dry bulb temperature



b. Daily solar radiation

Fig. 3 Weather conditions of Hong Kong

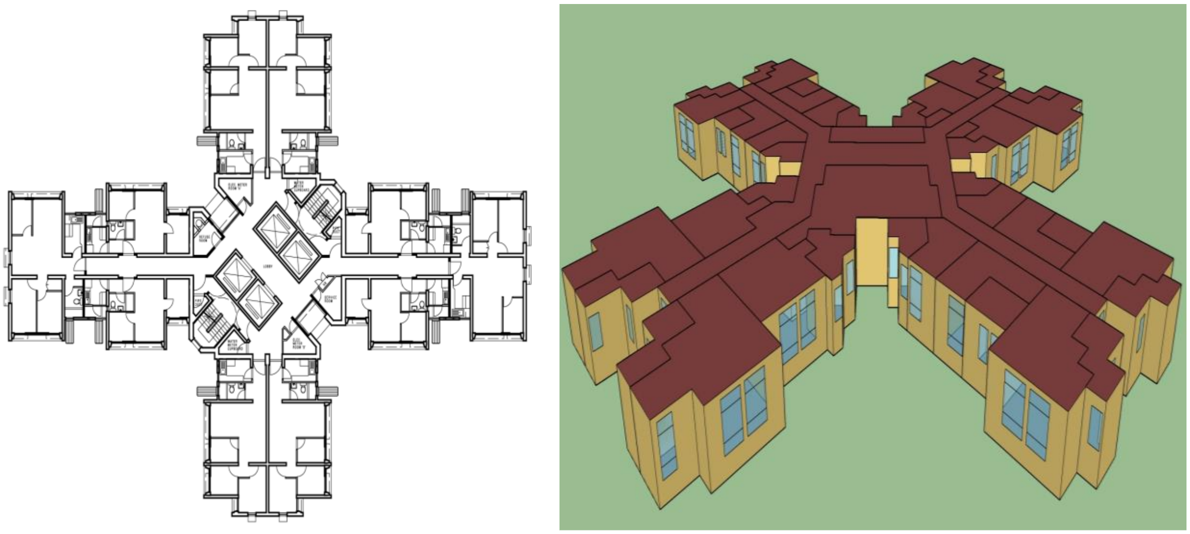


Fig. 4 Typical floor plan and model in the simulation environment

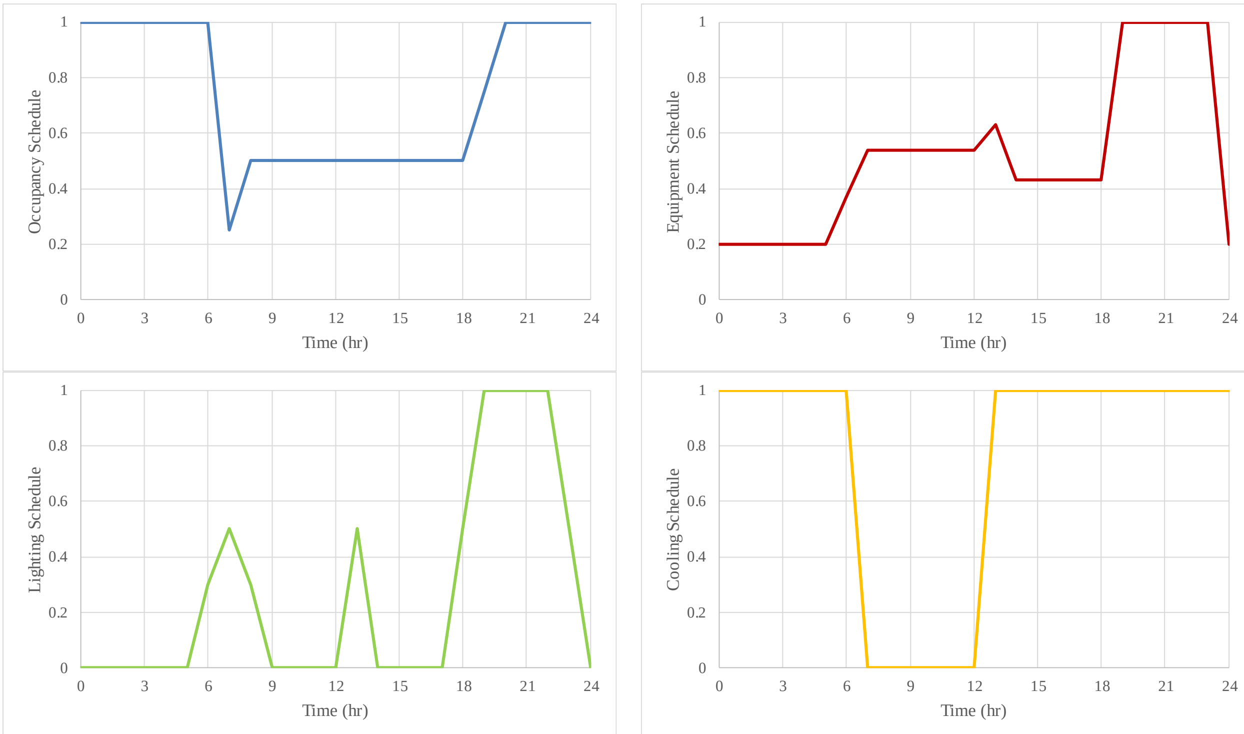


Fig. 5 Building operation schedules

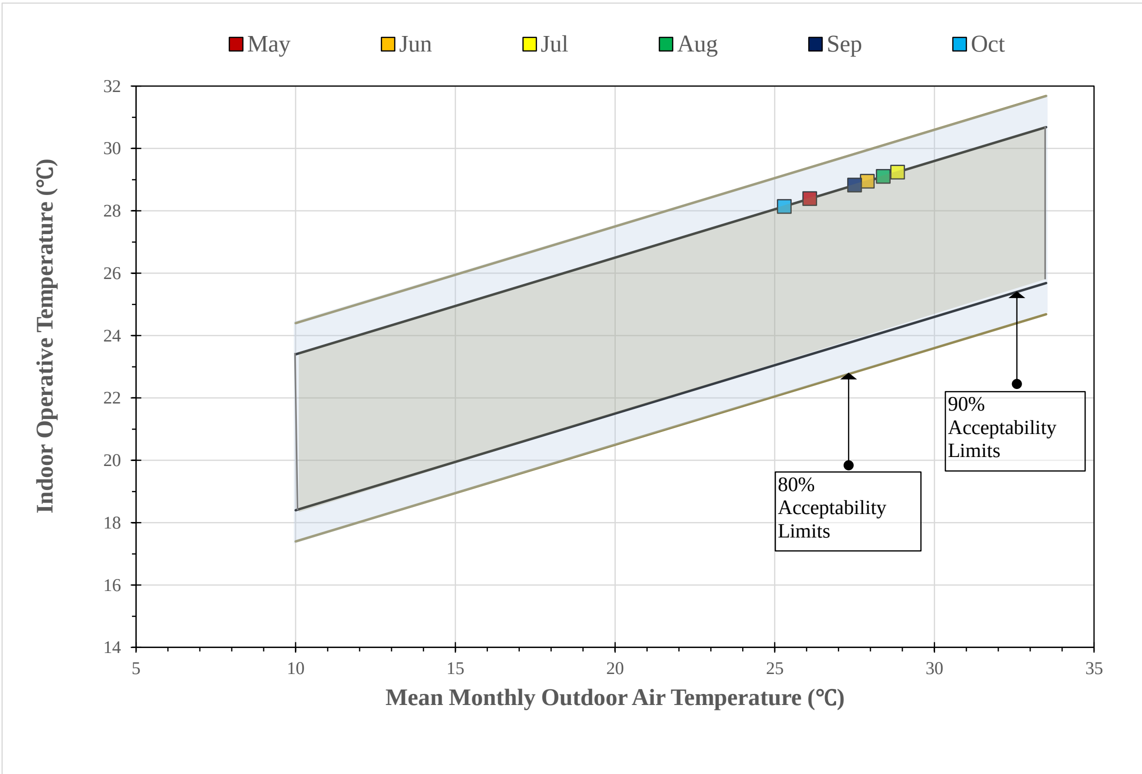


Fig. 6 Monthly cooling temperature setpoints according to the ASHARE 55 adaptive comfort model

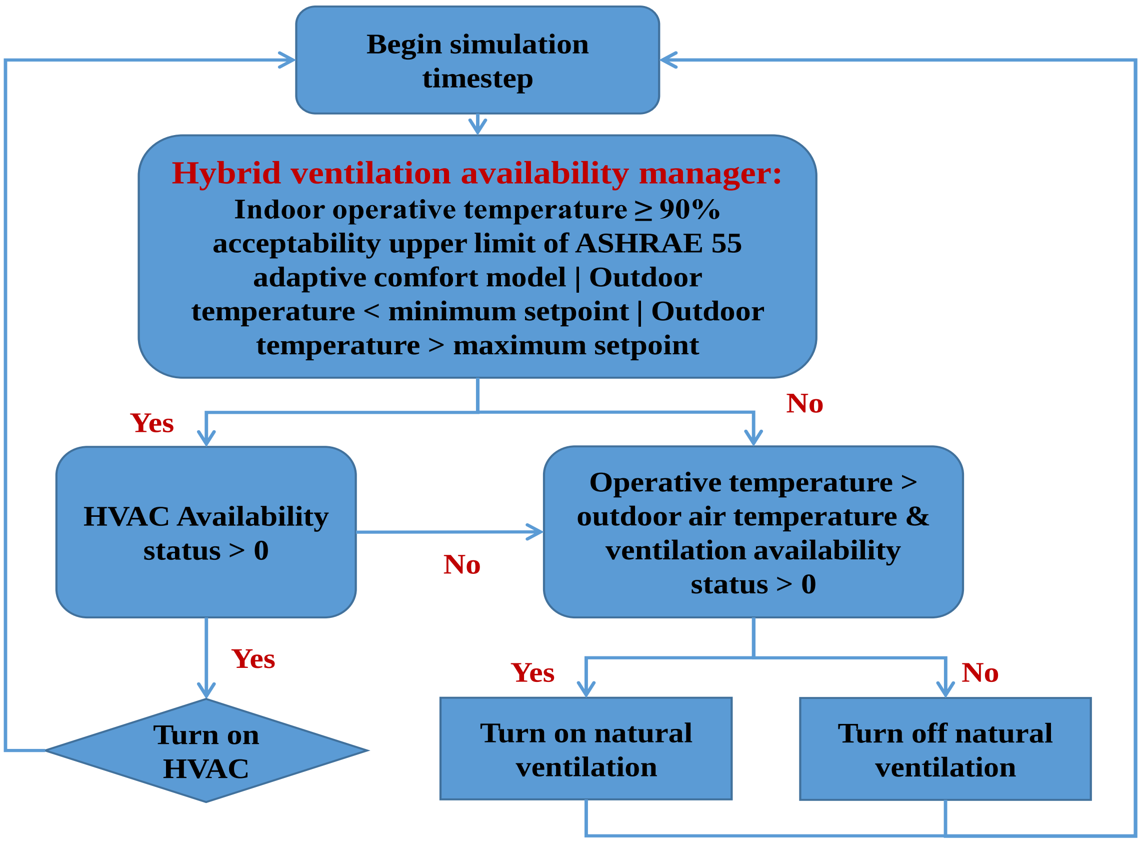


Fig. 7 The hybrid ventilation operation flowchart

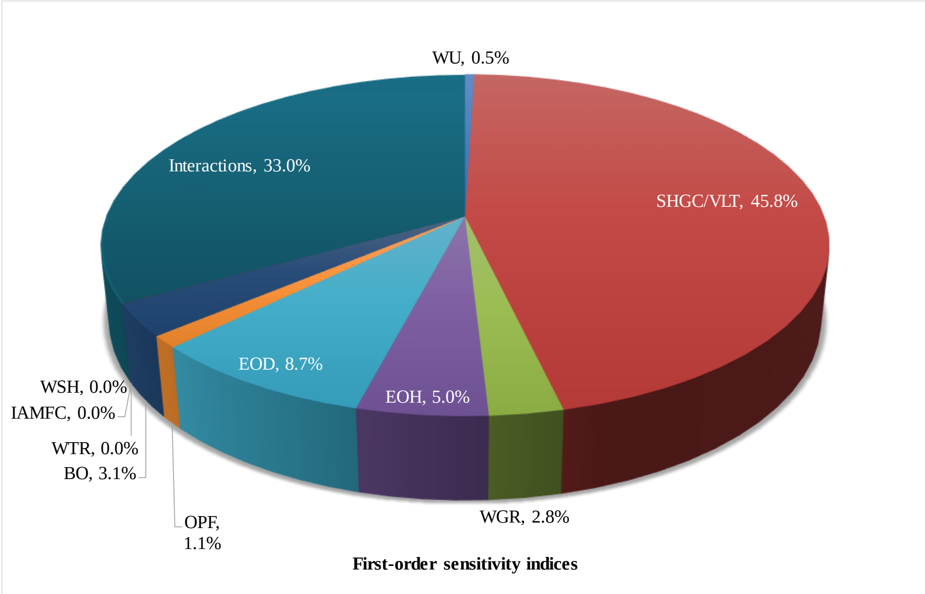


Fig. 8 First-order sensitivity indices by FAST

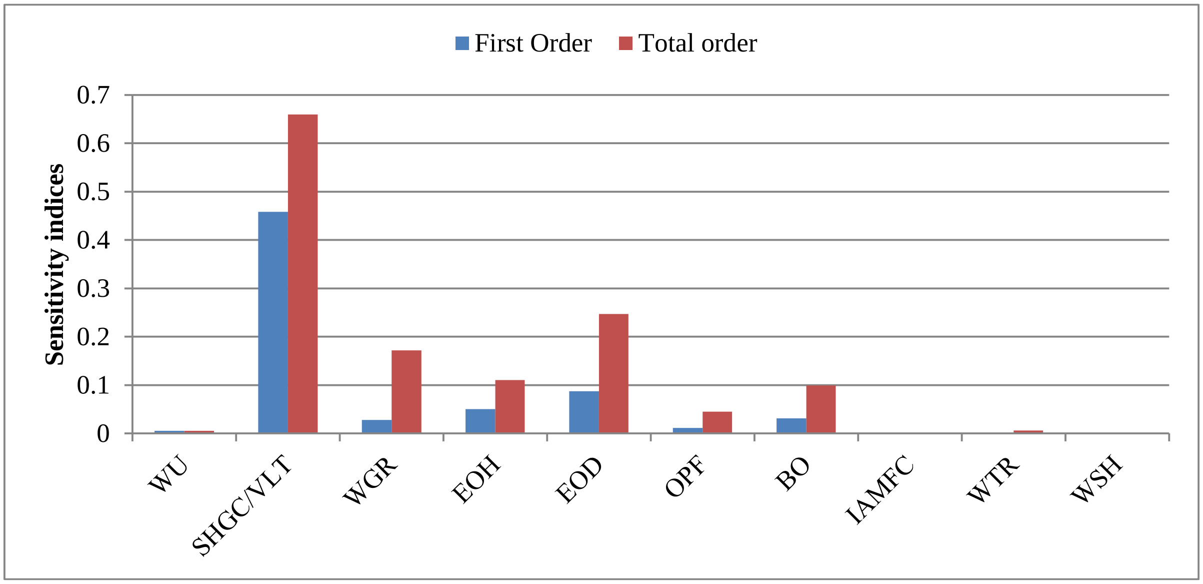
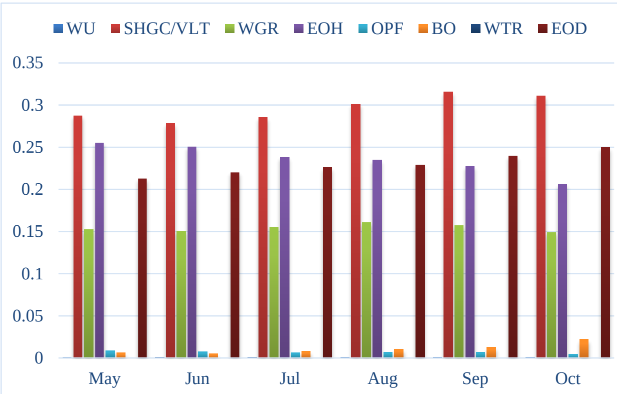
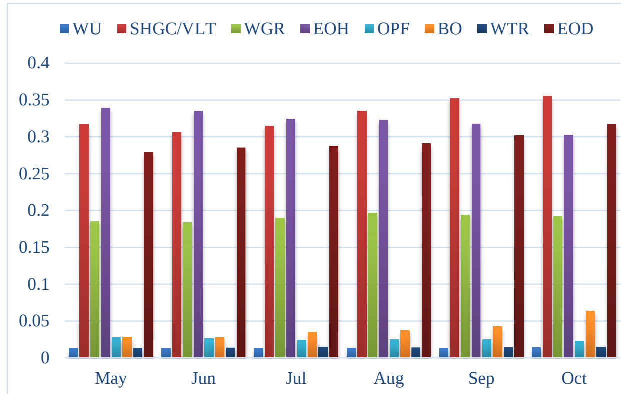


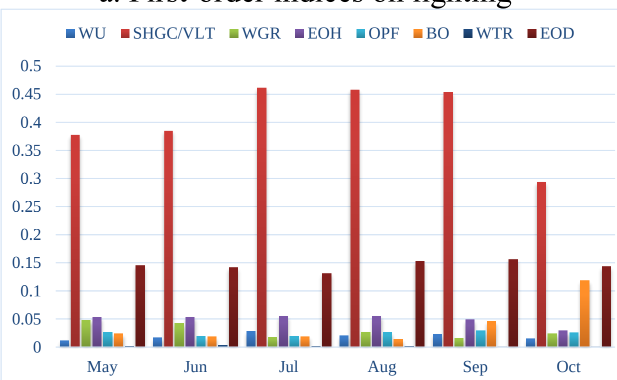
Fig. 9 The comparison of fist-order and total-order indices



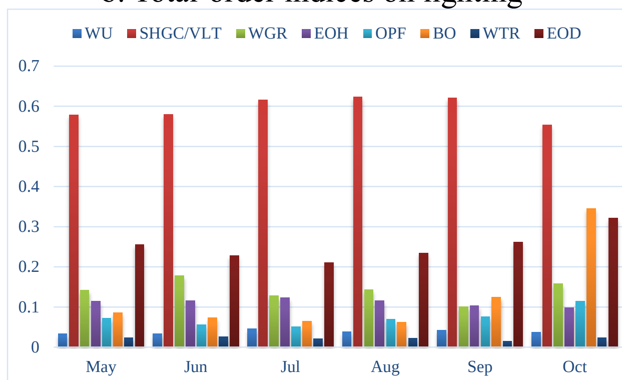
a. First-order indices on lighting



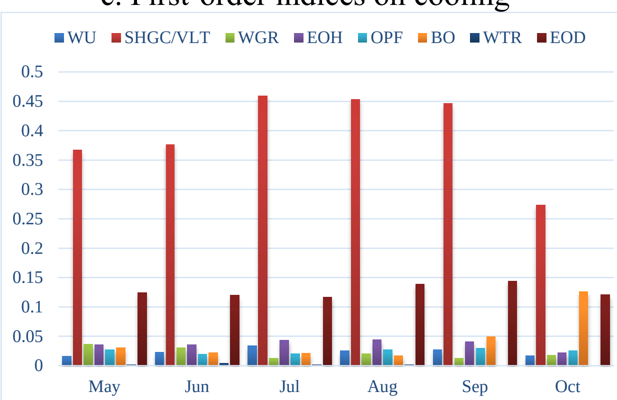
b. Total-order indices on lighting



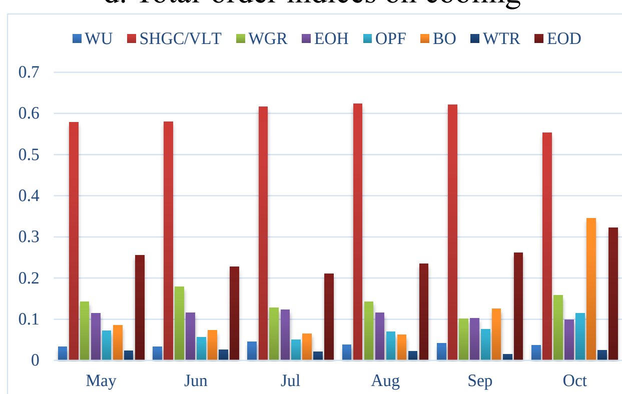
c. First-order indices on cooling



d. Total-order indices on cooling



e. First-order indices on total energy



f. Total-order indices on total energy

Fig. 10 Sensitivity monthly profile for the output of cooling, lighting and total energy

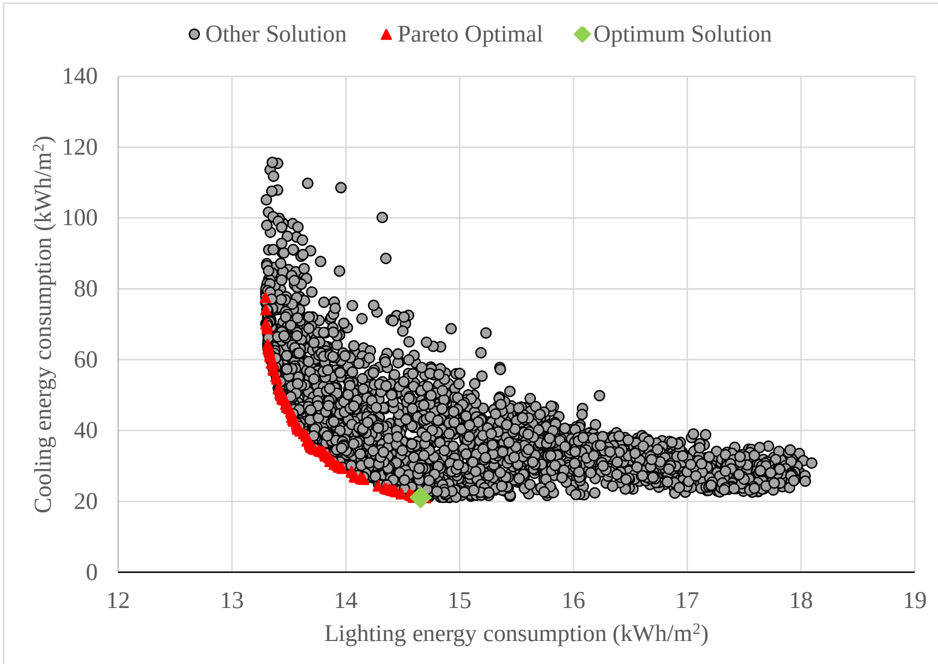
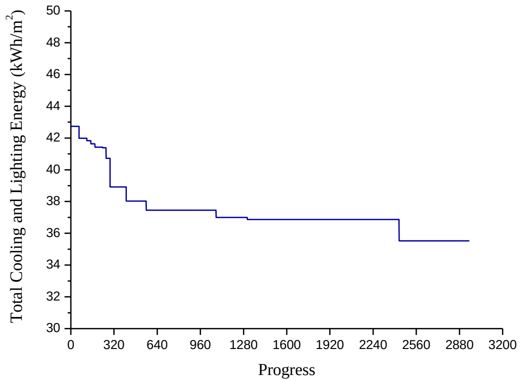
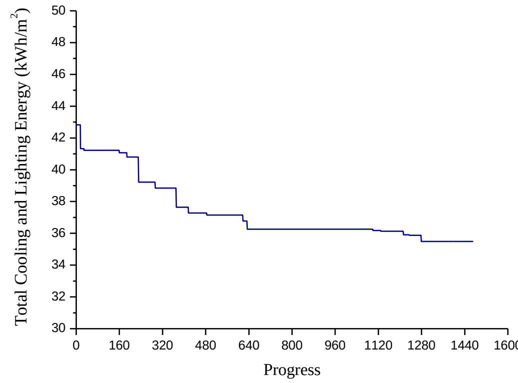


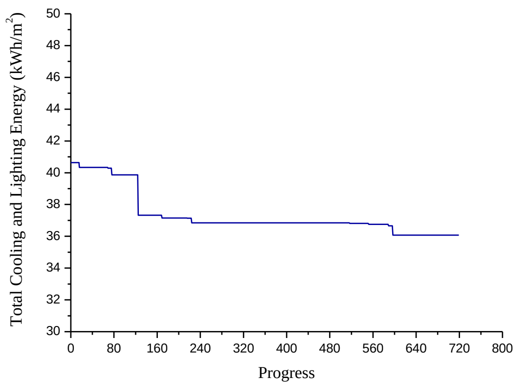
Fig. 11 Distribution of the Pareto frontier and optimum solution between the lighting and cooling energy consumption



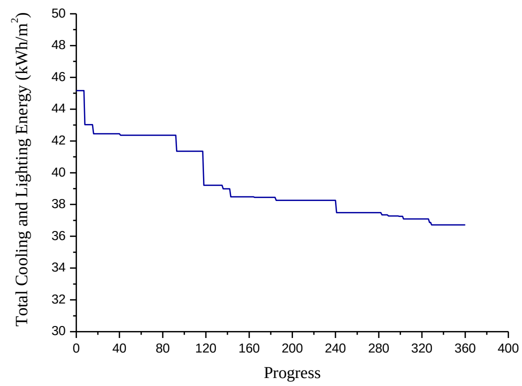
a. Population size = 32



b. Population size =16

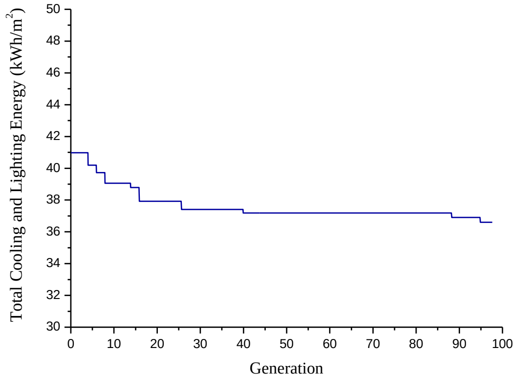


c. Population size = 8

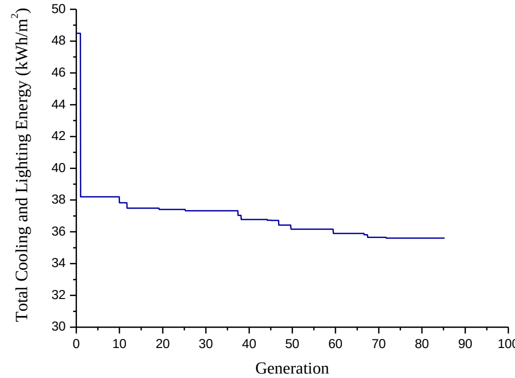


d. Population size = 4

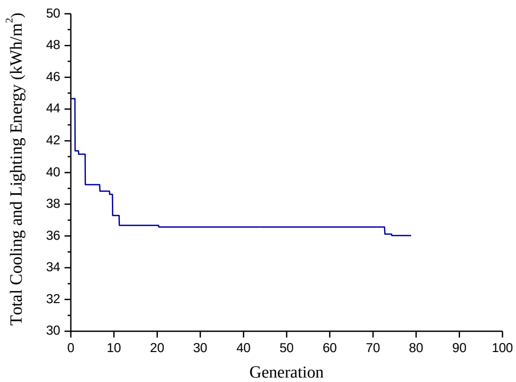
Fig. 12 The convergence progresses under different population size



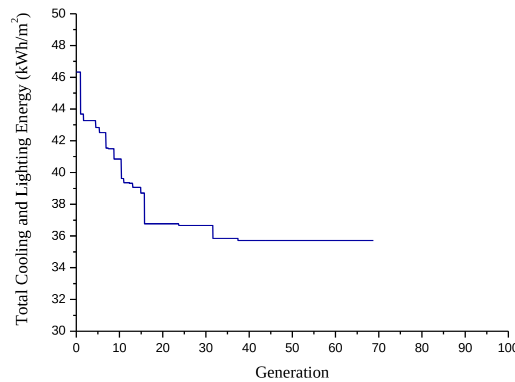
a. Crossover probability = 1.0



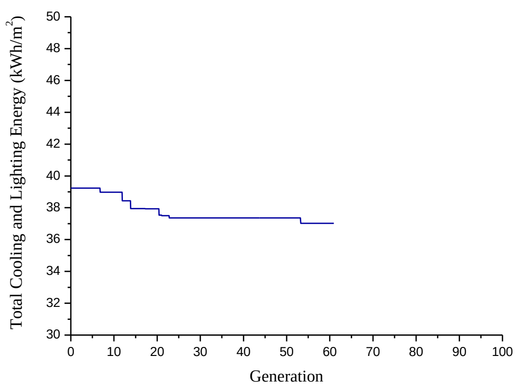
b. Crossover probability = 0.8



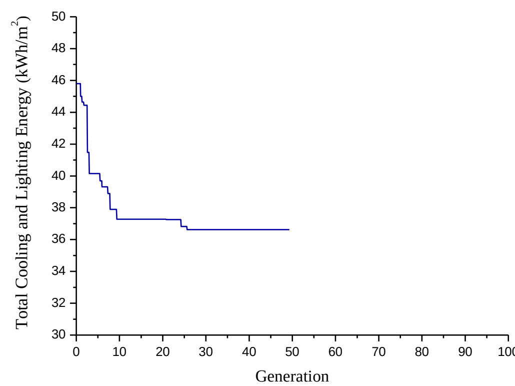
c. Crossover probability = 0.6



d. Crossover probability = 0.4

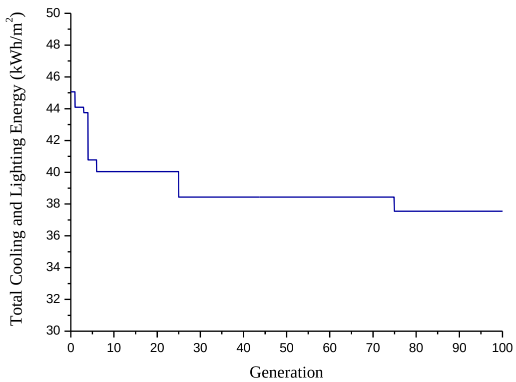


e. Crossover probability = 0.2

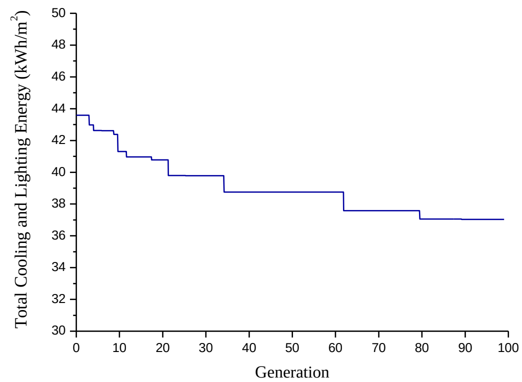


f. Crossover probability = 0.0

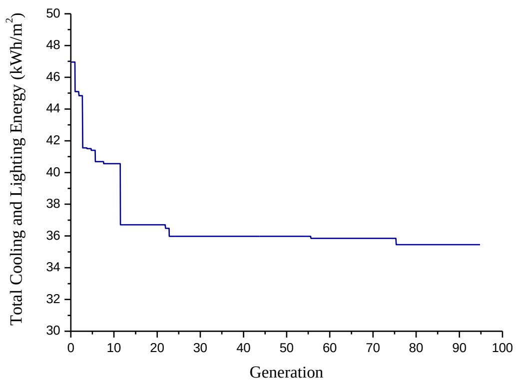
Fig. 13 The convergence progresses under different crossover probability



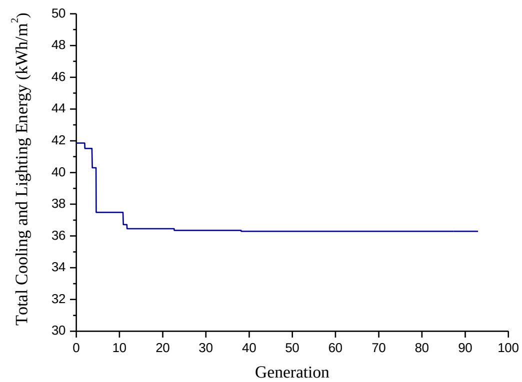
a. Mutation probability = 1.0



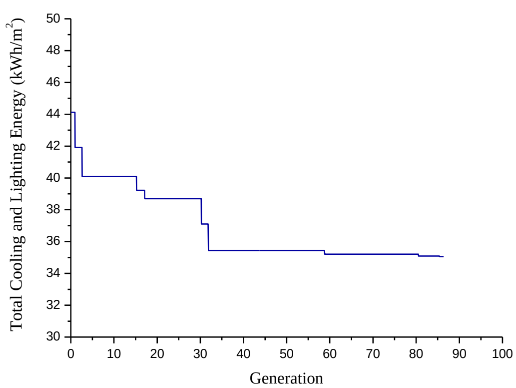
b. Mutation probability = 0.8



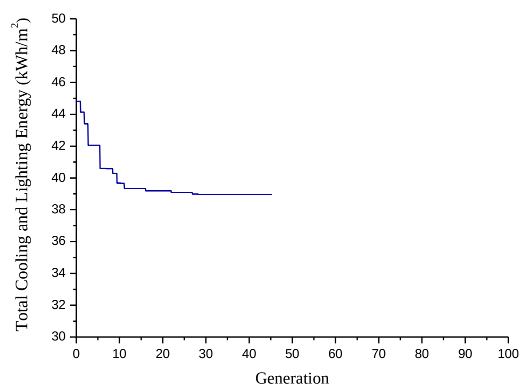
c. Mutation probability = 0.6



d. Mutation probability = 0.4



e. Mutation probability = 0.2



f. Mutation probability = 0.0

Fig. 14 The convergence progresses under different mutation probability

Table 1 General information of five selected representative cities

	Lat. (°)	Long. (°)	Elev. (m)	HDD	CDD
Hong Kong (HK)	22.33	114.17	62	237	1976
Guangzhou (GZ)	23.17	113.33	42	402	2036
Taipei (TPE)	25.07	121.55	6	242	2022
Bangkok (BKK)	13.73	100.57	4	0	3873
Singapore (SGP)	1.37	103.98	16	0	3537

HDD and CDD: Annual heating and cooling degree-days, base 18.3°C

Table 2 Summary of research on simulation-based passive design approach

Category of references	Reference indices
1. Local sensitivity analysis	[10], [11], [12], [13], [14], [15], [16], [17], [18]
2. Global sensitivity analysis (multi-method)	[19], [20]
2.1. Regression method	[21], [22]
2.2. Variance-based method	[24]
2.3. Screening-based method	[23]
3. Multi-objective Optimization (multi-method)	[37]
3.1. Evolutionary Algorithm	[27], [28], [30], [33], [34], [35]
3.2. Swarm Intelligence	[29], [32], [36]
4. Optimization with sensitivity analysis	[31] (Regression method)

Table 3 Optimum design conditions for five cities

	HK	TPE	GZ	SGP	BKK
WU ($W/m^2 \cdot K$)	5.81	5.87	5.27	5.67	5.82
SHGC/VLT (-)	0.11	0.10	0.11	0.11	0.10
EOA (°)	14.00	10.00	10.07	8.91	10.85
WGR (-)	0.49	0.50	0.50	0.49	0.50
OPF (-)	0.15	0.04	0.14	0.10	0.15
BO (°)	5.00	3.00	14.00	174.00	359.00
WTR ($m^2 \cdot K/W$)	0.26	0.14	0.09	0.11	0.61
Lighting (kWh/m^2)	14.66	14.12	14.83	15.25	14.39
Cooling (kWh/m^2)	21.07	18.15	18.98	21.86	38.72
Total (kWh/m^2)	35.73	32.27	33.81	37.11	53.11