PARAMETRIC SENSITIVITY STUDY IN DESIGN OF DOUBLE SKIN FACADES FOR LARGE SPACE BUILDINGS IN COLD REGIONS OF CHINA

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ABSTRACT

This paper presents a comprehensive sensitivity analysis (SA) and optimization to inform design decisions of the Double Skin Facades (DSFs) of large space waiting hall in cold regions of china. A geometric modelling, energy simulation and optimisation framework, which is based on the Rhinoceros / Grasshopper platform and associated plugins, is used to facilitate the simulation-based workflow for parametric exploration and optimization. During this process, the validated Airflow network (AFN) method is used to simulate multi-zone airflow in DSF cavity and its adjacent zones. The simulation results are finally used for local and global SA. As a result, the sensitivity ranking of selected parameters and optimized design solutions are both obtained. It is believed that the software framework and simulation-based workflow employed in this paper could enable designers to examine and optimize the application of DSF in early stage of design.

INTRODUCTION

The Increasing awareness of energy saving is driving a growing popularity of the use of double skin facades (DSFs) in China. However, it is quite difficult for non-expert designers to appropriately integrate this component with their initial design, especially for DSF in large space buildings with few literatures or guidelines to inform how to design and analyse it. The uncertainties in prediction lead to questions on its performance and economic feasibility of DSFs (Choi et al. 2012).

Against this background, Sensitivity analyses are conducted to identify the most important parameters in relation to DSF energy performance. Therefore, it will be possible to focus design and optimization works on these fewer, but most important parameters (Heiselberg et al. 2009).

BACKGROUND

Overview of the employed software framework

As shown in Fig.1, a geometric modelling, energy simulation, parametric analysis and optimisation framework is generated based on the Grasshopper platform and associated plugins, enabling designers to facilitate the parametric exploration and optimization of DSF in early design stage. The software used in this framework are given below:

1. *Rhino: a 3D modelling environment*
2. Grasshopper: parametric modelling tools
3. Archsim: for thermal simulations running on EP v.8.4
4. Fly component: to cycle through all connected sliders
5. Octopus plugin: for evolutionary optimization

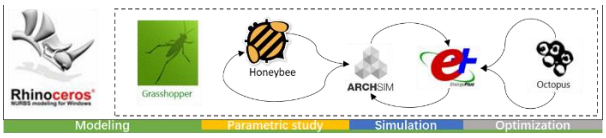

Figure 1 The software framework employed in this paper

Airflow network (AFN) method

Airflow network (AFN) model calculates multi-zone air flows driven by outdoor wind pressure, stack effect or forced air through cracks, window, door openings or air distribution systems. Based on the airflow rate, the model calculates node temperatures and humidity ratios, which determine the thermal load for each zone. The thermal load of AFN model is further coupled with zone air balance equations to acquire the final zone air conditions (Chen et al. 2015).

In this paper, AFN model is used to simulate multi-zone airflow in DSF and its adjacent conditioned zones. It is validated by measuring an actual behaviour of a multi-story DSF in Beijing during heating seasons. An atrium, with the properties of a large space, is adjacent to this DSF cavity. Fig.2 shows the view of the atrium and the location of the HOBO sensors shielded by the thin aluminium foil set around it. The validation was made against measured Zone Mean Air Temperature of DSF cavity and adjacent atrium on each floor. The details are given in another research. As Fig.3 shows, the fair agreement between measured and simulation results proves that the AFN method employed in this research is

reliable for predicting the thermal performance of DSF in large space buildings.

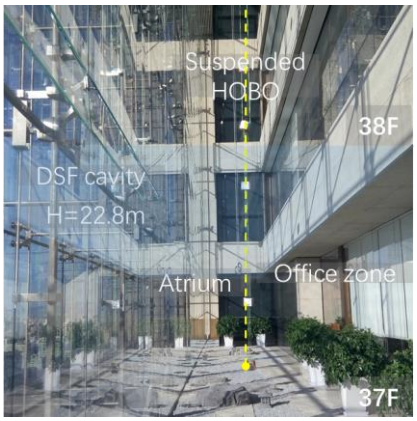

Figure 2 View of the tested atrium and DSF cavity

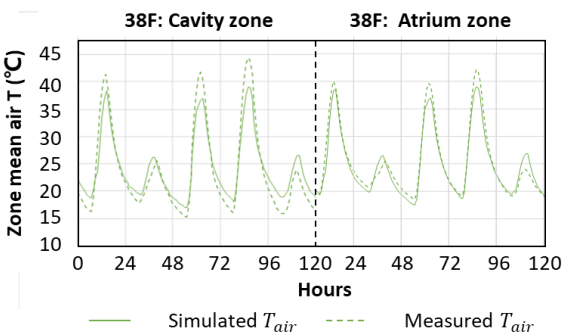

Figure 3. Comparison of predicted zone mean air temperature with measured data

METHODOLOGY

Based on the software framework displayed in Fig.1, two simulation-based workflows are developed to inform early DSF design: the parametric exploration workflow and the optimization workflow. The simulation results derived from above 2 workflows are then used to conduct local and global SA, respectively.

Generic model and modelling approach

On the background of reducing energy use in current large space waiting halls by replacing the large area SSF with DSF, this study mainly focuses on the design support of sensitivity analysis and optimization methods in initial design stage. Therefore, a detailed. whole building simulation with the entire facade at presence is not considered an effective approach especially when the façade is comprised of repetitive sub-façade-units (Chen et al. 2015). Therefore, a hypothetic generic sub-model, covering the length of one span, is separated from the long façade and used to generalize the large space waiting hall in this research. Besides, to highlight the influence of input variables on output variation, the WWR of the generic sub-model is set to its maximum value in reality. Besides, a conventional SSF model is also created for reference using the same settings except for the glazing types.

As shown in Fig.4, the cavity is divided into 6 stacked thermal zones (one for the inlet, one for the outlet and one for each floor) using a virtual horizontal surface with a constantly open window to simulate the airflow driven by buoyancy and wind pressure (Yoon et al. 2009). All component typology and parameters are defined in Archsim based on the validated AFN modelling method mentioned above. For each thermal zone, both the wind pressure and stack-effect-driven airflows are considered. The large vertical window opening on the external wall is defined as “simple opening” object and the constantly open window at the virtual horizontal surface is defined as “horizontal opening” object. Both have a constant air mass flow exponent of 0.65 and an air mass flow coefficient of 0.001 Kg/s·m when closed and a discharge coefficient of 0.65 when open. Infiltration is controlled by a crack in the external wall which has the same air mass flow exponent as the window. The air mass flow coefficient of the crack under reference test conditions is set to 0.01 kg/s. All horizontal openings are set as constantly open under a temperature control mode. The lower inlet opening, and upper outlet opening are closed in heating seasons and opened in non-heating seasons.

All materials and constructions used in this model are taken from EP-datasets which are included in its installation file. Internal gains are defined by an area calculation method. Outdoor air supply for one person was set to 10m3/h according to national code GB 50226-2007 for design of railway passenger station buildings. Interior shading is applied and controlled by window solar gain. It is activated when solar radiation incident on the window exceeds 300 W/m2. The stratified air-conditioning method is widely applied in train station buildings. Therefore, only the thermal zone on the 1st and 2nd floor of the waiting hall are air conditioned in this paper, and their internal temperature is set to constant 27 oC in summer and 18 oC in winter. To avoid complex input and thus be relevant for the early design stage, an ideal HVAC system is adopted to model heating and cooling energy demands in the large space waiting hall integrated with a DSF (Nembrini et al. 2014). Finally, the simulation results are extracted by “load CSV” component from Archsim and then output to perform corresponding sensitivity analysis.

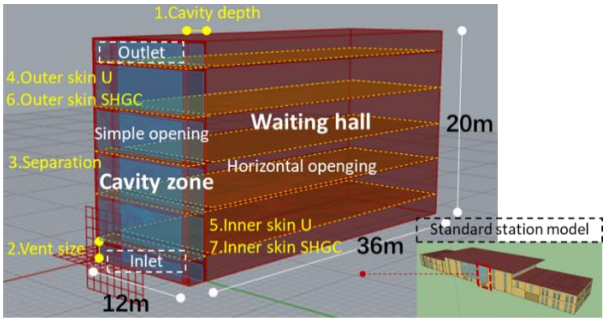

Figure 4. Constructed generic sub-model on the GH platform

Parametric exploration and optimization

Main DSF design parameters and their variation ranges summarized in Table1 are determined according to literature review and engineering experiences of DSF (Barbosa et al. 2014). Since there's few references for DSF applied in single-story large space buildings, the base case for parametric exploration and optimization is established by setting the selected inputs in compliance with the tested office building, to see whether its design solutions are applicable for the whole-year running period in this research.

All input variables are defined parametrically by slider values and then connected to "fly" component of honeybee, enabling an automatically parametric exploration. In this way, the impact of changing the values of each design parameter is evaluated in turn. For optimization, total energy is used as the objective function. An evolutionary algorithm in Octopus is used to generate a search space automatically, and the optimal solution could be found after many iterations.

Table 1 SA input variables and baseline value

NO	VARIABLES	UNIT	MIN	MAX	STEP	BASE
1	Cavity depth	m	0.2	2	0.2	2
2	Vent size	m	0.3	2.1	0.3	1.8
3	Cavity floors in winter	-	1	6	1	6
4	Outer skin U value	W/(m² K)	0.1	0.9	0.1	2
5	Inner skin U value	W/(m² K)	0.1	0.9	0.1	2
6	Outer skin SHGC	-	1	7	1	0.4
7	Inner skin SHGC	-	1	7	1	0.4

Oversized figures and tables may be included in the body of the text or collected at the end. Figure 2 is an example of an oversized figure.

Sensitivity analysis

SA is an effective method to investigate the impact of the individual design variables on the total energy consumption and identify the most important parameters in relation to building performance (Heiselberg et al. 2009). This technique can be categorized into two major categories: local SA and global SA.

Local SA method, also called OAT (One-at-a-Time) method, investigates the reaction of model output by changing one input factor at a time. It requires a chosen baseline case to make the comparison (Chen et al. 2015). To measure the importance of a certain input factor, the sensitivity coefficient is adopted, as defined by Eq. (1). For this method, the input-output relationship is assumed to be linear and the correlation between design parameters is not considered.

$$\mathrm{IC} = \frac{\Delta OP / \frac{OP_1 + OP_2}{2}}{\Delta IP / \frac{IP_1 + IP_2}{2}} \qquad (1)$$

where $\boldsymbol{\Delta IP}$, $\boldsymbol{\Delta OP}$ are the changes in input and output respectively; $\boldsymbol{IP_1}$, $\boldsymbol{IP_2}$ are two values of input; and $\boldsymbol{OP_1}$, $\boldsymbol{OP_2}$ are two values of the corresponding output.

Global SA evaluates the output effects of varying all input variables simultaneously. It is typically applied by using MCA (Monte Carlo analysis) and LHS (Latin hypercube sampling) of the solution space (Chen et al. 2015). MCA performs with randomly selected input samples, which are generated by the LHS strategy. After acquiring the inputs and outputs matrix, multiple regression between them is applied, and the standardized regression coefficient (SRC) of each parameter are calculated. The absolute value of SRC indicates the relative importance of different inputs, while the sign of it denotes a negative or positive correlation (Chen et al. 2015). SRC stands for the weight of each input variable in the regression model, and can be calculated by the below equations:

$$\mathrm{SRC}_j = \frac{\beta_j \sigma_x}{\sigma_y} \qquad (2)$$

Where σ_x and σ_y are the standard deviation of input and output values respectively, β_j is the regression coefficient.

The obtained regression model uses $\boldsymbol{R^2}$ value (coefficient of determination) in Eq. (3) to assess the correlation between the input and output. A $\boldsymbol{R^2}$ value

higher than 0.7 means the model can explain most of the variation in the output variable (Yoon et al. 2009).

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

Typical SA studies include the following steps: determine input variations, create building models, run energy models, collect simulation results, run sensitivity analysis and interpret results (Chen et al. 2015). It has been proved that the solutions found from a building design optimization can be used for sensitivity analysis (Wright et al. 2012). In this paper, local and global SA are conducted by using the data obtained from parametric exploration and optimization, respectively. Thus, the complexity and resources required to conduct sensitivity analysis are largely reduced, enabling designers to understand and determine the DSF parameters according to different climate conditions and design constraints.

RESULTS AND DISCUSSIONS

Parametric exploration and local SA

According to the method introduced above, the impact of each design parameter is evaluated in turn by changing one input factor at a time and holding all others to be constant. The correlation between total energy and seven selected parameters and the acquired regression model are given as follows (Fig.5-7), where the variables are categorized into 3 groups according to their variation ranges, and the base case is highlighted with red circles in each figure.

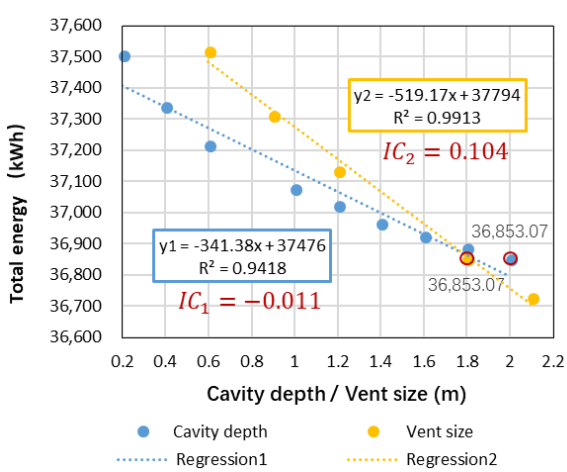

Figure 5. Correlation between the total energy and cavity depth or vent size

Cavity depth is first investigated as one of DSF geometry parameters, which affects the path of the airflow and the size of the buffer zone. As shown in Fig. 5, the total energy decreased with the increase of cavity depth. After the cavity depth exceeded 1m, the descending rate was slower but still apparent. A high R2 value of 0.9418 proves better correlation while the low sensitivity coefficient (IC) of -0.011 implies minor contributions to the variation in total energy. The total energy also dropped with the increase of vent size. Compared with the cavity depth, the vent size has more significant impact on building energy use based on a relatively high sensitivity coefficient of 0.104.

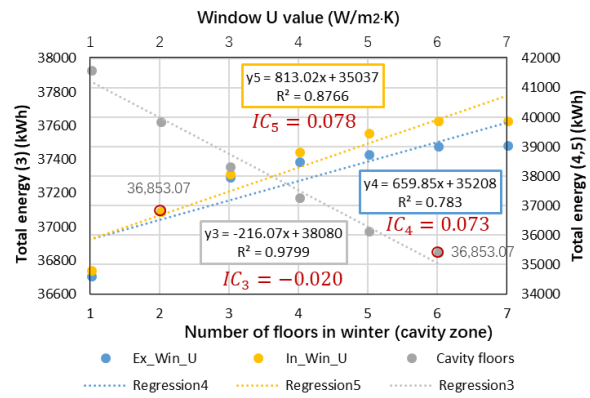

Figure 6 Correlation between the total energy and interior or exterior window U value or cavity separation conditions

During cooling seasons, DSF can be effective in extracting the excessive heat through its upper opening due to the stack effect. Therefore, a taller cavity extends almost the total height is beneficial for stronger buoyancy force (Nembrini et al. 2014), thus it will not be included as a parameter in warmer seasons. Whereas, in cold seasons, the apertures are closed, and the cavity is heated by solar radiation, working as an insulation and thermal storage space. It has been proved that the uppermost part of the cavity has the highest air temperature in winter, which may be negative for the lower part to warm the adjacent waiting area for energy saving. Therefore, the effect of the cavity separation (number of floors) on the total energy use was evaluated. Since the whole cavity was modelled as 6 stacked zones, the number of floors varies with different on/off combinations of the virtual horizontal openings, which is controlled by the venting availability schedule. A total of 32 (25) samples are categorized into 6 groups according to their number of floors from 1 to 6. The mean total energy of each group is plotted in Fig.4, showing a significant correlation to the total energy use with a R2 value of 0.98. The sensitivity coefficient was calculated

to be -0.02, indicating that the cavity with partition at each floor in winter is recommended.

As shown in Fig.6, the U value of exterior and interior window are both in positive relation with the total energy. The sensitivity coefficients are calculated to be 0.073 and 0.078 respectively, indicating their great importance over other factors. However, the linearity declines with an R2 value of 0.783 for exterior window U and 0.877 for interior window U. The increasing rate is apparently higher when the U value is increasing from 1 to 4 W/m2·K. After the U value exceeds 4 W/m2·K, the increasing rate levelled off with only minor impact on the total energy.

As shown in Fig.7, high R2 values over than 0.9 prove good correlations between the total energy and window SHGC. The small IC of 0.01 implies minor contributions of interior SHGC to the variation in the total energy. In contrast with it, an IC of -0.026 indicates a negative relation between the exterior SHGC and the total energy.

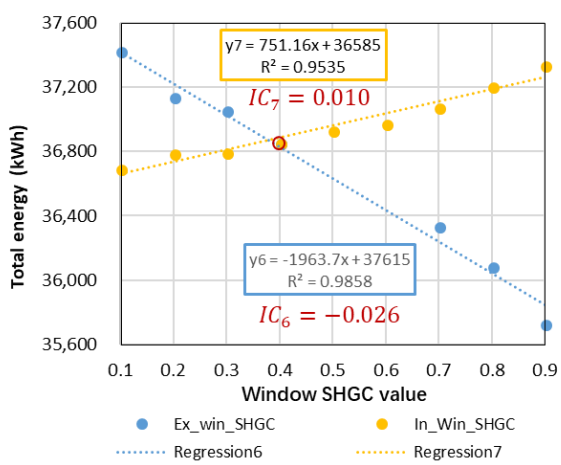

Figure 7 Correlation between the total energy and interior or exterior window SHGC value

Fig.8 shows the calculated IC of all input variables. Indicating that the vent size, interior window U, exterior window U and exterior window SHGC are the top 4 important parameters in initial design, while cavity depth and interior window SHGC are insignificant. Separation numbers of the cavity has limited effect on total energy use, may because it only takes effect in winter. Informed by above findings, a reasonable vent size can produce a considerable energy saving potential by making the best use of its natural ventilation effect in warmer seasons. Besides, the glazing types is very influential for its energy performance, a lower U value and higher SHGC for the external window is recommended when heating load reduction is the main concern in cold climates.

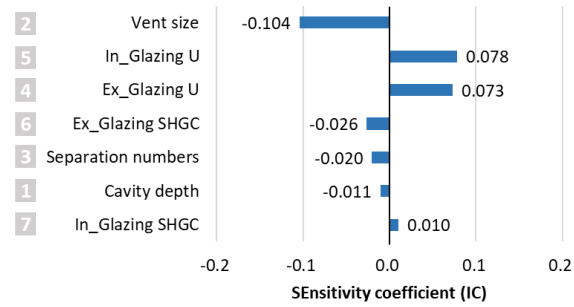

Figure 8 Sensitivity coefficients (IC) of DSF input variables

Optimization and global SA

The above session introduced findings of the local SA based on the simulation results obtained from the parametric exploration workflow. A single objective optimization was then conducted using a genetic algorithm in Octopus to search for an optimized solution and meanwhile generate a series of design iterations automatically. In this paper, the Archsim simulation was carried out 1050 times, in 21 generations. Fig.9 shows the total energy use of the local best (L_{best}) in each generation. An optimal solution was derived for the first time in the 18th generation, and then appeared repeatedly up to the 21st generation, indicating that all variables finally converged to the global best (G_{best}) (an optimal solution). Besides pareto front solutions, some near-optimal solutions were also developed. Fig.10 shows 9 alternative solutions with parallel good energy performance, which provide designers more diversity and freedom to choose according to other constraints in the early stage of design.

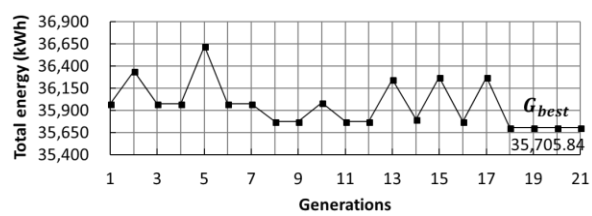

Figure 9 Local best of each generation

Base on the samples obtained from optimization, a global SA was then conducted to further validate the findings of local SA. Since many solutions appeared repeatedly in 21 generations, 1050 samples are finally cut down to 590 samples without duplication. Fig.11 shows the frequency distribution histogram and

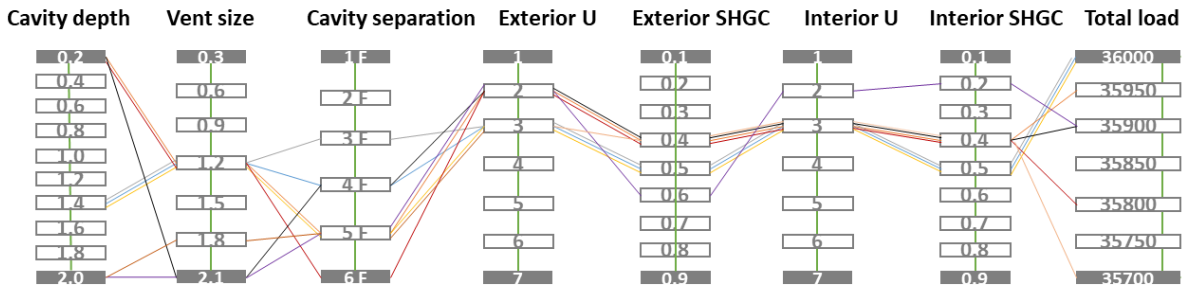

Figure 10 Results of optimization process that achieved the minimum energy use.

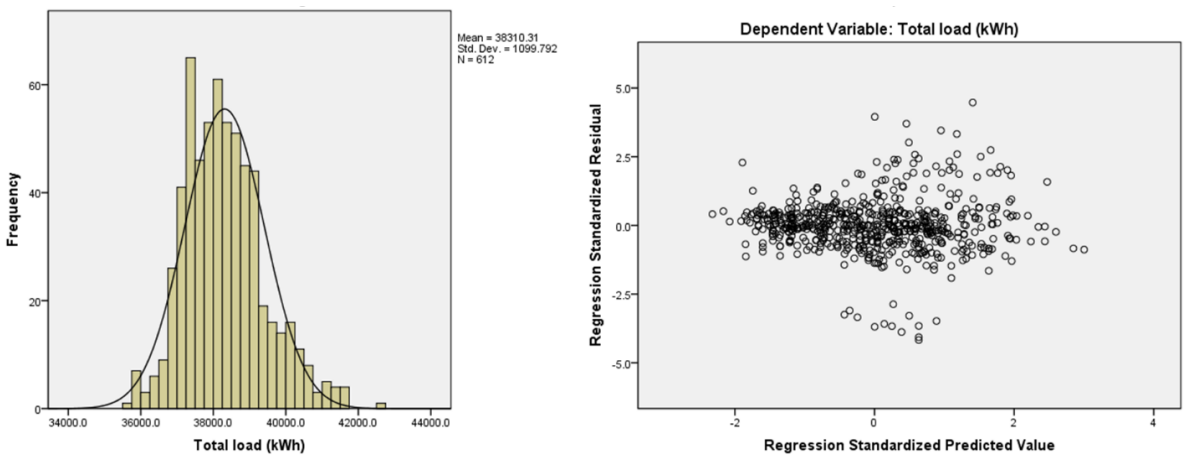

Figure 11 Distribution of the total energy and regression standard residual.

regression standard residual of the total energy. Based on a step-wise linear regression method, a multiple regression between inputs and outputs is obtained. The R2 value of the standard regression model is 0.783, which indicates an acceptable approximation of the simulated total energy. Fig.12 shows obtained SRCs of the multiple regression model, which signifies that the exterior window U, vent size, interior window U and cavity depth are the top four influential factors over the total energy.

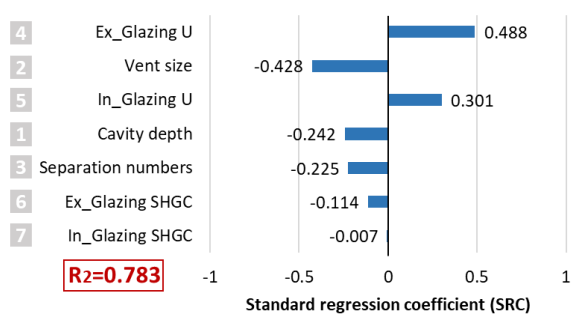

Figure 12 Obtained SRCs of DSF input variables for the total energy

When compared with sensitivity coefficients (IC) from the local SA in Table 2 (Fig.6, Fig.10), it is noticed that the outer window U, vent size, inner window U are constantly the top 3 influential factors over the total energy, followed by the cavity depth in global SA and exterior glazing SHGC in local SA. The inner skin SHGC and cavity separations rank with the same sequence in the 2 methods and are less significant. While the ranking sequence of the top 3 parameters is totally different, which may derive from the interactions between some pairs of variables.

Table 2: Comparisons of sensitivity indices for total energy

NO	PARAMETERS	IC	R2	SRC
1	Cavity depth	-0.011	0.9418	-0.242
2	Vent size	-0.061	0.9913	-0.428
3	Cavity separation numbers	-0.020	0.9799	-0.225
4	Outer skin SHGC	-0.029	0.9858	-0.114
5	Outer skin U value	0.080	0.783	0.488
6	Inner skin SHGC	0.011	0.9535	-0.007

7	Inner skin U value	0.091	0.8766	0.301

Energy conservation potential

Architects can use several types of techniques to discover an optimal solution including parametric analysis, sensitivity analysis, optimization algorithms, and even their intuitive determination (Konis et al. 2016). In this paper, both the SA method and optimization are used to generate the optimal solution. Table.3 and Fig.13 compare the recommended input variables and corresponding energy consumption of both methods. As a simplified optimization process, SA method defines all sensitive parameters as the upper or lower limits according to their respective relationship with the total energy. However, optimization addresses the interactions of all input variables and the optimal solution would be obtained from many iterations. It is found that the decreased total energy is 26% for optimization and 24% for SA method, compared to the SSF reference case, informing that the prediction of the local SA is identical with the global SA, which mainly due to the linear correlations between the inputs and outputs. Besides, during the optimization process, the decreased or increased total energy of the generic model shows variation from -3.72% to 10.86% when compared to the base case, which signifies the importance of the DSF design. While the small gap of the total energy between the optimal solution and the base case indicates a well initial design, which uses the same inputs as the tested building.

Table 3: Comparisons of two optimized DSF model derived from optimization and Global SA respectively

NO	INPUT VARIABLES	BASE CASE	SA METHOD	OPTIMIZATION
1	Cavity depth (m)	2	2	2
2	Vent size (m)	1.8	2.1	1.8
3	Cavity separation	6	6	5
5	Outer skin U value W/ (m^2 K)	2	1	3
7	Inner skin U value W/ (m^2 K)	2	1	3
4	Outer skin SHGC	0.4	0.9	0.4
6	Inner skin SHGC	0.4	0.1	0.4
8	Total energy (kWh)	37086.4	36592.0	35705.8

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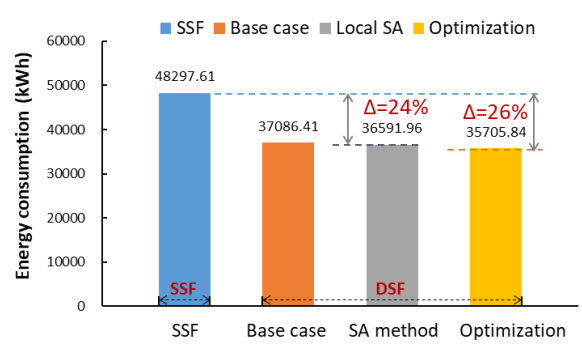

Figure 13 Energy consumption comparison

CONCLUSIONS

In this paper, an integrated software framework is developed to inform design decisions for Double Skin Façades in a large space waiting hall in cold regions of china. A generic model of DSF was firstly built in the Rhino platform and defined by the validated AFN modelling method through the Grasshopper plugin Archsim. Based on the simulation-based workflows, the parametric exploration and optimization are

implemented, and their results are used to perform Local SA and global SA, respectively. Finally, the energy saving potential of the optimal solution deriving from SA and optimization method are explored and compared with the base case and the SSF reference. Preliminary conclusions can be drawn as follows:

1. Both local and global SA method can be applied to assessing the importance of design parameters, whereas the results may be a little different due to the interactions between the input variables. Informed by the ranking sequence of all input parameters, when apply DSF in large space buildings, the design and optimization effort should be focused on glazing U value and the size of the opening.
2. Both the sensitivity analysis and optimization method can be used to inform design decisions. As a result, an additional energy saving of 2% could be obtained by optimization. It can be concluded that with the increase in complexity of the parameter interaction, the advantage of optimization method would be more significant, and the parallel design solutions derived from optimization suit better to the early stage of design.
3. The integrated software framework employed in this paper is a good candidate to help non-expert designers incorporate DSF into initial design and raise their understanding of this passive design strategy. This research fill in the gaps of DSF application in large space buildings. Although the conclusions are based on the cold climates, this approach can be easily modified and applied to other climate conditions.

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