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Global Sensitivity Analysis of Peak Cooling Load Applied to A High-rise Office Building at the Early Stage

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ABSTRACT

In order to identify the key variables affecting peak cooling load of a high-rise office building, especially the related elements of architectural design, a MC simulation method based on LHS is proposed and the meta-model GSA based on TGP is implemented in this paper. Finally, to illustrate the methodology in a clear way, a case study of a high-rise office building in Tianjin, China has been used in this paper. The results show that the key factors affecting peak cooling load are solar heat gain coefficient (SHGC), west window to wall ratio (Rw) and number of floors (NF), and the interaction terms of input factors are not significant. This process makes it possible for designer or decision makers to carry out building energy efficiency design and optimization design scheme.

Keywords: peak cooling load, global sensitivity analysis, Monte Carlo simulation, high-rise office building

NONMENCLATURE

Abbreviations	
SA	sensitivity analysis
GSA	global sensitivity analysis
LSA	local sensitivity analysis
VBA	visual basic application
LHS	Latin hypercube sampling
MC	Monte Carlo

1. INTRODUCTION

Sensitivity analysis (SA) plays an important role in building energy analysis. It can be used to identify the key variables affecting building thermal performance from both energy simulation models and observational study. SA can be divided into two main categories, local and global [1]. A local sensitivity analysis (LSA) evaluates the response of the model to one local parameter. Global sensitivity analysis (GSA) explores the response of the model to changes in all input parameters, which are varied simultaneously [2].

GSA provides more information about the effect of varying model inputs but demands more computational effort. GSA can be further subdivided into four categories [1]: regression, screening, variance-based and meta-models. Many variables affecting cooling and heating loads are uncertain at the early stage and the impact of these uncertainties is the reason for limiting the simulation accuracy.

However, previous dynamic BPS studies have not often focused on analyzing the sensitivity of peak cooling load of a high-rise Office building to input parameters, especially the related elements of architectural design. Therefore, the aim of this research is to implement a meta-modelling method for GSA to identify and analyze key variables influencing peak cooling load.

2. METHODOLOGY OUTLINE

One of the most important link for GSA of peak cooling load is to choose a methodology of uncertainty propagation. The Monte Carlo (MC) simulation method based on Latin hypercube sampling (LHS) and a new meta-model GSA based on Treed Gaussian Process (TGP) is used in this paper. The research process is illustrated in Fig. 1.

2.1 Specify distributions of input factors

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The first step of MC simulation method based on LHS method is to specify distributions of input factors, including certain factors and uncertain factors. For the certain factors, specific design values are determined according to the standards and codes. In this paper, uncertainties will be characterized assigning probability distributions to the uncertain input factors, including Gaussian distribution, triangular distribution, uniform distribution, etc.

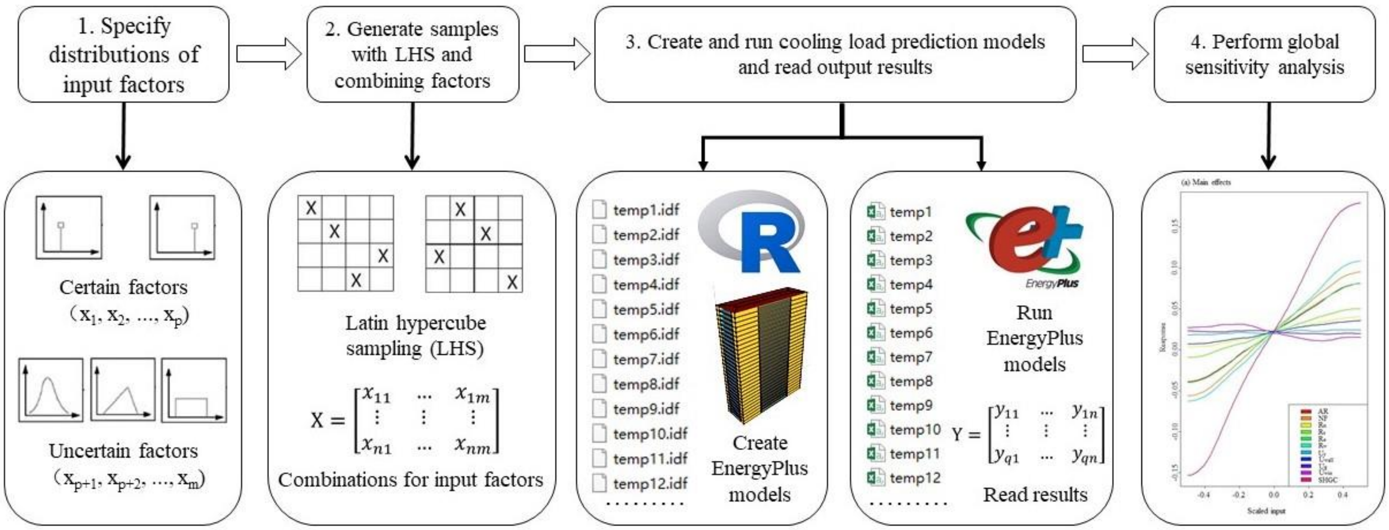

Fig. 1 Flow chat of Global sensitivity analysis method

2.2 Generate samples and combinations

The second step is to generate samples with LHS and combine the input factors. LHS is a very popular method suitable for computationally demanding models due to its stratification properties. LHS is implemented here using R software. Finally, a matrix X with m rows (sample size) and n columns (number of input factors) is generated by combining the certain and uncertain factors.

2.3 Create and run EnergyPlus models

The third step is to automatically create models of cooling and heating load forecasting using R software and run the models by EnergyPlus software. In this paper, R software can use the samples from the previous step to write the EnergyPlus models. In order to reduce the time cost, EnergyPlus models are run on a multi-core computer and Excel visual basic application (VBA) is used to automatically read the outputs from a large number of simulation runs in this paper.

2.4 Perform global sensitivity analysis

Two sensitivity indices can be provided by the meta-model GSA based on TGP: first order and total effects. The first order is to represent the main effect contribution of each input variable to the variance of the output. In contrast, the total effects is to represent the total contributions to the output variance due to each input factor by considering main effects and all higher-order effects. Therefore, the difference between the first order and total effects for one input variable indicates the interactions between this variable and other variables. The R tgp package provides fully Bayesian non-stationary non-linear models (called treed Gaussian processes, TGP) and contains the sensitivity index calculation functions based on variance method. The functions allow for easy calculation of two very important sensitivity indices associated with each input: the first order for the jth input variable, as shown in formula (3), and the total effects for input j, as shown in formula (4).

$$S_j = \frac{VAR(E[Y \mid X_j])}{VAR(Y)} \quad (3)$$

$$T_j = \frac{E(VAR[Y \mid X_{-j}])}{VAR(Y)} \quad (4)$$

Where S_j is the 1st order sensitivity indices; T_j is the total effect sensitivity indices; X_j is the input factors; X_{-j} are the other factors excluding X_j; Y is the model output; E is the expectation; VAR is the variance.

3. A CASE STUDY

3.1 Building description

To keep the discussion as tangible as possible, but without loss of generality, the paper is constructed

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around the case study that is presented in this section. The context of the problem is in the planning stage, where reliable estimates are required but little is known. It is known that an office building will be built on a planned land in Tianjin, China, with a site area of 6000m^2, a plot ratio of 8, a building density of 0.4 and a height limit of 160m. According to the known planning information, the floor area of the office building is 36000 m^2. Through site analysis and reference to office building design standards [3], the main entrance of the building is designed to face south. The typical floor of the building is designed to be rectangular, with the height of 4m.

3.2 Identification and quantification of model inputs

The peak cooling load forecasting models in this study comprise several input factors that will be divided into two groups: certain factors and uncertain factors.

The subgroup of certain factors includes those factors whose values can be determined by standards and codes. Detailed hourly schedules for occupants, equipment and lighting are also derived from a database of the Tianjin design standard for energy efficiency of public buildings [4]. The details of other deterministic parameters in the model are shown in Table 1.

The remaining inputs are affected by uncertainties. Table 2 shows the 11 uncertain factors identified in the model and the proposed probability distributions. These distributions have been proposed based on the survey data, theoretical considerations, literatures, standards and codes [3-5].

Table 1 Information on the certain inputs

Parameter	Unit	Value	Ref.
Indoor set temperature in summer	℃	26	[5]
Fresh air rate	m^3/(h·person)	30	[5]
Occupant density	m^2/person	8	[5]
Equipment density	W/m^2	15	[5]
Lighting density	W/m^2	9	[5]

3.3 Create and simulate models

In this study, 220 samples are generated with LHS. Based on the samples, R software is used to program and generate the peak cooling load forecasting models automatically. Then the simulation is carried out with EnergyPlus V8.3 software. In order to reduce the time cost, these models are run on two 16 core computers and Excel VBA is used to automatically read the outputs from a large number of simulation runs in this study.

4. RESULTS AND DISCUSSION

As can be seen from Fig. 2, the main effects, first order and total effects of all the eleven variables influencing peak cooling load are obtained. Solar heat gain coefficient (SHGC) of windows is the most important factor affecting peak cooling load. This factor accounts for more than half the variations of the output for both the first order and total effects. The next two important variables are west window to wall ratio (R_w) and number of floors (NF). The remaining factors provide only a minor contribution to the uncertainty in peak cooling load. Except for the window U-value (U_{win}), the other variables have a monotonic positive correlation with the output results. Therefore, the effective measures for reducing peak cooling load are to decrease SHGC, R_w, and NF. Moreover, the total effects for most of variables are slightly larger than the first order effects. Hence, the interactions between the variables are not significant.

In order to further explain the change of peak cooling load due to the first three important factors and a special factor. The mean and 90 percent interval of the main

Table 2 Information on the uncertain inputs

Parameter	Short name	Unit	Distribution type	Distribution	Ranges	Ref.
Building aspect ratio	AR	-	Truncated normal	N(1.2, 0.46^2)	1-3	[4-6]
Number of floors	NF	-	Uniform	U(20, 40)	20-40	[4-6]
East window to wall ratio	R_e	-	Truncated normal	N(0.46, 0.12^2)	0.2-0.7	[4-6]
West window to wall ratio	R_w	-	Truncated normal	N(0.46, 0.12^2)	0.2-0.7	[4-6]
South window to wall ratio	R_s	-	Truncated normal	N(0.55, 0.11^2)	0.3-0.7	[4-6]
North window to wall ratio	R_n	-	Truncated normal	N(0.55, 0.10^2)	0.3-0.7	[4-6]
Roof U-value	U_r	W/m^2·K	Uniform	U(0.1, 0.35)	0.1-0.35	[4-6]
Wall U-value	U_{wall}	W/m^2·K	Uniform	U(0.1, 0.45)	0.1-0.45	[4-6]
Ground U-value	U_g	W/m^2·K	Uniform	U(0.25, 0.45)	0.25-0.45	[4-6]
Window U-value	U_w	W/m^2·K	Uniform	U(1.0, 2.0)	1.0-2.0	[4-6]
Solar heat gain coefficient	SHGC	-	Uniform	U(0.15, 0.40)	0.15-0.4	[4-6]

Note: For the uniform distribution U(a, b), a and b are the lower limit and upper limit; for the normal distribution N(c, d2), c is the mean and d is the standard deviation

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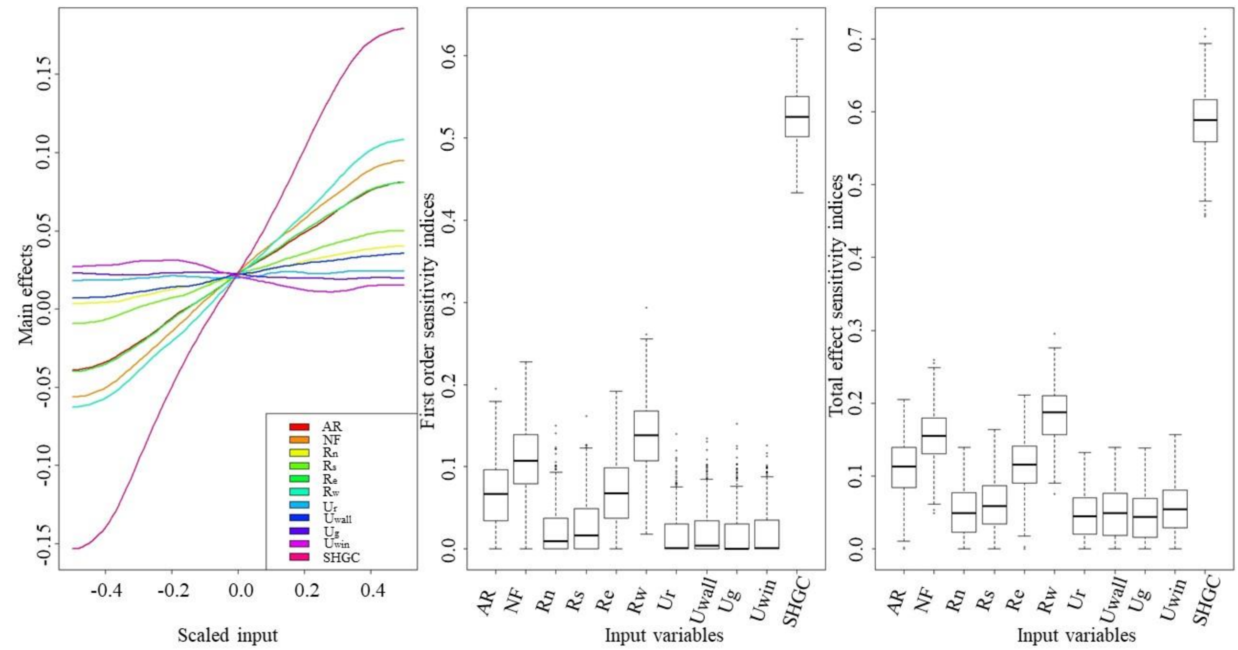

Fig. 2 The GSA plot of main effects, first order sensitivity indices and total effect sensitivity indices for peak cooling load (for full names of input variables, see Table 2)

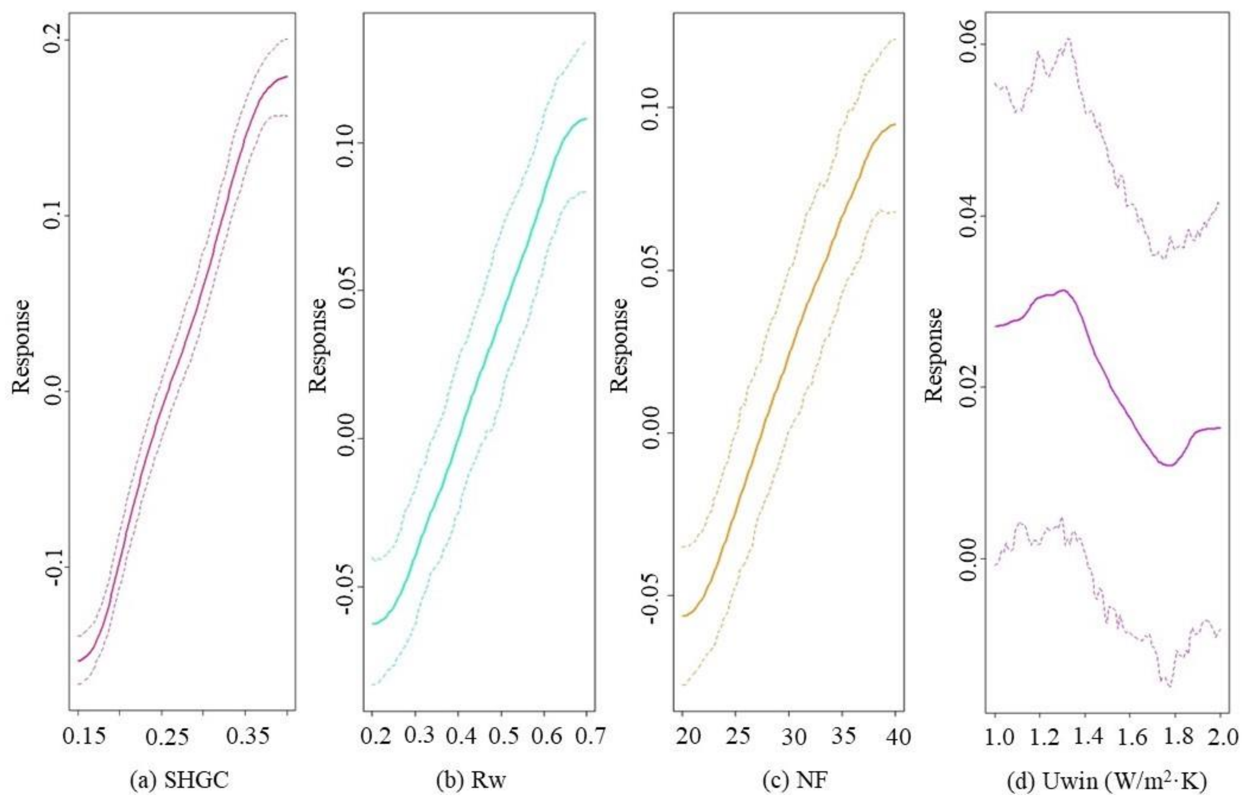

Fig. 3 The mean and 90 percent interval of the main effects of four important factors for peak cooling load: (a) SHGC; (b) Rw; (c) NF; (d) Uwin (for full names of input variables, see Table 2)

effects of four important factors for peak cooling load are shown in Fig. 3. The two dashed lines in this figure illustrate the 90 percent interval of the main effects, i.e. the lower and upper 5th percentile, respectively. Note that the unit for peak cooling load has been normalized with a mean of zero and a range of one for the purpose

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of comparison. As can be seen that there are linear relationships between peak cooling load and these three inputs of SHGC, Rw and NF. Therefore, an increase of SHGC, Rw and NF will lead to higher peak cooling load. More importantly, this figure can find the key nodes of variables that change the trend of output results. For example, the Fig. 5(d) clearly show that when the Uwin is about 1.35 $W/m^2 \cdot K$ or 1.8 $W/m^2 \cdot K$, there is an obvious inflection point in the output curve.

5. CONCLUSIONS

This paper focused on the application of sensitivity analysis to improve the building energy efficiency design. A comprehensive framework has been proposed to implement global sensitivity analysis at the early stage.

A new meta-model GSA based on TGP are implemented to identify and analyze key variables affecting peak cooling load. Besides the point estimate of sensitivity index, the variations of these sensitivity measures are also created to provide more robust analysis. Furthermore, the method used in this paper can also produce plots to show the main effects of varying each input on outputs. This type of figures can show not only the trend of loads change due to the corresponding input, but also quantify the relative change of thermal performance in building. This will help architecture designers to understand how the building cooling loads would be changed due to different energy saving measures.

To illustrate the methodology in a clear way, a case study has been used in this paper. The results show that the key factors affecting peak cooling load are solar heat gain coefficient (SHGC), west window to wall ratio (Rw) and number of floors (NF), and the interaction terms of input factors are not significant. This process makes it possible for designer or decision makers to carry out building energy efficiency design and optimization design scheme.

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