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Comparison of Sensitivity Analysis Methods in Building Energy Assessment

Song Yang[a], Wei Tian [a,b*], Eduard Cubi[c], QingXin Meng[a], YunLiang Liu[a], and Lai Wei[a]

[a]*College of Mechanical Engineering, Tianjin University of Science and Technology, Tianjin, China*
[b] *Tianjin Key Laboratory of Integrated Design and On-line Monitoring for Light Industry & Food Machinery and Equipment, Tianjin 300222, PR China*
[c] *Schulich School of Engineering, University of Calgary, Alberta, Canada*

Abstract

Sensitivity analysis is an important tool in building energy assessment to determine the key factors influencing energy use or carbon emissions for buildings. This research is focused on comparing the characteristics of four global sensitivity analysis: SRC (standardized regression coefficient), Morris design, extended FAST (Fourier Amplitude Sensitivity Test) and TGP (treed Gaussian process) method. A retail building located at Harbin (China) is used as a case study to demonstrate the advantages and drawbacks for these four methods. The results indicate that the TGP method (one of meta-modelling approaches) is the best choice in terms of both accuracy and computationally cost. Note that the TGP method needs more time to calculate the sensitivity index although it needs only moderate time for running building energy models. At least two fundamentally different methods for sensitivity analysis are recommended to be performed to provide more robust results in building energy assessment.

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*Keywords:*Sensitivity analysis; Building performance; Global method; Energy simulation

1. Introduction

Sensitivity analysis has been widely used in building energy analysis because it can not only provide prioritization of energy saving measures, but also explore the patterns of energy use for model calibration and energy optimization [1-4]. The sensitivity methods used in the field of building performance analysis can be categorized into local and global sensitivity analysis approaches [2].

* Corresponding author. Tel.: +086-22-60273495; fax: +086-22-60273495
E-mail address: tjtianjin@126.com

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More and more research has gradually implemented global methods because they can explore more thoroughly the relationship among inputs and outputs in the whole input space in order to provide more reliable energy saving measures. In contrast, the local sensitivity analysis can only study the relationship around the data points used in the analysis without considering the interactions among inputs [5]. The global sensitivity analysis can be further divided into four methods: regression-based, Morris design, variance-based, and meta-modelling [2]. Tian and Choudhary [6] used SRC (standardized regression coefficient) method to determine the key factors affecting energy use for London school buildings. Heo et al. [3] applied Morris design method to summarize the ranking of energy use intensity for office buildings located in the business district of Chicago. Spitz et al. [7] used the variance-based Sobol approach with 6669 simulation runs to determine the most influential parameters for an experimental house in France. Song et al. [8] implemented treed-based Bayesian Gaussian model (one of meta-modelling sensitivity analysis methods) for assessing the patterns of energy use of an office building located in London. However, there is lack of comparative study to demonstrate the advantages and disadvantages of various global sensitivity approaches in assessing building thermal performance.

Therefore, the aim of this study is to compare the suitability of four global sensitivity analysis methods (regression-based, Morris, variance-based, and meta-modelling) in assessing building energy performance. A retail building located in Harbin (China) is used as a case study for this purpose. More detailed information for the building used in this study will be described in the next section "Energy models".

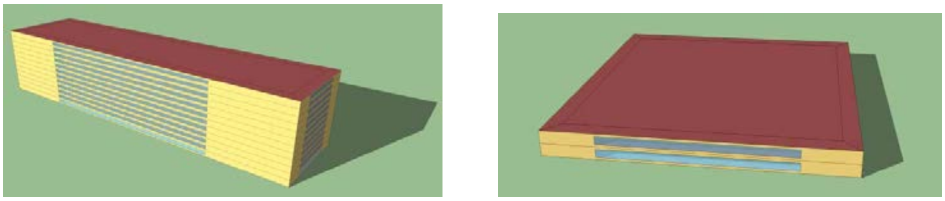
2. Energy models

A retail building considered in this study are assumed to be constructed after 2005. Hence, these buildings have construction standards commensurate with good practices based on the design standard for energy efficiency of public buildings in China [9]. The main parameters and detailed schedules are obtained from this energy efficiency standard [9].

Table 1.Variations of input parameters for sensitivity analysis of energy use in buildings

Variables	Short names	Range
Aspect ratio	X1	1,2,3,4 (building length/width)
Window-wall ratio	X2	0.2-0.8
Number of floor	X3	1-12
Orientation	X4	0~360o (0 denotes north)
Overall scale	X5	1000~5000 m^2 (main floor area)
Wall U-value	X6	0.1-0.5 W/m^2K
Roof U-value	X7	0.1-0.4 W/m^2K
Window U-value	X8	1.0-3.0 W/m^2K
Solar heat gain coefficient	X9	0.3-0.7
Lighting peak density	X10	12-19 W/m^2
Equipment peak density	X11	11-15 W/m^2

Table 1 shows the variations of input factors for sensitivity analysis in which the aspect ratio (X1) and number of floor (X3) are discrete variables and the remaining variables are continuous variables. The hourly schedules for all the internal heat gains (including occupants, lighting and equipment) are derived from the same standard [9]. A fan-coil system is used to provide heating, cooling, and ventilation. An electric screw chiller provides cooling and a gas-fried boiler provides hot water to maintain indoor thermal comfort. The operating time for this fan-coil system is from 8:00 to 21:00 [9]. The heating and cooling set-point temperatures are 18^{o}C and 25^{o}C, respectively [9]. The three output performance indicators are annual heating energy, cooling energy, and electricity per floor area (unit: kWh/m2). The buildings are located at Harbin in China [9]. The annual 99.6% dry bulb temperature for designing heating systems is -28.4^{o}C, while the 0.4% cooling dry bulb temperature is 31.1^{o}C [10].



(a)X1:4,X2:031,X3:12 (b)X1:1,X2:0.41,X3:2

Fig. 1. Two 3-D energy models (X1 aspect ratio;X2 window-wall ratio;X3 floor number)

The simulation is carried out with EnergyPlus program developed by USA Department of Energy [11]. Figure 1 illustrates two examples of energy models (created using EnergyPlus program) for retail buildings with different parameters as listed in Table 1. Figure 2 shows the flow chart used in this research, including two main steps: run multiple energy models; use these energy simulation results for sensitivity analysis. Detailed methods for creating the combination of these input factors will be described in the next section.

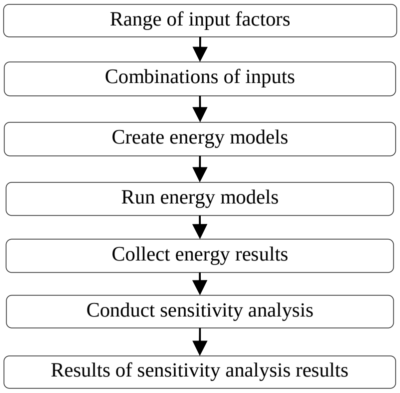


Fig. 2. Flow chart used in this research

3. Sensitivity analysis methods

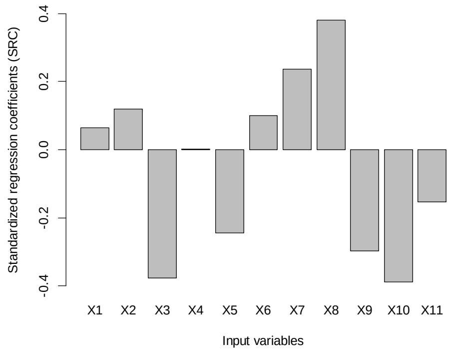
Four global sensitivity analysis methods are used in this study for the purpose of comparison, including regress-based, Morris, variance-based, and meta-modelling. R tgp [12] is used for meta-modelling sensitivity analysis and R sensitivity package [13] is applied for the other three methods. R is a language and environment for advanced statistical computing [14].

For regression-based method, the SRC (standardized regression coefficient) is the most popular choice in the field of building energy assessment [2]. This is because it is fast to compute and easy to understand. Compared with the common regression coefficient, the SRC removes the units of independent variables and their values are directly comparable for relative importance of input factors. A higher absolute SRC value means a more important variable. The negative values for SRC indicate that inputs and outputs tend to move in the opposite direction. The disadvantage of this method is only suitable for linear models. Before implementing SRC method, it is necessary to create energy models for retail buildings described in the last section. All these eleven factors in Table 1 are taken as uniform distributions since they are equally likely to occur in this research. Latin-hyper cube sampling method is used to propagate input factors because of its efficient stratified sampling strategy [2]. The sampling number is 110 based on the recommendation (10 times of input numbers) from Loeppky et al. [15]. R program [14] is used as a text editing language to automatically construct these 110 energy models.

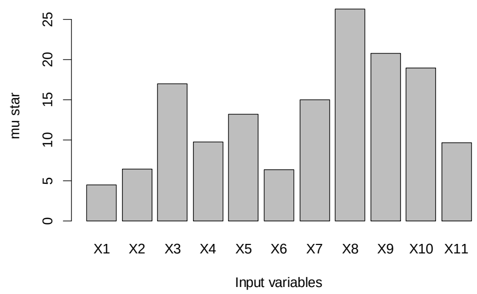
Morris design is an effective experimental design for sensitivity analysis [16]. The main advantage of this approach is less computationally expensive compared to the other three global sensitivity analysis methods. The two sensitivity measures from Morris method are μ* (mu star) and σ (sigma). For one specific input factor, the μ* indicates the overall influence on the output, while the σ can be used to determine whether there are interactions with other factors or non-linear effects. The higher μ* or σ means a more important factor.

FAST (Fourier Amplitude Sensitivity Test) is to explore the hyperspace of input variables with a periodic curve using a different frequency for every variable [16]. The next step is to decompose the variance of outputs using spectral analysis for each input factor. The classical FAST only considers the non-linear effect without including interactions among inputs. An extended FAST is used in this study to allow the computation of higher order terms [5]. The sensitivity analysis measures from this method are both main and total effects. The main effect is the overall influences for one variable but not considering interactions with other variables, whereas the total effects include both main effects and interactions between this input and other input factors. The larger the total or main effects for one specific variable, the more important this variable is. The variance-based Sobol method is also very useful, which is regarded as the most reliable approach [5]. The Sobol method is not used here because it is found that there are some issues on numerical instability after running preliminary studies. Even using 3600 simulation runs for EnergyPlus models, the results for sensitivity measures are still not converged.

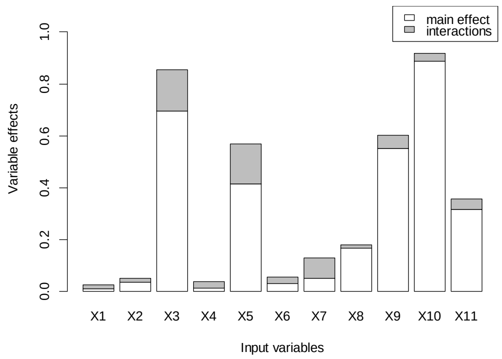
The meta-modelling sensitivity analysis is a two-step method: firstly create meta-models (also called surrogate models) from building engineering model; then run computationally cheap energy model based on variance-based method. In this study, a meta-model is firstly created using TGP method, a fully Bayesian non-stationary, semi-parametric non-linear regression technique. The extra advantage of this TGP sensitivity analysis is to incorporate the variability from the Monte Carlo estimation and the function output. More detailed information on this method, please refer to Gramacy and Taddy [12]. The sampling results for the SRC method are also used for this meta-modelling sensitivity analysis in this research.



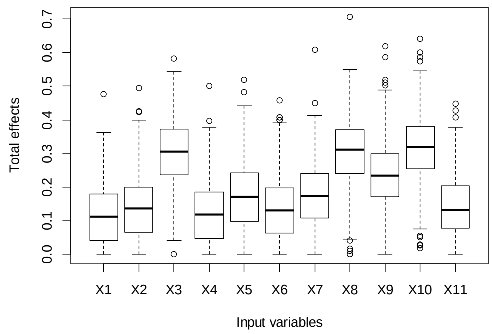
(a) Standardized regression coefficient (SRC)



(b) Morris design



(c) Extended Fourier Amplitude Sensitivity Test



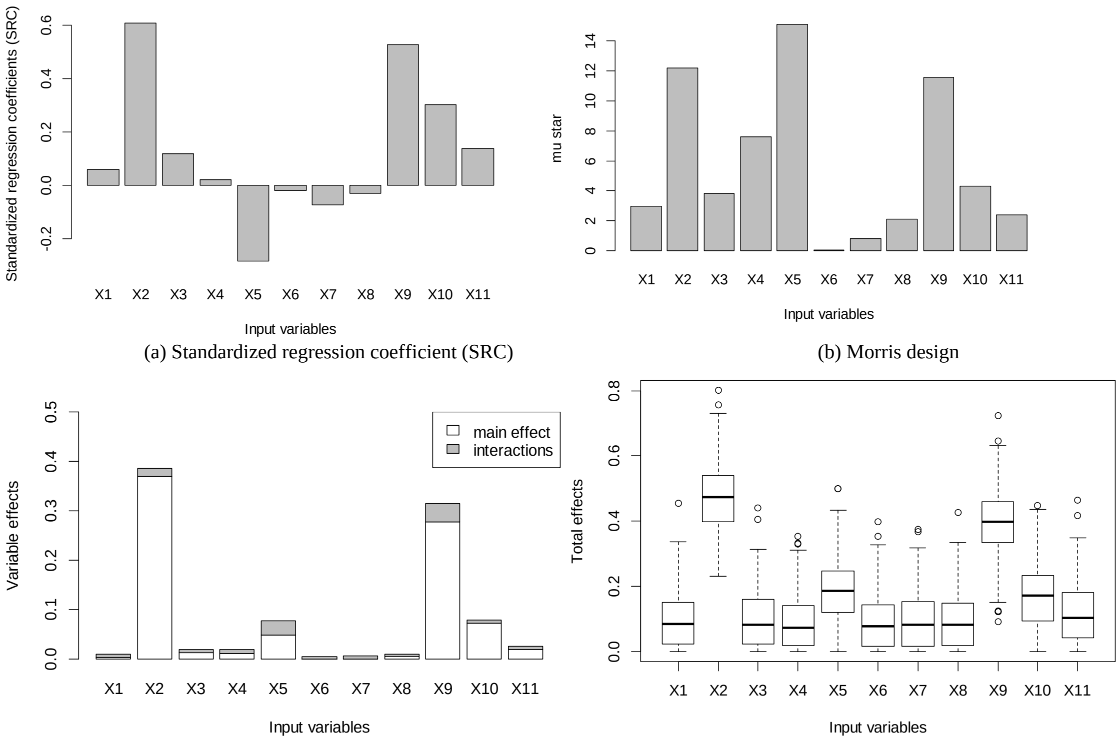
(d) Treed Gaussian model sensitivity

Fig. 3. Comparison of sensitivity analysis results from four methods for heating use

4. Results

4.1. Sensitivity analysis results for heating energy use

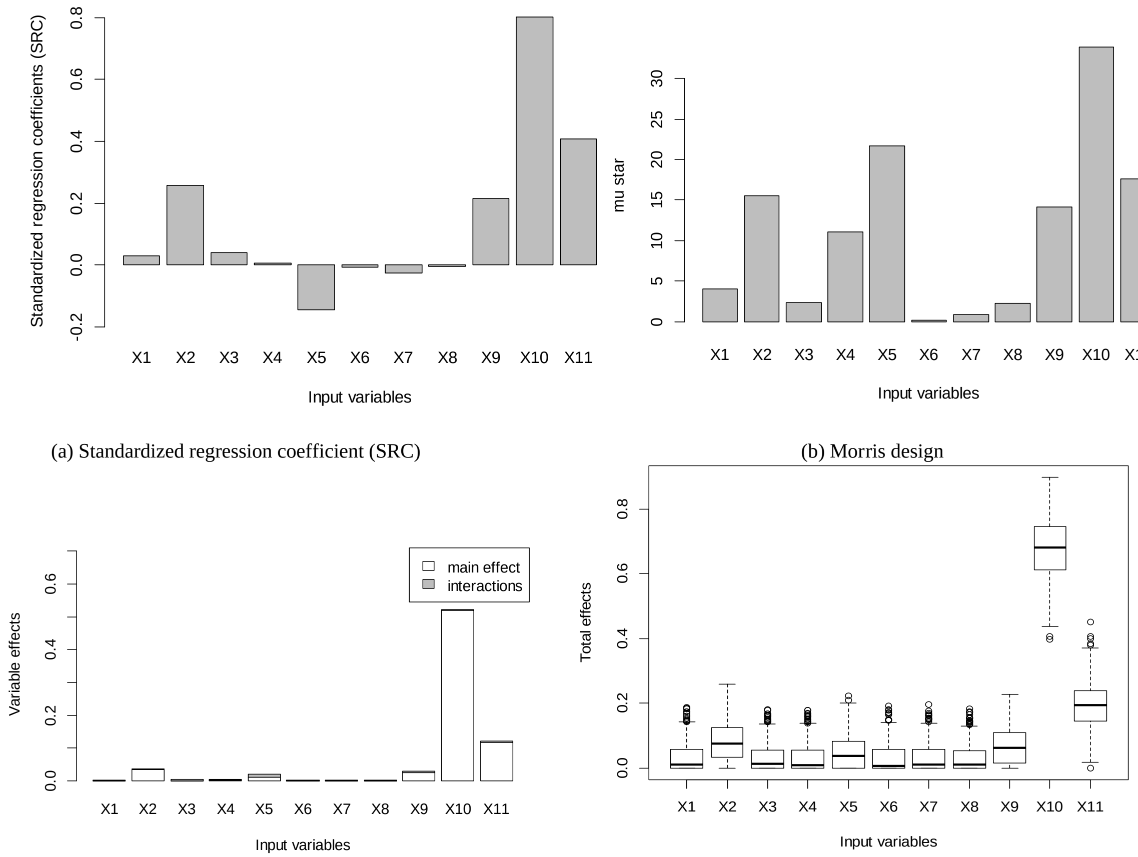
Figure 3 shows the results from sensitivity analysis for annual heating energy for this retail building. The variables of X3 (floor number), X9 (solar heat gain coefficient of windows), and X10 (lighting power density) are listed in the first four important factors from all the four methods although the rankings for these three factors are different. The X8 (window U-value) can also be seen as a very important variable except for the result from the extended FAST method. This may be due to the fact that the FAST method may be impractical for discrete distributions (Saltelli et al., 2012) and the number of floors (X3) is a discrete variable in this study. The method used here is firstly to obtain the values for a continuous variable and then convert them into discrete values using a specific interval. For example, if this value ranges from 0-0.1, then the floor number is taken as 1, and so on. Therefore, the X8 (window U-value) is not identified as an important factor from the extended FAST. This method does have some other advantages as shown in Figure 3c that the X3 (floor number), X5 (overall scale), and X7 (roof U-value) have more strong interactions with other variables influencing heat energy use. This finding is in agreement with the analysis from the Morris design in which the X3 (floor number) has the largest of σ value and the following two variables are X5 and X7. High σ values indicate strong interactions among input variables. The effect due to the variable of X4 (building orientation) is almost zero from the SRC method. This is because the influences cancel each out when the orientation changes from 0 to 360o. The relationship between the building orientation and energy use is a symmetrical sine wave as might be expected. Therefore, the findings from the SRC method based on the assumption of linear model may be misleading in this case. It is also found that the number of floors has non-linear effects on heating energy intensity according to the TGP method. The heating energy intensity would decrease sharply and then this trend becomes slow when the floor number varies from 1 to 12.



(a) Standardized regression coefficient (SRC) (b) Morris design

(c) Extended Fourier Amplitude Sensitivity Test (d) Treed Gaussian model sensitivity

Fig. 4. Comparison of sensitivity analysis results from four methods for cooling use



(a) Standardized regression coefficient (SRC)

(b) Morris design

(c) Extended Fourier Amplitude Sensitivity Test

(d) Treed Gaussian model sensitivity

Fig. 5. Comparison of sensitivity analysis results from four methods for electricity use

4.2. Sensitivity analysis results for cooling energy use

As can be seen from Figure 4, the results from three methods are quite similar, including the SRC, extended FAST, and TGP approaches. The two dominant factors affecting cooling energy use per floor area are X2 (window-wall ratio) and X9 (window SHGC) from these three methods. In contrast, the X5 (overall scale) is the most important factor based on the Morris design, which is very likely not the case in this study. Further study is required to find out the exact reason for this discrepancy between Morris and other three methods. One possible explanation is that more simulation runs are required for Morris design to obtain reliable results. The next two important factors from three methods (SRC, extended FAST, TGP) are also the same, X5 (overall scale) and X10 (lighting power density). The remaining variables only have slight influences on cooling energy use. Two factors with strong interactions are X5 (overall scale) and X9 (window SHGC) based on the revised FAST method. As discussed in the last section, the variable of X5 also has clear interactions for annual heating energy use shown in Figure 3c. Hence, the X5 may not be the key factor affecting both heating and cooling energy use for this retail building. However, care should be taken in analyzing the interaction among input factors, especially for the variable of X5 (overall scale, i.e. main floor area).

4.3. Sensitivity analysis results for electricity use

Figure 5 shows the comparison of results from four sensitivity analysis methods for annual electricity in this case study. The only dominant factor is the X10 (lighting power density) from all the four methods influencing annual electricity use per floor area for this retail building. Therefore, it is important to reduce electricity use by using the lights with high luminous efficacy (lm/W) for retail buildings. Luminous efficacy is a measure of the efficiency for a light source how well it can provide visible light from electricity. The following three variable are X11 (equipment peak density), X2 (window-wall ratio), and X9 (window SHGC) from the SRC, extended FAST, and TGP methods. Again, the results from Morris design are different from the other approaches. It is possible that the Morris design exaggerates the influences of X5 (overall scale) on electricity use, which also occurs for cooling energy use as described in the last section.

From the analysis above, the TGP method is the best choice in terms of result accuracy. The extended FAST method has problems in determining whether the X8 (window U value) is an important factor for heating energy analysis. For the Morris design, an issue occurs for the X5 (overall scale) when assessing cooling energy use. The SRC method cannot take non-linear effects into account.

4.4. Comparison of computational time

Table 2.Comparison of calculation time for four sensitivity analysis methods

Method	Number of EnergyPlus models	Calculation Time (s)	
		Energy simulation	Sensitivity measure
SRC	110	2,408	< 1
Morris design	60	1,335	< 1
Extended FAST	770	14,390	< 1
TGP	110	2,408	138

Table 2 compares the calculation time for four sensitivity analysis methods. The computational time mainly includes the time for EnergyPlus models and sensitivity measures. It is apparent that more time is required if the method for sensitivity analysis needs more simulation runs for energy models. As shown in Table 2, the time for running energy models is much larger than that for sensitivity measures. The simulation runs for energy models used a desktop workstation installed with two 10-core processors and 20 threads for a single CPU. As a result, this workstation can run 40 EnergyPlus models at the same time. It takes around 4 hours to finish all the EnergyPlus energy models (number of models: 770) when using the extended FAST method. The SRC and TGP methods have the same calculation time since the same sampling method has been used in this study. The Morris design is the least computationally expensive sensitivity analysis method in this case. As for the calculation time for sensitivity measures, the TGP method needs significantly more time compared to the other three methods due to the construction of complicated non-parametric models. This disadvantages of using the TGP approach can be offset by using multi-core computers with parallel computing to speed up the calculation.

5. Conclusion

This paper implements four global sensitivity analysis methods for energy assessment in a retail building, including SRC (standardized regression coefficient), Morris design, extended FAST (Fourier Amplitude Sensitivity Test), and TGP (treed Gaussian process) methods. The results indicate that the TGP method is the best choice based on overall performance for both accuracy and computational cost. The accuracy of sensitivity analysis is not easy to determine because it is impossible to run all the four types of sensitivity analysis in most of building energy assessment projects. Therefore, it is recommended to run at least two fundamentally different sensitivity analysis for building energy analysis. For instance, SRC and TGP methods can be used together since the same sampling results can be applied for both sensitivity approaches. The variance-based methods are too computationally expensive for most of building energy projects. The Morris approach may be used in the case of a large number of input factors that need to be considered in a project. After running Morris analysis, the SRC or TGP method can be also be implemented for sensitivity analysis using the same sampling results from Morris design. Further research will include more factors (HVAC system) and also study the generalization for other types of buildings (office and hotel) to provide more robust results.

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