Implementation of Meta-modelling for Sensitivity Analysis in Building Energy Analysis

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Abstract

Sensitivity analysis can provide invaluable insights in both creating building energy models and prioritizing energy saving measures. Thus sensitivity analysis has been widely applied in building energy analysis. A meta-modelling method for sensitivity analysis is a new approach that is still rarely used in assessing building energy performance. This method consists of two steps: firstly construct a meta-model from detailed dynamic building energy simulation; then implement a variance-based method using this meta-model. This paper implemented a meta-modelling method for sensitivity analysis based on the treed Gaussian process model for an office building. The results indicate that this method can show not only the trend of energy change due to the corresponding input, but also quantify the uncertainty of change of building thermal performance for every input. This will help both researchers and building managers to understand how the energy consumption would be changed due to different energy saving measures.

1 Introduction

Sensitivity analysis plays an important role in building energy analysis. It can be used in both creating building energy models and applying these energy models to prioritize energy efficiency measures (Yildiz et al. 2012; Hygh et al. 2012; Tian and de Wilde 2011; Domínguez-Muñoz et al. 2010; He et al. 2009).When creating building performance models, sensitivity analysis can provide an insight on how to choose important variables for model calibration whether using traditional or Bayesian methods. When implementing these energy models in building retrofit, sensitivity analysis can identify effective energy saving strategies. In these two types of application, the methods used for sensitivity analysis are the same. The difference between them is that the uncertainties of the variables (even variables themselves) are different. For instance, occupant behaviour has significant influences on building thermal performance and then these variables should be regarded as variables in calibrating models. However, not all the occupant behaviour can be regarded as energy saving strategies and consequently it is unnecessary to treat all occupant behaviour as variables in building retrofit analysis. This research will focus on the latter, i.e. assessing energy saving measures.

Sensitivity analysis can be divided into local and global methods (Saltelli et al. 2012; Tian 2013). In the field of building energy simulation, global sensitivity analysis has been increasingly applied to identify key variables influencing building thermal performance (Tian and de Wilde 2011; Yildiz et al. 2012). The advantage of using global methods is that this method would explore the whole input space. In contrast, local sensitivity analysis only concentrates on derivatives at a single data point (or a base case) (Saltelli et al. 2008; de Wilde and Tian 2010). There are many types of global sensitivity analysis, such as regression (Yildiz et al. 2012), screening method (Garcia Sanchez et al. 2014), variance-based (Spitz et al.

2012), meta-modelling . For detailed descriptions of these methods, please refer to (Saltelli et al. 2012; Levy and Steinberg 2010). For an overview on the application of sensitivity analysis in building energy analysis, please see (Tian 2013).

The meta-modelling method for sensitivity analysis is a new method among these methods and consists of two steps: firstly construct a meta-model from detailed dynamic building energy simulation; then implement a variance-based method using this meta-model (Saltelli et al. 2012). The meta-models, also called surrogate models, are statistical models which approximate the objective function using the design of computer experiments (Levy and Steinberg 2010). The variance-based sensitivity method is to determine the contributions of individual factors to the variance of the output. This method is appropriate for non-additive non-linear model because of its model independence (Saltelli et al. 2008). The combination of meta-models and variance-based method has several advantages in comparison with other approaches for sensitivity analysis. Firstly, it needs less simulation runs compared to variance-base method because the disadvantage of variance-based sensitivity analysis is very time-consuming for engineering models and the meta-models have low computational cost. Secondly, it is suitable for complicated relationships between inputs and outputs due to the use of variance-based method, while the regression methods are appropriate for linear or monotonic models. Thirdly, it can quantify output variances due to every input, whereas the screening methods are usually only for qualitative purpose. Furthermore, the method used in this paper can incorporate the uncertainty of both function outputs and integral estimation for sensitivity index, which are rarely used in most of sensitivity analysis methods (Gramacy and Taddy 2012). Lastly, the method applied in this study has a visual tool to show how the model output responds to every input factor (Gramacy and Taddy 2012), which can be very useful to show whether there are linear or non-linear relationships in the models.

The aim of this research is to implement a meta-modelling method for sensitivity analysis to identify key variables influencing annual heating, cooling, and carbon emissions in an office building. Furthermore, the variations of sensitivity index are also created to provide more robust analysis. The meta-models used in this paper is treed Gaussian process model (Gramacy and Taddy 2012), one of the state-of-art machine learning methods, to approximate non-additive non-linear relationships between inputs and outputs in a mathematical model. This method is suitable for exploring the relationship between building input factors and energy use. For instance, if the analyst is interested in investigating the effects of several building design parameters on energy use, this method can show how energy use would change with the variations of the corresponding input variables. This method firstly constructs an approximate statistical model (named treed Gaussian process model, TGP) based on engineering-based energy models to simulate complicated relationships between building inputs and energy use. Then this statistical energy model is used for sensitivity analysis based on a variance-based method by running this TGP model many times to obtain the contributions (i.e. expectation and variance) of every input factor and their interactions for building energy use.

This paper is structured as follows. Section 2 describes building energy models and meta-model sensitivity analysis methods used in this article. Section 3 presents the results from this meta-model sensitivity analysis.

2 Methodology

Building energy model

An air-conditioning office building is used as case study to demonstrate the application of meta-modelling sensitivity analysis. This is a five-storey building with the total floor area of 4000 m^2 as shown in Figure 1. The window-wall ratio is 40%. Fan coil with dedicated outside air system is used to maintain thermal comfort (Korolija et al. 2011). This system includes a four-pipe fan coil unit and a separate air system to meet ventilation demands (10 L s^{-1} per person) (CIBSE 2006). The hourly schedules for lighting, equipment, and occupant are from UK National Calculation Method (BRE 2012). Other inputs are treated as variables for sensitivity analysis listed in Table 1.

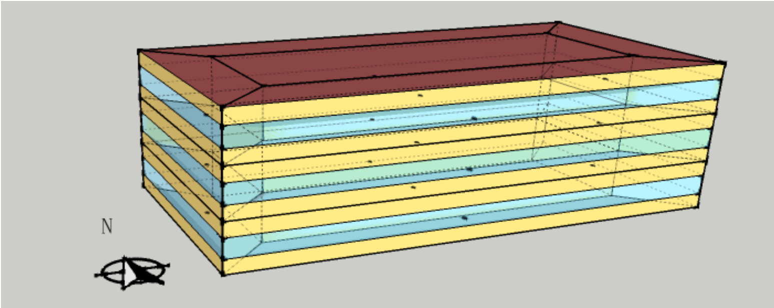

Figure 1: An office building in Google Sketchup

The energy simulation is carried out using EnergyPlus V7.1 (DOE 2012). EnergyPlus is a whole building performance simulation program, which has been tested extensively and widely used. EnergyPlus is suitable for this analysis because its input files are txt format, which are easily changed using computer languages. The weather data used in this paper is downloaded from EnergyPlus website for London Gatwick.

In this study, the thermal performance for this office building is assessed in terms of three outputs: annual heating energy, annual cooling energy, and annual carbon emissions. They are all normalized by building floor area. Annual heating and cooling energy are directly calculated from EnergyPlus models. Annual carbon emissions are computed from all the energy (heating, cooling, and other electricity) using carbon emission factors from UK government (UK Defra & DECC 2012). Carbon emissions here are defined as carbon dioxide equivalent (CO2e), which allows measuring global warming potential of different GHGs (greenhouse gases). The carbon emission factors for electricity and gas are 0.547 and 0.204 kg CO2e/kWh, respectively. These emission factors have included the factors from both direct and indirect emissions. The direct GHG emissions are emitted at the point of use of energy, while the indirect GHG emissions are emitted due to extracting and transforming the primary energy sources into site energy.

Variables used in sensitivity analysis

The building parameters are regarded as variables in sensitivity analysis listed in Table 1. These factors considered in this study can be divided into three categories: building envelope, internal heat gains, and HVAC system.

The input factors relating to building envelope include wall U value, roof U value, window U value and window SHGC (solar heat gain coefficient). These value ranges are from CIBSE documents and previous research (CIBSE 2006; Tian and de Wilde 2011; CIBSE 2005). The variations of U-values are obtained by changing the thickness of insulation layer in this study.

The input factors related to internal heat gains include peak equipment and lighting heat gains, the use of day-lighting. The peak equipment heat gains can be reduced by using more energy efficient equipment and this value may be also be changed based on occupancy density. The peak lighting gains can be decreased using high luminous efficacy light sources. The hourly schedules for both equipment and lighting are assumed to be the same in this analysis (BRE 2012). Day-lighting (400 lux) is used to reduce electric lighting energy consumption.

The third type of variables is related to HVAC (heating, ventilation, and air-conditioning) system. The heating and cooling set-point temperatures have been regarded as variables to explore the influences of these two factors. Heat recovery unit (HRU) has been installed in this building to reduce heating energy consumption. This HRU is a plate heat exchanger with the efficiency of 0.6 (CIBSE 2006). Furthermore, the effects of infiltration rate when ventilated will be investigated. For commercial buildings, the air-conditioning systems are typically designed to operate at slight pressurization in order to reduce infiltration (ASHRAE 2013). Therefore, the infiltrate rate is usually assumed to zero or very low ratios when building is ventilated (Langner et al.; Fernandez et al. 2012). This research also regards this factor as a variable in sensitivity analysis.

Table 1: Input parameters for sensitivity analysis

Type	Variable	Short name	Unit	Ranges
Building envelope	Wall U value	UW	$W/m^2 K$	0.1-0.5
	Roof U value	UR	$W/m^2 K$	0.1-0.4
	Window U value	UG	$W/m^2 K$	1-2.2
	Window SHGC	SH	-	0.2-0.5
Internal heat gains	Peak equipment gain	EH	W/m^2	10-15
	Peak lighting gains	LH	W/m^2	8-12
	Daylighting	DL	-	0 no; 1 yes
HVAC system	Heat recovery unit	HR	-	0 no; 1 - yes (0.5% efficiency)
	Heating setpoint temperature	HS	C	20-22
	Cooling setpoint temperature	CS	C	23-25
	Infiltration rate when building is ventilated	IR	ach (air changes per hour)	0-0.35

Meta-model sensitivity analysis

This study will use the meta-modelling of sensitivity analysis based on Treed Gaussian Process (TGP) to determine the key variables affecting building thermal performance. TGP is one of the state-of-art machine learning methods, developed by Gramacy (Gramacy and Lee 2008). Gramacy et al further developed this method to be suitable for sensitivity analysis (Gramacy and Taddy 2012). TGP couples stationary Gaussian process with treed partitioning. As a result, this TGP method provides a flexible and powerful nonparametric and non-stationary regression model. After constructing TGP models, sensitivity analysis can be used to identify key variables in the models by using variance-based method. The approach to sensitivity analysis used here is based on the Sobol method (Saltelli et al. 2008). Compared to other types of meta-model sensitivity analysis, the TGP method incorporates two types of variations for sensitivity index: uncertainty on function outputs; variability from integral estimation. For more detailed descriptions on BTGP method, please see (Gramacy and Lee 2008).

Two sensitivity indexes are used here: first order and total effects. The first order index is to represent the main effect contribution of each input variable to the variance of the output. In contrast, the total effect 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 effect for one input variable indicates the interactions between this variable and other variables. It should be noted that this method is not suitable for correlated inputs and for brief discussion on this point, please see (Tian 2013).

The sensitivity analysis can be divided into seven steps as shown in Figure 2.

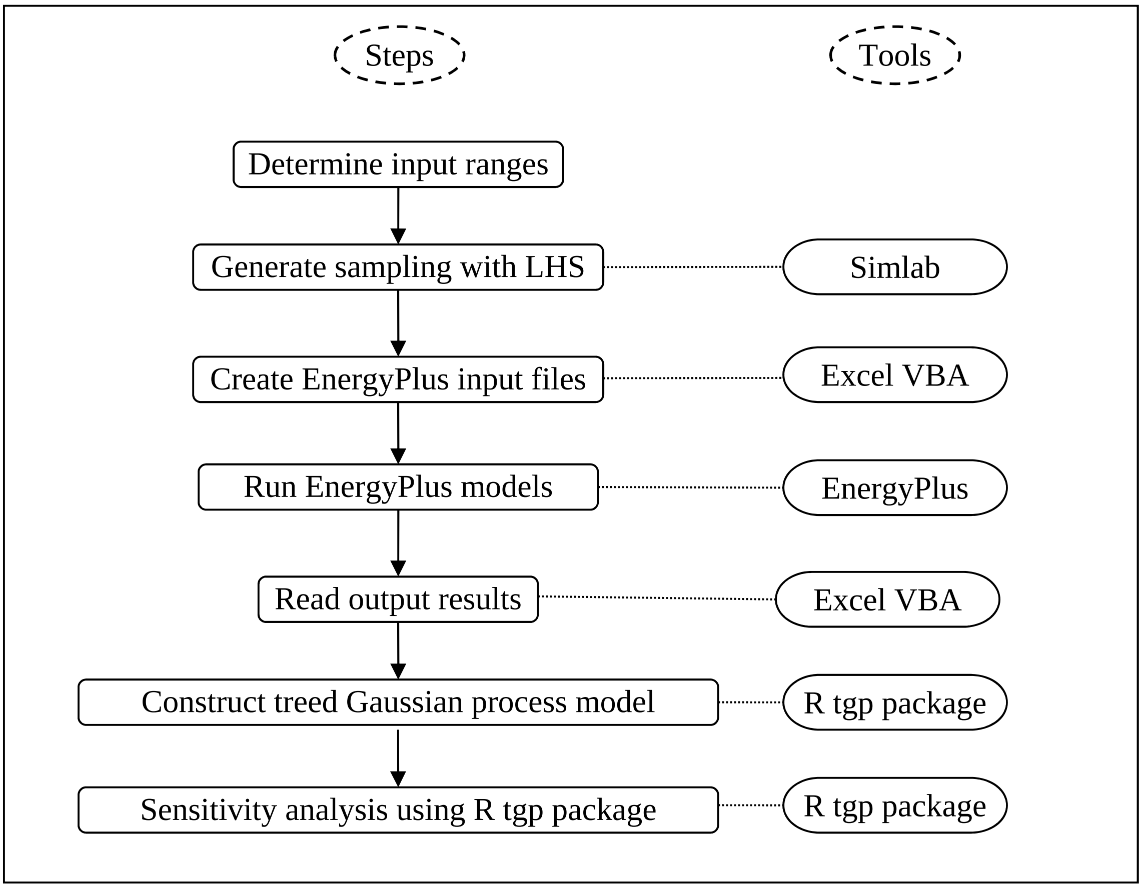

Figure 2: Schematic flow diagram for sensitivity analysis

The first step is to determine the distributions of the inputs. The purpose of this analysis is to understand the main factors affecting building thermal performance and prioritize the energy saving measures. Therefore, the distributions can be regarded as uniform distributions. If the research purpose is to quantify the uncertainty of potential energy use or calibrate building energy models, more specific distributions for different inputs are usually needed (Macdonald and Strachan 2001; Tian and de Wilde 2011).

The second step is to generate the combinations for the inputs. Latin-hypercube sampling is implemented here using Simlab (SIMLAB 2011). Simlab is a free tool for sensitivity and uncertainty with graphical user interface. Latin hypercube sampling is a very popular method suitable for computationally demanding models due to its stratification properties. The simulation runs are taken as 110 (10 times of the number of inputs) as suggested by Simlab and Levy et al (Levy and Steinberg 2010; SIMLAB 2011).

The third step is to automatically create 110 EnergyPlus models using Excel VBA. Excel VBA can use the sample from the last step to write the energy models. This is because

EnergyPlus input files are txt format, which is easy to process with simple script languages, such as Excel VBA.

The fourth step is to run EnergyPlus models. The total calculation time would be around 2 hours by using one core computer since every model takes around one minute. Since most of modern computers have multiple cores, the actual calculation time is less than 2 hours. In this case, it took approximately half an hour to finish all the calculation in a desktop with a quad-core processor.

The fifth step is to collect the calculation results from the last step. Excel VBA is used to automatically read the outputs from 110 simulation runs.

The last two steps are to use R tgp package for meta-model sensitivity analysis. R tgp package was developed by Gramacy (Gramacy and Taddy 2012). This package provides fully Bayesian non-stationary non-linear models (called treed Gaussian processes, TGP) and also has sensitivity analysis functions with this TGP model.

3 Results and discussion

This section will discuss the results from meta-modelling sensitivity analysis for this office building. The first three subsections will present the results for heating, cooling, and carbon emissions. The last subsection will summarize the results for all these three performance indicators. Note that in the following sub-sections, there are two figures for every output. For example, there are Figure 3 and Figure 4 for annual heating energy. The first figure (Figure 3) is to show the first-order and total effects on output variable using two subplots, respectively. The difference of two subplots for the same variable is to demonstrate whether there are interactions between this variable and other variables. The second figure (Figure 4) is to show both the main effects (without considering the interactions) of a building input factor on the output variable and the variances of this sensitivity indicator. This explanations is also applied to annual cooling and carbon emissions in this paper.

Heating Energy

Figure 3 shows the box plots for the first order and total effects of all the eleven variables influencing annual heating energy. As can be seen from this graph, using heat recovery unit is the most important factor affecting heating energy use. 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 heating set-point temperature and window U-value. The remaining factors provide only a minor contribution to the uncertainty in heating energy consumption. As a result, the effective measures for reducing heating energy in this building include the use of heating recovery unit, slightly decreasing heating set-point temperature, and improving window thermal performance. As also can be seen from Figure 3, the total effects for most of variables are very similar to the first order effects. Hence, the interactions between the variables are not significant in this case.

Figure 4 shows the change of the heating energy due to the first three important factors identified from Figure 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 annual heating energy has been normalized with a mean of zero and a range of one for the purpose of comparison. As expected, an increase of either heating set-point temperature or window U-value would increase annual heating energy consumption. Therefore, these trends can be used to validate the results from sensitivity analysis. More importantly, this figure can compare the magnitude of change in output due to different inputs. For example, this figure clearly show that the use of heat recovery unit has more benefits for heating energy use than installing new windows by decreasing window U value from 2.2 to 1.0 W/m2 K. As also be seen from this figure, there are linear relationships between annual heating energy and two inputs (heating set-point temperature and window U value). Moreover, this figure also illustrates the uncertainty of heating energy using different energy saving measures.

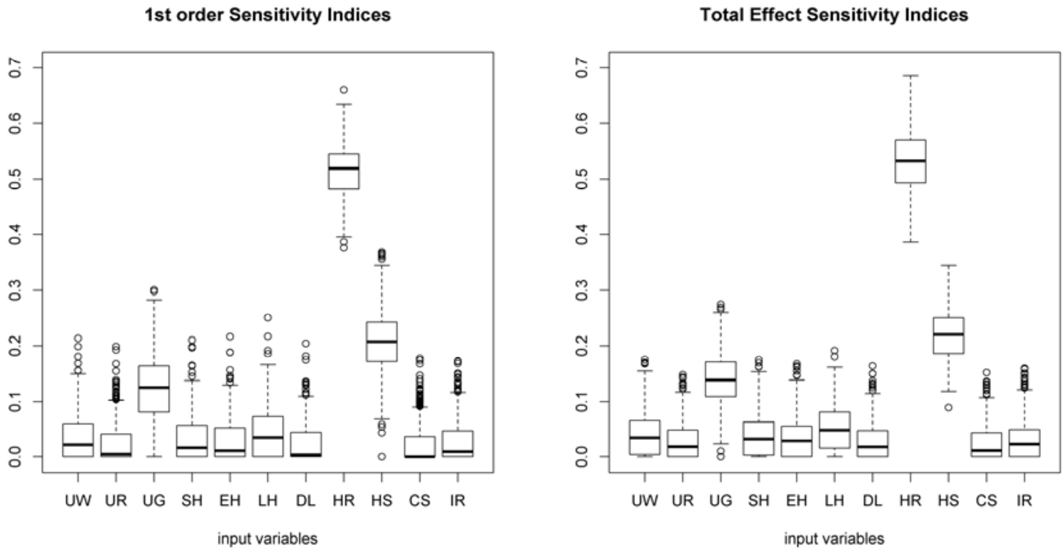

Figure 3: The first order and total effect sensitivity indices for annual heating energy (for full names of input variables, see Table 1)

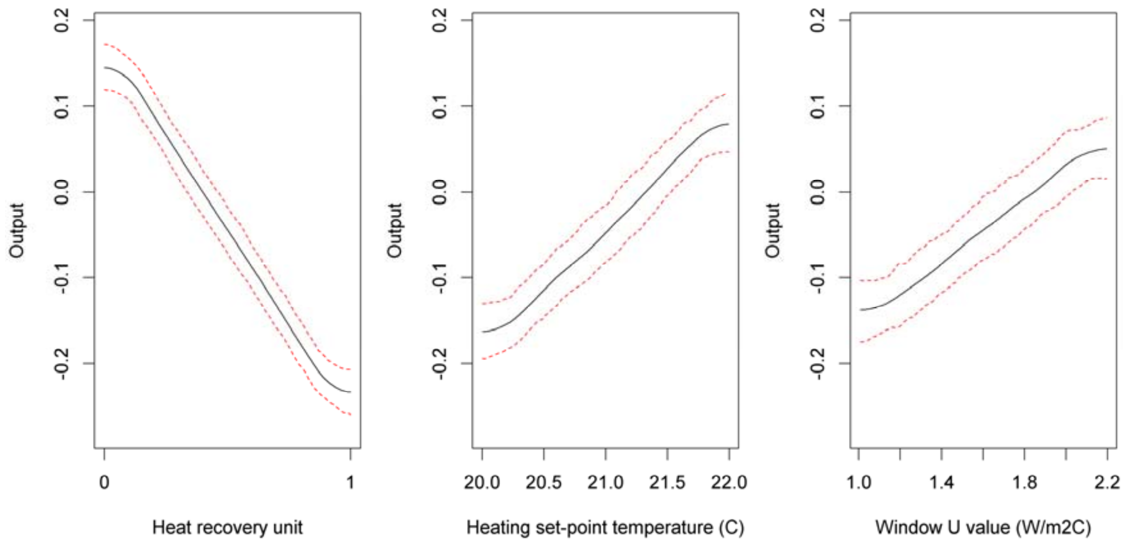

Figure 4: The mean and 90 percent interval of the main effects of three important factors for annual heating energy

Cooling Energy

Figure 5 shows the first order and total effects of sensitivity indices for all the eleven input factors which affect annual cooling energy. The solar heat gain coefficient (SHGC) of windows is a dominant factor in this case as shown in this figure. Window SHGC is responsible for around 50% of the variance of the output, which is markedly higher than any other factors in terms of both the first order and total effects of sensitivity index. Therefore, it is very important to install low SHGC windows or external shading in order to reduce cooling energy demands in this building. The next four variables have similar effects, which include day-lighting, cooling set-point temperature, lighting and equipment peak heat gains. These four factors account for more than 40% of the total variations of the output. Hence, internal heat gains due to lighting and equipment also have important influences on cooling energy use. The remaining factors only contribute small proportions of variations for annual cooling energy.

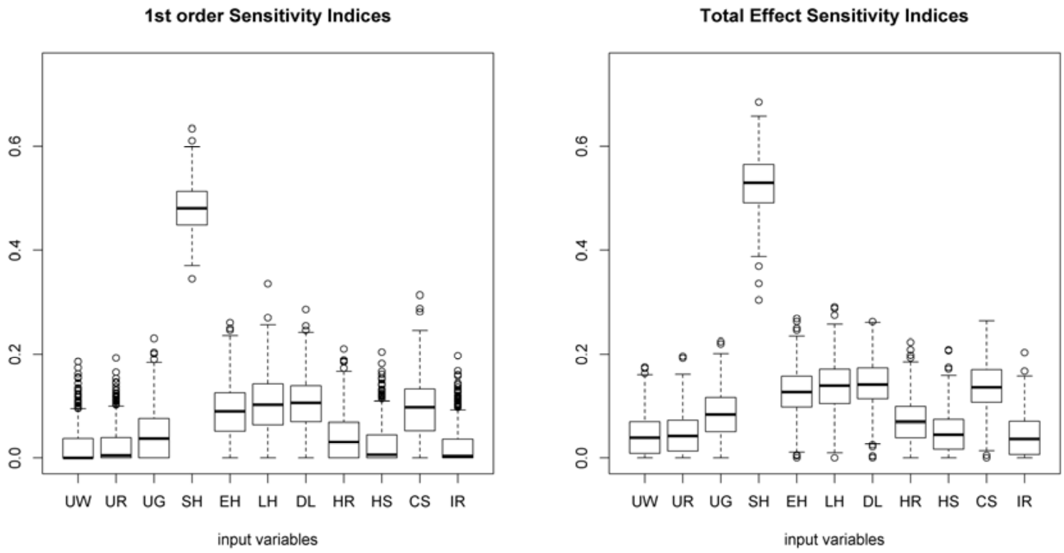

Figure 5: The first order and total effect sensitivity indices for annual cooling energy (for full names of input variables, see Table 1)

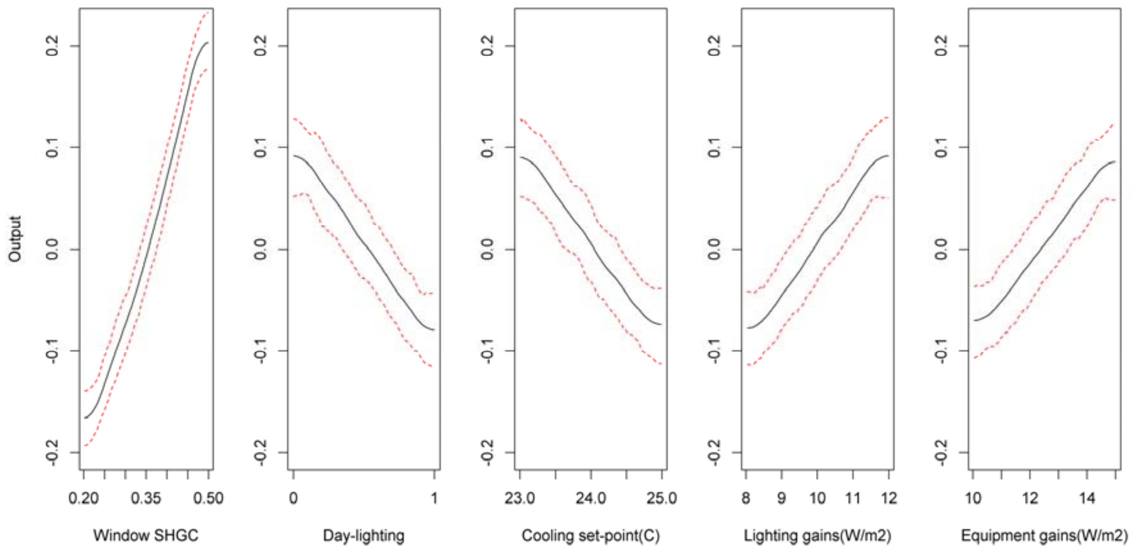

Figure 6: The mean and 90 percent interval of the main effects of five factors for annual cooling energy

Figure 6 shows the change of the output due to the first five important factors determined from Figure 5. The two dashed lines in this figure denote the 90 percent interval of the main effects. This figure further confirms that the change of SHGC would lead to significant variations of cooling energy use compared to the other four factors. As also can be seen from this figure, using day-lighting and increasing cooling set-point temperature would result in a decrease in annual cooling energy. These patterns are expected. The interesting point is that all these changes are almost linear as shown in Figure 6.

Carbon emissions

Figure 7 shows the first order effects and total effects of sensitivity measures for all the eleven input factors affecting annual carbon emissions. The first three important factors are lighting peak gain, using day-lighting, and equipment peak heat gain. Two box plots for day-lighting and equipment gains have significant overlapping, which indicate the actual effects for these two variables may be very similar. These three variables can account for around 73% of the output variation based on the first order effects. In terms of the total effects (by including interactions between these three factors and any other factors), they can be responsible for around 82% of the output variation. Hence, in order to reduce carbon emissions from this building, the priorities are to reduce lighting and equipment consumption.

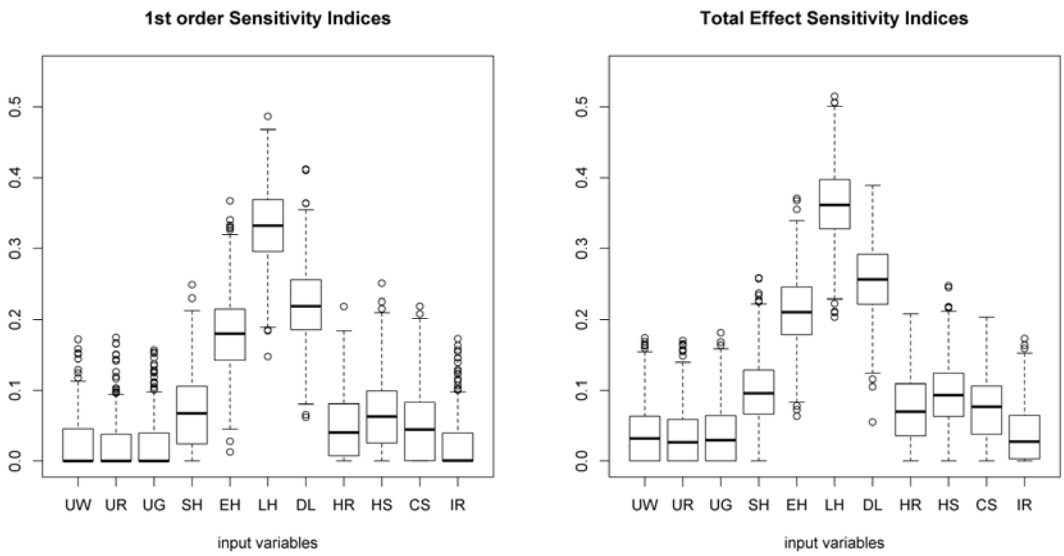

Figure 7: The first order and total effect sensitivity indices for annual carbon emissions (for full names of input variables, see Table 1)

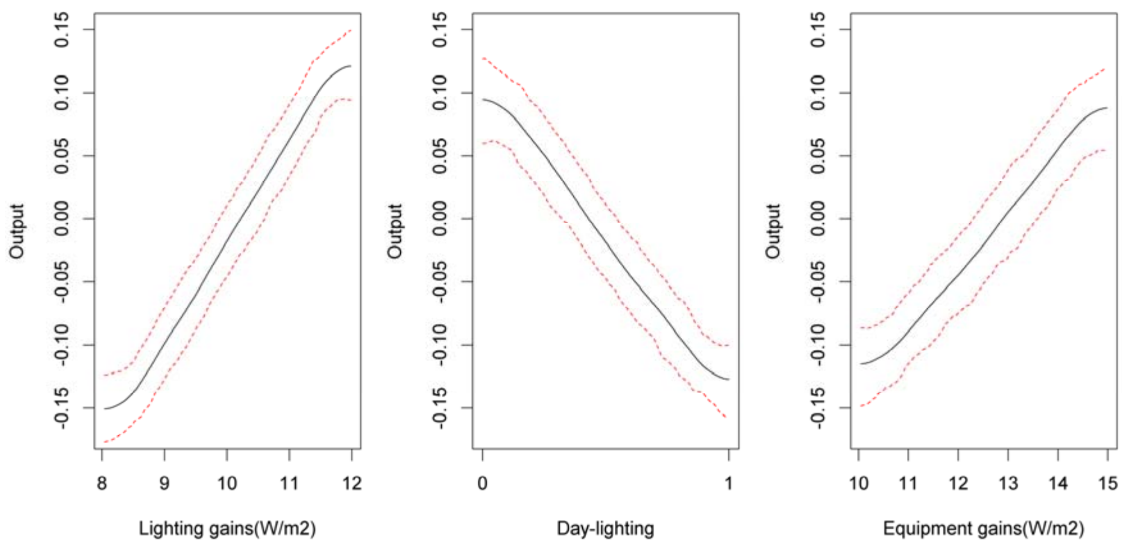

Figure 8: The mean and 90 percent interval of the main effects of three important factors for annual carbon emissions

Figure 8 shows the change of annual carbon emissions due to three important inputs. The increase of both equipment and lighting would increase cooling energy. It is also found that the relationship between lighting (or equipment) heat gains and carbon emissions is almost linear in this case.

Summary

From the discussion above, the key factors are very different in terms of heating and cooling energy use. This means that reducing internal heating gains are effective measures for decreasing cooling energy, but not necessarily significantly increase heating energy in this building. This is because the internal heat gains from equipment and lighting are important factors affecting cooling energy, while they are not key factors influencing heat energy. Heating energy can be reduced by adding heat recovery unit, more flexible heating set-point temperature, and installing high thermal performance windows.

As shown in Figures 3, 5 and 7, the interactions are not very significant for all the three outputs (heating, cooling, and carbon emissions). The interactions between the variables are more significant for cooling and carbon emissions than those for annual heating energy consumption. The interaction terms can account for extra 15% of the output variances for both cooling and carbon emissions. For heating energy, these interactions are only responsible for 3% of the output variances.

As shown in Figures 4, 6, and 8, the relationships between inputs and outputs are approximately linear for all important variables. This means linear models can be used to approximate the relationship between inputs and outputs in this case.

4 Conclusions

This paper implemented meta-modelling sensitivity analysis to identify key variables affecting building heating, cooling, and carbon emissions in an office building in the UK. 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 energy change due to the corresponding input, but also quantify the relative change of thermal performance in building. This will help both researchers and building mangers to understand how the energy consumption would be changed due to different energy saving measures.

For this case study building, the following conclusions can be drawn. Note that these conclusions may not be suitable for other buildings.

(1) For annual heating energy, the three most important factors are heat recovery unit, heating setting-point temperature, and Window U-value.

(2) For annual cooling energy, the dominant variable is solar heat gain coefficient (SHGC). The other four variables also have important effects, which include cooling set-point temperature, day-lighting, peak lighting and equipment heat gains.

(3) For annual carbon emissions, the important factors are internal heat gains from lighting and equipment.

(4) The outputs are mainly driven by main effects and the interaction terms are not significant in this case. Interactions have more effects on cooling energy and carbon emissions than heating energy consumption.

(5) The relationships between inputs and outputs are approximately linear in this case.

5 Acknowledgements

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