SENSITIVITY ANALYSIS OF BUILDING ENERGY PERFORMANCE BASED ON POLYNOMIAL CHAOS EXPANSION

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ABSTRACT

Global sensitivity analysis based on polynomial chaos expansion (PCE) shows interesting characteristics, including reduced simulation runs for computer models and high interpretability of sensitivity results. This paper explores these features of the PCE-based sensitivity analysis using an office building as a case study with the EnergyPlus simulation program. The results indicate that the predictive performance of PCE models is closely correlated with the stability of the sensitivity index, depending on sample number and expansion degree. Therefore, it is necessary to carefully assess model accuracy of PCE models and evaluate convergence of the sensitivity index when using PCE-based sensitivity analysis. It is also found that more simulation runs of building energy models are required for a higher expansion degree of the PCE model to obtain a reliable sensitivity index. A bootstrap technique with a random sample can be used to construct confidence intervals for sensitivity indicators in building energy assessment to provide robust sensitivity rankings.

KEYWORDS

sensitivity analysis, building energy, polynomial chaos expansion, model accuracy

INTRODUCTION

Building energy simulation has been widely used to assess energy performance for new or existing buildings [1, 2]. A large number of simulation models are often required for energy optimization or model calibration to provide robust results [3]. Sensitivity analysis can be used to reduce computational cost for these problems by choosing key variables influencing building energy performance [4, 5]. Global sensitivity analysis has generally received more attention since this global technique can explore the full parameter space of inputs in order to evaluate complex nonlinear and interaction relationships among inputs and outputs in buildings, compared to local sensitivity analysis methods [4, 6]. Various types of global sensitivity analysis have been used in building energy assessment [7, 8]. Menberg et al. [6] compare the characteristics of three global sensitivity analysis methods, including the Morris method, linear regression, and

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variance-based Sobol method, in the context of building energy modelling. Delgarm et al. [9] investigate the choice of energy saving measures in the early phase of building design based on variance-based sensitivity analysis. Tian et al. [10] apply a sequential sensitivity analysis to evaluate the convergence of global sensitivity analysis results based on meta-model methods. Mastrucci et al. [11] simplify the housing stock model of Esch-sur-Alzette (Luxembourg) by using two types of global sensitivity methods (elementary effects and Sobol). Among these global sensitivity analysis methods, meta-modelling sensitivity analysis can reduce the computational cost of sensitivity analysis at the price of slightly reducing accuracy of energy estimation [12]. Hence, it is important to assess the prediction performance of meta-models in building energy analysis when implementing a meta-modelling sensitivity approach. The common meta-modelling sensitivity analysis methods are to compute Sobol indices using the Monte Carlo sampling methods after obtaining meta-models [13], which means that the meta-models need to be run a large number of times. In contrast, the polynomial chaos expansion (PCE) sensitivity analysis method [14, 15] has interesting characteristics of easy interpretation and low computational cost. This is because the PCE surrogate model can compute Sobol indices analytically from the PCE coefficients [16]. However, there are only a few studies that implement this PCE-based global sensitivity analysis in the field of building energy assessment [17]. Faggianelli et al. [17] apply the polynomial chaos expansion sensitivity analysis to compare the performance of three types of sampling methods (random, Latin hyper-cube, and quasi Monte-Carlo) in building energy analysis. There are still a number of issues that need to be explored when applying this PCE-based sensitivity analysis in building energy analysis. Key issues to explain are the connection between model accuracy and stability of the sensitivity index of PCE models, and how to construct confidence intervals of the PCE sensitivity index to provide more informed results in building energy assessment.

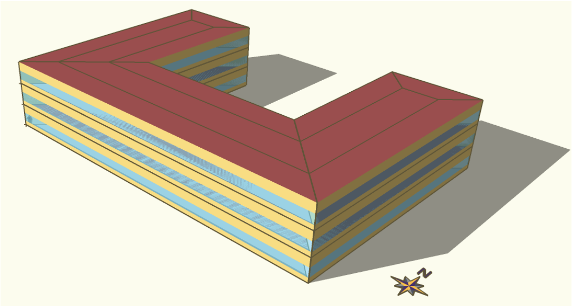
Therefore, this paper explores the characteristics of PCE-based sensitivity analysis in building energy assessment. An office building is used as a case study to demonstrate the application of the PCE-based sensitivity method. The main contributions of this paper are two-fold. One is to make connections between model accuracy and stability of sensitivity index in order to better explain the results in determining key variables influencing building energy performance. The other is to construct confidence intervals of the PCE sensitivity index in order to make informed decisions in building energy design or retrofitting. Moreover, the importance of assessing the stability of the sensitivity index has been discussed in this research, which is often ignored in the field of building simulation.

METHODS

Building energy models

Figure 1 shows a U-shaped office building used in this study, located in Tianjin, China. This is a three-storey building with a total floor area of 4850 m^2 and a window-wall ratio of 40%. The parameters of building envelope and HVAC system for this building are consistent with the energy efficiency standard of commercial buildings in China released in 2015 [18]. The hourly schedules for occupants, lighting, and equipment are also derived from this standard code [18]. A VAV (variable air volume) system with a gas boiler and a centrifugal chiller is used to provide heating, cooling, and ventilation to maintain thermal comfort in this building. Note that the office building used in this paper is a notional building in accordance with the latest China building code for the purpose of evaluating characteristics of the PCE sensitivity method.

FIGURE 1. The office building used in this study.



Hence, there is no need for calibrating the building energy model in this case study since there are no actual measurements of energy use for this office building.

The parameters and associated values used for sensitivity analysis are listed in Table 1 [18, 19]. It is assumed that these parameters follow uniform distributions since they are design parameters with equal probabilities within the intervals specified in Table 1. Random sampling and Latin hyper-cube sampling (LHS) methods [20] are used to obtain the combinations of these parameters to compare the suitability of PCE models in building energy assessment. Different sampling size numbers from 30 to 500 are applied to evaluate the stability of PCE results. The 'R lhs' package is used to generate Latin hypercube samples [21]. The EnergyPlus V8.8 program, which has been intensively validated and widely applied in building energy simulation, is used to compute the energy use of this office building [22]. The two main performance measures are annual heating and cooling energy normalized by total floor area (unit: kWh/m^2). The R program [23] is used to automatically edit and run EnergyPlus models since thousands of simulation runs are required in this study.

Polynomial chaos expansion

It is assumed that there is a computational model $y = G(x)$, where x denotes independent variables with the dimension of d, and y denotes dependent variables. The x is described by a probability density function $fx(x)$. The dependent variable y in most engineering problems can be expressed using spectral representation with a new set of random variables z and the corresponding coefficients y_j where j is from 0 to ∞ [24]. The new set of z is multivariate orthonormal

TABLE 1. Parameters used for sensitivity analysis.

Factor	Short names	Unit	Range
Wall U-value	WU	W/m^2K	0.2–0.4
Roof U-value	RU	W/m^2K	0.1–0.3
Window U-value	GU	W/m^2K	1–2.5
Solar heat gain coefficient	SH	—	0.2–0.5
Lighting power density	LD	W/m^2	8–10
Equipment peak value	ED	W/m^2	14–16

polynomial in the input variables x based on the polynomial chaos expansions. If the $fx(x)$ density functions are standard functions, the associated families of orthogonal polynomials are readily available [16]. For uniform distributions, the resulting family is that of the Legendre polynomials. For standard normal distributions, the resulting family is that of the Hermite polynomials. More families of orthogonal polynomials associated to standard distributions are available [14]. For nonstandard distributions, it is necessary to transform these distributions to standard distributions. For instance, the non-standard uniform or normal distributions can be changed to standard forms using linear functions [14].

The expansion degree (j in y_j) is usually truncated for computational purposes to a specific value using truncation schemes, typical 3–5 [14]. The number of unknown coefficients is (d + p)! / (d! p!) in the PCE model [16]. PC coefficients can be computed using two non-intrusive methods: projection and regression. The projection method is based on the orthogonality of the basis function to minimize the distance between the function and its surrogate. The regression method is similar to the response surface methods to create approximate relationships among inputs and outputs using experimental design approaches. Here the regression method is used based on [24] since it is more suitable for various types of DOE (design of experiments) methods and more stable for noisy training data, especially in the case of low-dimension inputs. The PCE and Sobol decompositions are both sums of orthogonal function. As a result, the Sobol sensitivity indices can be analytically derived from the PCE coefficients [15]. The first coefficient (i.e. constant term) of PCE is the mean value of model output, and the variance of output is the sum of squares of the remaining coefficients. Two types of sensitivity indicators are usually used in Sobol sensitivity analysis: 'main effects' and 'total effects'. The main effect of a specific variable denotes the separate influence of this variable on outputs without considering the effects of other variables. In contrast, total effects take into account the influences of both this variable and interactions with other variables under consideration. Main and total effects can be computed using the weighted sum of squares for the selected PC coefficients in PCE models. Higher-degree interaction effects can be also easily obtained using the same method and the interaction degrees are dependent on the expansion degree used in the truncation process of PCE models. The R polychaosbasics package is used to obtain the PCE-based sensitivity index [25].

RMSEP (root mean square error in prediction) is used to assess the performance of regression for expansion coefficients. The RMSEP is calculated by the square root of the PRESS (predicted residual error sum of squares) divided by the number of data [25] in which the PRESS is computed based on the cross validation method in regression analysis. Hence, the RMSEP can provide reliable out-of-sample performance of regression models. A lower RMSEP value means a more accurate regression model. In the specific case in this paper, RMSEP (unit: kWh/m^2) can be interpreted as average deviation between EnergyPlus simulation results and predictions of PCE regression models, although this value remains sensitive to outliers.

RESULTS AND DISCUSSION

Regression performance of PCE models

The expansion coefficients are obtained from the least square method. Therefore, it is necessary to assess the regression performance for polynomial chaos expansion models before implementing the PCE models for sensitivity analysis. Table 2 shows the regression performance for building energy estimation at the expansion degrees of 2 and 3 using the Latin hyper-cube and random sampling methods for annual heating and cooling energy, respectively. Note that the number of coefficients in the PCE model is 28 at the expansion degree of 2 and the number of coefficients in the PCE model is 84. The sampling size of energy models cannot be less than these numbers for the corresponding degree number to obtain regression equations using the ordinary least square method. This is the reason for different initial sample numbers in Table 2.

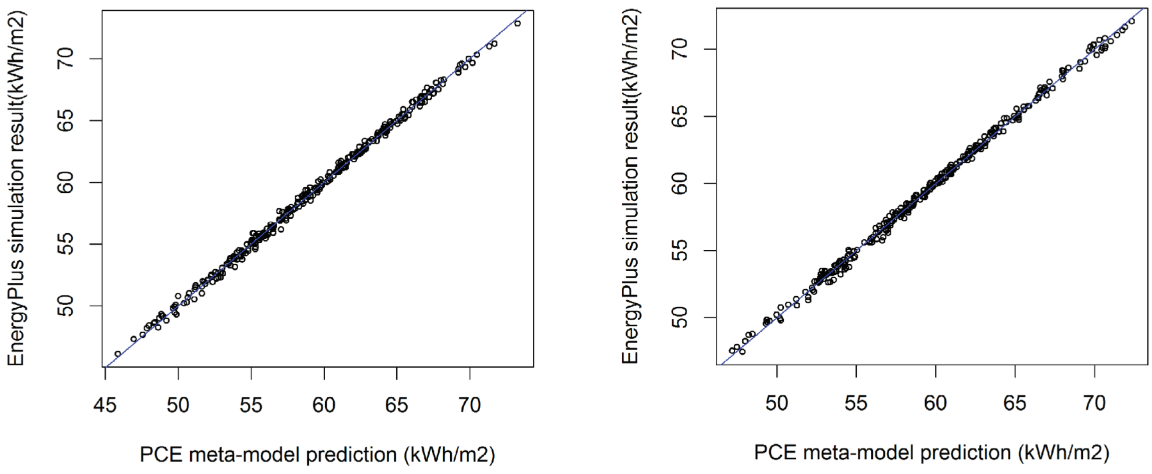
Table 2 indicates that the RMSEP for heating energy use would decrease with an increase in sample size using Latin hyper-cube sampling at the expansion of degree 2. Hence, a sufficient sample size is required to obtain reliable PCE models. The improvement of model accuracy is very limited for large sample size, for instance, from 400 to 500. The same trend can be also observed for cooling energy, where again more simulation runs can be helpful to obtain accurate PCE models. It is also found that the predictive capability is slightly worse for cooling energy than that for heating energy in terms of RMSEP. Therefore, there are more complex relationships among inputs and outputs for cooling energy in comparison with heating energy in this case study. Table 2 also shows the regression performance as a function of sample size for heating and cooling energy at the expansion of degree 2 using Monte-Carlo random sampling. For both heating and cooling energy, the RMSEP values would be reduced with an increase of sample size, which is the same as the conclusion obtained from Latin hyper-cube sampling method.

It is observed that the sampling method (LHS or random) has a strong impact on the model accuracy of PCE in this case study. For a sample size of 30, the low sample size does not yield sufficient data to produce reliable PCE models for both LHS and random sampling methods. As a result, the RMSEP values are higher for these two sampling methods. When the sample size is above 30 for the expansion degree 2, the accuracies from LHS are higher than those from random heating and cooling energy use. However, this is not the case for the expansion degree 3. This indicates that the influence on sampling methods varies a lot, depending on performance measure, expansion degree, and sample number. By comparing the results from expansion degrees 2 and 3 in Table 1, the RMSEP values for heating energy are smaller

TABLE 2. Predictive performance (RMSEP) of PCE models as a function of sample number, sample method, and expansion degree for annual heating and cooling energy use.

Sample number	Heating				Cooling			
	Expansion degree 2		Expansion degree 3		Expansion degree 2		Expansion degree 3	
	LHS	Random	LHS	Random	LHS	Random	LHS	Random
30	5.646	1.508	—	—	38.567	2.837	—	—
50	0.385	0.512	—	—	0.772	0.914	—	—
75	0.396	0.440	—	—	0.723	0.832	—	—
100	0.340	0.371	1.251	0.866	0.604	0.696	2.180	1.783
200	0.332	0.346	0.326	0.312	0.623	0.634	0.562	0.541
300	0.326	0.328	0.283	0.260	0.587	0.599	0.496	0.461
400	0.293	0.319	0.246	0.240	0.542	0.585	0.436	0.425
500	0.293	0.321	0.223	0.233	0.537	0.597	0.404	0.417

FIGURE 2. Comparison of EnergyPlus simulation and PCE model outputs at the expansion degree 3 and sample number 300 for annual heating energy use.



(a) Latin hyper-cube sampling (b) Random sampling

at the degree of 3 than those at the degree of 2 in the case of same sample number except for the sample number of 100. Hence, the increase of expansion degree can increase PCE model accuracy as long as sufficient sample size is attained to obtain all the coefficients required for PCE models. For the cooling energy, the same conclusion can be also reached.

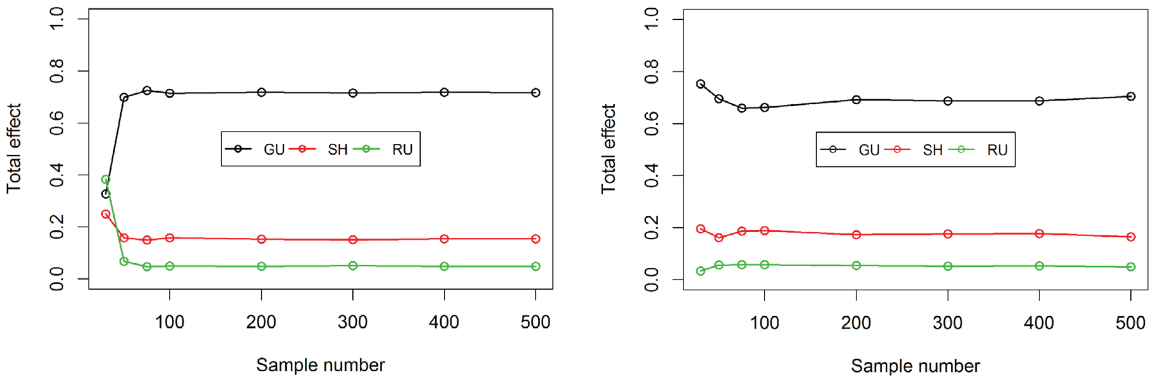
Figure 2 compares the EnergyPlus simulation results and PCE model outputs at the expansion degree 3 and sample size 300 for annual heating energy use from LHS and random sampling, respectively. The deviations between energy simulation and PCE regression models are small in this case, which is consistent with the results shown in Table 2. As also can be seen from Figure 2, the differences between two sampling methods are small. Hence, the PCE model accuracy is influenced by several factors, including sampling approach, sample number, and expansion degree.

Sensitivity analysis for heating energy use

Figure 3 shows the sensitivity results of heating energy for the first three important factors at the expansion degree of 2 in this office building. The ranking results tend to become stable after the sample size of 100 using Latin hyper-cube sampling. In contrast, a larger sample is needed to obtain reliable results with random sampling and here the sensitivity analysis results remain almost constant after the sample size of 200. This difference can be explained by the fact that the model accuracy RMSEP using Latin hyper-cube sampling is around 0.340 at the sample size 100 as shown in Table 2 and the sample number with random sampling is around 200 to obtain the same degree of accuracy as listed in Table 3. More accurate PCE models would lead to more reliable results from sensitivity analysis. The most important factor among six variables listed in Table 1 is the U-value of external windows (GU) in this case study building. The next two important variables are solar heat gain coefficient of windows (SH) and roof U-value (RU).

Figure 4 shows the results of sensitivity analysis at the expansion degree of 3 for heating energy. The third-degree PCE models lead to more stable results compared to the second-degree PCE models. This is because more simulation runs are required for higher degree PCE models.

FIGURE 3. Total effects of the first three important factors for heating energy using the PC expansion degree of 2.



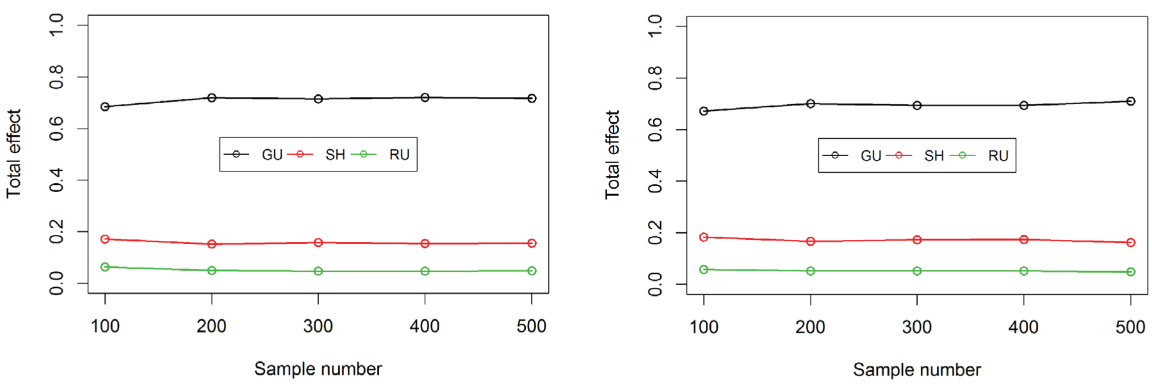
(a) Latin hyper-cube sampling (b) Random sampling

After the sample size of 200, the results become stable for both Latin hyper-cube and random sampling methods as shown in Figure 4. The results from Figure 4 are consistent with those from Figure 3. This is due to the fact that the second-order or third-order interaction terms are not significant in this case study, which can be used to explain small differences of RMSEP between the expansion degree of 2 and 3 as discussed in the last section.

Sensitivity analysis for cooling energy use

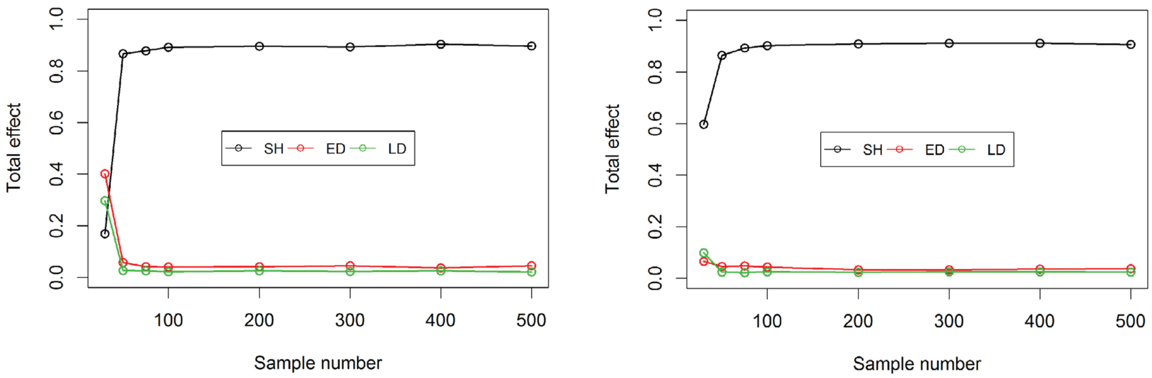
Figure 5 and Figure 6 illustrate the total effects of the first three important factors influencing cooling energy at the expansion degree of 2 and 3, respectively. More simulation runs are required for high expansion degree of PCE models. The sensitivity results become stable after a sample size of 200 for both the degree of 2 and 3 of PCE models. The random and Latin hyper-cube sampling methods lead to similar results in this office building. The solar heat

FIGURE 4. Total effects of the first three important factors for heating energy using the PC expansion degree of 3 with Latin hyper-cube sampling.



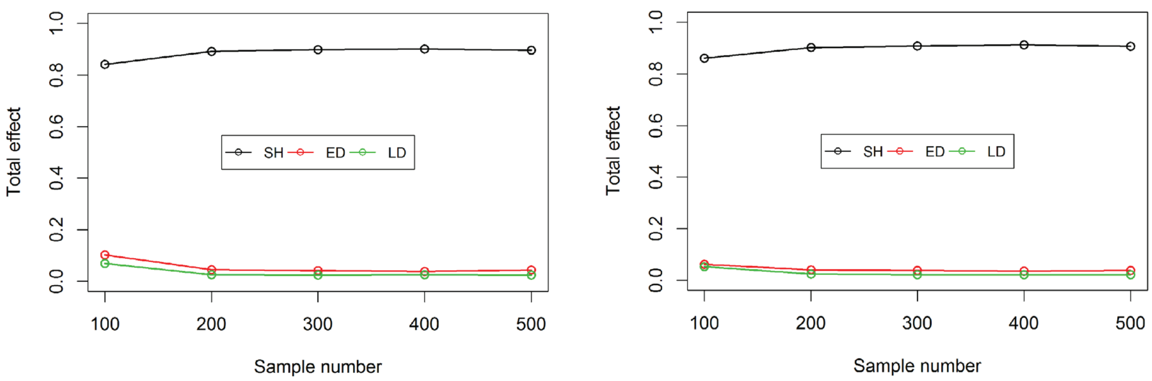
(a) Latin hyper-cube sampling (b) Random sampling

FIGURE 5. Total effects of the first three important factors for cooling energy using the PC expansion degree of 2 with Latin hyper-cube sampling.



(a) Latin hyper-cube sampling (b) Random sampling

FIGURE 6. Total effects of the first three important factors for cooling energy using the PC expansion degree of 3 with Latin hyper-cube sampling.



(a) Latin hyper-cube sampling (b) Random sampling

gain coefficient (SH) of external windows is identified as the most dominant variable influencing cooling energy. The next two variables are equipment and lighting heat gains in this office building.

To further validate the results from PCE sensitivity method, Sobol sensitivity analysis is conducted for the same data. It is found that the relative deviation of total effects for dominant variable (solar heat gain coefficient of windows) between the Sobol method and PCE method at a sample size of 200 is less than 1% although the deviation of total effect at the expansion degree of 3 is slightly less than that at the expansion degree of 2. Therefore, the PCE sensitivity analysis can provide reliable results as long as the sensitivity indicators become stable.

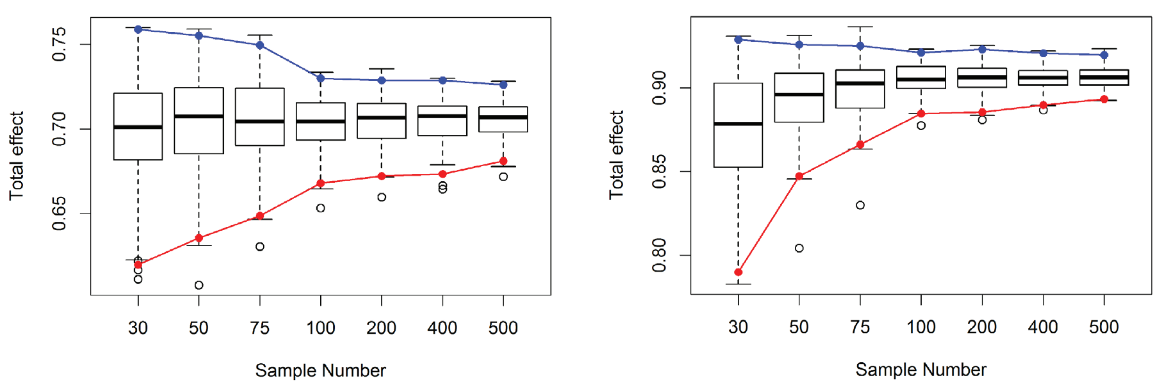
Confidence intervals of total effects using the bootstrap approach

Confidence intervals of sensitivity indicators should be provided to to assess the reliablity of sensitivity analysis in building energy assessment [3]. The bootstrap technique may be used to obtain the percentile bootstrap confidence by resampling the data with replacement to recalculate PCE sensitivity indicators [26]. The bootstrapping sampling size is chosen as 200 in this study since preliminary simulation indicates that the bootstrapping results become stable after reaching approximately 200. This implies that 200 PCE models need to be created for both a given original sampling number and a given expansion degree. Different types of confidence intervals from boostrap resampling are available, including standard interval, percentile bootstrap, and bias corrected interval. The precentile confidence intervals are chosen in this study since this method does not need any hypothesis on variable distributions. For a more detailed description on the approach used here, please refer to [26]. Note that this bootstrap method is only used for the data from random sampling, not for Latin hypercube sampling, since the stratification for new boostrapping data may not be preserved by directly bootstrapping the orginal LHS data [27]. A replicated bootstrap may be implemented in this case, however, much more computatonal cost is needed for this replicated sampling approach [28].

Figure 7a shows the 95% confidence intervals and box plot for total effects of window U-values affecting annual heating energy at the degree of 2 of PCE model. The confidence interval would be reduced significantly when the sample number changes from 30 to 100. After that, the 95% confidence interval would decrease slowly, around 0.03 at the sample number of 500. This indicates that the results from PCE sensitivity method are reliable after the sample size of 100. The box plot for window U-value is obtained directly from 200 samples of bootstrap resampling technique. There is a clear trend that variations of total effect would become stable after an original sample number 100. Note that the original sample size 100 is the number of simulation runs to create EnergyPlus models, where the 200 bootstrap number is the resampling number to create PCE models based on energy data from a fixed orignal sampling number of 100 with replacement. Figure 7b shows the 95% confidence interval and box plot from total effects of solar heat gain coefficients of windows for annual cooling energy at the expansion degree of 2. The trends are similar to the results obtained from Figure 7a. The total effects become stable after the sample size of 100 and the corresponding 95% confidence interval is from 0.894 to 0.914.

Further study is required to explore the combination of replicated Latin hypercube sampling and PCE-based sensitivity analysis to obtain confidence intervals of sensitivity index in building energy analysis. The advantages and disadvantages of random and Latin hypercube

FIGURE 7. Confidence intervals (95%) and box plot for total effects of window U-value and solar heat gain coefficients influencing heating energy with random sampling.



(a) Window U-value

(b) Solar heat gain coefficients

sampling methods in PCE-based sensitivity analysis should be further explored for different types of buildings with various numbers of input variables to evaluate the consistence of the results obtained from this case study. It is also an interesting topic to explore characteristics of sensitivity analysis using various types of meta-models in order to make guidance on choosing suitable meta-models for sensitivity analysis in building energy assessment.

CONCLUSIONS

This paper implements global sensitivity analysis based on polynomial chaos expansion (PCE) in building energy assessment. The results suggest that model accuracy and the stability of sensitivity indicators are closely connected, depending on sample size and expansion degree. It is important to assess the accuracy of PCE models before implementing them in global sensitivity analysis. Model accuracy indicators can be useful to guide the stability of the sensitivity index. Conversely, the results from sensitivity analysis can be helpful to interpret PCE model accuracy for different sample numbers and various expansion degrees. More simulation runs for building energy models are required to obtain a reliable sensitivity index for higher expansion degrees in PCE models. Moreover, the bootstrap technique can be combined with random sampling to provide confidence intervals for a PCE-based sensitivity index in building energy assessment. The Latin hypercube sampling can slightly improve model accuracy and stability of the sensitivity index when compared to random sampling.

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