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Bootstrap techniques for sensitivity analysis and model selection in building thermal performance analysis

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HIGHLIGHTS

- Bootstrap method computes sensitivity index variation in building energy analysis.
- Probabilistic sensitivity method provides valuable insights in building energy use.
- Bootstrap resampling method is suitable for validation of building energy models.

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ABSTRACT

In regression analysis, there are two main aims: interpretation and prediction, which can be also applied in building performance analysis. Interpretation is used to understand the relationship between input parameters and building energy performance (also called sensitivity analysis), whereas prediction is used to create a reliable energy model to estimate building energy consumption. This article explores the implementation of a distribution-free bootstrap method for these two purposes. The bootstrap is a resampling method that enables assessment of the accuracy of an estimator by random sampling with replacement from an original dataset. An office building is used as a case study to demonstrate the application of this method in assessing building thermal performance. The results indicate that the probabilistic sensitivity analysis incorporating the bootstrap approach provides valuable insights into the variations in sensitivity indicators, which are not available from typical deterministic sensitivity analysis. The single point values from deterministic methods may lead to misleading prioritization of energy saving measures because they do not provide the distributions of sensitivity indicators. Information on prediction errors obtained from the bootstrap method can facilitate the selection of an appropriate building energy metamodel to more accurately predict the energy consumption of buildings, compared with the traditional one-time data splitting method (also called holdout cross-validation method), which partitions the data into a training set and a test set.

1. Introduction

The building sector is responsible for 35% of global final energy consumption and accounts for about one-third of total carbon dioxide emissions in 2010 [1]. The global energy consumption from fossil fuels in buildings has increased by around 36% from 32 EJ to 43 EJ between 1971 and 2010 [1]. Over this time period, there is a significant change in the composition of the fossil fuels mixed used in buildings. The use of natural gas in buildings has increased around three times, whereas the use of coal has decreased by approximately half and the use of oil use is slightly reduced. Therefore, it is necessary to understand building energy characteristics thoroughly in order to reduce energy use and associated carbon emissions in the building sector.

Regression analysis usually has two main purposes: interpretation and prediction [2]. The aim of interpretation is to assess the relationship between explanatory variables and the response, while prediction is the estimation of future observations. In building energy assessment, the explanatory variables refer to input parameters, such as building envelope properties, internal heat gains, efficiency of chillers or boilers. The response can be the energy consumption or carbon emissions for a building. The two corresponding research areas in the field of building energy studies are sensitivity analysis (i.e. interpretation) and statistical energy models. Sensitivity analysis can provide invaluable insight into effective ways of finding the patterns in energy consumption to help with the prioritization of energy saving measures in buildings

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[3–9]. Statistical energy models are very useful for energy prediction [10–12], uncertainty analysis [4], and energy optimization [13,14].

Sensitivity analysis has been widely applied in understanding building energy characteristics to explore the relationship between input parameter variations and overall energy performance of the building. Sensitivity analysis can be used to determine the important parameters affecting building thermal performance [3–9,15–17]. The methods used in building energy assessment can be categorized into local and global sensitivity analysis methods. Local sensitivity analysis only studies the variations of energy performance around a point or base case, whereas global sensitivity methods explore the whole search space of input variables [4]. Global approaches to sensitivity analysis include regression analysis [18,19], variance-based analysis [20,21], screening [22,23], and meta-models [4,15]. Both local and global sensitivity analysis approaches have been extensively employed in the field of building energy analysis. However, most of the previous studies did not calculate the variations of sensitivity indexes in assessing building energy [9]. The single point values for sensitivity indicators may result in the misleading prioritization of energy efficiency measures. This is because a single point value is usually obtained from deterministic analysis that only concerns one value, such as sensitivity indexes with value 0.5 for the window *U*-value, and 0.6 for boiler efficiency. Therefore, it does not have the complexity/distributions of a sensitivity index. For example, if the distributions of sensitivity indicators from two different energy saving measures have more than 50% overlap, the effects may be very similar even though from a deterministic analysis the two sensitivity indicators may be very different. Another example is that energy saving may be very different if two sensitivity indicators from deterministic analysis have similar point values but their variations have significant differences. For this case, the factor with small variation in the sensitivity index may be more reliable (or conservative), while the factor with large variation may be more risky (very large or small influences on energy use). Archer et al. [24] pointed out that it is necessary to estimate the variability of sensitivity analysis from a statistical point of view. Compared to deterministic sensitivity analysis, the sensitivity index calculated from probabilistic analysis can provide more complete and robust information for experts in building energy to make informed decisions.

Statistical energy models have been widely used in the assessment of building energy performance [4,10–16,25]. Models based on statistical regression can be divided into two categories: data-driven and surrogate models. The difference between them is that the data-driven models are usually obtained from actual monitored energy data, while surrogate energy models (also called metamodels or emulators) are constructed using the simulation results from detailed engineering-based energy models. Data-driven energy models can be used to estimate energy savings after retrofits or to detect problems in HVAC (heating, ventilation, and air conditioning) systems [26]. In contrast, the aim of surrogate energy models is to provide computationally cheap models for optimization, uncertainty and sensitivity analysis. Common statistical models in the field of building energy analysis are linear models [27–29], neural networks [30,31], MARS (multivariate adaptive regression splines) [5,32], support vector machines [33,34] and random forest [35,36]. For detailed descriptions of these methods, see Hastie et al. [37] or Harell [38].

One of the most important questions for both types of statistical energy model is how to estimate the prediction errors when selecting a model. The one time data-splitting method is the simplest approach [38] and is widely used in the field of building performance analysis. This method (also called holdout cross-validation method) partitions the data into a training set and a test set [38]. The training data is used to fit the statistical models based on actual measured or simulated results for building performance. The test set is to validate the models obtained from the training set. This simple data-splitting approach has several disadvantages: different results for a new, split dataset; the test dataset needs to be large enough to assess the accuracy of models; and finally, it might be impossible to validate the final model due to incomplete data used for model fitting [38]. Therefore, new methods are needed to overcome these shortcomings.

The bootstrap method, developed by Efron and Tibshirani [39], is a resampling method to assess the accuracy of a statistic from a dataset. The bootstrap method has been applied in many disciplines, such as engineering, chemistry, psychology, and econometrics. Chernick provides a detailed list of literature related to this methodology [40]. However, the bootstrap method is rarely used in assessing building energy performance. This approach can be very useful to estimate the intervals of sensitivity measures and the prediction errors from statistical energy models in the field of building performance analysis. In this case, the statistic is a sensitivity index for sensitivity analysis or a prediction error for model selection. The sensitivity index is used to measure the importance of an input (such as *U*-value, internal heat gains) in influencing the thermal performance of a building. The prediction error is to assess the accuracy of a statistical model of building thermal performance.

This paper will assess the implementation of the bootstrap method in both sensitivity analysis and statistical energy model selection for building energy analysis. The bootstrap method allows an expert to account for the variability of parameter importance in sensitivity analysis. The bootstrap validation method can estimate the prediction error of statistical energy models in order to obtain robust predictions of building thermal performance. In this paper, a UK office building is used as a case study to demonstrate how to use the bootstrap method in the context of building energy analysis.

The organization of the remainder of this paper is as follows. Section 2 briefly describes the building energy model used in this analysis. Then, details are given in Section 3 on how to implement the bootstrap method in building energy analysis for sensitivity analysis and estimating the prediction errors of surrogate energy model. Section 4 discusses the results of the variations in sensitivity measures and the model selection based on the bootstrap prediction errors.

2. Building energy models: a case study

This section describes the building energy model used in this paper. Fig. 1 shows the case study building considered in this study. This is a five-storey office located in London, UK. The total floor area of this building is 7200 m^2. The construction standards in this building are commensurate with the energy efficiency of present-day good practices in the UK [4,41]. Detailed hourly schedules for occupants, equipment and lighting are derived from a database of UK national calculation method [42]. The heating in this office is provided by a radiator central heating system with a condensing boiler, while the cooling is provided by an electrical chiller. Table 1 shows the eleven input parameters, which will be changed in both sensitivity analysis and creating surrogate energy models [4,41,43,44]. These inputs in Table 1 can be categorized into three types: building envelope, internal heat gains, and HVAC (Heating, Ventilation and Air Conditioning) system.

The first type of inputs are related to thermal properties of building envelope, such as wall, roof, and windows. The *U*-value is the overall thermal property of building envelope [1]. Lower *U*-values represent building material with higher insulation levels. The *U*-value for ground floors has been assumed to be the same as that of walls in this study. The solar heat gain coefficient (SHGC) is the proportion of incident sunlight transmitted through a window.