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ENERGY USE OF BUILDINGS AT URBAN SCALE: A CASE STUDY OF LONDON SCHOOL BUILDINGS

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ABSTRACT

The diversity of non-domestic buildings at urban scale poses a number of difficulties to develop building stock models. This research proposes an engineering-based bottom-up stock model in a probabilistic manner to address these issues. School buildings are used for illustrating the application of this probabilistic method. Two sampling-based global sensitivity methods are used to identify key factors affecting building energy performance. The sensitivity analysis methods can also create statistical regression models for inverse analysis, which are used to estimate input information for building stock energy models. The effects of different energy saving measures are analysed by changing these building stock input distributions.

INTRODUCTION

Non-domestic buildings are responsible for 17% of UK carbon emissions (UK GBC, 2011). Therefore, it is essential to develop building stock models in order to prioritize energy saving measures on regional or national scales. In contrast to domestic sector, it is more challenging to gather necessary information for model descriptions of non-domestic buildings: a large number of diverse building usages need to be considered; building information is often inaccessible; and even when available, the form and levels of information varies widely. Hence, a non-domestic stock model should be flexible enough to deal with these data issues and robust enough to provide reasonable estimations for missing data.

Two types of building stock energy models exist at regional or national level: top-down and bottom-up approaches (Bruhns, 2008; Kavgic et al., 2010). The top-down approach is based on investigating the relationship between energy consumption and widely available aggregated data, such as gross domestic product, price indices, population-weighted temperature etc. Models using a top-down approach cannot therefore distinguish energy use for individual end-uses. In contrast, the bottom-up method can obtain end-use energy consumption by using a hierarchy of disaggregated input data.

Two types of bottom-up building stock energy models are available at city or national levels: statistical and physical (also called engineering-based) models (Bruhns, 2008). Both models need two steps to quantify energy consumption in building stocks. The first step is to estimate the total floor areas (or number of building or other proxy indicators) for the building types based on activity, age, size, or other characteristics of buildings. The second step is to estimate the energy use intensity (kWh/m2/year) for each type of buildings from statistical or physical models. The net building stock areas per building type are multiplied by their corresponding energy use intensity to derive the total building energy consumption at city or national level. The statistical method is based on energy bills or surveys to analyse building energy consumption and consequently only contains minimal technical information for end-use energy. The engineering approach, although requiring detailed input data by using heat transfer and thermodynamic principles, can directly assess the impact of energy conservation measures or new technologies. For an example of statistical bottom-up method, please refer to (Bruhns, 2008), while please see (Griffith et al., 2008) for an example of engineering bottom-up approach.

The work reported in this paper is part of research project that aims to develop an engineering-based bottom-up model in a probabilistic manner for dominant classes of non-domestic buildings in London. School buildings are selected for guiding the model development because schools fall within the definition of public sector buildings, which means necessary information is more readily available.

This paper is structured as follows. Firstly, the main difficulties in developing UK non-domestic building stock models are described. Then, a probabilistic method is proposed to address these issues by using sensitivity analysis and inverse method. The advantages and disadvantages of using this method are discussed in detail. Lastly, the application of this method is demonstrated by estimating distributions of building energy use in London school buildings.

OVERVIEW OF PROBABILISTIC METHOD FOR BUILDING STOCK SIMULATION

In comparison with well-researched field of individual building energy simulation, building stock modelling is much less documented. A main challenge for building stock simulation is how to deal with high diversity among different buildings. In order to estimate building energy performance for a particular building, it is possible to obtain reasonable accuracy for building input parameters, such as insulation, heating and cooling set-point temperature, occupant behaviour. However, large uncertainties exist for most input parameters in building stock models, even for a specific type of building: First, detailed building stock information, such as CBECS (commercial buildings energy consumption survey) in USA, is unavailable in the UK. Hence, model inputs have to be extrapolated from representative averages. Second, even for a specific type of buildings, there are still large variations in energy use intensity due to varying levels of services provided in buildings. For example, secondary schools with swimming pools consume more energy per square meter than average (BRE, 2006). This means the conventional approach of one-deterministic-model-for-one-building-type cannot reflect the actual situation well. Third, the level-of-detail of available data can vary significantly across different building types. This can be challenging since engineering-based models require the same detailed level of data for all different types of buildings. Due to large variations of input data, some form of model calibration and validation is also necessary. A sampling-based probabilistic approach has great potential to address these issues reasonably. However, few studies have been performed with a probabilistic method in this field. The proposed methodology is illustrated in Figure 1, which consists of five steps.

The first step is to collect physical information about the buildings including floor area, typical heights, percentage glazing, construction materials, heating, cooling, lighting, and ventilation equipment, schedules of use, and building controls. This data typically needs to be gathered from a variety of sources such as GIS (geographic information system) mapping services, government records, benchmark values, and published literature for a building type. Data from different sources must be collated with caution because misuse can potentially lead to large cumulative deviations of energy use. For example, floor areas of buildings are reported in terms of gross values, net external, net internal, or usable surfaces depending on the source (Steadman et al., 2000). Similarly, published benchmark values of energy use intensity are normalized by varying versions of the floor area in different sources.

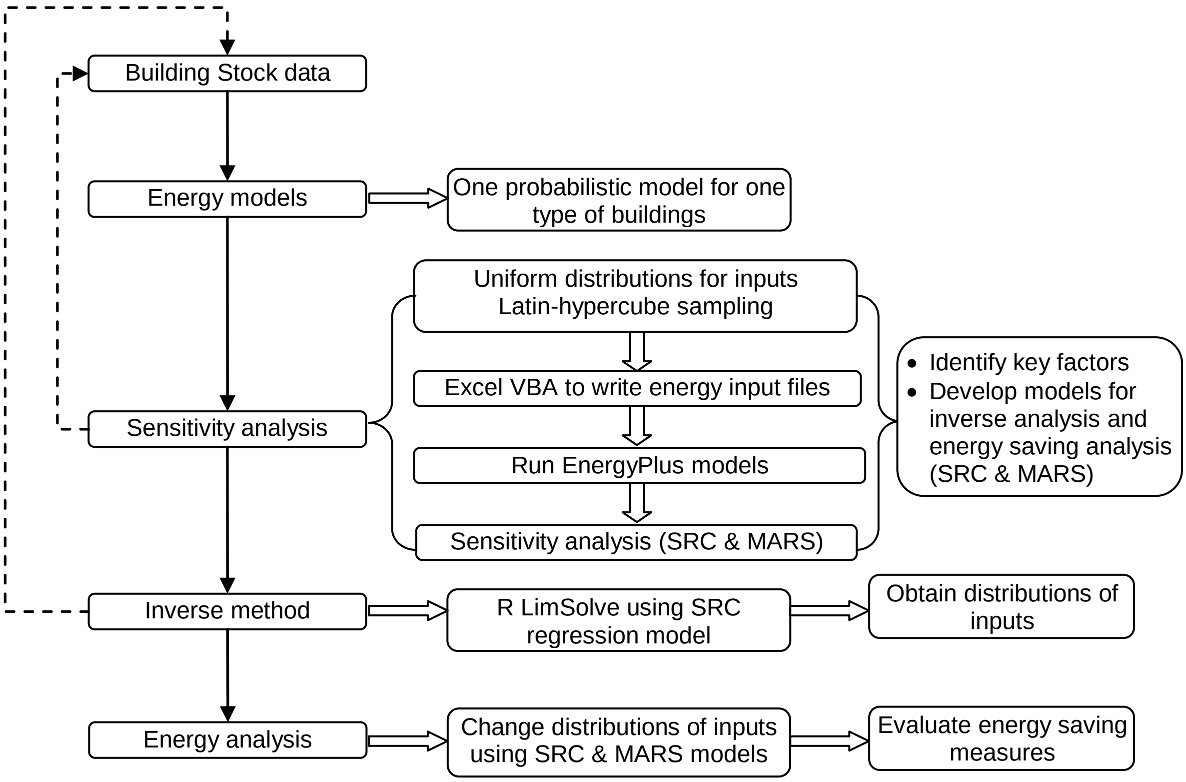

Figure 1 Schematic diagram of probabilistic building stock model (SRC: Standardized regression coefficient; MARS: multivariate adaptive regression splines, see section "overview of probabilistic methods for building stock simulation"; R LimSolve: (Van den Meersche et al., 2009))

The second step is to develop a representational energy model for the building category being considered. In this study, one building type has one corresponding probabilistic model in which building inputs can have large variations. In order to limit the spread of input parameters, it is important to categorize the building stock into sufficient number of uniform building types. For example, putting all educational buildings into one category will result in larger spread of input parameters than individual categories for primary and secondary schools, colleges, and universities.

It should also be pointed out that it is typical for a dynamic building energy model to have hundreds of input parameters. It is usually unnecessary to regard all these inputs as variables. For building stock models, more attention should be given to those parameters that significantly affect building energy use or are of interest for further research and analysis. Therefore, the third step is to implement sensitivity analysis for each building energy model in order to identify key factors affecting energy consumption.

The possible combinations of parameters for the sensitivity analysis are obtained by using Latin-Hypercube method, which is a stratified sampling method and can produce more stable analysis results than random sampling (Carnell, 2009). Two global sensitivity analysis methods are implemented in this research: Standardized Regression Coefficient (SRC) and Multivariate Adaptive Regression Splines (MARS). SRC uses linear regression to provide a measure of relative importance of parameters, but works best when the model is close to linear. The important factors are associated with high value of SRCs. A negative value of SRC means that the inputs and outputs are moving in opposite directions. On the other hand, MARS is a nonparametric regression, which combines spline regression, stepwise model fitting, and recursive partitioning. A nonparametric method does not have a predetermined form, so it is suitable for non-linear models. For a more detailed description of these two methods, see (Storlie et al., 2009). We use these methods to identify the most dominant model parameters. In addition, we also derive a statistical model (either linear or non-linear regression model) that approximates the simulation model. We will only use the linear model in the next two steps of our analysis.

The fourth step is to use an inverse method to infer the probability distribution functions (pdfs) of the dominant model parameters. For that goal, we compare observed and modelled energy consumptions for each building category. Inverse problems are often overdetermined or underdetermined. An underdetermined problem has less independent equations (constraints) than unknowns whereas an overdetermined problem has more constraints than unknowns. For an underdetermined case, unknowns can be inferred by satisfying the equalities (i.e. regression models from sensitivity analysis) and by enforcing inequality constraints (i.e. data ranges) or by explicitly specifying prior knowledge about these unknowns. When the problem is overdetermined, a set of values for the unknowns is generated by approximately satisfying the linear system. LimSolve is used here to apply the inverse method (Van den Meersche et al., 2009). It samples the feasible region and derives pdfs for all unknown parameters. Sampling is implemented through a Markov Chain Monte Carlo algorithm.

In the final step, we evaluate different energy saving measures by changing the input distributions obtained from the previous step.

ADVANTAGES AND DISADVANTAGES OF PROBABILISTIC METHODS

Advantages of probabilistic approach

The probabilistic method has many advantages compared to deterministic methods used in previous studies. First, this method can accommodate the variability of input parameters among buildings. The outcomes (distributions of energy use) are thus representative of the whole stock of buildings in that category. To have the same results from a conventional deterministic method, hundreds or even thousands of models would be needed to reasonably cover all combinations of input parameters. Secondly, the proposed method is much more flexible than deterministic method and easily updated when new information becomes available. For example, if reliable data is available for some input parameters, the distribution of these inputs can be directly obtained. If some inputs only have limited information, then there are two choices: One is to simply assign a constant value for these input parameters. The other choice is to infer these input distributions if they are important variables affecting building performance indicators as identified by using sensitivity analysis. Additionally, the statistical model used in assessing energy saving measures is computationally fast compared to running the full dynamic energy model, thus allowing full probabilistic analysis of different energy saving scenarios. Finally, the global sensitivity analysis used in this analysis is more robust compared to local or change-one-factor-at-one-time method. Global sensitivity analysis approaches evaluate the relative importance of input variables over a wide range, while the local or one-factor-at-a-time sensitivity analysis used in most previous research in this field is more interested in the influences of inputs factors around a point (de Wilde and Tian, 2010).

Disadvantages of probabilistic approach

However, the method suggested in this paper also leads to some difficulties.

The probabilistic method usually involves more simulation runs in contrast with deterministic approach which requires long calculation time. In this research, Excel VBA has been used to automate the process of writing EnergyPlus models as EnergyPlus input files are text-based, while for graphical-based building simulation programs it would be hard to implement this method. High-throughput computing by using grid technologies suitable for independent/sequential simulations, can further expedite model runs.

Another issue is availability of reliable energy consumption data per building type for the inverse analysis. The recent release of Display Energy Certificate (DEC) data by the UK department of Communities and Local Government (CSE, 2011) is extremely beneficial for the development and validation of building stock models. However, the data is not corrected for weather, and is only available for public-sector buildings.

In some cases, the input parameters may be correlated. In such cases, correlated inputs need to be considered when sampling the combinations of inputs. Simlab, an uncertainty and sensitivity program, has three methods for sampling these correlated factors: Iman and Conover method, Dependence-tree method, and Stein method (SIMLAB, 2004).

It should also be noted that statistical regression models do not usually extrapolate well because they are more reliable when interpolated with the specific set of inputs. These regression models should be hence validated and tested.

APPLICATION OF PROBABILISTIC METHOD TO LONDON SCHOOL BUILDINGS

As described in Introduction section, this research is focused on school buildings. This method can also be applied for other types of buildings. Schools account for 15% of the UK public sector emissions. Total carbon emissions due to building energy consumption have increased by 24% from 1990 to 2006. In this period, the carbon emissions from electricity use have increased by 31% (DCSF, 2010).

Energy model

The secondary school building used for developing the representative energy model is based on the building in (DfES, 1998). This is a three-storey building with a total floor area of 7680 m^2 and accommodates 900 students. Figure 2 illustrates the 3-D view of this secondary school building in Google SketchUp. The areas for indoor space such as classroom, staff/administration, halls, storage, dining/social area, are based on the Building Bulletin 98 (DfES, 1998). The heating is provided by radiators served by gas boiler and constant-speed pump. This building is assumed to have no active cooling system and natural ventilation is used to provide cooling in summer. The schedules for occupants, equipment, and lighting are from BRE NCM National Calculation Method (BRE, 2011).

The simulation here is carried out using EnergyPlus V6.0 (DOE, 2010). The weather file (Gatwick, London) used in this analysis is downloaded from EnergyPlus website and the annual heating degree days with a base temperature 15.5^{o}C from this weather file are 2167.

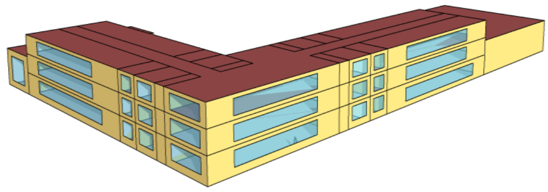

Figure 2. 3-D view of secondary school building

Sensitivity analysis

In this paper, 16 inputs are considered as variables for sensitivity analysis. These are listed in Table 1. The data ranges shown in the table are chosen based on possible values of these variables from previous studies on school buildings (Ajiboye et al., 2006; CIBSE, 2005; Demanuele et al., 2010; Jenkins et al., 2010; Mumovic et al., 2009; Pegg et al., 2007).

Typical hourly schedules for equipment in school buildings are from UK national calculation method NCM (BRE, 2011). However, the schedules for equipment usage at night and weekends (about 5 percent of daytime loads) have been shown to not represent actual situations. The research from (Pegg et al., 2007) indicates that the night-time electricity usage are around 35% of the daytime loads. The half-hour electricity data from 10 secondary schools (Carbon Trust Advanced Metering Trial) also indicates that the electricity usage at night and on weekends is much higher than we had assumed (around 32% of daytime loads). Considering the daytime electricity contains lighting use, the night equipment loads are around half the daytime equipment use. The changed schedule is called M-schedule in Table 1.

Indoor temperatures in some schools are much higher than assumed temperatures (18^{o}C) in NCM (Mumovic *et al.*, 2009). For the purpose of compliance with UK building codes, this heating set-point value may be appropriate, but for building stock models, the setpoint temperature must reflect actual typical room temperature. Previous research also indicates that the ventilation rate in classrooms is often below the minimum recommended levels (Ajiboye et al., 2006; Mumovic et al., 2009). Therefore, ventilation rate is also considered as a variable for sensitivity analysis in this study. It should be noted that the sensitivity analysis results are very much dependent on the choice of input ranges. Therefore, it is important to set these values as rigorously as possible.

Sensitivity analysis results from SRC are shown in Table 2. The heating set-point temperature, ventilation, and infiltration rate are three most important factors affecting heating energy use. These three factors are responsible for over 85% of the uncertainty in annual gas use. The negative SRC for boiler efficiency and window SHGC suggest that gas use would decrease as these two factors increases.

Table 1 Input ranges for sensitivity analysis

INPUTS		UNIT	VALUES
Wall U-value		W/m^2 K	0.2-1.5
Roof U-value		W/m^2 K	0.2-1.5
Ground U-value		W/m^2 K	0.2-1.5
Window U-value		W/m^2 K	1.5-4
Window SHGC[1]		-	0.2-0.8
Infiltration rate [2]		ACH	0.25-1
Equipment [3]	Classroom	W/m2	3-9
	Staff room	W/m2	9-18
Lighting [3]	classroom	W/m2	5-12
	Staff room	W/m2	8-15
Daylighting [4]		-	0-1
M-Schedule [5]		-	0-1
Boiler efficiency		-	0.7-0.9
Heating set-point [6]		°C	17-25
Ventilation [7]		-	0-1
Window Wall ratio		-	0.2,0.4,0.6

Notes: 1: SHGC: solar heat gain coefficient
2: ACH: air changes per hour (uncontrollable)
3: This is peak heat gain and hourly schedules for equipment are from (BRE, 2011)
4: 0: no daylighting; 1: daylighting
5: 0-from (BRE, 2011); 1-change night time fraction from 0.05 to 0.5;
6: Operative temperature
7: 0-no ventilation; 1-ventilation rate from (BRE, 2011)

Table 2 Sensitivity analysis results using SRC

	SRC		
	Input	**SRC**	**R2**
Gas use	Heating setpoint	0.710	0.537
	Ventilation	0.432	0.726
	Infiltration	0.405	0.866
	Roof-U	0.178	0.897
	Boiler efficiency	-0.143	0.917
	Window SHGC	-0.112	0.930
	Wall-U	0.106	0.941
Electricity	M-schedule	0.831	0.721
	Equipment class	0.347	0.836
	Daylighting	-0.274	0.915
	Lighting Class	0.185	0.947
	Heating setpoint	0.116	0.962
	Infiltration	0.081	0.969
	Equipment Staff	0.066	0.973

Note:
1. SRC, standardized regression coefficient;
2. R2 (coefficients of determination) with entry of each variable into the model

Table 3 Sensitivity analysis results using MARS

	MARS		
	input	**T.hat**	**S.cum**
Gas use	Heating setpoint	0.533	0.501
	Ventilation	0.214	0.705
	Infiltration	0.177	0.895
	Roof-U	0.039	0.933
	Boiler efficiency	0.016	0.948
	Wall-U	0.012	0.964
	Window SHGC	0.010	0.981
Electricity	M-schedule	0.728	0.724
	Equipment class	0.128	0.860
	Daylighting	0.077	0.929
	Lighting class	0.035	0.967
	Heating setpoint	0.020	0.988
	Equipment Staff	0.008	0.988
	WinSHGC	0.005	0.992

Note:
1. MARS: multivariate adaptive regression splines;
2. S.cum: the cumulative contribution of variance explained by the input and the others entered in the model;
3. T.hat: the contribution of the total variance explained by the input and any of its interactions with other inputs

For electricity usage, M-schedule (i.e. change of night and weekend equipment schedule) is the only dominant variable, which accounts for around 72% of the output variations. The equipment in classroom, daylighting, and classroom lighting are responsible for about 11% of the variations. The remaining factors have little effect on annual electricity use, less than 5% of the output variations.

The results in Table 2 also show that the linear model from SRC has very good performance. To further assess this conclusion, MARS (multivariate adaptive regression splines) is also used for sensitivity analysis. As can be seen from Tables 2 and 3, there is high consistency in the variables selected based on these two methods. Hence, the linear model obtained from SRC method is reliable and accordingly can be used for further analysis.

Inverse Analysis

In this section, we derive building stock information from actual building energy use. We focus on fossil fuel consumption. Electricity consumption is mainly due to lighting and equipment use, which is directly related to assumed inputs (most schools in the UK do not have mechanical cooling systems). The distributions of fossil fuel use in London school buildings are obtained from two sources: (DfES, 2004) and (CSE, 2011). The data from the first source is more reliable, while the data from the second source is more recent. We used the first source for this inverse analysis as these data have been corrected by ambient temperatures with annual heating degree days (1913 HDD).

The linear model obtained from SRC is used to infer building input distributions. The DfES data give the key quantiles (10%, 25%, 50%, 75% and 90%) of gas consumptions, not observed individual values (DfES, 2004). To match modelled values and observations, we generated 300 synthetic gas consumptions compatible with these quantiles. We employed a rescaled beta distribution whose interquartile range was equal to the DfES range. In this way, we are also able to generate plausible values of gas consumptions in secondary schools. Since we thus create as many constraints as observations, the linear system is overdetermined. Figure 3 shows the resulting distributions of the seven key parameters identified by our sensitivity analysis.

Figure 4 illustrates the comparison of the distributions of energy use from these estimated distributions and two sources (CSE, 2011; DfES, 2004). In these three box plots, the lower and upper box bounds are the 25th and 75th percentile of energy use distribution and the band in the box denotes the 50th percentile. The ends of the whiskers represent the 10th and 90th percentile of distributions, respectively. The modelled energy use covers the range of actual energy use.

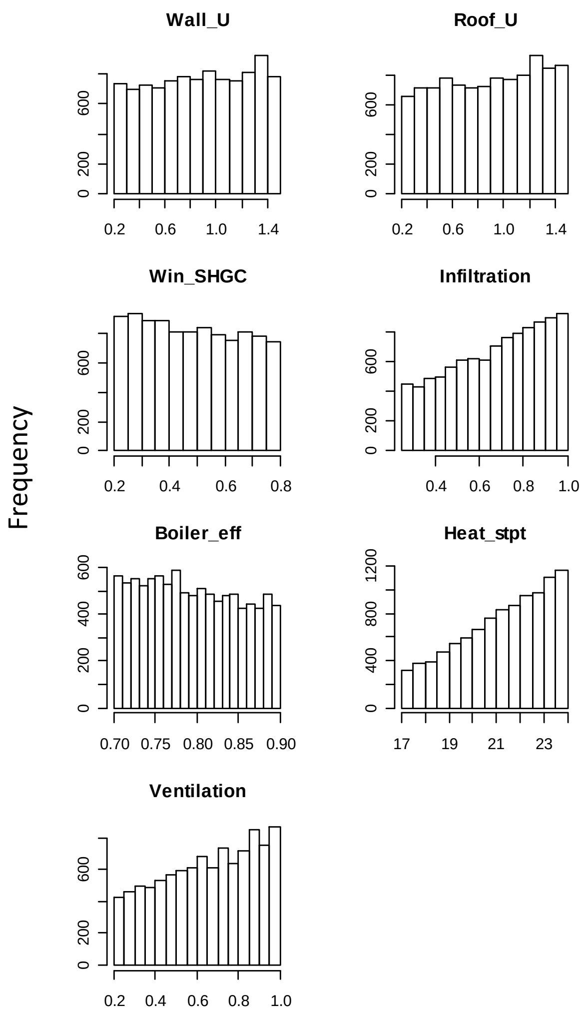

Figure 3 Histograms of estimated input distributions for secondary schools (see Table 1 for units of variables).

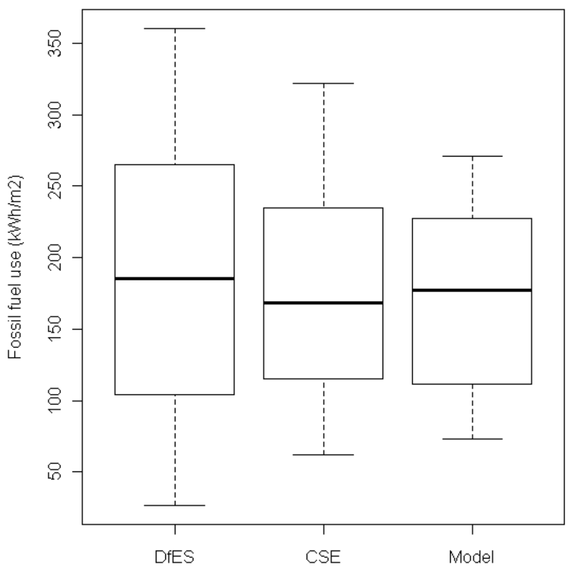

Figure 4. Comparison of fossil fuel energy use for London secondary schools (DfES: from (DfES, 2004) ; CSE: from (CSE, 2011)*; Model: obtained from inverse analysis)*

The long tail (high energy) in the distribution of actual energy use is likely because the statistical data includes buildings that use oil for heating, which tends to consume more energy. The energy model, on the other hand, assumes all buildings to have gas boilers for heating. Additional reasons for the extreme outlier may be due to unexpected use of buildings, failures of heating control systems, delayed maintenance, improper installation, which are nearly impossible to take into account in simulating energy use and should be addressed by building commissioning. More research is needed to identify whether these very high (or very low) energy use intensities are true energy efficiency (or inefficiency), or simply due to errors in estimating floor area or energy readings.

Energy saving analysis

The distributions of inputs obtained from the last section are used to assess energy saving measures by using two regression models (SRC and MARS) described in the section on sensitivity analysis.

Two scenarios are considered for demonstrating the effects of different energy saving measures: Case1 is that wall U-value will be reduced to 0.6 W/m2K if this value is above 0.6 W/m^{2}K in all London school buildings. For other school buildings with U-value less than 0.6 W/m^{2}K, there is no improvement in insulation for these walls. Case2 is that infiltration rate will be reduced to 0.6 ACH for all the secondary school buildings with infiltration rate above 0.6 ACH.

Figure 5 shows the results due to application of these two different energy saving measures by using SRC regression model. As can be seen from this figure, the buildings due to implementation of Case2 are more energy efficient than those in Case1. If the total buildings floor area is the same in three scenarios (reference, Case1 and Case2), then the total fossil fuel use will reduce by around 11% in Case2 in comparison with the reference case, while for the Case1 this reduction is only around 4.5%.

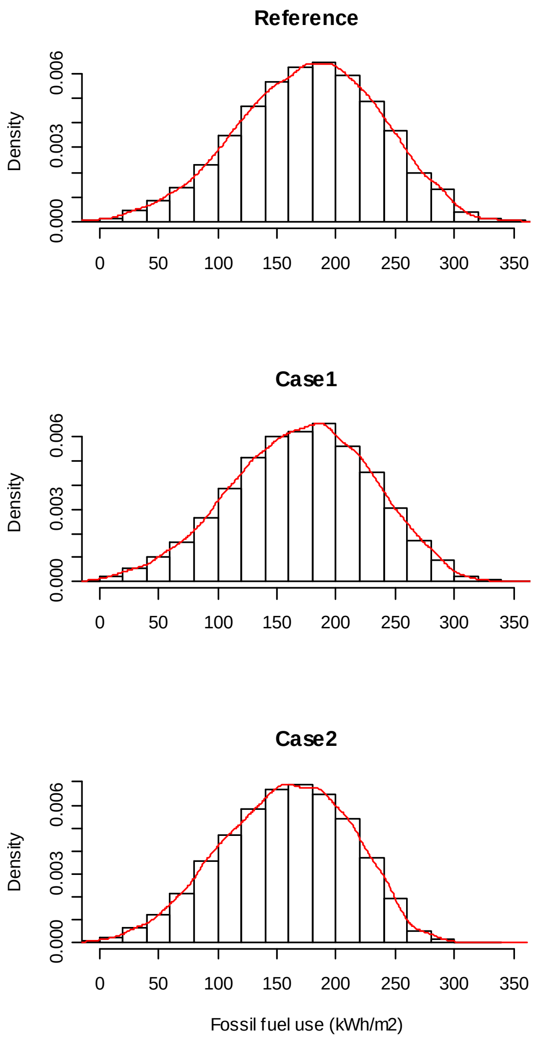

Figure 5. Probability density histograms of fossil fuel use in three scenarios (Case1: reduced to 0.6W/m^{2}K for wall U-values; Case2: reduced to 0.6 ACH for infiltration in all secondary school buildings)

The results from MARS method are very similar to those from SRC approach. No significant differences in the distributions from these two methods were found by using two-sample Kolmogorov-Smirnov Z test, which is based on the maximum absolute difference between the observed CDF (cumulative distribution function) for two samples in order to detect differences in both the locations and shapes of the two distributions (Field, 2009).

CONCLUSIONS

This paper proposes a probabilistic bottom-up engineering approach to analyse energy saving measure in London non-domestic buildings. Secondary school buildings are used to demonstrate application of this method. Important model parameters can be identified by using sensitivity analysis, which is also used to create a statistical regression model for inverse analysis. The distributions of the dominant model parameters affecting building energy performance can be inferred by inverse analysis. Finally, these distribution and the regression models can be used together to analyse building energy performance in non-domestic building stock.

It should be noted that the availability of building stock information varies widely depending different countries and regions. Hence, the appropriate methods used to estimate building stock energy consumption might be also different. The proposed method in this research is more suitable for the situation in which there is a lack of building stock information but sufficient and reliable energy use data is available.

Further research will apply this probabilistic method to other types of non-domestic buildings in the London. The impact of different built forms on energy use will be analysed and GIS (geographic information system) will be more incorporated in this research project in order to assess spatial heterogeneity of building energy use in urban environment.

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