ABSTRACT

Energy performance of residential buildings depends on a large and diverse number of interrelated factors. The present study outlines a detailed procedure for developing a model to estimate energy use, highlighting the importance of uncertainty and sensitivity analyses. Toward this end, three apartment buildings, located in Kosovo, were selected. Using multiple data sources, initial energy use models were created. Model outputs were evaluated via comparison with available energy use data and studied using sensitivity analyses. Consequently, the most influential input parameters were identified and adjusted to calibrate the models. Currently, we deploy these calibrated models to investigate the potential of retrofit measures.

INTRODUCTION

The evaluation of energy performance in buildings is a challenging task because it depends on such a large and diverse number of interrelated factors. Energy use evaluation in residential buildings is particularly challenging, given the variety of energy services and complex patterns of people's presence and behavior. Hence, the proper representation of existing energy services and people's presence and behavior is of utmost importance.

It is a common knowledge that people's presence and behavior influence the building energy performance and indoor comfort (Mahdavi 2011). While there have been significant developments in studies concerning methods and practices regarding building geometry, building materials, and weather conditions, there is a lack of simplified methods to assess and model the occupants' pattern (Larsen & Nesbakken 2004, Page et al. 2008, Stokes et al. 2004, Yao & Steemers 2005). Such patterns include, amongst other factors, the occupants’ presence and their interaction with specific energy services (lighting, electric appliances, hot water, heating, and cooling). To properly model the occupancy and behavior, it is essential to address influential factors relating to the environment and context. These factors include outdoor weather conditions, which may impact the operation of the windows, lighting, and heating and cooling devices (Andersen et al. 2009, Mahdavi & Pröglhöf 2008). Moreover, energy use in buildings is influenced specifically by occupancy characteristics - such as age, family size, income, lifestyle, and cultural background (Engvall et al. 2014, Santamouris et al. 2007).

In these circumstances, the accurate and effective estimation of energy use becomes very difficult. Monitoring the pattern of occupancy and the operation of energy services can provide adequate information for occupancy-related modeling (Firth et al. 2008, Mahdavi & Tahmasebi 2015, Widén et al. 2009). A number of research projects are being undertaken to model occupants’ presence and behavior using data collected on available energy use information (Park et al. 2016). This confirms that, data pertaining to occupancy and behavior is one of the sources of uncertainty in energy use modeling (Clevenger & Haymaker 2006, Hoes et al. 2009). Due to the uncertainties in the modelling process, the resulting modeling data may deviate from the actual energy performance data (Fabrizio & Monetti 2015). Thus, the calibration of the models is of crucial importance (Reddy et al. 2007). Needless to say, this depends on the reliability of the model input parameters (Polly et al. 2011). The calibration process can be improved by narrowing down the most influential input parameters using statistical methods, such as sensitivity analysis (Reddy et al. 2007, Saltelli et al. 2008).

Given this background, we present a simplified method to calibrate an energy model based on information on building geometry, user presence and behavior, microclimate, and socio-economic background. For this purpose, three existing multi-family apartment buildings were selected. The study assessed only the electric energy, which is used for lighting, electric appliances, domestic hot water, heating, and (on rare occasions) cooling. Electricity use data for these buildings is available through monthly electricity bills for each building unit. However, the available energy use data does not provide information on specific energy services (lighting, electric appliances, domestic hot water, heating, cooling). Therefore, there is no available information on peoples’ presence and interaction with energy appliances and devices. To get an insight into this missing information, we conducted structured interviews with at least one representative of each building unit. These interviews were...
collected in 2013 and included general questions on residents, family size, occupation, installed electric appliances and devices, behavior, and residents’ perception of the indoor environment. The participation level was 75% in building A, 92% in building B, and 76% in building C. Using the collected information on each building unit, the initial model of energy use pattern for each energy service (lighting, hot water, appliances) was created. The generated model was further evaluated through comparison with available monthly energy use data (energy bills) for a non-heating period of five months. The deviation of model results and actual energy use data were studied using sensitivity analyses. Consequently, the input parameters that most affect buildings’ energy use were identified and adjusted to calibrate the models. Currently, we are deploying these calibrated models to investigate and compare the cost-effectiveness of energy efficiency measures in the pertinent building sector in Kosovo.

Toward this end, three existing multi-family apartment buildings that are representative of typical design and construction practices in Kosovo were selected. These buildings are exposed to similar weather conditions and their inhabitants share a similar socio-economic background. An overview of these buildings is presented in Table 1. A general description of the case studies and information regarding their respective energy performance have been presented in a previous study (Rashani & Mahdavi 2015).

**MODELING AND CALIBRATION APPROACH**

The study involved three steps. First, the collected data was used to define input parameters regarding occupancy-related patterns and electric equipment and devices. Second, the initial model was generated. Third, the initial model was calibrated using sensitivity analyses. The study approach is illustrated in Fig 1.

**Figure 1: A schematic illustration of model calibration**

**Model input parameters**

Initially, the information for each building unit relating to the building geometry, occupancy related information, installed power of appliances, luminaires and boilers, was collected. The next step involved the construction of occupants’ presence patterns. These, depend mostly on residents’ age, employment status and lifestyle. Moreover, the occupancy patterns vary from apartment to apartment, and from day to day. Therefore, it was necessary to create a simplified occupancy schedule.

<table>
<thead>
<tr>
<th>Table 1: General description of the buildings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building A</td>
</tr>
<tr>
<td>Gross floor area (m²)</td>
</tr>
<tr>
<td>Year of construction</td>
</tr>
<tr>
<td>Number of stories</td>
</tr>
<tr>
<td>Number of apartments</td>
</tr>
<tr>
<td>Number of residents</td>
</tr>
<tr>
<td>Structure type</td>
</tr>
</tbody>
</table>
To address this, three general occupancy scenarios were generated based on employment status and the information collected (see Table 2).

The occupancy schedules are of high importance given that artificial lighting and most of the electric appliances are used mainly during the occupied periods. However, lighting is generally used in an occupied room, thus the number of rooms should be taken into consideration as well. Additionally, the use of artificial lighting also depends on daylight duration. Given these issues, the energy demand for lighting was estimated based on assumptions regarding total lighting power, hours of usage, and factor pertaining to daylight and apartment size.

Estimations regarding type, quantity, and power of electric appliances were based on general information gathered from interviews. Unlike lighting, energy use for appliances depends on the number of occupants in the apartments. Thus, the appliances energy use can be calculated based on the electric power of appliances, hours of use, and number of occupants.

Domestic hot water energy use was estimated according to BREDEM 2012 (Henderson & Hart 2013).

The model calibration was performed for the non-heated period, thus the energy demand for heating was not estimated.

\[
E_{L,m} = P_l \cdot O \cdot f_1 \cdot f_2 \cdot N_d \quad [kWh] \quad (2)
\]

\[
E_{AP,m} = P_{AP} \cdot h \cdot f_o \cdot N_d \quad [kWh] \quad (3)
\]

Here \( N_d \) is the number of days in a month, \( P_l \) is the electric power of luminaires, \( O \) the hours of use (three scenarios), \( f_1 \) the daylight contribution factor, \( f_2 \) a factor associated to apartment size, \( P_{AP} \) the electric power of electric appliances, \( h \) the hour of use, and \( f_o \) a factor related to the number of occupants.

**Table 2:** Occupants’ presence scenarios with regard to employment status and occupation

<table>
<thead>
<tr>
<th>Period of time</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>00:00-08:00</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>08:00-13:00</td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>13:00-18:00</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18:00-24:00</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

**Initial energy use model**

In a previous contribution, we presented a methodology for estimating the monthly energy use for each building unit (Rashani & Mahdavi 2015).

The following equation was used to generate the monthly energy use for lighting, hot water, and electric appliances:

\[
E_m = E_{L,m} + E_{AP,m} + E_{HW,m} \quad [kWh] \quad (1)
\]

Here, \( E_{L,m} \) and \( E_{AP,m} \) are the monthly electrical energy usage for lighting and appliances, \( E_{HW,m} \) for domestic hot water.

The energy use for lighting and appliances was estimated as follows:

\[
E_{L,m} = P_l \cdot O \cdot f_1 \cdot f_2 \cdot N_d \quad [kWh] \quad (2)
\]

\[
E_{AP,m} = P_{AP} \cdot h \cdot f_o \cdot N_d \quad [kWh] \quad (3)
\]

**Calibration of the energy use model**

Create a reliable energy use model of residential buildings is a challenge due to the inevitable uncertainties of input parameters and the errors caused by simplifications. This being the case, evaluation and calibration of the energy use model is of utmost importance. In the present study, the input parameters that most likely impact the model outputs were identified based on uncertainty and sensitivity analysis, and further adjusted resulting in a calibrated model.

In the calibration process, the predicted values (in the present case, electricity demand) are compared to measured values (electricity bills) to measure how well the predicted values match the measured values at the selected time interval: that is, the 'goodness of fit'. This measure is expressed by the 'Coefficient of Determination' \( (R^2) \), which ranges from 0 to 1. Given that the \( R^2 \) value of 1 indicates perfect fit, it is usually aimed to maximize the \( R^2 \) values in the calibration process. The deviation between the model and the measured data is further evaluated using the ‘Root Mean Square Deviation’ RMSD and ‘Coefficient of Variation of the Root Mean Square Deviations’ CV (RMSD). These two statistical indicators are used to test the modeling error, while maintaining the goodness of fit (Polly et al. 2011).

The equations pertaining to the statistical indicators used in the present study are as follows:

\[
R^2 = \left( \frac{\sum_{i=1}^{n} x_i y_i - \left( \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i \right)}{\sqrt{\left( \sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2 \right) \left( \sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2 \right)}} \right)^2 \quad (4)
\]

\[
RMSD = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}} \quad (5)
\]

\[
CV(\text{RMSD}) = \frac{\text{RMSD}}{\bar{y}} \cdot 100 \quad [%] \quad (6)
\]

In Equations 4 to 6, \( x_i \) is the actual monthly electricity consumption for each month, \( y_i \) is the estimated electricity demand for each month, \( n \) is the...
sum of total number of units, \( \bar{x} \) is the mean of electricity consumption. In general, the initial model may not correspond well with the actual data, thus further adjustments of the model need to be undertaken in order to fulfill the criteria for considering a model as calibrated. The input parameters, which were selected as the most important for the model, were initially modified using one at a time method (OAT) (Saltelli et al. 2008). For this purpose, each parameter was individually modified while all the others were kept the same in order to find the best matching values for calibrating the model. Moreover, the impact of calibrating all the variables at the same time was further investigated.

Given this approach, the present study intends to calibrate an initial energy use model, which can be used to estimate energy demand for multi-unit residential buildings in Pristina. As the study was planned to be performed in a non-heated period, the calibration process involved a period of five months, from May to September. To match the year of data collection, the energy use estimations were compared to energy use data for the year 2013. The calibration process was initially performed in the building B and evaluated further by investigating the modeling results in two other buildings selected for the study. In the first step, only the building units that provided reliable data were selected for the calibration process (69% of total number of units). The exclusion of units from the study was based on validity of the information obtained from the interviews (2 apartments), discontinuous occupancy (3 apartments), large discrepancy in energy bills (2 apartments), and the use of air conditioning (1 apartment).

After generating the initial model, the calibration process was undertaken. To assess the reliability of the calibrated model, the same model was applied to both building A and building C. The participation of building units in the calibration process in Building A was limited to 52% of total units and in Building C to 63%.

RESULTS

The selected influential input parameters are: lighting use duration (denoted by \( O \) in Equation 2), appliances usage per occupant (expressed \( f_0 \) in Equation 3), daylight contribution factor (\( f_1 \) in equation 2), and apartment size factor (\( f_2 \) in Equation 3). Table 3 illustrates the variables and their calibration steps. The four selected input parameters are linked to occupancy-related patterns and weather condition. The initial and calibrated values of input parameters pertaining to the duration of use of lighting luminaries for three proposed occupancy scenarios are shown in Table 5. The initial and calibrated values for the daylight contribution factor for each month of the year are presented in Table 4. The initial and calibrated values for the factor regarding the occupants number (appliances use) and apartment size are summarized in Table 6 and in Table 7 respectively. The energy use model evaluation statistics for building B, for both initial and calibrated model, are shown in Table 8. To assess the reliability of the estimations, the calibrated model was further applied in two other buildings and the results are presented in Table 9.

Table 3:
<table>
<thead>
<tr>
<th>Calibration variables and steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>CALIBRATION VARIABLES</td>
</tr>
<tr>
<td>Lighting usage (( O ))</td>
</tr>
<tr>
<td>Appliances usage (( f_0 ))</td>
</tr>
<tr>
<td>Daylight duration (( f_1 ))</td>
</tr>
<tr>
<td>Apartment size (( f_2 ))</td>
</tr>
</tbody>
</table>

DISCUSSION

As it can be seen from Table 8, the calibration process generated output results with relatively high \( R^2 \) values in both the initial and the calibrated model outputs, whereas the error of estimations were significantly improved, as denoted by the reduced \( CV(RMSE) \) values.

The results point to the improved predictive performance of the initial model by adjusting selected variables, particularly the parameters concerning the occupancy and use patterns (see step 1 and step 2 in Table 8). However, seasonal effect and the size of the building unit did not indicate any substantial impact on the model’s performance (step 3 and step 4 in Table 8). As it can be seen in Table 8 (step 5), the combination of all calibrated parameters significantly improved the model performance, meeting the criteria for calibration to monthly data (ASHRAE 2002). The calibrated model also performed relatively well in Building A and Building C, whereas the initial model, as expected, did not show good modeling results (see Table 9).

The high values of \( R^2 \) and satisfactory values of CV (RMSE) confirm the reliability of the estimation of the energy use with respect to actual energy use data. The present study therefore proved to be promising in view of generating a calibrated model of energy

Table 4:
<table>
<thead>
<tr>
<th>Initial and calibrated values of the daylighting factor (( f_1 ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Months</td>
</tr>
<tr>
<td>Initial value</td>
</tr>
<tr>
<td>Calibrated value</td>
</tr>
</tbody>
</table>
demand patterns in residential buildings using sensitivity analysis. However, the performance of the present calibration method could be further improved by including a larger number of diverse case studies, in different locations and with participants from a wider range of socio-economic background.

**SUMMARY**

We presented a building energy use model for a case study of typical multi-unit residential buildings in Pristina, Kosovo. The objective of the study was to generate a calibrated model of electric energy use via high-level energy use information (i.e., monthly energy bills), highlighting the importance of uncertainty and sensitivity analysis. Toward this end, three buildings were selected. Interviews and local observations provided basic data on occupancy-related patterns and relevant electric equipment and devices. The initial energy use model was applied to each building unit, in terms of energy requirements for different energy services (lighting, hot water, appliances). To evaluate the model, we compared the estimation results with electrical energy use information during a non-heating period of five months of the year 2013. The deviation between model outputs and energy bills were investigated using sensitivity analyses, which enabled the identification and the adjustment of the input parameters that most influence the building energy consumption. This resulted in the calibrated model. The approach and the calibrated models are currently being deployed to investigate potential cost-effective measures for energy-efficiency measures in the pertinent building sector in Kosovo.

**Table 5:**
Initial and calibrated values of total lighting power used during the occupied periods (O)

<table>
<thead>
<tr>
<th>Nr. of rooms</th>
<th>Studio</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial value</td>
<td>11.30</td>
<td>10.9</td>
<td>8.75</td>
<td>6.05</td>
<td>6.25</td>
<td>5.75</td>
<td>5.30</td>
<td></td>
</tr>
<tr>
<td>Calibrated</td>
<td>6.40</td>
<td>4.90</td>
<td>3.85</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 6:**
Initial and calibrated values of the factor related to the occupants number regarding appliances use (f0)

<table>
<thead>
<tr>
<th>Nr. of occupants</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial value</td>
<td>1.0</td>
<td>1.3</td>
<td>1.5</td>
<td>1.8</td>
<td>2.0</td>
<td>2.3</td>
<td>2.5</td>
</tr>
<tr>
<td>Calibrated value</td>
<td>0.7</td>
<td>1.0</td>
<td>1.2</td>
<td>1.4</td>
<td>1.6</td>
<td>1.8</td>
<td>2.0</td>
</tr>
</tbody>
</table>

**REFERENCES**


