Monitoring and modelling the energy efficiency of municipal public buildings—case study in Catalonia

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ABSTRACT

Energy-efficiency benchmarking can be used to monitor changes in overall efficiency of buildings. Benchmarking models, based on energy-efficiency indicators are valuable tools for both public and private stakeholders because they allow an improvement in the building energy management. For the last decade, some governments have used these tools to define their building regulations (M. Santamouris, 2005, W. Chung 2005). This paper tries to go further, integrating a benchmarking and a modelling process, in the same energy efficiency analysis. The connections between the energy-use intensities (EUIs) and the characteristic building factors are modelled using network techniques. The process is divided in two stages: the data acquisition stage, and the benchmarking and modelling stage.

The benchmarking and modelling stage is focused in the adjustment of these EUIs within the climate conditions (with a degree days modified method) and the development of a prediction model for calculating the relationship between these climate adjusted EUI and the significant factors of a building. In order to validate this methodology, an application to schools in Catalonia is presented.

2. INTRODUCTION

2.1 Literature review

Energy consumption of real buildings generally does not perform as well as anticipated during the design stage. There are many reasons for that: wrong equipment selection and installation, lack of rigorous commissioning and proper maintenance, and poor feedback on operational and energy performance. For the last years, a big amount of methods to address this lack of prediction accuracy have appeared.

In the Euroclass European project (Santamouris, 2006) the energy performance of a high number of European residential buildings was studied and two methods of analysis were defined: the Billed Energy Performance method (BEP) and the Monitoring Energy Performance method (MEP) The BEP method aims at determining the normalized EUI and the heating, lighting, and equipment energy demand using the monthly energy bills. The MEP method includes a short monitoring period of the building energy consumption and indoor temperature and gets a more accurate monthly energy profile. The energy performance of buildings based in auditing and short monitoring methods (Yew Wah, 2001) (Fuji et al, 2001) are widely developed lately. They combine an auditing phase followed by a short monitoring period of very few parameters (e.g. energy consumption, indoor and outdoor temperature), and then a model analysis using computer simulation is applied (Wang, J, 1999) (Gieseler, 2003). (Oloffson et al, 2001).

An identification of some specific energy conserving opportunities (ECOs), is also included in these methods. The main result of these methods is a detailed analysis of each ECO, including the costs and savings to be expected, which may allow the building owner to define the energy conservation goals to be established and achieved in their energy management programme. These methods are often combined with energy information systems (EIS), (Brambley, 2004), (Clarke, 2004), (Motegi, 2002), which monitor and organize building energy consumption and related trend data over the Internet. This technology helps perform the key energy management functions.

2.2 Objectives

This project aims at benchmarking, in a seasonal period, the energy performance of school buildings and predicting the reduction EUIs with the implementation of saving measures.

The study is divided into two stages, firstly adjusting the EUIs within the climate conditions, secondly, development of a predictive model based in neural network techniques. The relationship between the EUIs and the significant factors of a building are obtained with modelling stage. The basic data used by the predictive model are a limited amount of measured parameters, coming from the energy audit and monthly energy bills grouped in periods of 4 months (winter, summer, and spring and autumn). They are obtained from 30 schools placed in Catalonia and the data were collected during 2005 and 2006. Some basic connections among the envelope, the occupancy schedule, the occupants behaviour and the performance of lighting, electric equipment, boilers or chillers, are defined and included in the predictive model.

In order to validate the accuracy of the model, the pre
dicted energy will be compared with the energy bill measured. Finally, the reduction of the energy consumption of one school, due to the substitution of the conventional boiler by a low temperature boiler, will be calculated. The estimated energy saving proposed by the Spanish energy certification label (CALENER) for the low temperature boiler will be used to compare the accuracy range of prediction.

3. BENCHMARKING AND MODELLING PROCESS

The benchmarking and modelling process consists of three steps: (1) Climate adjustment of EUI, using degree day normalization, to obtain \( (EUI)^N \) (kWh/m\(^2\)). In this step, the normal distribution calculation is applied to provide a percentile cumulative table of energy consumption. (2) Calculation of the explanatory components of the building through elimination of the non significant factors by applying the statistical factorial analysis method; and (3) Modelling the EUI performance of 30 school samples by using the Flood A Neural Network. Details of the steps (2) and (3) are given in the following sections.

3.1 Climate adjustment and benchmarking table

The chosen schools are primary and secondary schools without A/C systems. Outdoor gardening and outdoor playground area are excluded of the calculation of the gross floor area. The degree-day value is defined as the difference between the daily mean temperature and the defined base temperature. The overall daily mean-temperature \( (20^\circ C) \), recorded by the Catalonian weather stations, is adopted as the base temperature. The corresponding degree-days in the specific period are adjusted, based on the average of the past 20 years annual heating degree-days. The adjustment factor is CDD20 years/CDD school.

The figure 1 shows the cumulative histograms of the building energy use intensities (EUI). The building’s annual total energy use intensity must be placed on the x-axis, then, the intersection with the curve shows in the y-axis, the percentage of buildings, in the selected region, which are more efficient than the analysed building. This graph is accompanied by a benchmarking percentile table which aims at defining a degree level of standard \( (EUI)^N \) with description assessment, it is shown in table 1.

![Figure 1: Cumulative histogram percentile table of \((EUI)^N\) in schools in Catalonian region.](image)

If we analyse the figure 1, we notice that the average value (half of schools within 145 kWh/m\(^2\)/yr) and the minimum value (25% inferior to 105 kWh/m\(^2\)/yr) are very much higher than the maximum energy demand requirements for new and renovated school buildings defined in the Current Procura+ Criteria. This criteria was calculated for public buildings (based in many samples of 5 European countries), and developed by ICLEI (ICLEI, 2006).

<table>
<thead>
<tr>
<th>Degree Level of Standard</th>
<th>Description Assessment</th>
<th>Total Building Energy Efficiency (kWh/year/m(^2))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class I</td>
<td>Very Good</td>
<td>105 &lt; Class I</td>
</tr>
<tr>
<td>Class II</td>
<td>Good</td>
<td>105&lt; Class II &lt;145</td>
</tr>
<tr>
<td>Class III</td>
<td>Fair</td>
<td>145&lt; Class III &lt;185</td>
</tr>
<tr>
<td>Class IV</td>
<td>Poor</td>
<td>Class IV &gt; 185</td>
</tr>
</tbody>
</table>

The Procura+ Criteria fixes a threshold value of 67 kWh/m\(^2\)/yr, and a target value of 44 kWh/m\(^2\)/yr.

![Figure 2: Seasonal EUI for sample schools](image)

In comparison with the Energy Star National Energy Performance Rating System regression-based
model, developed by the U.S. Environmental Protection Agency’s, the results of EUI are also greater. The energy star method fixes an optimal rating in schools of 67 kWh/m²/yr (Matson, 2005). In figure 2 the seasonal energy consumption is showed. We notice that the main energy consumption occurs in winter season. In some cases this energy consumption duplicates the sum the two other consumptions. These big differences may be due to several factors:
- The building average age of these schools is over 30 years (around 1968), see table 2.
- Most of the seasonal efficiency of heating in buildings is below 80% (the average is 75%), thus, the heating energy consumption is higher than expected (see figure 2).
- Preventive maintenance protocols are not still implanted for the heating and lighting systems in most of the schools.
- The occupancy hours ratio is 6 h/day (8 month per year) however, the heater operation rate reaches 24 h/day in many of these schools.
- There is a lack of good occupant operations and maintenance practices.

3.2 Potential parameters of energy consumption

The climate-adjusted energy-use intensity EUI (in kWh/m²) is chosen as the output variable in the model. The previous e-Benchmarking method developed in Singapore (University of Singapore, 2003), and other Benchmarking methods, discussed some factors that influence annual energy performance of many buildings. These are people factors, occupancy factors, etc. We developed a model based in seasonal period, which is formed by seasonal parameters varying in each period (e.g., occupancy hour, indoor set point temperature) but also by remaining constant factors. All the relevant factors which remain constant, such as factors concerning the building type, system type, power of systems, or others, are also included in the model. The model is based in twenty four potential parameters. These parameters are presented in Table 2.

3.3 Selection of explanatory components

After the potential parameters are obtained, we must select a set of “explanatory components” which mainly affect the energy consumption of the schools. These explanatory components must be a reduced number of components which leads to a simple interpretable model (a few significant factors with small variance).

The factorial analysis method is used to reduce the original data to a small selected relevant data. This small number of data should be responsible of most of the variance observed in a greater number of variables. The SPSS software is used in this factorial analysis (Statistical for Package the Social Science) (SPSS, 2005).

The variables $x_i$ and $x_{10}$, which are linearly independent from the others, are selected like independent variables. The variable $x_9$ is eliminated along the process due to his low representativeness in the sample. The variable called Season was added. Finally 6 components and 3 independent variables are chosen like “explanatory components” representing the 85% of the total variance of the parameters. These components were calculated with the combination of “standardized parameters” $x_{i}'$ which are obtained with this formula:

$$x_{i}' = \frac{x_i - \mu_i}{\sigma_i}$$
Where the mean value is \( X_i \), and the standard deviation is \( S_i \). The connections among the explanatory components and the potential.

2) Number 1 = instantaneous electrical water heater, 2 = gas boiler, 3 = accumulation system. (3) 1 = good, 2 = fair, 3 = poor parameters showed in Table 2 can be expressed as three arrays (see figure 3). Where \( |X| \) is the potential variables matrix, \( |a| \) is the factor matrix, \( |C| \) is the explanatory components matrix.

Where, and \( X_1 \) and \( X_{10} \) are the independent variables. In Table 3 the explanatory components matrix calculated for the sample is shown.

\[
\begin{pmatrix}
X_{11} & X_{12} & X_{124} & a_{11} & a_{17} & a_{16} & C_{11} & C_{17} & C_{16}
X_{31} & \ldots & \ldots & a_{31} & \ldots & \ldots & C_{31} & \ldots & \ldots
X_{71} & \ldots & X_{724} & a_{71} & \ldots & a_{746} & C_{71} & C_{77} & C_{76}
\end{pmatrix}
\]

and

\[
\begin{pmatrix}
X_{11} & X_{101}
X_{12} & X_{102}
X_{17} & X_{107}
X_{187} & X_{1087}
\end{pmatrix}
\]

Figure 3: Matrix of explanatory components

4. RESULTS

We used the Flood A application, which implements a neural network called multilayer perceptron. A neuron model is the basic information processing unit in a neural network.

Mathematically, a perceptron neuron model may be viewed as a parameterized function \( V \) from an input \( X \subset \mathbb{R} \) to an output \( Y \subset \mathbb{R} \). Each processing element (neuron) is supplied with a transfer function \( y_k \) and a weight \( b_k \) in each connection.

Input data are transferred from the input layer and forward through the network to the output layer, where an output value is obtained (see figure 4). Several parameters must be fixed: number of hidden units, weight decay or another learning parameter.

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Figure 5: \( R^2 \) quadratic mean error and linear regression parameters for calculated and measured EUIs.
The learning process followed in the study was 1) select input training variables, select the size of the hidden layer, select the learning parameters (e.g., maximum error, maximum iterations), 2) use the error square adjustment to modify the weights, 3) repeat the sequence over all patterns of the learning database and all iterations, and 4) stop the procedure when the accuracy is obtained or the number of iterations has been reached.

After the process, we obtained a perceptron multilayer with 9 input variables (6 components and 3 independent variables), 12 neurons in the hidden layer, and 1 output neuron, with stopping criteria of 100 iterations. The result of validating dataset comparing with measured EUI for the 29 schools is shown in figure 5 and figure 6. As it is observed, the accuracy of EUI prediction is less than 5% (linear $R^2$ of 0.99).

Finally we calculated the EUI saving predicted by improvement of the efficiency of heating from 0.61 to 0.85. The result is showed in figure 7. The predicted energy saving is 3% in summer, 10% in winter, and 45% in intermediate season.

5. CONCLUSIONS

We conclude that the proposed method shows promising features in order to become an easy to use tool for predicting the energy consumption of public buildings. The number of inputs is big enough. In order to limit the data acquisition to only a few parameters we propose the selection of only the most representative parameters.

The model predicts with good accuracy, but we noticed that the generalisation of results for other schools or public buildings will need more buildings from other climate regions, and more detailed parameters. The occupants’ behaviour, and the building structure should be more detailed in future models.

REFERENCES


