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Development of surrogate models using artificial neural network for building shell energy labelling

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HIGHLIGHTS

- We model several typologies which have variation in input parameters.
- We evaluate the accuracy of surrogate models for labelling purposes.
- ANN is applied to model the building stock.
- Uncertainty in building plays a major role in the building energy performance.
- Results show that ANN could help to develop building energy labelling systems.

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ABSTRACT

Surrogate models are an important part of building energy labelling programs, but these models still present low accuracy, particularly in cooling-dominated climates. The objective of this study was to evaluate the feasibility of using an artificial neural network (ANN) to improve the accuracy of surrogate models for labelling purposes. An ANN was applied to model the building stock of a city in Brazil, based on the results of extensive simulations using the high-resolution building energy simulation program EnergyPlus. Sensitivity and uncertainty analyses were carried out to evaluate the behaviour of the ANN model, and the variations in the best and worst performance for several typologies were analysed in relation to variations in the input parameters and building characteristics. The results obtained indicate that an ANN can represent the interaction between input and output data for a vast and diverse building stock. Sensitivity analysis showed that no single input parameter can be identified as the main factor responsible for the building energy performance. The uncertainty associated with several parameters plays a major role in assessing building energy performance, together with the facade area and the shell-to-floor ratio. The results of this study may have a profound impact as ANNs could be applied in the future to define regulations in many countries, with positive effects on optimizing the energy consumption.

1. Introduction

Building sustainability has become an important part of the building industry, particularly with the increasing demand for sustainability certifications, such as Leadership in energy and environmental design (LEED) and the building research establishment environmental assessment method (BREEAM). Thus, researchers in many countries are realizing the importance of having more energy efficient buildings and are developing local certification programs to assist with improving the efficiency of their building stock, usually assigning labels to indicate the building energy performance (ASHRAE, 2010; CALIFORNIA, 2001; Dascalaki et al., 2012; Gram-Hanssen et al., 2007; Hernandez and Kenny, 2011; Klotz et al., 2010; Kong et al., 2012; Lee and Rajagopalan, 2008; Mlecnik et al., 2010; Wiel and McMahon, 2003; Yang et al., 2010b).

In most labelling programs, building energy simulation (BES) is a key element to assess building performance, both for new and existing buildings. It is therefore essential to have reliable BES programs available in order to assign labels correctly, improving the public trust in the labelling program. High-resolution dynamic BES programs, such as EnergyPlus, EQuest, ESP-r, IES, EDSL-TAS, TRNSYS, VABI, are generally accepted as reliable programs to assess building energy performance due to numerous validation exercises carried out over the past few decades. However, these

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Nomenclature

a_{roof}	roof absorptance of solar radiation [-]
a_{wall}	wall absorptance of solar radiation [-]
b_n	bias of hidden node n
b_S	bias of the output node
$\bar{e}$	mean bias error—MBE
E_{con}	energy consumption [kW h/m^2 yr]
E_{max}	maximum energy consumption used in the ANN training [kW h/m^2 yr]
E_{min}	minimum energy consumption used in the ANN training [kW h/m^2 yr]
H	number of nodes in the hidden layer
I	infiltration [ACH]
ILD	internal load density [W/m^2]
NETinput	as defined in Eq. (3)
PU	patterns of use [h/day]
R^2	coefficient of determination
U_{wall}	wall thermal transmittance [W/(m^2 K)]
$W_{i,n}$	weight values for each pair of nodes connecting the input and hidden layers
$W_{n,s}$	weight values for each pair of nodes connecting the hidden and the output layers
X	number of input nodes
x_i	input value i of the ANN model
x_{MAXi}	maximum values of the input i used in the ANN training
x_{MINi}	minimum values of the input i used in the ANN training
σe	error standard deviation, also known as root-mean squared error—RMSE

Acronyms

ACH	air changes per hour [1/h]
ANN	artificial neural network
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BES	building energy simulation

programs require expert users, detailed inputs and considerable computational resources depending on the building complexity. These requirements compromise the wide adoption of dynamic BES simulation in most building energy labelling programs, as labelling tools must provide reliable results within an acceptable time frame and at an affordable cost.

Dynamic BES is usually adopted for innovative and unusual buildings, while the majority of the building stock is labelled using low-resolution low-cost models. These models can be divided into two groups: (a) first-principle models, based on physical equations (such as the Fourier law) in combination with large simplifications of reality or; (b) surrogate models based on statistical modelling of large datasets produced using dynamic BES. While low-resolution first-principle models can provide reasonably accurate results in heating-dominated climates, the complex dynamics of solving problems related to cooling-dominated climates has proven to be difficult to capture using extensive simplifications of reality (Hensen and Radosevic, 2004). Therefore, surrogate models have been adopted in countries with cooling-dominated buildings, such as in the Brazilian energy regulations for building labelling (BRASIL, 2009).

Surrogate models are simple and affordable to use, but the accuracy of the results is strongly dependent on the particularities of the building stock, climate, quality of the input data used and modelling technique adopted in the development of the surrogate model. The use of surrogate models for labelling purposes is a new field, and recent results have shown that the accuracy of such models is still far from ideal (Melo et al.). The current Brazilian energy regulations for commercial buildings, for example, adopts a surrogate model with known accuracy issues, highlighting the importance of further research on this topic. However, the importance of research on surrogate models for labelling purposes goes far beyond the Brazilian case, as most developing countries with cooling-dominated buildings face similar challenges in their programs for energy conservation.

Of the many techniques available for surrogate modelling, the artificial neural network (ANN) has been successfully used in many fields (Basheer and Hajmeer, 2000; Ben-Nakhi and Mahmoud, 2004; Sung, 1998), and in particular for energy calculations at different levels (Ben-Nakhi and Mahmoud, 2004; Ekici and Aksoy, 2009; Fonseca et al., 2013; González and Zamarreño, 2005; Karatasou et al., 2006; Li et al., 2011; Magnier and Haghighat, 2010; Mahmoud and Ben-Nakhi, 2003; Neto and Fiorelli, 2008; Ruano et al., 2006; Wong et al., 2010; Yang et al., 2005; Zemella et al., 2011). An ANN is able to learn from examples, storing the experimental knowledge for use when required. However, the development of a typical ANN architecture requires a specific understanding of how it can be applied to obtain the desire performance (Hippert et al., 2001). An ANN usually consists of an input layer, some hidden layers and an output layer. The input layer consists of data which represent the problem and the output layer shows the response with regard to each problem. The main function of the input layers is to relate each input to the output. A training process is carried out so that the ANN minimizes the mean square error of the entire data set. The learning process allows the behaviour of the ANN inputs and outputs to be modified as a result of changes in the environment, thus enhancing the ANN performance (Battiti, 1994). Therefore, it is important that all of the information the network needs to learn is supplied to the network as a dataset. The capabilities and advantages of ANNs are widely known, such as the resistance to errors and noise (Bezdek and Pal, 1992). These capabilities combined with the compact nature of the models makes ANNs strong candidates for use as an energy performance assessment tool in compulsory labelling programs in developing countries. However, to the best of our knowledge, ANNs have not yet been used for building energy labelling purposes. Therefore, in this study we investigate the applicability of an ANN as a surrogate modelling technique for building energy labelling purposes. This work is concentrated on the development of an accurate ANN model based on extensive dynamic BES of the building stock. The labelling of commercial buildings in the Brazilian city of Florianópolis was chosen for the case study, but the methods described in this paper are, in principle, applicable to any other locations, climates and building stock properties.

The paper is organized into 5 sections as follows: Section 2 describes the methods and input information adopted in this paper, comprising: (a) description of the key performance indicators addressed in the Brazilian building energy regulations (BRASIL, 2009), (b) details regarding the building stock in Florianópolis which is the subject of the labelling process, (c) simulations using the dynamic BES program EnergyPlus, which were later used as a data source in the surrogate modelling process, and finally (d) details on the development of the ANN. Section 3 presents the results, with a