Energy and Buildings 151 (2017) 332–343

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Modelling the relationship between heating energy use and indoor temperatures in residential buildings through Artificial Neural Networks considering occupant behavior

Sara M.C. Magalhães [a,*], Vítor M.S. Leal [b], Isabel M. Horta [c]

[a] Institute of Science and Innovation in Mechanical and Industrial Engineering, Faculty of Engineering of University of Porto, Rua Dr. Roberto Farias, 4200-465 Porto, Portugal
[b] Department of Mechanical Engineering, Faculty of Engineering of University of Porto, Rua Dr. Roberto Farias, 4200-465 Porto, Portugal
[c] Department of Industrial Management and Engineering, Faculty of Engineering of University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal

ARTICLE INFO

Article history:
Received 8 October 2016
Received in revised form 20 June 2017
Accepted 30 June 2017
Available online 1 July 2017

Keywords:
Heating energy use
Indoor temperatures
Residential buildings
Artificial neural networks
Modeling

ABSTRACT

The heating energy demand stated in energy performance certificates (EPC) and in other instruments used in the of evaluation of building's energy performance is usually determined assuming very specific (reference) indoor behavioral/heating patterns. Particularly, they tend to assume that households heat (nearly) the entire house to a “comfort” temperature during (nearly) all the heating season. However, several field studies have shown that there are major niches of the housing stock which do not follow this pattern (even the majority, in some geographical areas). Considering this matter, it would be interesting to build models able to estimate heating energy use values resultant from occupation and heating patterns different from those considered as “reference”.

This work aimed at producing tools to assess the relationship between heating energy use and indoor temperatures at different levels of occupant behavior (in terms of where, when and at what temperature households heat their dwellings). This relationship was expressed through models while still takes advantage of the information from the certificates.

The work developed artificial neural networks (ANN) that characterize the relationship between heating energy use, indoor temperatures and the heating energy demand under reference conditions (typically available from energy rating/certificates) in the residential buildings, for different occupant behaviors/heating patterns. Theoretically, these models can be applicable to any national geographical context.

The data for building the ANNs was obtained from dynamic thermal building simulations using ESP-r, considering a large number of housing types and hypothetical occupation and heating patterns (i.e., which parts of the house are heated, when and at what temperature). From the analysis performed, it was possible to conclude that the developed ANN models proved to perform well ($R^2 > 0.93$) in estimating either heating energy use or indoor temperature, both at an individual and at the building stock level.

This work may have important contributions in the energy planning practices regarding the residential building stock.

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Abbreviations: AI, artificial intelligence; ANN, artificial neural networks; M, building archetype; R^2, coefficient of determination; EPC, energy performance certificates; EPB, energy performance in buildings; EPBD, European Performance Building; L, geographical location; HDRC, heating energy demand under reference conditions; HEU, heating energy use; Hpat, heating pattern; HP, heating period; HG, indoor heat gains; MAE, mean absolute error; MAPE, mean absolute percent error; MSE, mean square error; HA%, percentage of heated area; $HPat_{ref}$, reference heating pattern; HG_{ref}, reference indoor heat gains; Tsp_{ref}, reference set point temperature; Tsp, set point temperature; $HDRC_{st}$, standard heating energy demand under reference conditions.

* Corresponding author.
E-mail addresses: sara.magalhaes@fe.up.pt (S.M.C. Magalhães), vleal@fe.up.pt (V.M.S. Leal), imhorta@fe.up.pt (I.M. Horta).

http://dx.doi.org/10.1016/j.enbuild.2017.06.076
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1. Introduction

The energy needs for heating a dwelling depend crucially on the physical characteristics of the building, on the climate where it is located, and also on the occupant's behaviour, with emphasis to the magnitude, space and time distribution of the temperatures required (i.e., which parts of the house are heated, when and at what temperature). The physical characteristics of the building are well-defined by nature. They only change in time when there are upgrades to the envelope. Although it may sometimes be difficult to know the physical details, in the case of existing buildings (e.g., the thickness of thermal insulation hidden inside walls), it is usually possible to make a reasonable inference from energy performance certificates (EPC). Despite its inherent variability from year to year, the climate is nowadays also reasonably well characterized through databases.

The magnitude, space and time distribution of the temperatures desired are however a much volatile aspect, which depends on the occupants preferences and/or capacity to afford heating. While 'reference' patterns are assumed for computing the energy needs, e.g., for energy labeling and certification purposes, it is known that these may significantly differ from those found out in practice. For example, Magalhães et al. [1] from a monitoring campaign to 141 dwellings in the Northern region of Portugal found that bedroom and living temperatures were much lower than the reference values of 18 °C assumed in the current Portuguese regulation of the thermal performance of the residential buildings [2]. Also, Kane et al. [3] studied the heating patterns in 249 dwellings in Leicester in UK and concluded that indoor temperatures were much lower than those often assumed by BREDEM-based energy models. This often leads to undervaluing (or even disregarding) the information from the assessments and/or energy performance certificates (EPC). However, given that those assessments contain a good description of the building physical characteristics and of the climate, a more valuable use of the information could be extracted if a relationship between the reference energy demand, the indoor temperature and the heating energy use was known. For example, given the reference energy needs and a certain indoor temperature intended, it would be possible to estimate the actual heating required. Conversely, given the maximum amount of heating than can be afforded, it would be possible to estimate the resultant indoor temperatures.

There is a constant search for user-friendly models to predict heating energy use in the residential buildings with the possibility of assuming different values of occupant behaviour (i.e., operating conditions) [4]. Furthermore, EPC databases, such as those derived from the European Performance Building (EPBD) hold an extensive number of certificates already issued with important information on building data (e.g., values for the theoretical heating energy demand under reference conditions (HDRC)). Provided that there is an understanding of the relationship between the heating energy use, occupant behavior (e.g. indoor temperatures) and HDRC, and using the HDRC values from EPC databases, it should be possible to estimate heating energy use or indoor temperatures values for different types of occupant behaviour.

Dynamic modeling of individual dwellings can estimate accurately the heating energy use, but it is complex and time-consuming [5,6].

Statistical models have increasingly gained recognition as a viable alternative to predict thermal performance in buildings. Many studies in the literature have explored the ability of different statistical models to predict variables in the context of energy performance in buildings (EPB) [6–26]. They use historical, simulated or calculated energy use data to predict a building's energy dynamic performance. The preference for a statistical model relies on the fact that it is possible to predict outputs without resorting to the simulation building software. Thus, these techniques allow to reduce significantly the computation time [27]. There are different statistical models used in the literature, such as the traditional statistical approaches (e.g., the regression analysis), or the artificial intelligence (AI) models (e.g., the artificial neural networks (ANN), the support vectors machine, the genetic algorithm, or the decision trees) [28,29]. This paper explores the use of ANN models to predict heating energy use or indoor temperatures in the residential buildings applied to any national geographical context.

2. Modeling concept

The European Commission fostered the advance of energy efficiency in the building sector by publishing the EPBD in 2002 (Directive 2002/91/EC) [30]. This Directive proposes the adoption of structured methodologies for calculating the energy use in buildings, quality requirements for new and existing buildings, and the periodic inspection of boilers and air conditioning central systems. In addition, it requires the existence of an energy certificate of all buildings when undergoing a commercial transaction. In this regard, the directive changed the focus from new buildings to the entire building stock. This Directive was recast on May 2010 as 2010/31/EU Directive [31] and was adopted by the European Parliament and the Council of the European Union.

According to the EPBD all European Union Member States require an energy performance certificate (EPC) when buildings are constructed, sold and rented. The EPC was considered a pioneering instrument that would overcome a deficit of information, hindering consumer interest in energy efficient dwellings [32]. The copies of all the EPC certificates issued both for new and for existing buildings are compiled in databases. The implementation of these databases, their availability and who holds them varies nationwide.

Each certificate can provide a HDRC value. The HDRC, in a form of 'useful energy', of a particular building depends on several factors, such as physical characteristics of the building archetype (M); geographical location of the building (L); reference heating pattern ($HPat_{ref}$); reference indoor heat gains (HG_{ref}), and reference set point temperature (Tsp_{ref}). This relationship can be expressed, in a general form, by Eq. (1) as follows:

$$HDRC = f(M, L, HPat_{ref}, HG_{ref}, Tsp_{ref}) \quad [kWh/m^2.year] \tag{1}$$

The heating energy use (HEU) of a particular building, which is also named as 'useful' energy, depends on the building characteristics, climate conditions, and occupantís heating behaviour [4,33–41]. More specifically, it depends on the geographical location of the building (L); physical characteristics of the building archetype (M); heating pattern (HPat); indoor heat gains (HG) and set point temperature (Tsp). The latter three are defined by the occupantís behaviour.

The heating energy use can be therefore expressed, in a simple manner, by the relationship described in Eq. (2).

$$HEU = f(M, L, HPat, HG, Tsp) \quad [kWh/m^2.year] \tag{2}$$

It is possible to create a more operational and simple version of the model (Eq. (2)) by replacing the variables building archetype (M), the geographical location (L), the heating patterns (HPat) and indoor heat gains (HG) by the theoretical heating energy demand under reference heating conditions (HDRC). Despite the assumptions behind the methodology used to estimate HDRC, the convenience of using the HDRC as a *proxy* variable lies on the fact that, in principle, this information can be directly gathered from any energy rating/certification databases. Other major benefit of using HDRC is that it overcomes the difficulty of getting access to detailed data at building level.

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