Energy & Buildings 170 (2018) 170–182

Contents lists available at ScienceDirect

Energy & Buildings

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

Modelling aggregate hourly electricity consumption based on bottom-up building stock

Marta J.N. Oliveira Panão*, Miguel C. Brito

Instituto Dom Luis, Faculdade de Ciências, Universidade de Lisboa, Campo Grande, Lisboa 1749-016, Portugal

ARTICLE INFO

Article history:
Received 12 September 2017
Revised 9 March 2018
Accepted 5 April 2018
Available online 19 April 2018

Keywords:
Building stock
Hourly electricity consumption
User behaviour modelling
Bottom-up model
Validation
Residential buildings

ABSTRACT

This paper presents a building stock energy model for the estimation of hourly electricity consumption for a large group of residential buildings. A Monte Carlo model stochastically generates a large sample of dwellings representative of the building stock and the correspondent number of user profiles, statistically supported by a web survey about the use of energy in dwellings for space heating and cooling. The model uses hourly energy balance equations to estimate energy needs and calculates the mean annual electricity consumption for regularly occupied dwellings with an error below 3%. Model is also validated against independent smart-metered data of about 250 dwellings. Hourly electricity consumption results feature an overall normalised mean absolute error of 11% and normalised root mean square error of 16%. The maximum relative difference is ±72% and the maximum absolute error is ≃217 Wh/h. The model is considered to be able to predict hourly electricity consumption accurately.

1. Introduction

The energy demand of the residential sector represents about 30% of the world electricity demand [1]. This is an energy sink difficult to characterise since it features a wide variety of buildings and occupant behaviors, and large-scale collection data is hindered by its spatial distribution and privacy issues. Hence, many different models and approaches have been developed for estimation of the residential sector energy load, as reviewed by Swan and Ugursal [2] and Li et al. [3].

The development of realistic models capable of estimating hourly or sub-hourly aggregated demand profiles is more recent. They are critical tools for accurate load forecasting, the planning of electricity distribution grids and optimisation of the generation capacity. In fact, focus on hourly data allows addressing emerging matters such as peak demand management or demand-supply balancing strategies developed in the context of fast emerging distribution generation (e.g. rooftop photovoltaics) [4].

This type of models is also relevant for the understanding of the impacts of changes in climate or energy policies on the consumption patterns of the residential sector.

The main goal of this paper consists of developing and validating a building stock energy model for the estimation of hourly electricity consumption for a large group of residential buildings (at the regional and national scale). The option of selecting the Lisbon city in the validation process is justified by the availability of smart-metering data of about 250 dwellings during a monitoring campaign in 2011–2013 by Lisboa E-Nova, in the framework of "Intelligent Monitor for Efficient Decisions" project, funded by Energy Services Regulatory Authority (ERSE), under the National Plan for Promoting Efficiency in Electricity Consumption 2011–2012 [5].

This paper is organised as follows: Section 2 presents a review of the state of the art on building stock energy models; Section 3 describes the energy model with the exception of user behaviour that is explained in Section 4; Section 5 presents the model results compared with validation data; and finally, Section 6 synthesises the main conclusions and discusses the potential for future work.

2. Literature review

Predictive tools to estimate how much energy a large group of buildings use are known as *building stock energy models* [6]. What these models have in common is their focus on large areas, instead of a single or a small number of buildings. There are a large multiplicity of models specifically developed to predict the residential sector energy consumption that Swan and Ugursal [2] classified into top-down or bottom-up, the latter subdivided into statistical or physics-based.

Top-down models use as main data source historical data of the use of energy combined with macro-scale indicators from differ-

* Corresponding author.
E-mail addresses: mopanao@ciencias.ulisboa.pt, mopanao@fc.ul.pt (M.J.N. Oliveira Panão).

https://doi.org/10.1016/j.enbuild.2018.04.010
0378-7788/

nomenclature

Symbols

A	area [m^2]
A_f	net floor area [m^2]
$\hat{A}$	normalised area (by net floor area) [–]
$\hat{A}_{sol}$	effective solar collecting normalised area [–]
b_{tr}	adjustment factor [–]
c	specific heat [J kg^{-1} K^{-1}]
F_g	frame correction factor [–]
F_s	shading factor [–]
F_w	selective glazing correction factor [–]
g	solar heat gain coefficient [–]
G_{sol}	solar irradiation integrated over time [Wh m^{-2}]
h	ceiling-to-floor height [m]
$\hat{H}$	normalized (by net floor area) global heat transfer [W K^{-1} m^{-2}]
l_Ψ	length of linear thermal bridges [m]
Q_C	cooling energy demand [Wh]
Q_{gn}	heat gains [Wh]
Q_{ht}	heat losses [Wh]
Q_H	heating energy demand [Wh]
Q_{sol}	solar gains [Wh]
$\overline{Q}$	average annual electrical consumption [Wh]
U	overall thermal transmittance [W m^{-2} K^{-1}]
t	hour interval [h]
$\hat{\upsilon}$	air change rate [h^{-1}]
y	observed (or measured) variable
$\hat{y}$	modelled variable
δ	relative difference [–]
θ_i	indoor air temperature [°C]
θ_o	outdoor air temperature [°C]
$\overline{\theta}$	mean temperature [°C]
κ	(first) shape factor of Weibull and Burr distributions
λ	scale factor of Weibull and Burr distributions
ν	average of Gaussian distribution
μ	second shape factor of Burr distribution
ρ	volumetric density [kg m^{-3}]
σ	standard deviation of Gaussian distribution
Ψ	linear thermal bridge transmittance [W m $^{-1}$ K^{-1}]

Subscripts

$1 \to n$	1 to n batches
$1 \to n-1$	1 to $n-1$ batches
$\perp$	normal incidence
a	air
e	external envelope
g	ground floor
E	all end-uses
gl	glazing
i	internal envelope
i	time-step (hourly, monthly, annual)
j	façade orientation
H	space heating
m	total number of time-steps (hourly, monthly, annual)
min	average of daily minimum
max	average of daily maximum
op	opaque envelope
n	number of batches
sh	fully active shading devices
tr	transmission
ve	ventilation
w	windows

Acronyms

ANN	artificial neural networks
COP	coefficient of performance
EER	energy efficiency ratio
DHW	domestic hot water
EPC	energy performance certification/certificates
GIS	geographic information system
MAXAD	maximum absolute difference
MAXRD	maximum relative difference
NMAE	normalised mean absolute error
NRMSE	normalised root mean square error
NUTS III	third level division of territorial units for statistics
TMY	typical meteorological year
UBEM	urban building energy models

ent categories: macroeconomic, climatic, housing stock rates, demographic or technological. Examples of top-down residential final energy estimation are those developed for Denmark [7], Switzerland [8] and UK [9]. The model developed for Turkey includes final energy of the commercial sector [10]. Top-down models do not require an intensive characterisation of the buildings, appliances or end-uses. Since time-series for disaggregated end-uses are seldom available, top-down models are not adapted to predict energy consumption by end-use.

Bottom-up models require the setting of a group of buildings, usually theoretical buildings representative of the building stock defined as 'archetypes' or 'prototypes' [11,12]. The building stock is rebuilt by attributing a representative factor to each one of the building types. An alternative strategy is to focus on a group of real buildings (a 'sample') representative of the overall building stock.

The energy demand of the buildings may be determined by physics laws (e.g. energy conservation principles) or statistical models. Statistical models include artificial neural networks (ANN), time series models, similar day look-up and regression-based approaches. The smaller amount of input data constitutes the main strength of this type of models. However, the uncertainty of the predictions of the statistical models evaluated in Soto and Jentsch [13] are higher than for physics-based model, which is attributed to their inherent simplifications.

The outputs of the building stock models are generally restricted to annual, and in a few cases monthly, energy consumption. From the nine models included in the revision of Kavgic et al. [6] only three of them make monthly estimates [14–16], all other models make annual estimates.

Urban Building Energy Models (UBEM) are specifically targeted to predict hourly energy for neighbourhoods (urban scale), an intermediate scale between the single building and building stock, based on Geographic Information System (GIS) buildings description [17]. Increasing the order of magnitude of the number of time-steps ($\sim 10^4$ for the hourly scale) requires handling a significant amount of information, massive in time and space, leading to very simplified models or the definition of a limited number of buildings archetypes and users' types. Currently, this is not a real constraint since most of the urban energy models applied to neighbourhoods, cities or regions of Table 1, use physical models with hourly time-step even if results focus on annual and monthly energy consumption [12,18–22]. Explicit hourly profiles are only found in [11,23].

Providing hourly (or sub-hourly) energy estimates requires hourly (or sub-hourly) data for validation. None of the models listed in Table 1 use hourly data in the calibration process. Sokol et al. [22] used monthly energy consumption data to calibrate a UBEM [24] based on a 76 archetypes library of a mix of residential