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Monte Carlo housing stock model to predict the energy performance indicators

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ABSTRACT

This study presents a new physics-based model of housing stock energy using Monte Carlo, where inputs are probability distribution functions originated from Energy Performance Certification (EPC) Portuguese database. The overall performance of the model in predicting the energy indicators used in EPC is extremely satisfactory, considering that the inputs required to run the calculations are not always available. The model outputs are validated against EPC data with residual sum of squares (RSS) below 2×10^{-3}, except for cooling energy benchmark with RSS below 4×10^{-2}. The main output of EPC, the distribution among classes, is successfully reproduced by the model, with differences in the number of occurrences below 3.1%. The developed model constitutes a tool that helps on further research on energy policies, namely, studying the impact evaluation of more restrictive thermal quality requirements; evaluating other methodological approaches to calculate energy indicators; analysing policies of building elements retrofitting and bottom-up estimations of housing stock energy consumption.

1. Introduction

Housing stock energy models are predictive tools of the total energy consumption of a large set of houses in a regional or national domain. The data source of top-down models are energy consumption time-series of residential sector by energy carrier as well as other macro-scale indicators. One of the main disadvantages of these models is their inability to disaggregate energy consumption by end-use, when used alone. Bottom-up models, instead, extrapolate aggregate values from a sample of houses where energy consumption by end-use, or even by appliance, are known for the housing stock. Examples of bottom-up models are statistical models where historical data are used to find the mathematical functions that predict energy consumption, this can be done by regression methods, conditional demand analysis or neural networks, according to the categorisation introduced by Swan and Ugursal [1]. Statistical methods have in common the use of mathematical functions not based in building physics.

Physics-based models are also bottom-up models, but are based on heat transfer analysis and, therefore, they do not require historical data, even if those can be very useful in validating model assumptions. Bottom-up physics based models can be categorised in *distributions*, *archetypes* and *samples* [1]. In the first case, the required inputs are characterised by distributions from existing surveys. The main difference between *archetypes* and *sample* approaches is that archetypes are theoretical houses representative of the common characteristics of a group of real houses, while the sample approach is constituted by real houses that have been intensively surveyed.

An important data source for bottom-up physics based models are the Energy Performance Certificates (EPC) [2], currently mandatory for housing transactions such as renting or selling, in most of the European countries. This data source constitutes a large *sample* representative of the housing stock. However, not always all the information required to apply bottom-up physics based models is directly available and assumptions from complementary sources are required in order to provide the required model inputs. A certain level of assumptions uncertainty exist and should be taken into account.

Handling uncertainty in building simulation is a well explored issue, where parameters errors associated with different groups of variables are taken into account in the prediction of energy consumption, air temperature or peak loads. Lomas and Eppel [3] suggested that Monte Carlo is the preferential technique to obtain the total model sensitivity to multiple variables. Pettersen [4,5] developed a simplified energy calculation model, using

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Nomenclature

a	dimensionless parameter of inertia [–]
A	area [m^2]
$\hat{A}$	normalised area (by net floor area) [–]
ACH	air changes per hour [h^{-1}]
b_{tr}	adjustment factor [–]
c	specific heat [$J\,kg^{-1}\,K^{-1}$]
$\hat{E}_{res}$	normalised (by net floor area) annual energy generated using renewable energy sources [$kWh\,m^{-2}$]
f	fraction of energy supplied by a system [–]
f_w	fraction of windows by orientation [–]
F_f	fins shading correction factor [–]
F_g	glazed windows fraction [–]
F_h	horizon shading correction factor [–]
F_o	overhangs shading correction factor [–]
F_s	shading correction factor [–]
F_{sh}	time fraction for movable shading devices activation [–]
F_w	correction factor for non-scattering glazing [–]
$g_{gl\perp}$	glazing g-value at normal incidence [–]
g_{sh}	glazing g-value with fully active shading devices [–]
G_H	monthly horizontal global solar radiation [$kWh\,m^{-2}$]
G_S	monthly global solar radiation on South façade [$kWh\,m^{-2}$]
h	ceiling-to-floor height [m]
H	global heat transfer [$W\,K^{-1}$]
$\hat{H}$	normalised (by net floor area) global heat transfer [$W\,K^{-1}\,m^{-2}$]
HDD	heating degree-days [K day]
l_Ψ	length of linear thermal bridges [m]
M	heating season length [months]
N	number of bins
$\hat{Q}$	normalised (by net floor area) annual energy [$kWh\,m^{-2}$]
p	certificates fraction by bins interval [–]
R	ratio between total energy demand and the corresponding benchmark [–]
R^2	determination coefficient [–]
R_{se}	external thermal resistance [$m^2\,K\,W^{-1}$]
U	overall thermal transmittance [$W\,m^{-2}\,K^{-1}$]
V	water volume [m^3]
w	weighted energy factor [–]
α	absorption coefficient of external envelope [–]
γ	gain-to-heat transfer ratio [–]
δ	overheating index [–]
$\Delta\theta$	water temperature difference [K]
η	system efficiency, COP or EER [–]
η_{gn}	gain utilisation factor [–]
$\bar{\theta}_e$	average air temperature [K]
κ	(first) shape factor of Weibull and Burr distributions
λ	scale factor of Weibull and Burr distributions
μ	average of Gaussian distribution
ν	second shape factor of Burr distribution
ρ	density [$kg\,m^{-3}$]
σ	standard deviation of Gaussian distribution
Ψ	linear thermal bridge transmittance [$W\,m^{-1}\,K^{-1}$]

Subscripts

a	air
b	benchmark
C	cooling
e	external envelope
f	net floor
g	ground floor
gn	gains
ht	heat transfer
H	heating
i	internal envelope
n	orientation
j	energy carrier
k	energy supply system
op	opaque envelope
sol	solar effective collecting
tr	transmission
T	total
ve	ventilation
w	windows
W	water

Monte Carlo, for a dwelling where a large number of parameters – climate, building and inhabitants related – are inputs in the form of probability distribution functions. Macdonald and Strachan [6] introduced in ESP-r, a building simulation tool, the capability of taking into account the inputs error using the Monte Carlo approach. However, most of the studies, such as the aforementioned, concern the uncertainty analysis on a single building where the number of uncertain parameters is already high.

For building stock analysis the uncertainty is even more relevant by the enormous number of required inputs [7]. Hughes et al. [8] analysed the uncertainty of 37 parameters, using Monte Carlo, on a domestic energy consumption model in order to assess the energy and environmental impacts of changes in the housing stock. The main constraint of the study is that most of the variables are described by uniform distribution functions around a mean value with a range of error. Authors recognise that this issue could be improved with better information sources. On the other hand, Kavgic et al. [9] used also Monte Carlo to study the space heating energy consumption of the Belgrad's housing stock, applying different types of probability distribution functions. However, calculations use as a starting point standard space heating energy demand and, therefore, the model is a bottom-up model, but not a physics based one. Soto and Jentsch [10] tested the Monte Carlo analysis to study the uncertainty of seven bottom-up models, from those only three of them are physics based, since they effectively calculate energy demand.

The current study aims at implementing and testing the use of Monte Carlo, to handle with the large amount of EPC data. This database could theoretically constitute a valuable *sample* of the building stock if all the parameters required to apply physics based models were known. However, for a large number of parameters some 'guessing' exercise is required and other complementary sources should be used. In synthesis, the main goal is to use Monte Carlo to create a theoretical *sample*, made of all the inputs required for physics based models, that has the same behaviour of a real but incomplete *sample*.

The Monte Carlo is here tested to describe the variability of climate and building related parameters because those can be directly validated by EPC data. However, the methodology can be extended to other groups of inputs, for example those related to energy use behaviour, where uncertainty and variability is much higher. The next section explores the fundamental pillars that characterise housing stock bottom-up physics based models.