Thermal comfort prediction in a building category: Artificial Neural Network generation from calibrated models for a social housing stock in southern Europe

Rocío Escandón [a,*], Fabrizio Ascione [b], Nicola Bianco [b], Gerardo Maria Mauro [b], Rafael Suárez [a], Juan José Sendra [a]

[a] *Instituto Universitario de Arquitectura y Ciencias de la Construcción, Escuela Técnica Superior de Arquitectura, Universidad de Sevilla, Av. de Reina Mercedes 2, 41012 Seville, Spain.*
[b] *Università degli Studi di Napoli Federico II, Piazzale Tecchio 80, 80125 Napoli, Italy.*
[*] *Corresponding author, e-mail address: rescandon@us.es*

Abstract

A significant part of the housing stock in southern Europe is obsolete and in need of extensive retrofitting to improve its energy performance and thermal comfort. However, before adequate retrofit measures can be proposed for this housing stock, the characterization of current building performance is fundamental. Although the simulation tools frequently used and widely accepted by the scientific community ensure accurate results, these require high computational times. The main aim of this paper is the development of a surrogate model to speed up the thermal comfort prediction for any member of a building category, ensuring high reliability by testing the entire simulation process with real data measured in-situ. To this end, an artificial neural network (ANN) is generated under MATLAB® environment using the data obtained from EnergyPlus simulations for linear-type social housing multi-family buildings in southern Spain, which were constructed in the post-war period. The developed ANN provides a regression coefficient between simulation targets and ANN outputs of 0.96, with a relative error between monitored and simulated data below 9%. A further result is that the building category characterization shows a general lack of suitable indoor thermal comfort conditions, thereby showing the great need for effective retrofit strategies.

Keywords: social housing stock; thermal comfort; building performance simulation; sensitivity analysis; simulation model calibration; surrogate models.

Nomenclature	
Acronyms	
ACH	Air changes per hour
ANN	Artificial neural network
CV(RMSE)	Coefficient of Variation of the Root Mean Square Error
HVAC	Heating, ventilating and air conditioning
LHS	Latin hypercube sampling
MM	Thermal comfort standard for hybrid or 'Mixed Mode' buildings
NMBE	Normal Mean Bias Error
PMV	Predicted mean vote
PPD	Predicted percentage of dissatisfied
RefCS	Reference case study
RMSE	Root Mean Square Error
SA	Sensitivity analysis
SLABE	Simulation-based large-scale uncertainty/sensitivity analysis of building energy performance
UA	Uncertainty analysis
Symbols	
DH	Yearly percentage of discomfort hours
DH_h	Percentage of discomfort hours during the heating period
DH_c	Percentage of discomfort hours during the cooling period
N	Number of cases representing the building category stock (sample size)
R	Coefficient of regression
SRRC	Standardized rank regression coefficient
Tco	Optimum comfort temperature [ºC]
Text, ref	Monthly average outdoor dry bulb temperature [ºC]
U	Thermal transmittance [W/m^2 K]

1. Introduction

The building sector accounts for around 40% of total energy consumption within the European Union (EU) [1], making the reduction of the energy use in this sector a common goal for all European regulations [2]. Given the low rate at which existing buildings are being replaced by new ones (i.e., around 1-3% per annum [3]) the EU 2030 and 2050 energy consumption reduction goals would be very difficult to achieve just through the construction of new buildings, with almost zero energy consumption. It is therefore essential to encourage the improvement of energy efficiency in existing buildings. Particularly in southern Europe, between 63% [4] and 76% [5] of the existing housing stock was built prior to the first regulations enacted for limiting the energy demand of buildings (1976-1979). Consequently, most of this housing stock was built without specific thermal insulation measures and is obsolete from an energy perspective [6].

Several studies highlight the importance of energy characterization prior to the proposal of adequate retrofit measures [7], as well as taking into account real user profiles, not just the standardized ones [8]. This initial step provides information on how the energy is being used and allows the environmental deficiencies in a specific building category to be identified. If generalized retrofitting proposals that are not based on calibrated simulations of the case study are used, the energy-saving predictions will be very far from the reality [9].

When evaluating the energy and thermal behaviour of the residential stock, rather than that of a residential unit, the different methods can be grouped into two categories: top-down and bottom-up [10]. The former, which uses historical data, is usually applied when investigating the correlation between the economy and the use of energy, while the latter is based on data collected from a study sample to obtain information about energy consumption and extrapolate it at a regional or national level. Bottom-up engineering techniques specifically are based on energy simulations and used in the detailed calculation of energy performance, allowing the impact of retrofitting strategies to be determined [11]. In order to harmonize the main objectives of building energy retrofitting (i.e., minimization of energy consumption and maximization of economic benefits) multi-objective optimization approaches are recommended [12, 13].

The simulation tools most commonly used among the scientific community, including EnergyPlus [14], ESP-r [15] and TRNSYS [16], if properly used, may ensure highly accurate results, albeit at the expense of high computational times. When the aim of the research is to evaluate the energy and comfort performance of large samples – such as whole housing stocks – other methods must be explored in order to reduce computational times [17]. Surrogate models, that is to say 'models of the model', are a good solution for large samples given that despite the long time required to develop them, once built they become very fast evaluation tools. The surrogate modelling techniques most widely used for the prediction of energy performance and thermal behaviour in buildings are Kriging (KG), Support Vector Regression (SVR) and Artificial Neural Networks (ANNs), all of which offer good reliability and accuracy [18]. In particular, ANNs are the most used surrogate models for evaluating energy performance in large samples of heterogeneous buildings.

For what concerns some applications, it is worth highlighting the model developed by Melo *et al.* [19], which accurately simulates the energy consumption of the building stock of an entire city in Brazil, based on the results provided by EnergyPlus for a sample of 3200 heterogeneous buildings. Magalhães *et al.* [20] also developed ANNs that characterize the relationship between heating consumption and indoor temperatures, using data provided by ESP-r on a sample of 2600 residential buildings. However, within the bibliography there is a higher presence of ANNs developed to assess the demand or energy consumption of specific individual buildings. An example of this is the ANN developed by Buratti *et al.* [21], which uses simplified methods to check the energy certification of buildings, and that by Karatasou *et al.* [22], which aims to model energy use and predict hourly load profiles.

In the case of social housing in southern Spain, one of the main conclusions drawn from previous audits [23, 24] is that the energy consumption of this building category is very low. This is due to the total absence of central HVAC (Heating, Ventilating and Air Conditioning) systems and severe limitations in the use of local heating and cooling equipment due to unfavourable socio-economic conditions. Therefore, in this building category, the retrofitting strategies and the prior characterization must be geared towards thermal comfort levels rather than energy consumption. Although this is not the most frequent, various references to ANNs developed to evaluate the thermal comfort level in buildings can be found, including the prediction of indoor temperature [25, 26] and the Predicted Mean Vote (PMV) [27, 28]. It is more usual to find in the available bibliography studies based on ANNs to optimize the buildings thermal control [29]. As regards naturally ventilated buildings without HVAC systems, although some references can be found evaluating their thermal performance in mild (central Europe) [30] or hot and humid climates in summer (Asia) [31,32], few studies focus on the hot dry climate characteristic of the Mediterranean-area summers. This work will use the SLABE (Simulation-based Large-scale uncertainty/sensitivity Analysis of Building Energy performance) methodology developed by Ascione *et al.* [17] as a starting point, as it provides a reliable evaluation model for the percentage of discomfort hours for any member of a building stock category in the Mediterranean climate. However, given that this methodology focuses on climatized office buildings, its applicability to residential and free-running buildings (no mechanical heating or cooling systems used) should be verified. In this study, compared to the original SLABE methodology, the thermal comfort prediction is based on calibrated models through real data measured in-situ.

The main aim of this paper is to determine whether it is possible to develop a surrogate model to evaluate the thermal behaviour of any member of the category of social housing stock in southern Spain, accurately and with low computational times. To this end, ANNs are generated under MATLAB® environment using EnergyPlus simulated data in order to provide a reliable and fast prediction of thermal comfort.

In the following section, the proposed methodology is described. Its main originality consists in the evaluation of the thermal performance of a free-running building category – naturally ventilated without HVAC systems – in the Mediterranean climate, something seldom found in the available bibliography. The analysis of this building category entails the application of specific and accurate thermal comfort models. One of the strengths of this research is also the possibility of testing the entire simulation process with real data measured in-situ, unlike most of the examples above, which limited the calibration of ANNs to their adjustment with the results obtained in the detailed simulations carried out using tools such as TRANSYS® or EnergyPlus.

2. Methodology

The methodology developed in this work takes as a starting point the research carried out and tested by Mauro *et al.* [33], and Ascione *et al.* [17, 34]. The needs for a particular case study – a naturally ventilated building category – force this model to be focused on the analysis of the percentage of discomfort hours (DH), which entails the use of accurate thermal comfort models. This methodology stands out for the inclusion of model calibration throughout the whole process, based on previous one-year-long monitoring of a Reference Case Study (namely, RefCS), within the investigated building category.

This methodology is made up of 4 stages (figure 1) that allow the development and calibration of simulation models that represent and characterize – in terms of DH – all members of the explored building category: multi-family social housing from the linear geometrical typology built in southern Spain between 1950 and 1980. This period of study was selected to cover the period between the initial Spanish public plans promoting social housing in 1950 after the Civil War, and the implementation of the first national regulations limiting energy demand in 1980, following the 1970s energy crisis. Within the text this period is referenced as 'post-war period'.

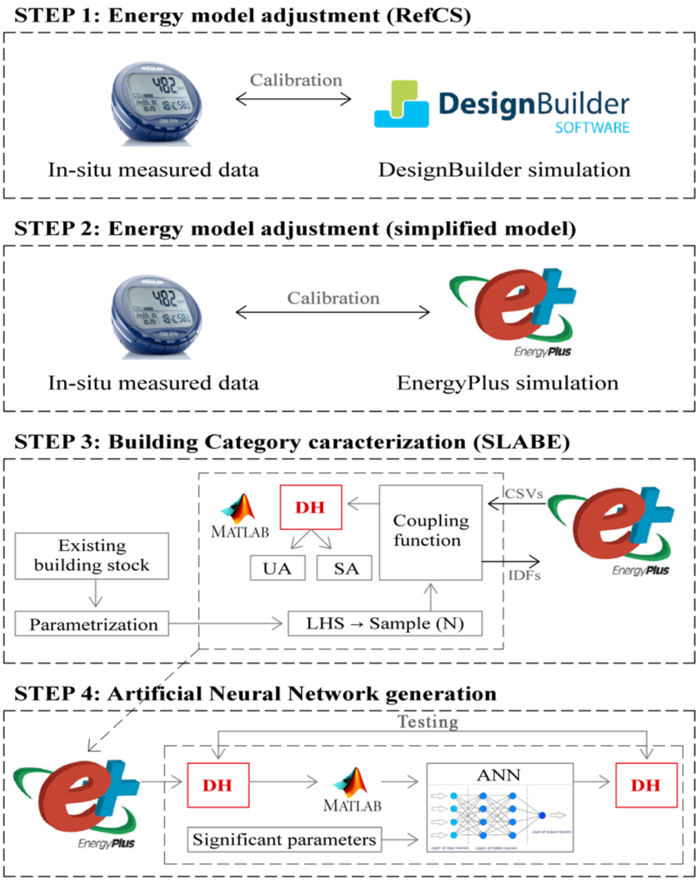


Figure 1. Methodology framework

2.1 Step 1: Energy model adjustment (reference case study)

The starting point of the models developed in this work is the exhaustive characterization of the reference case study, defining constructive characteristics, user patterns (occupation schedules, lighting, use of local cooling/heating systems, windows opening and use of sun protections) and infiltration rate [23, 24]. The first energy model was developed with the DesignBuilder® (v.4.7.0.027) simulation tool, which uses the EnergyPlus engine [14]. This model recreated the heat transfer and shading conditions of the monitored housing unit and its boundary conditions. Each room was simulated as an independent thermal zone in order to compare the results and the measured data (in the main bedroom and living room) with greater accuracy.

The climate data used for this energy simulation were obtained from a meteorological station belonging to the Spanish State Meteorological Agency [35] and located in Seville. These data were compared with spot measurements taken outside the case studies for the purposes of validation.

The initial manual adjustment of the model focused on indoor temperature in the winter and summer periods, as the housing units analysed are free-running most of the time. The results of energy simulations and monitoring are compared both graphically (for a representative week) and statistically (for the entire period).

In order to determine whether the model is well adjusted to the real behaviour, this research followed the statistic validation established in ASHRAE Guideline 14-2014 [36], setting two error indicators: the Normal Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error (CVRMSE), following equations (1) and (2), respectively. ASHRAE Guideline 14 considers a building model to be calibrated with hourly data when monthly NMBE values fall within ±10% and monthly CV(RMSE) values fall below 30%.

$$\text{NMBE} = \frac{1}{m} \times \frac{\sum_{i=1}^{Ni} (\text{Mi} - \text{Si})}{\text{n} - \text{p}} \times 100\ (\%) \tag{1}$$

where:
m: mean of measured values;
n: number of measured data;
p: number of adjustable model parameters. Recommended to use 0;
Mi: measured data at instance i;
Si: simulated data at instance i;
Ni: number of dates used in the calibration.

$$\text{CV(RMSE)} = \frac{1}{m} \times \sqrt{\frac{\sum_{i=1}^{Ni} (Mi - Si)^2}{\text{n} - \text{p}}} \times 100\ (\%) \tag{2}$$

2.2 Step 2: Energy model adjustment (simplified model in EnergyPlus)

The EnergyPlus [14] tool was chosen for the building performance simulations, and ANNs are developed based on its results. This allows indoor temperature to be assessed in detail, while also working with text-based format inputs (.idf) and outputs (.csv), which makes the interaction with mathematical tools easier.

For this proposal, the DesignBuilder simulation model was exported to the .idf format. But prior to exporting it, this model initially developed for a specific housing unit was completed and simplified. The entire building was defined, with each housing unit simulated as a thermal zone and the floor geometry reduced to a rectangle (the SLABE method is limited to rectangular buildings [37]).

In this step, a second calibration of the simulation model was carried out, comparing the results obtained with the indoor temperature measured in RefCS throughout a year (average value of the temperature measured in the two main rooms). The statistic validation established by ASHRAE Guideline 14-2014 [36] is used to ascertain whether the model is well adjusted.

An additional calibration check was developed focusing on the comfort analysis performed for the summer and winter period (based on the measured data) [23, 24]. According to the conclusions of the above research, thermal comfort levels are assessed according to:

- Winter period (December – February): the adaptive optimum comfort temperature (Tco) equation defined in ISO-EN-15251 (equation 3) [38], applicable only in buildings without HVAC systems which are used for low metabolic rate activities and where occupants can freely operate windows and change their clothing level. An acceptability range is applied according to building category III, for a moderate level of expectation (PPD < 15%), with a temperature interval of ± 4 ºC.

  $$Tco_{winter} = 0.33 \times T_{eR} + 18.8 \tag{3}$$

  where:
  T_{eR}: *running mean dry bulb outdoor temperature for today (equation 4)*

  $$T_{eR} = (1 - \alpha) \times T_{ed-1} + \alpha \times T_{eR-1} \tag{4}$$

  where:
  T_{ed-1}: *daily mean dry bulb outdoor temperature for previous day;*
  T_{eR-1}: *running mean dry bulb outdoor temperature for previous day;*
  α: a constant between 0 and 1. Use of 0.8 is recommended.

- Summer, spring and autumn periods (March – November): the adaptive Tco equation defined by Barbadilla-Martín *et al.* (equation 5) [39] for the specific case of hybrid or 'Mixed Mode' buildings (naturally ventilated through windows and with air conditioning equipment used intermittently) in the Mediterranean climate. In this case, the acceptability range applied corresponds to 80% of satisfied occupants (PPD < 20%), with a temperature interval of ± 3.5 ºC.

$$Tco_{summer} = 0.24 \times T_{eR} + 19.3 \tag{5}$$

where:

T_{eR}: running mean dry bulb outdoor temperature for today (equation 4)

2.3 Step 3: Building category characterization (SLABE)

In this step thermal comfort is predicted for the building category stock using an uncertainty analysis (UA) and a sensitivity analysis (SA). Discomfort hours represent the occupied hours during which indoor temperature is outside the comfort range defined in Section 2.2. Thermal comfort is evaluated for the whole building, based on the average value of the DH of each dwelling.

The input data of the previous energy model (simplified model of the RefCS in EnergyPlus) must be replaced by parameters in order to pass from a model representing only RefCS to another which could represent a stock. In order to define the building category stock, characteristic parameters related to building geometry, envelope and operation are set. Thanks to information previously compiled, a range of variability and a probability distribution (uniform or normal) are assigned to these parameters. The building category should be limited, avoiding excesses in the range of variability of the parameters, in order to prevent the dependence between parameters (as the use of insulating materials is more common in certain periods of construction than in others). Latin hypercube sampling (LHS) is applied to these parameters within a Monte Carlo framework in order to generate a determinate number (N) of cases representing the building category stock. This statistical method ensures the uniformity and coverage of the sample [40]. All cases are simulated in EnergyPlus, automatically launched by MATLAB [41] obtaining a set of DH values.

Once the results are obtained, the UA is performed in order to investigate the distribution of DH in the building category stock. The UA is also used to define the optimum sample size (N) for ensuring stability in the mean value and standard deviation of DH. Bibliography on the UA and SA of buildings [42] describes a ratio between the number of sampled cases (N) and the number of characteristic parameters from 2 to 5.

Finally, SA is carried out to evaluate which parameters have the most influence on DH and which can be ruled out for ANN development. In this work, a global approach is used for the SA, assessing the Standardized Rank Regression Coefficients (SRRCs) [33]. In this regard, a global SA approach is more reliable for the purposes of building energy analysis than local ones [43, 44]. Furthermore, most reliable building performance simulation (BPS) tools provide non-linear and discontinuous outputs [43]. However, there is generally a monotonic relation between inputs and outputs. In fact, as outlined in the comprehensive review by Tian [44] regression methods, which assume monotonic relations, are the most widely used for SA in building energy analysis. Therefore, SRRCs are selected as SA indices given that they are suited to non-linear but monotonic functions between inputs and outputs, such as those researched in the proposed study. This choice is also shared by the BPS community, as shown in the studies [33, 45, 46].

The SRRC sensitivity indices are calculated to measure the influence of each parameter on the output, ranging from -1 to 1. A positive value means that parameter and output change with the same sign, while the opposite occurs for a negative value. The SRRC is based on the rank transformation of outputs and inputs in a multiple linear regression model with a standardized input-output matrix [**Error! Bookmark not defined.**].

2.4 Step 4: Artificial Neural Network generation

One of the most used techniques for surrogate modelling, regarding energy and thermal performance of buildings, is the Artificial Neural Network. ANNs store and process the experimental knowledge, obtained from the relationship between inputs and outputs from the original model, for use when required. In this work, ANNs were chosen as meta-modelling techniques, both for their reliability when evaluating the energy performance of building stocks [19], and because MATLAB® has a pre-programmed development tool [17]. The most used ANN architecture, applied in this work, is the multi-layer perception, which is made up of several layers of 'neurons' or computation units (figure 2):

- An input layer which receives information
- One or more hidden layers
- An output layer which provides the results

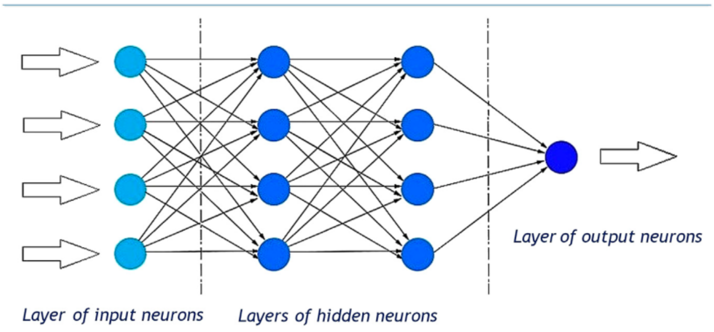


Figure 2. Architecture of a multi-layer perception ANN [17]

In order to set the input parameters to be included in the ANN, previous SA results are used selecting only the parameters with relevant influence on the output parameter, set as a |SRRC| value greater than 0.05 [33]. The number of hidden neurons was set using 'trial and error' to find the best ANN performance. The output parameter is the annual percentage of discomfort hours, as this variable is of interest for evaluation when proposing retrofitting strategies in this specific building category. The results obtained in this process are explained in Section 4.4. In this case, the ANN was composed of:

- An input layer, made up of 18 characteristic parameters
- One hidden layer with 6 hidden neurons
- An output layer providing the annual percentage of discomfort hours

The network is trained with a Levenberg-Marquardt back-propagation algorithm coupled with Bayesian regularization. A sigmoidal transfer function is used for the hidden layer, while a linear one is used for the output layer. A similar network configuration was used in previous relevant studies, concerning the performance simulation of a single building [21] or a building stock [19] with optimal results. The training is stopped when either the Root Mean Square Error (RMSE) stabilizes or the maximum number of epochs, set at 1000 [47], is reached. The network is then tested on a second sample of input and output data using the performance indicators of coefficient of regression (R) and the distribution of the relative error between the ANN outputs and the EnergyPlus simulation targets.

A sensitivity analysis on the reliability of ANNs as a function of the number of samples is also performed in this study by creating four ANNs, each with 250, 500, 750 and 1000 samples respectively.

3. Case study

The methodology defined in the previous section was applied to a specific building category: multi-family social housing buildings constructed in southern Spain between the 1960s and 1980s, and belonging to the linear geometrical typology. The location selected was the city of Seville, where this linear typology represents 44% of the post-war-period social housing stock. It is the most representative typology, with over 4000 buildings in total [48].

The city of Seville belongs to the Mediterranean climate, one of the most representative in southern Europe. The location is classified as Csa climate according to the Köppen-Geiger classification [49] and zone B4 according to the Spanish Government [50]. Zone B presents one of the lowest values in the scale of winter climate severity in Spain, while zone 4 is the highest value in the scale of summer climate severity. The main climate characteristics for Seville are summarized in table 1.

In previous work developed within a research project, morphological and constructive information was compiled for over 100000 dwellings built during the post-war period in Seville [48, 51], of which over 42000 belong to the building category studied in this paper. The data collected were used to define the upper and lower limits of the range of variability of the input parameters for this building category, taking the extreme values found in the sample. The ranges of variability and probability distribution are defined in table 2 for each parameter. In order not to increase the number of variable parameters, the surface properties of surrounding buildings were set according to the weighted average value of the façade properties of the building category studied.

From this housing stock defined, a real reference case study (RefCS) was selected for further analysis (figure 3). A dwelling from RefCS was monitored throughout a year and its energy and environmental performance evaluated during the winter and summer periods [23, 24]. This housing unit has a floor area of 58 m^2 and is inhabited by a young couple. As tends to be the case in social housing in southern Spain, it only has local thermal conditioning systems (a reversible heat pump in the secondary bedroom and a portable electric air heater) with a very sporadic use.

The main RefCS façades are composed of two layers of brick (a 10 cm external layer and 4 cm internal one) separated by an air cavity. The building's flat roof is made up of an external layer of ceramic tile, coal dust and the roof structure (reinforced concrete joins and lightened ceramic blocks). The 6-mm single-glazed windows have aluminium frames and roller blinds for solar protection. Table 2 summarizes the main typological and constructive characteristics of RefCS.

Figure 3. Exterior view and floor plan of the reference case study (RefCS)

Table 1. Annual standard climate values, period 1981 – 2010 [35]

Seville: Climate characteristics	
Altitude [m]	34
Latitude	37º 25' 0'' N
Longitude	5º 52' 45'' W
Average temperature [ºC]	19.2
Average maximum daily temperature [ºC]	25.4
Average minimum daily temperature [ºC]	13.0
99% winter design temperature (annual) [ºC]	4.5
Winter mean DTR [ºC]	12.9
1% summer design temperature (annual) [ºC]	37.6
Summer mean DTR [ºC]	17.4

Average relative humidity [%]	59
Average daily global irradiation [kWh/m²]	5.23
Average hours of sunlight	2917

Table 2. Characterization of the parameters of the reference case (RefCS) study and its building category

Parameter			RefCS	Building Category Stock	Distribution
General	-	Year of construction	1964	1940 – 1980	
	-	Typology	Linear	Linear	
	-	No. dwellings	260	42140	
Surface properties of surrounding buildings	-	Thermal conductivity [W/m K]	0.38	0.38	
	-	Density [kg/m³]	1200	1200	
	-	Specific heat [J/kg K]	1000	1000	
Geometry	P_1	Orientation (North Axis)	24°	0°; ±30°; ±60°; 90°	Uniform
	P_2	Area of each floor [m²]	105	90 - 300	Uniform
	P_3	Form ratio (*)	2.1	1 – 5	Uniform
	P_4	Floor height [m]	2.5	2.4 – 3.5	Uniform
	P_5	Window to wall ratio: S	21%	10% – 40%	Uniform
	P_6	Window to wall ratio: E	0%	10% – 40%	Uniform
	P_7	Window to wall ratio: N	32%	10% – 40%	Uniform
	P_8	Window to wall ratio: W	0%	10% – 40%	Uniform
	P_9	Number of stories	5	3 – 7	Uniform
Envelope	P_{10}	Roof solar absorptance (a)	0.7	0.1 – 0.9	Normal
	P_{11}	Façade solar absorptance (a)	0.6	0.1 – 0.9	Normal
	P_{12}	Floor thickness [m]	0.25	0.15 – 0.30	Normal
	P_{13}	Floor thermal conductivity [W/m K]	0.80	0.70 – 1.80	Normal
	P_{14}	Floor density [kg/m³]	1500	1500 – 1800	Normal
	P_{15}	Floor specific heat [J/kg K]	1000	500 – 1500	Normal
	P_{16}	Roof thickness [m]	0.35	0.20 – 0.40	Normal
	P_{17}	Roof thermal conductivity [W/m K]	0.55	0.31 – 0.57	Normal
	P_{18}	Roof density [kg/m³]	1300	1000 – 1800	Normal
	P_{19}	Roof specific heat [J/kg K]	1000	500 – 1500	Normal
	P_{20}	Façade thickness [m]	0.16	0.10 – 0.35	Normal
	P_{21}	Façade thermal conductivity [W/m K]	0.40	0.19 – 0.46	Normal
	P_{22}	Façade density [kg/m³]	2000	1000 – 3000	Normal
	P_{23}	Façade specific heat [J/kg K]	1000	500 – 1500	Normal
	P_{24}	Internal partitions thickness [m]	0.08	0.07 – 0.24	Normal
	P_{25}	Type of window glass	Single	Single; Double	Uniform
	P_{26}	Type of window frame	Aluminium	Aluminium; Wood	Uniform
Operation	P_{27}	People density [people/m²]	0.09	0.01 – 0.15	Normal
	P_{28}	Infiltration rate [h⁻¹]	0.4	0.3 – 1.0	Normal
	P_{29}	Night-time natural ventilation rate [h⁻¹]	6	0; 2; 4; 6	Uniform

(*) Form ratio = Major façade length / Minor façade length

The first energy model was developed using the DesignBuilder® interface (figure 4). In addition to the constructive definition of the envelope (described above), a real use and occupation pattern (table 3) was applied to the energy model. This pattern includes the use of local heating and cooling systems, natural ventilation (window opening), and use of sun protection (shutters, awnings…). Another aspect that helps to reduce the uncertainty of the model is the introduction of the rate of infiltration measured in an air permeability test (table 2).

Figure 4. Axonometric view of energy model of the reference case study (RefCS)

Table 3. Use and occupation pattern of the reference case (RefCS).

	Schedule (ON)
Winter period	
Occupancy (man)	21:00 – 12:00 h
Occupancy (woman)	21:00 – 8:00 h
Natural ventilation	8:00 – 9:00 h
Local heating	9:00 – 10:00 h
Summer period	
Occupancy (man)	24 hrs
Occupancy (woman)	15:00 – 7:00 h
Natural ventilation	23:00 – 9:00 h
Local cooling	15:00 – 19:00 h
Solar protection (roller blind)	11:00 – 21:00 h

4. Results and discussion

4.1 Step 1: Energy model adjustment (reference case study)

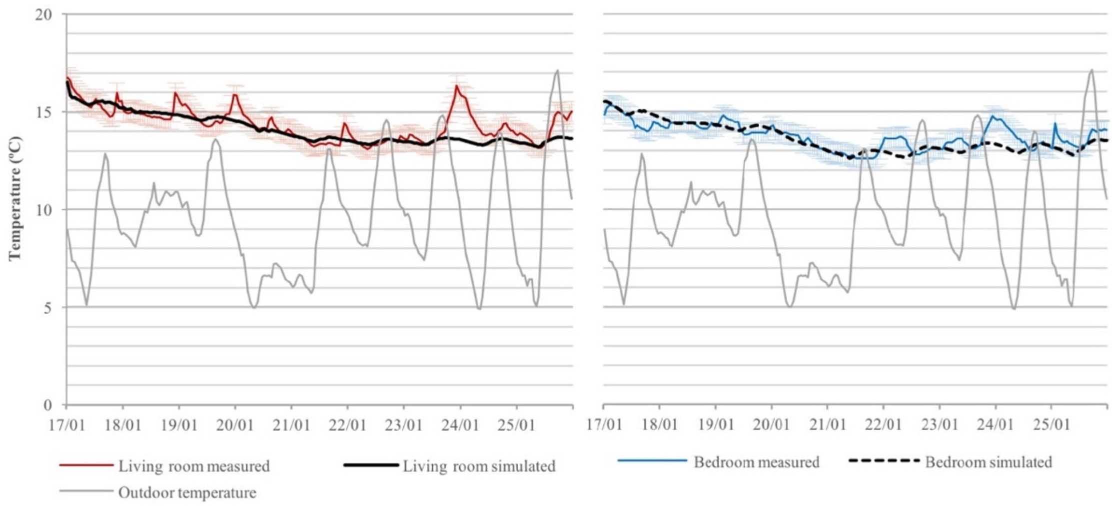
The indoor temperatures measured in RefCS during the winter and summer periods were compared with the results of the energy model simulation using the DesignBuilder® tool. According to this, the capacity of the first energy model (recreating the monitored dwelling) for reproducing the real scenario was evaluated and the relative error was quantified.

Firstly, the results of energy simulations and monitoring for a typical winter and summer week were compared in graphs (figure 5). The selected periods show a representative thermal behaviour of the case study, avoiding the coolest and hottest days of the winter and summer period respectively. The presence of the typical user pattern has also been taken into account for the selection of these typical weeks. For the adjustment, the degree of error of the measurement equipment (+/- 0.5 ºC) was taken into account and represented in the graph using error bars.

A good graphic adjustment of the model with the real data was achieved, and was better in summer due to more iterative environmental behaviour. During this manual adjustment process, variables with some degree of uncertainty due to the impossibility of measurement were determined, including the natural ventilation rate through opening windows or the occupants' metabolic rate.

During the winter period, logically, the poorer results were found when users modified their regular use pattern, for instance with exceptional increases in occupation rates or use of local heat radiators. In the summer, slight differences were found when users clearly increased the night-time natural ventilation rate or switched on local cooling systems (bedroom). This was also the case in instances where solar protections were not used or when occupation rates increased (living-room).

In addition, the statistical validation of the energy model was verified hourly throughout the entire winter (from December to February) and summer (from June to August) periods, following the indicators established by ASHRAE [36] (table 4). A good seasonal adjustment of the model with the real data was demonstrated, achieving values for NMBE and CV(RMSE) much lower than the maximum values set by ASHRAE as 'acceptable calibration tolerances' (10% and 30%, respectively). Seasonal overall values of NMBE for RefCS were around 5%, while those for CV(RMSE) were around 11% in winter and 9% in summer.



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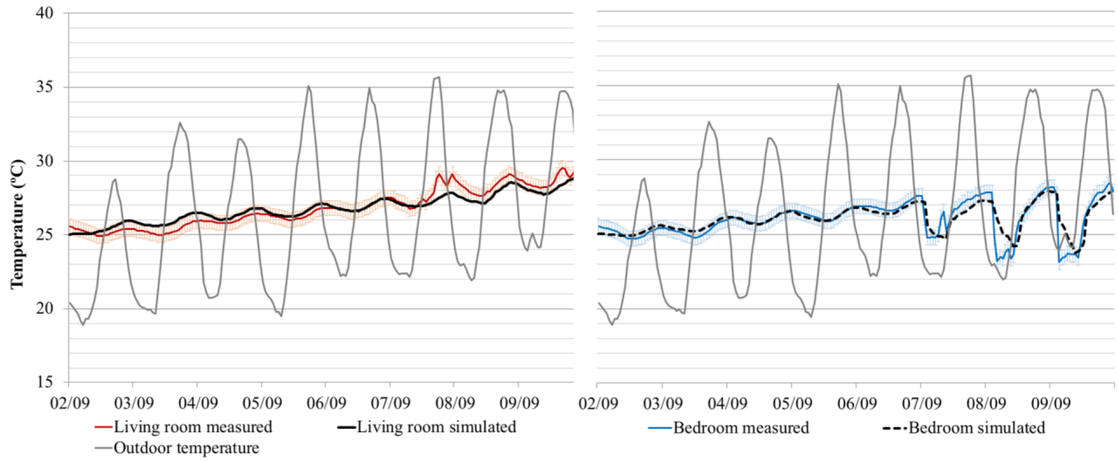


(b)

Figure 5. Graphic validation of the energy model over typical weeks: (a) winter period (17-25 January); (b) summer period (2-9 August)

Table 4. Statistical validation of the energy model based on hourly values over the year: indoor air temperature measured vs simulated (DesignBuilder®)

	NMBE Living room	NMBE Bedroom	CV(RMSE) Living room	CV(RMSE) Bedroom
Winter period (December - January)	-5.33%	-5.06%	10.14%	11.27%
Summer period (June – August)	-7.23%	-3.84%	9.96%	8.68%
ASHRAE Standards [36]	MBE < 10%		CV(RMSE) < 30%	

4.2 Step 2: Energy model adjustment (simplified model in EnergyPlus)

In this stage, a second energy model is built by means of the simplification of the previous one (of the RefCS), in order to allow the development of *Step 3* of this methodology. Thus, further validation is required and will be carried out with the comparison between the indoor temperature measured in RefCS throughout a year (average value of the temperature measured in the two main rooms) and the results of the energy model simulation using the EnergyPlus tool.

The validation of the second energy model was verified hourly throughout the whole year, following the indicators established by ASHRAE [36] (table 5). The simulation shows high reliability, with an annual value of NMBE below 3% and of CV(RMSE) around 7%, far from the maximum values set by the ASHRAE.

An additional calibration check was developed, focusing on the relative error in the percentage of discomfort hours (DH) during winter (from December to February) and summer (from June to August) periods (table 6). The results of a previous comfort analysis [23, 24], based on the monitored indoor temperature, and a current one, based on the EnergyPlus results, are compared. A very good seasonal adjustment of the model with the real situation is demonstrated, achieving relative errors below 1%.

Table 5. Statistical validation of the energy model based on hourly values over the year: indoor air temperature measured vs simulated (simplified model in EnergyPlus)

	NMBE	CV(RMSE)
Year	-2.93%	7.28%
ASHRAE Standards [36]	MBE < 10%	CV(RMSE) < 30%

Table 6. Testing of the simulation simplified model (EnergyPlus) in relation with DH

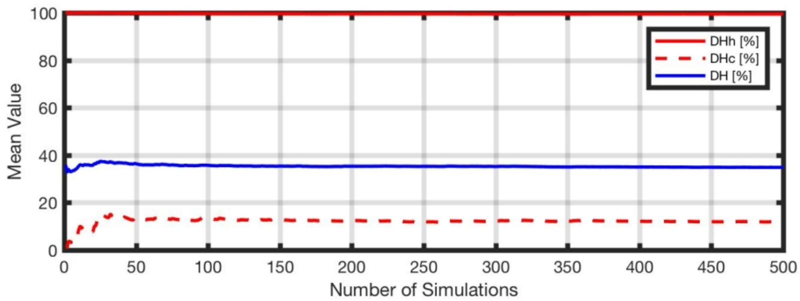
	DH (based on measured data)	DH (based on EnergyPlus simulation)	Relative Error
Winter period (December - January)	99.9%	99.0%	0.90%
Summer period (June – August)	11.4%	11.4%	0.00%

4.3 Step 3: Building category characterization (SLABE)

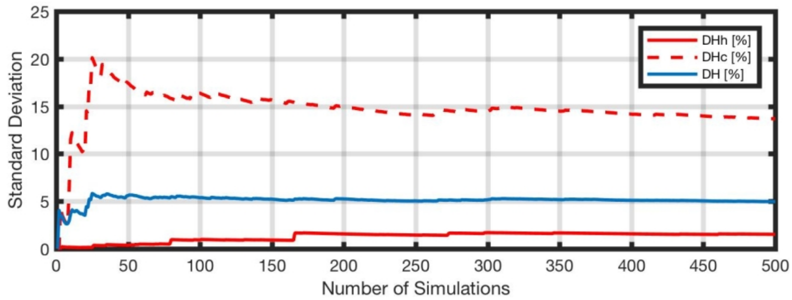
For the evaluation of the thermal comfort in the building category stock, 29 characteristic parameters and their variability range were defined to represent the entire building category (table 2). Although the scientific community considers a ratio between the number of sampled cases (N) and the number of characteristic parameters around 2-5 to be valid [42], in this study N was increased to ensure the representativeness of the results since the study of a building category entails higher ranges of variability in the characteristic parameters. Another reason to increase N was the aim of developing an ANN, since this requires a higher number of samples [17]. According to Conraud [52], the sample size should be in agreement with the network's architecture and size, setting a minimum value of 5 x number of inputs x number of outputs. As an initial hypothesis to evaluate whether it is possible to develop a reliable ANN for a building category, based on the results obtained from a sample of this size, the number of cases (N) was set at 500, a ratio of 17.2. These 500 cases were generated via LHS and their DH calculated with the EnergyPlus simulation tool. In a later phase (at the end of Section 4.4), it will be ascertained whether the reliability of the ANN depends on sample size.

The first item analysed from the results obtained was to ascertain whether the sample size could ensure reliability. For this purpose, the trends of mean value and standard deviation of the percentage of discomfort hours were evaluated during the winter (also named heating period, December-January) (DH_h), summer (also named cooling period, June-August) (DH_c) and throughout the whole year (DH), according to the sample size (figure 6). In this case, the standard deviation of the results was stabilized from the 70 simulated cases, so that a ratio of 2.5 would have been sufficient to ensure reliable results.

Secondly, the results obtained for the 500 case studies were analysed through their individual histograms and the normal distribution considered the best fit. As can be observed, the DH_h (figure 7a) and DH_c (figure 7b) results do not follow a normal distribution, since more than 80% of the cases result in 100% of discomfort hours during the heating period and more than 60% have less than 10% discomfort hours during the cooling period (with 0% being the most frequent result). The median value of DH_h is 99.9%, with a maximum of 100% and a minimum of 95%, and the median value of DH_c is 5.9%, with a maximum of 60% and a minimum of 0%. The generalized lack of thermal insulation in this building category brings about a concentration of DHh results around value 100 – the maximum value possible –, while the widespread habit of using night-time natural ventilation as a passive cooling strategy concentrates the DHc results around 0 – the minimum value possible. This leads to these specific distribution patterns of results. However, when DH is evaluated over a full year (figure 7c) the distribution of the results is close to a normal one, with values between 20% and 50%. The median value of DH is 34.4%. The results for RefCS are also represented, and in all three cases (DH_h, DH_c and DH) they are close to the mean value of the normal distributions.



(a)



(b)

Figure 6. Main value (a) and standard deviation (b) of DH values in the building category, according to the sample size

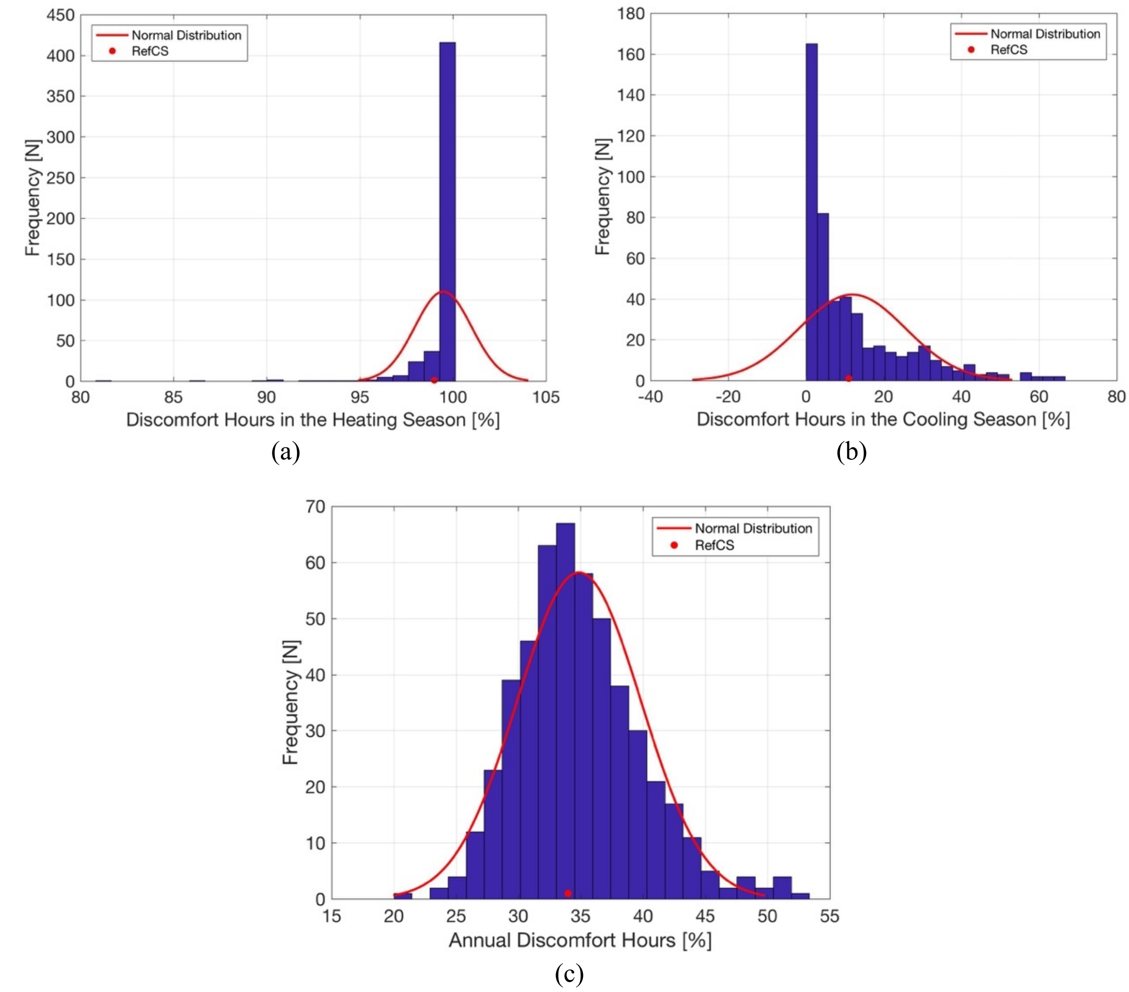
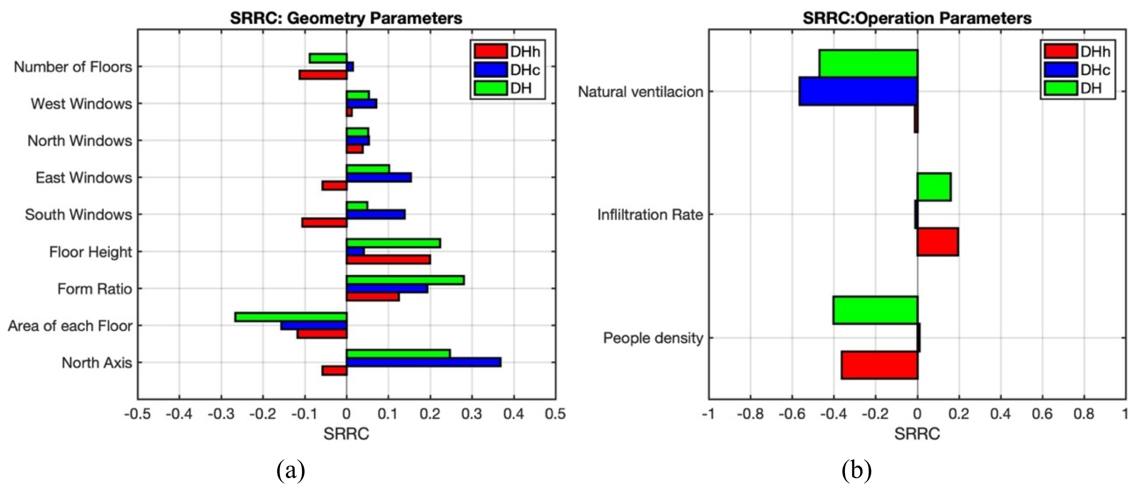
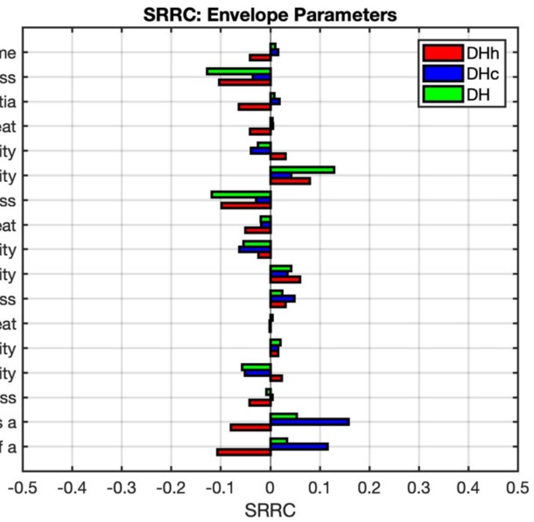


Figure 7. Distribution of DH values in the building category, during the heating (a) and cooling seasons (b) and the whole year (c)





(c)

Figure 8. Standard rank regression coefficients (SRRCs) in relation to discomfort hours (DH_h, DH_c and DH) for geometry (a), operation (b) and envelope parameters (c)

Finally, the results of the performed SA were evaluated as represented in figure 8. As regards the geometry (figure 8a), the most relevant parameters (with the highest |SRRCs|) for the DH_h are 'floor height' (0.20) and 'form ratio' (0.15), for the DH_c these are orientation ('north axis', 0.35) and 'form ratio' (0.20). The most relevant parameters for DH throughout the year are 'form ratio' (0.30) and 'area of each floor' (-0.25). In general, the greater the compactness (low 'form ratio' and low 'floor height'), the lower the DH, due to the lower exposure to outdoor environmental factors.

Some operation parameters (figure 8b) have the highest influence on DH values. This is the case of 'natural ventilation' which reaches a SRRC value of around -0.60 for DH_c and -0.50 for DH. Higher 'natural ventilation' rates reduce DH during much of the year, due to the mild outdoor temperatures during spring, autumn and summer-nights. As could be expected, DH decreases with higher 'people density', especially in winter.

Envelope parameters (figure 8c) generally present the lowest |SRRC| values, as only 'type of glass' and 'roof a' exceed -0.10 for DH_h; 'roof a' and 'wall a' exceed 0.10 for DH_c; 'façade conductivity' exceeds 0.10, just as 'type of glass' and 'façade thickness' exceed -0.10 for DH. The improvement in glass and façades (greater thickness and lower conductivity) reduces DH, particularly in winter, as heat dissipation capacity is also limited in summer due to these factors. The increase in absorptivity of the envelope's external layer clearly raises DH in the summer period and most of the year.

4.4 Step 4: Artificial Neural Network generation

The results obtained in the previous section show that the distribution of DH_h and DH_c for the building category is far from normal and is concentrated around a specific value located at the extreme of the variability range. This significantly decreases the reliability of an ANN developed based on these data. In addition, and in view of the fact that the case study is a free-running building category where future retrofitting measures should aim to improve environmental behaviour improvement year-round (rather than improve specific conditions to reduce heating or cooling energy demand), the development of ANNs for the seasonal comfort conditions is ruled out. This study focuses on the development of an ANN whose output parameter will be the annual percentage of discomfort hours.

Not all 29 starting characteristic parameters are taken into account for this development as those with less influence (|SRRC| values below 0.05 [33]) on DH will be discarded. In this case, according to the SA results presented in the previous section, only the 18 characteristic parameters included in table 7 will be the inputs for the ANN. By means of trial-and-error, six hidden neurons are set as optimal to maximize the reliability of the surrogate model (figure 9). ANN development was tested with different numbers of hidden neurons - from 1 to 18, the input layer size - and the best reliability was found with six hidden neurons.

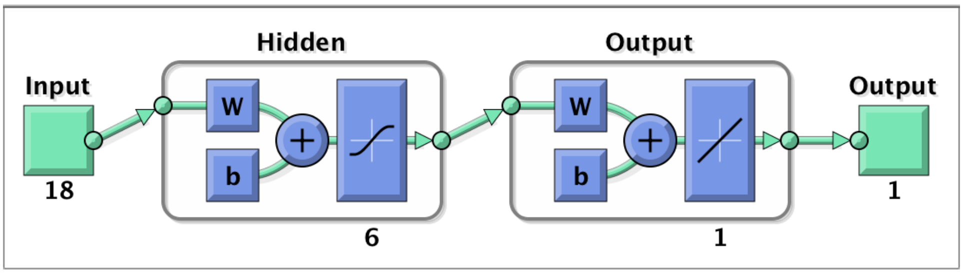


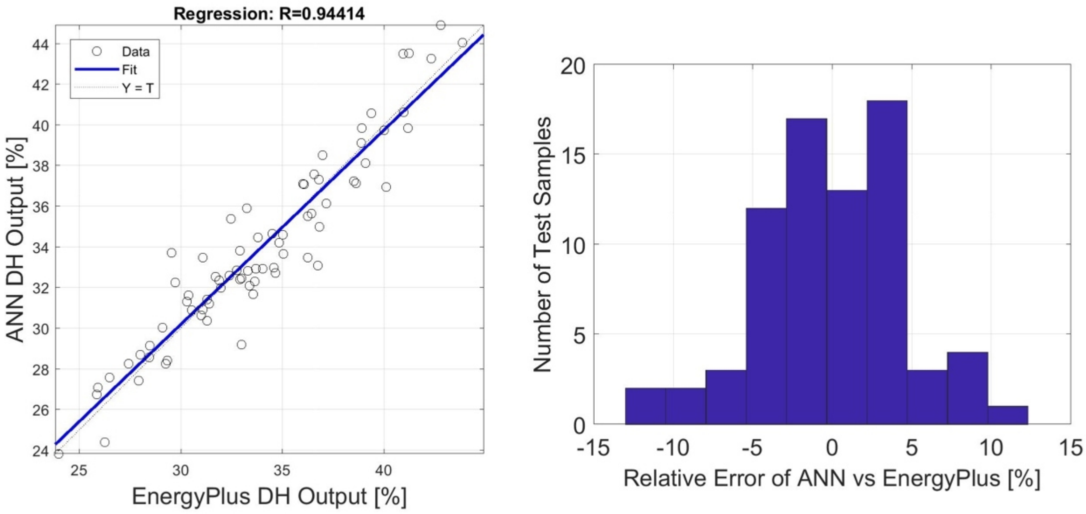
Figure 9. ANN structure

Table 7. Characteristic parameters selected as ANN inputs

Parameter			ANN input
Geometry	P_1	Orientation (North Axis) [º]	Yes
	P_2	Area of each floor [m^2]	Yes
	P_3	Form ratio (*)	Yes
	P_4	Floor height [m]	Yes
	P_5	Window to wall ratio: S [%]	Yes
	P_6	Window to wall ratio: E [%]	Yes
	P_7	Window to wall ratio: N [%]	Yes
	P_8	Window to wall ratio: W [%]	Yes
	P_9	No. stories	Yes
Envelope	P_{10}	Roof solar absorptance	No
	P_{11}	Façade solar absorptance	Yes
	P_{12}	Floor thickness [m]	No
	P_{13}	Floor thermal conductivity [W/m K]	Yes
	P_{14}	Floor density [kg/m^3]	No
	P_{15}	Floor specific heat [J/kg K]	No
	P_{16}	Roof thickness [m]	No
	P_{17}	Roof thermal conductivity [W/m K]	No
	P_{18}	Roof density [kg/m^3]	Yes
	P_{19}	Roof specific heat [J/kg K]	No
	P_{20}	Façade thickness [m]	Yes
	P_{21}	Façade thermal conductivity [W/m K]	Yes
	P_{22}	Façade density [kg/m^3]	No
	P_{23}	Façade specific heat [J/kg K]	No
	P_{24}	Internal partitions thickness [m]	No
	P_{25}	Type of window glass	Yes
	P_{26}	Type of window frame	No
Operation	P_{27}	People density [people/m^2]	Yes
	P_{28}	Infiltration rate [h^{-1}]	Yes
	P_{29}	Night-time natural ventilation rate [h^{-1}]	Yes

According to similar studies [17, 53, 54], 9/1 is considered a suitable ratio between the sizes of training and testing sets. In this case, of the 500 cases previously simulated (Section 4.3), 450 (90% selected at random [52]) were used to train the ANN, while the remaining 50 were used to test it. ANN performance is evaluated by means of the regression and the distribution of the relative error between ANN outputs and EnergyPlus targets (figure 10). The outcomes of these tests are summarized in table 8. Regression analysis, with a coefficient of regression (R) above 0.94, and relative errors, with an average value of 3.5%, show high reliability of the developed ANN, similar to previous studies related to a building stock [17]. The development of surrogate models related to stocks is more complex, and therefore slightly poorer results than in studies concerning specific single buildings can be expected [13].

In addition, the comparison between ANN prediction and the EnergyPlus target for RefCS is evaluated (table 9). The result, specifically as regards the Reference Case Study, shows a relative error above 8%, which means that the RefCS unfortunately belongs to the 21% of cases overcoming a 5% relative error according to the overall evaluation of the ANN (table 8). The evaluation is completed by comparing the ANN prediction for RefCS with the results of a comfort analysis based on the real indoor temperature measured in-situ (table 10). The result shows a relative error above 10% which could be improved by optimizing the ANN generation.



(a) (b)

Figure 10. DH prediction for the building category: ANN outputs vs EnergyPlus targets. Regression (a) and relative error distribution (b)

Table 8. Testing of the ANN for DH in the building category. ANN outputs vs EnergyPlus targets

	Epochs	R	Percentage of cases with absolute value of relative error					Average of the absolute values of relative errors
			< 1%	< 2.5%	< 5%	< 10%	< 25%	
ANN	168	0.944	17%	41%	79%	96%	100%	3.49%

Table 9. Testing of the ANN for RefCS. ANN output vs EnergyPlus target

	EnergyPlus target (DH)	ANN output (DH)	Relative error
RefCS	33.9%	30.9%	8.85%

Table 10. Testing of the ANN for RefCS. ANN output vs Real measured data

	Measured data (DH)	ANN output (DH)	Relative error
RefCS	35.5%	30.9%	12.96%

Table 11. Testing of the ANN for DH in the building category. ANN outputs vs EnergyPlus targets

N	Epochs	R	Percentage of cases with absolute value of relative error					Average of the absolute values of relative errors
			< 1%	< 2.5%	< 5%	< 10%	< 25%	
250	132	0.907	8%	32%	74%	84%	100%	4.97%
500	168	0.944	17%	41%	79%	96%	100%	3.49%
750	314	0.958	22%	48%	79%	96%	100%	3.27%

1000	353	0.957	18%	46%	81%	96%	100%	3.17%

Table 12. Testing of the ANNs for RefCS. ANNs outputs vs EnergyPlus target

N	EnergyPlus target (DH)	ANN output (DH)	Relative error
250	33.9%	28.0%	17.40%
500		30.9%	8.85%
750		32.5%	4.13%
1000		30.9%	8.85%

Table 13. Testing of the ANNs for RefCS. ANNs output vs Real measured data

N	Measured data (DH)	ANN output (DH)	Relative error
250	39.5%	28.0%	21.13%
500		30.9%	12.96 %
750		32.5%	8.45 %
1000		30.9%	12.96 %

In order to establish the ANN performance optimization and to answer the question of whether the reliability of ANNs depends on sample size, new neuronal networks were generated from samples of 250, 750 and 1000 cases simulated by EnergyPlus. For this purpose, the same methods described above were followed and the results summarized in table 11. All models provide a valid R value above 0.9 which improves as the sample size increases, with the exception of the 1000-sample model, where the R coefficient does not improve with respect to the one from 750 samples.

This improvement in model reliability is also reflected in the results obtained for RefCS (tables 12 and 13), successfully reducing the relative error between ANN output and EnergyPlus target by up to 4% and between ANN output and measured data by up to 8.5%, when the ANN is developed from 750 samples (that is, after 750 samples ANN reliability does not improve). The relative error for RefCS also increases by almost 5% when the ANN increases from 750 to 1000 samples. Therefore, it could be determined that the optimal ratio between the number of sampled cases (N) and the number of characteristic parameters to ensure the trade-off between ANN reliability and computational time is around 42 (N of 750, divided by the number of characteristic parameters used as input, 18).

The good results achieved in the 750-sample model offered the possibility to accurately predict the thermal behaviour of an entire building category with very low computational times. This methodology is a highly significant tool for future steps such as identifying building categories whose population is at serious risk of significant discomfort and fuel poverty as well as assessing the technical and economic profitability of energy retrofitting measures. Politicians and city planners, as well as architects and engineers, could apply this methodology to different building categories in the Mediterranean climate in order to promote a feasible energy retrofitting for buildings and cities.

5. Conclusions

This study has featured the entire process for the generation of a predictive model of the environmental behaviour of a building category, including model calibration throughout the whole process based on the earlier one-year-long monitoring of RefCS. A surrogate model with high reliability was developed, reducing computational times by 98%.

Following the characterization of the environmental performance of linear-type multi-family social housing built in southern Spain during the post-war period it was concluded that:

- For this building category, the minimum number of samples required to ensure reliable results is around 70. This results in a ratio of 2.5 between the sample size and the number of characteristic parameters.
- There is a generalized lack of adequate thermal comfort conditions. This problem is more serious during the winter period, as the results for the entire sample are between 95% and 100% of discomfort hours. In summer the results are more dispersed, going between 0% and 60% of discomfort hours.

When the full year is evaluated, the distribution of the results is close to normal, with values between 20% and 50% of discomfort hours.

- The most influential parameters on thermal comfort for this building category are operational (essentially natural ventilation rate and people density) and geometric (particularly form ratio, floor area and height). Some of the parameters related to the envelope could be neglected due to their low influence on thermal comfort, since the range of variation of this parameter is quite narrow within this building category (there are no cases with thermal insulation making a clear difference).
- Although the Mediterranean climate is known to be warm globally during the winter, the result shows that the users of the studied building category are greatly at risk from energy poverty during much of the year unless an energy retrofitting process is carried out.

After the ANN generation and testing, it can be stated that it is possible to develop a surrogate model which accurately evaluates the thermal behaviour of any member of a building category, with low computational times. The best compromise between reliability and computational effort of the neuronal network was reached from the simulation of 750 samples, with a regression coefficient between simulation targets and ANN outputs of around 0.96. This means that the optimal ratio between the number of sampled cases (N) and the number of characteristic parameters is around 42. This model has a low average relative error between ANN outputs vs EnergyPlus targets (3.3%) and an acceptable relative error between the ANN output for RefCS and the results from measured data (8.5%).

Previous adjustment between the energy models and the measured data is essential in order to achieve reliable surrogate models, both for a given building category and a particular case study. The methodology developed in this work can be easily extended to other building categories and locations of the Mediterranean climate, effectively completing the characterization of the existing housing stock (essential for the optimization of energy retrofitting). Therefore, this methodology can become a robust and reliable tool for planning the energy retrofit of large housing stocks, optimizing computational times. This would be fundamental in order to avoid the risk of falling into a situation of fuel poverty, which is now a reality in these building stocks.

Future studies will include the evaluation of retrofitting strategies in the surrogated models, as well as the analysis of the impact of the future climate scenario focused on global warming.

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