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# DEVELOPMENT OF SURROGATE MODELS USING ARTIFICIAL NEURAL NETWORK FOR BUILDING SHELL ENERGY LABELING

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## Abstract

Surrogate models are an important part of building energy labelling programs, but so far these models still present low accuracy, particularly in cooling dominated climates. The objective of this study is to evaluate the feasibility of using artificial neural network (ANN) to improve the accuracy of surrogate models for labelling purposes. ANN is 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 analysis were carried out to evaluate the behaviour of the ANN model, and the variations in best and worst performance for several typologies were analysed in face of variation in input parameters and building characteristics. Results indicate that ANN can represent the interaction between input and output data in a vast and diverse building stock; with errors of  $\pm 16\%$  for a confidence level of 90% of the cases. Sensitivity analysis shows that no single input parameter can be identified as the main responsible for the building energy performance. Uncertainty in building usage plays a major role in the building energy performance, as well as the facade area and the shell-to-floor. Results of this work may have a profound impact as ANN may be applied in the future in the regulation of many other countries, with further impact in the energy consumption and life quality of large amounts of people.

**Keywords:** artificial neural network, building energy simulation, surrogate model, low-resolution model, regulation, labelling, Latin Hypercube method.

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## 1 **1 Introduction**

2 Building sustainability has become an important part of the building industry, particularly with the  
3 increasing demand for sustainability certifications, such as Leadership in Energy and Environmental  
4 Design (LEED) and Building Research Establishment Environmental Assessment Method (BREEAM).  
5 Thus, many countries are realizing the importance of having more energy efficient buildings and are  
6 developing local certifications programs to assist on the improvement of efficiency on their building  
7 stock, usually assigning labels to indicate the building energy performance (ASHRAE, 2010;  
8 CALIFORNIA, 2001; Dascalaki et al., 2012; Gram-Hanssen et al., 2007; Hernandez and Kenny, 2011;  
9 Klotz et al., 2010; Kong et al., 2012; Lee and Rajagopalan, 2008; Mlecnik et al., 2010; Wiel and  
10 McMahan, 2003; Yang et al., 2010b).

11 In most labelling programs, building energy simulation (BES) is a key element to assess building  
12 performance, both for new and existing building. It is therefore essential to have reliable BES programs in  
13 order to assign labels correctly, improving the public trust in the labelling program. High-resolution  
14 dynamic BES programs, such as EnergyPlus, EQuest, ESP-r, IES, EDSL-TAS, TRNSYS, VABI and  
15 others are usually accepted as reliable programs to assess building energy performance due to numerous  
16 validation exercises carried out over the last decades. However, these programs require expert users,  
17 detailed input and considerable computational resources depending on the building complexity. These  
18 requirements compromise the wide adoption of dynamic BES simulation in most building energy  
19 labelling programs, as labelling tools must be provide reliable results within affordable time and costs.

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

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

10 Among many techniques available for surrogate modelling, the Artificial Neural Network (ANN) has  
11 been successfully used in many fields (Basheer and Hajmeer, 2000; Ben-Nakhi and Mahmoud, 2004;  
12 Sung, 1998), and in particular for energy calculation in different levels (Ben-Nakhi and Mahmoud, 2004;  
13 Ekici and Aksoy, 2009; Fonseca et al., 2013; González and Zamarreño, 2005; Karatasou et al., 2006; Li et  
14 al., 2011; Magnier and Haghghat, 2010; Mahmoud and Ben-Nakhi, 2003; Neto and Fiorelli, 2008; Ruano  
15 et al., 2006; Wong et al., 2010; Yang et al., 2005; Zemella et al., 2011). The capabilities and advantages  
16 of ANN are widely known, such as the resistance to faults and noise (Bezdek and Pal, 1992). These  
17 capabilities combined with the compact nature of the models makes ANN a strong candidate for energy  
18 performance assessment tool in compulsory labelling programs in developing countries. However, to the  
19 best knowledge of the authors, ANN has not yet being used for building energy labelling purposes.  
20 Therefore, in this work we investigate the applicability of ANN as surrogate modelling technique for  
21 building energy labelling purposes. This work is concentrated on the development of an accurate ANN  
22 model based on extensive dynamic BES of the building stock. The labelling of commercial buildings in  
23 the Brazilian city of Florianópolis is chosen as a case study, but the methods described in this paper are in  
24 principle applicable to any other location, climate and building stock properties.

25 The paper is structured in 5 sections, as follows. Section 2 describes the methods and input  
26 information adopted in this paper, comprising: (a) the key performance indicators addressed in the  
27 Brazilian building energy regulation (BRASIL, 2009), (b) the building stock in Florianópolis which is the  
28 subject of the labelling process, (c) the simulations using the dynamic BES program EnergyPlus, which  
29 were later used as data source in the surrogate modelling process, and finally (d) the details on the ANN

1 development. Section 3 presents the results, firstly with a descriptive analysis of the developed ANN,  
2 followed by an evaluation of accuracy of ANN results. Section 3 also addresses the role of uncertainty in  
3 the building use pattern for the application of ANN in the labelling process. Moreover, Section 3  
4 discusses the sensitivity of the ANN model as it is a fundamental aspect of modelling for labelling  
5 purposes. Section 4 discusses limitations of this research and further requirements for the use of ANN in  
6 labelling programs. The paper is then concluded in Section 5 with a summary of main findings.

## 7 **2 Methodology**

### 8 *2.1. Certification goal and approach*

9 The development of any surrogate model for labelling purposes shall be preceded by a clear definition  
10 of goals for this model. In the current Brazilian building energy regulation, this goal is clearly the  
11 reduction of energy consumption (in particular by heating, cooling and air conditioning (HVAC) systems)  
12 in the whole building stock. This approach is rather different from high-performance building  
13 certification such as LEED and BREEAM, where only a small fraction of innovative building is subject to  
14 evaluation. In this sense, the Brazilian regulation is close to the approach of several countries in the  
15 implementation of the European Energy Performance of Buildings Directive (EPBD), where low-  
16 resolution models estimate the performance of the majority of buildings in Europe.

17 The Brazilian regulation assumes the existence of HVAC systems, hence comfort is guaranteed and  
18 consequently comfort calculations are excluded from the surrogate model output. The surrogate model  
19 shall provide an indication of the performance of the shell (i.e. facades and roof), and a fixed coefficient  
20 of performance equal to 3.20 is assumed in all analysis. The importance of these assumptions is later  
21 discussed in the paper. Electricity energy consumption at the building site is reported in kWh/m<sup>2</sup>y.  
22 Brazilian energy matrix is fundamentally based on hydroelectric power, therefore CO<sub>2</sub> emissions,  
23 commonly used in other countries (José Vinagre Díaz et al.), are not the primary performance indicator  
24 for the building sector. In a higher level, the purpose of the existing regulation is to reduce the increasing  
25 pressure for power plants driven by fossil fuels.

26 Brazil, as most countries, was divided in a number of zones with similar climate conditions for  
27 regulation purposes. This study addresses only the climate zone where the city of Florianópolis is located,  
28 and the next section describes the existing building stock of this city, which is the subject of the labelling  
29 process.

## 2.2. *Relevant characteristics of the building stock regarding the certification process*

A proper description of the building stock is fundamental in any labelling process, and particularly in the development of surrogate models. In many cases detail information is not available, and large assumptions have to be made. This is the case in this section, where the information is based on a preliminary survey of characteristics of the building stock. The information provided here shall be improved in the future; nevertheless the methodology related to the use of ANN in the labelling process remains useful and, probably valid as well (although new information on the building stock requires a new validated ANN).

Buildings typologies with different constructed areas, numbers of floors, conditioned areas, and other characteristics, were taken into account to cover most of the characteristics present in the buildings located in Florianópolis, Brazil. Moreover, it was assumed that the typologies have the principal facade to North-South or East-West. A total of sixteen building typologies were adopted, taking into account small and large offices/stores, vertical offices and hotels (main dimensions in Appendix and in Figure 1). The main buildings properties are described in Table 1, where each property may assume a number of predefined discreet values chosen to represent the majority of the complex existing (and future) building stock.

Some relevant characteristics of a building may not be under the control of designers, or may be unknown during the design phase. Characteristics such as “internal load density” and “patterns of use” were considered as uncertainties in the development of the surrogate model using ANN. The same applies for infiltration rate, which is in a sense a design variable that can be improved by careful detailing. However, it is not common practice in Brazil to perform detailed studies on infiltration in commercial buildings; therefore infiltration is also considered as a source of uncertainty. Uncertainty parameters and their values are listed in Table 2.

In addition to the sixteen building typologies used in the development and validation of ANN, four extra building typologies were chosen to allow an additional quality assurance test on the accuracy of ANN results (as described in the Appendix).

## 2.3. *High-resolution simulation of the building stock performance*

The energy performance of each of the sixteen typologies in the building stock was simulated using the BES program EnergyPlus version 6.0 (2010). EnergyPlus is a state-of-the art BES program with

1 extensive validation. Simulations were carried out using ideal control for the HVAC system. In the cases  
2 with fixed external shading device, this device was modelled explicitly using an external surface which is  
3 considered in the solar gains calculation engine of EnergyPlus.

4 Latin Hypercube Sampling was adopted to generate design variations based on values in Tables 1 and  
5 2 (de Wit and Augenbroe, 2002; Olsson et al., 2003; Xu et al., 2005) . This method allows a reduction in  
6 the number of cases generated, without a reduction in the quality of the results (Mckay et al., 1979). A  
7 total of 200 samples were created for each of the sixteen typologies, in a total of 3200 cases simulated in  
8 EnergyPlus (raw data file with all input and output will be available for download in the journal website).  
9 The interaction between different parameters in the Latin Hypercube method took place using scripts  
10 developed by Ref. (Hoes, 2007), which uses the programs SimLab (2011) and MatLab (2011). In each  
11 case, all facades have the same properties. Each building floor was modelled as a single zone.

#### 12 **2.4. Surrogate modelling using ANN**

13 The EasyNN-Plus program was used to develop the ANN model. The structure of the neural network  
14 was set as feed-forward, in which the output layer connects only to the previous layer. ANN training used  
15 50% of the 3200 cases and 25% of cases were selected for the validation set. The other 25% of cases were  
16 selected to verify the performance of the network and these cases were not part of the training and  
17 validation. All cases were randomly selected by the EasyNN-Plus program. The parameters considered  
18 the input layer for the neural network training can be seen in Tables 1 and 2, combined with other  
19 parameters describing the geometry of the buildings. A total of nineteen input parameters were used in the  
20 development of the ANN model (see Appendix).

21 Several configurations of ANN were tested in other to find the best performing combination of  
22 number of hidden layers and nodes per layer. In all configurations, Eq. (1) was used as activation function  
23 to smooth the output signal of each node:

$$24 \quad s(x) = 1/(1 + e^{-x}) \quad (1)$$

25 where x is the sum of the weighted input of each previous node plus the bias of the node itself.

26 ANN results were evaluated based on the coefficient of determination ( $R^2$ ), the mean bias error - MBE  
27 ( $\bar{\epsilon}$ ) and the error standard deviation, also known as root-mean squared error RMSE ( $\sigma_{\epsilon}$ ). The frequency of  
errors between EnergyPlus results and neural network results were also analysed using histograms.

1 The role of uncertainty (from Table 2) in the ANN predictions was investigated with the support of  
2 additional ANNs. In these additional ANN, the uncertain parameters were not included as input variable.  
3 A total of four additional ANNs were constructed for this purpose: a) one ANN with all nineteen input  
4 parameters except the infiltration rate, b) one without pattern of use, c) one without internal load density,  
5 and d) one without any of the uncertain parameters from Table 2. The accuracy of these additional ANNs  
6 was then compared to the accuracy of the original ANN (which includes all nineteen input parameters).

7 Once the role of uncertainty was clarified, the sensitivity of the ANN to different input parameters  
8 was investigated. For this purpose, ANN was used to calculate 39 additional variations for each one of the  
9 3200 original simulation cases. In these variations, only one parameter was change at a time using the 39  
10 discreet input values from Table 1. This procedure allowed the calculation of individual changes in the  
11 output due to individual changes in each one of the inputs. Uncertainty was not taken into account in the  
12 sensitivity analysis, and the following values were assumed: infiltration of 1 ACH, pattern of use of 11  
13 hours and ILD of 35 W/m<sup>2</sup>.

14 Finally, results from sensitivity analysis were used to define scenarios with the best and worst  
15 performance for each of the sixteen typologies. These scenarios are useful to clarify the performance  
16 boundaries for each case, which is essential information to define the appropriate ranges for each energy  
17 label. ANN accuracy is then discussed in face of the possible variation in performance for each typology.

### 18 **3 Results**

#### 19 **3.1. Optimum ANN configuration**

20 From the several configurations of ANN tested in this work, the best performing ANN to model the  
21 energy performance of this building stock has one hidden layer with nine nodes. Weights, biases,  
22 maximum and minimum values are provided in the appendix. Such simple ANN can be represented in a  
23 few equations, and a general formulation of an ANN with one hidden layer and one output node is given  
24 in eq. 2 and 3:

$$E_{CON} = E_{MIN} + (E_{MAX} - E_{MIN}) \cdot \left[ \frac{1}{1 + e^{-NETinput}} \right] \quad (2)$$

25



$$NETinput = \sum_{n=1}^H \left\{ \left[ 1 / \left( 1 + e^{-\left\{ \sum_{i=1}^X \left[ \left( \frac{x_i - x_{MIN_i}}{x_{MAX_i} - x_{MIN_i}} \right) \cdot W_{i,n} \right] + b_n \right\}} \right) \right] \cdot W_{n,S} \right\} + b_S \quad (3)$$

1 where  $E_{con}$  is the energy consumption,  $E_{max}$  and  $E_{min}$  are the maximum and minimum values of energy  
 2 consumption used in the ANN training,  $H$  is the number of nodes in the hidden layer,  $X$  in the number of  
 3 input nodes,  $x_i$  are the input values for calculation,  $x_{MAX_i}$  and  $x_{MIN_i}$  are the maximum and minimum values  
 4 of the input used in the ANN training,  $W_{i,n}$  and  $W_{n,s}$  are the weight values for each pair of nodes and  $b_n$   
 5 and  $b_s$  are the biases of hidden and output nodes respectively.

### 6 **3.2. ANN results and error analysis**

7 Figure 2A shows a comparison of the reference energy consumption calculated using EnergyPlus and  
 8 the output of the trained ANN, where a general good agreement can be observed. This agreement can be  
 9 better quantified by analysing the difference between EnergyPlus and ANN results, as shown in the  
 10 histogram in Figure 2B. This histogram shows that the majority of differences between the EnergyPlus  
 11 and ANN results are in the range of  $\pm 10$  kWh/m<sup>2</sup>y (84% of cases). This level of confidence is in line with  
 12 calculations based on normal distribution, as follows. The mean error and the standard deviation for the  
 13 cases were -3.7 kWh/m<sup>2</sup>y and 8.7 kWh/m<sup>2</sup>y, respectively. The mean error is quite small when compared  
 14 to the magnitude of the energy consumption calculated (from 30 to 200 kWh/m<sup>2</sup>.y). Assuming a normal  
 15 distribution of errors, the standard deviation indicates a confidence interval of  $\pm 14.2$  kWh/m<sup>2</sup> in the  
 16 results (for a confidence level of 90% of the cases, equivalent to 1.6 standard deviations). In relative  
 17 terms, ANN results have a confidence interval of  $\pm 16\%$  of the calculated value (also for a confidence  
 18 level of 90%).

19 Results in Figure 2 are in line with the results for the four extra building typologies used for additional  
 20 quality assurance of the ANN model (Table 3). In these four extra buildings the differences between  
 21 EnergyPlus and ANN results are inside the confidence for most cases. This section demonstrated that the  
 22 ANN can represent the relationship between input and output data, taking into account the large variation  
 23 in the typologies and properties addressed in this study. The next sub-section discusses the impact of  
 24 uncertainties in the input during the development of the ANN models for building energy labelling.

### 25 **3.3. Role of uncertainty in the definition of ANN input parameters**

1 The influence of three inputs data (patterns of use, infiltration and internal load density) into the  
2 performance of the ANN model was analysed. Four additional ANNs were constructed for this purpose as  
3 described in Section 2.4. Figure 3 shows histograms of errors in each one of these ANNs, where the  
4 standard deviation of the errors is also indicated. Figure 3A, 3B and 3C show large spread in the results.  
5 In the three cases the standard deviation of errors is twice higher than in the ANN described in the  
6 previous section. Figure 3D shows errors in the predictions of the ANN three times higher when patterns  
7 of use, infiltration and internal load density are not included as input values. These results demonstrate  
8 the importance of these parameters in the energy consumption of buildings and in the ANN output. These  
9 results are also in line with previous research which demonstrated the importance of these variables in  
10 other similar applications (Hassouneh et al., 2012; Kwok and Lee, 2011; Probst, 2004; Shukuya and  
11 Matsunawa, 1988; Wan and Yik, 2004). All of these parameters should therefore be considered in the  
12 ANN for labelling purposes to assure its precision.

### 13 **3.4. Sensitivity of ANN results to each input parameter**

14 The proper sensitivity of the ANN model to various input parameters is essential for building energy  
15 labelling. Energy consumption results by ANN should react to variations in input, both in qualitative  
16 terms (such as increase in energy consumption due to increase in WWR) and in quantitative terms (based  
17 on the magnitude of the change in consumption to variations in WWR). Figure 4 shows the variation of  
18 performance calculated using the ANN model for different input variables, for the case of a one-storey  
19 small office buildings. Most input parameters have a positive correlation, i.e. an increase in their value  
20 leads to an increase in the model output. This is in accordance to expectation, as higher values of WWR,  
21 SHGC, solar absorption and thermal transmittance are all associated with higher energy consumption for  
22 cooling. Vertical shading angle (AVS) is the only parameter with negative correlation, as an increase in  
23 shading reduces the energy consumption of the building. Results in this figure also show the proper  
24 behaviour of ANN regarding input values different from discreet input on Table 1, as some additional  
25 input values used in the construction of this figure were different from values in Table 1. The maximum  
26 and minimum values for each input were, nevertheless, the same ones used in the development of the  
27 ANN model. In Figure 4, the performance of this specific typology is between 71 to 86 kWh/m<sup>2</sup>y,  
28 indicating a small variation in the performance as the higher value is only 20% larger than the smaller

1 one. However, Figure 4 only shows the effect of one input value changing at a time, therefore combined  
2 effects are not taken into account.

3 Results in Figure 4 are only applicable for a particular building. Figure 5, however, shows the average  
4 sensitivity for all 200 variations of each of the sixteen typologies. Results in Figure 5 show the absolute  
5 average change in the energy consumption for the correspondent change in one of the input parameters.  
6 For example, an increase of 1 W/m<sup>2</sup>K in the U-value of wall leads to a correspondent increase of 1  
7 kWh/m<sup>2</sup>.y in the calculated energy consumption. The order of magnitude of changes in the results  
8 indicates that no single parameter is responsible for large changes in the calculation output. Sensitivity  
9 results reinforce the importance of integrated assessment of building energy performance, as the output is  
10 function of complex interaction between the relevant input parameters.

### 11 **3.5. *Boundary of the performance range for various typologies***

12 Based on the sensitivity results of Figure 5, two scenarios were defined with input parameters for the  
13 best and worst shells regarding energy performance. These scenarios define the boundary performance  
14 values for a building, assuming the constraints used in this paper. The best and worst performing shells  
15 were defined using the maximum and minimum values of each input parameters, arranged according to  
16 the direction of the sensitivity in Figure 5. In the best scenario, for example, all variables with positive  
17 correlation assume minimum value, and the one with negative correlation assumes the maximum value.  
18 ANN results for the best and worst scenarios of each of the sixteen typologies are shown in Figure 6.  
19 Typologies are ordered by the minimum energy consumption value (see typology ID in the appendix).

20 Regarding the best performing shells, it is noticeable that values largely vary among the typologies,  
21 and in many cases the worst performing shell of one typology still have lower energy consumption than  
22 the best performing shell of another typology. The behaviour of best and worst scenarios if further  
23 analysed in Figure 7. Figure 7A shows the clear correlation between the best performance and the total  
24 facade area, where large facades (such as in cases 15 and 16 in figure 6) have the highest value for the  
25 best performing energy performance. This ANN result suggests that buildings with small facades will in  
26 general perform better than the ones with large facades.

27 Regarding the range of variation between best and worst shells, Figure 6 also shows a large variation  
28 between typologies. In some typologies, the best and the worst shells have similar performance (such as  
29 in typology 12), while in other typologies the worst design has up to 150% higher energy consumption

1 (such as in typology 4). This variation in the performance range of each typology is closely related to the  
2 ratio between conditioned volume and the area of the building shell (i.e. facades and roof), as  
3 demonstrated in Figure 7B. A larger shell-to-floor ratio indicates a higher degree of interaction with the  
4 outdoor environment; therefore changes in the facade design have larger impact in the building energy  
5 performance.

6 This preliminary analysis of ANN results highlights the challenges on defining acceptable  
7 performance targets for the whole building stock, as the best performing facade leads to different  
8 performance depending on other building characteristics.

9 The behaviour of the surrogate model for labelling purposes must be carefully evaluated in face of  
10 energy policy targets, as the required accuracy depends on the performance range of each typology. In  
11 cases where the best and worst performances are quite similar, the surrogate model must have high  
12 accuracy in order to differentiate correctly these two scenarios. However, one may argue that cases where  
13 the performance range is too narrow shall not be addressed by energy conservation measures, as the social  
14 and economic costs will not lead to high energy savings. These questions are beyond the scope of this  
15 paper, and in spite of these concerns, this paper demonstrates the applicability of ANN models for energy  
16 labelling purposes, as ANN can predict the energy consumption of a large and heterogeneous building  
17 stock under uncertainty.

## 18 **4 Discussion**

### 19 *4.1. Limitations of this study*

20 This paper is based on a large amount of assumptions, and some of them are briefly discussed in this  
21 section.

22 The definition of relevant input parameters and the range for these parameters is essential for the  
23 success of the labelling program. This paper adopts a larger number of input parameters than the currently  
24 used model in the Brazilian regulation. In spite of this improvement, other parameters with known impact  
25 in energy performance were not included, such as thermal mass. Thermal mass was omitted because  
26 currently commercial buildings in Brazil have very little variation in this parameter, but this and other  
27 input must be considered if the methods described in this paper are applied for other countries or other  
28 building functions.

1 Labelling programs must promote the adoption of proven energy conservation measures. However,  
2 many of these measures were not included in this paper, such internal manually operated shading devices  
3 and smart shading devices (both internal and external) (Aste et al., 2012; Baldinelli, 2009; Inoue, 2003;  
4 Inoue et al., 2008; van Moeseke et al., 2007). At the current stage, the goal was to investigate the  
5 applicability of ANN in the development of the surrogate model for labelling. This paper demonstrates  
6 the potential of ANN to model the building stock, but the ANN model presented here requires  
7 improvements in order to handle a variety of proven energy conservation measures. Moreover, advanced  
8 features shall be included in the future as well, such as: climate adaptative building shells (Gosling et al.,  
9 2013; Loonen et al., 2013), adaptable thermal storage (Hoes et al., 2011; Parameshwaran et al., 2012;  
10 Soares et al., 2013), integration of thermal and lighting performance of the shell (Nielsen et al., 2011).

11 This paper is focused on the energy performance of the building shell; therefore variations in the  
12 efficiency of the HVAC system are not included in the model. Known strategies for energy conservation  
13 in the HVAC level shall be included in the model in the future, such as night ventilation (Artmann et al.,  
14 2008; Geros et al., 2005; Pfafferott et al., 2003; Pfafferott et al., 2004; Wang et al., 2009), thermally  
15 activated building systems (de Wit and Wisse, 2012; Lehmann et al., 2007; Pomianowski et al., 2012;  
16 Rijksen et al., 2010; Saelens et al., 2011) and of course systems with higher performance such as ground  
17 coupled heat pumps systems (Florides et al., 2011; Hackel and Pertzborn, 2011; Yang et al., 2010a; Zhai  
18 et al., 2011).

19 Cooling dominated buildings can be divided in three groups regarding the HVAC approach adopted:  
20 naturally ventilated, artificially conditioned and building operating in mixed-mode. Comfort requirements  
21 are different in buildings of each group (Brager and de Dear, 1998; Cândido et al., 2011; de Dear and  
22 Brager, 2002; Kim and de Dear, 2012), and so is the optimum building shell. This paper only addresses  
23 fully conditioned buildings, therefore the ANN model cannot be used to analyse buildings of the other  
24 two groups. Future work should investigate the applicability of ANN models to evaluate the performance  
25 of naturally ventilated buildings and mixed-mode buildings, as these buildings many more degrees of  
26 freedom when compared to fully conditioned ones.

27 This paper is based on a limited description of the building stock, and results are intrinsically  
28 connected to this description. Further work is required on describing the building stock and trends in new  
29 constructions. Moreover, a comprehensive and systematic program of building energy monitoring is

1 essential to support the development of surrogates models for labelling programs, as done in many  
2 develop economies (D&R International, 2012; Dall’O’ et al., 2012; Dascalaki et al., 2010; Fracastoro and  
3 Serraino, 2011; Ravetz, 2008; Theodoridou et al., 2011), In addition, the proportion of cases of different  
4 typologies in the building stock must be quantified, as the surrogate modelling process is highly  
5 influenced by the amount of buildings with similar properties. For example, in this paper a large number  
6 of small commercial buildings was considered, while just a few high-rise buildings were taken into  
7 account. This relation between number of small and high-rise buildings is valid for the city of  
8 Florianópolis, but this ratio should be properly defined for each location where ANN models are applied.

9 The accuracy of surrogate models usually vary within the cases modelled, and this aspect was not  
10 taken into account in this paper. The occurrence of particularly higher errors in specific typologies may  
11 compromise the adoption of surrogate models in the labelling program as a specific group of user will  
12 systematically face large discrepancies between results of the surrogate model and results from high-  
13 resolution models. Therefore future work shall evaluate cases with extreme errors as well as the error in  
14 different clusters of typologies with similar properties. Moreover, analysis of error in benchmark cases,  
15 such as the BESTEST, must be performed.

#### 16 **4.2. Comparison with the surrogate model currently used in the Brazilian building energy** 17 **labelling program**

18 The surrogate model currently used in the Brazilian regulation was developed in the last decade and  
19 represented a major step forward in the Brazilian program for energy conservation in buildings (Carlo and  
20 Lamberts, 2010). However, limitations of this surrogate model were known even before the publication of  
21 the Brazilian regulation. Previous study on the accuracy of the current surrogate model concluded that  
22 results are up to 60% outside the limits defined in the BESTEST (Melo et al., 2012b). Regarding the  
23 accuracy, the ANN model proposed in this paper shows large improvements when compared to the  
24 current surrogate model in the Brazilian regulation.

25 Another limitation of the current model is the lack of support for several relevant input data for  
26 energy performance, such as the thermal transmittance which is assumed as a fixed value (Carlo, 2008;  
27 Yamakawa and Westphal, 2011). The proposed ANN shows the capability of handling a large and diverse  
28 number of input variables. Moreover, the surrogate model currently used in the Brazilian regulation is  
29 divided in two sub-models, one for large and one for small buildings, in order to improve accuracy in the

1 results (which still show large deviations from the results of high-resolution dynamic BES (ASHRAE,  
2 2004)). The ANN model proposed in this paper can describe the whole building stock in one simple and  
3 straightforward set of equations (Eq. 2 and 3).

4 One of the main limitations presented in the current surrogate model in the Brazilian regulation is the  
5 very limited description of the building stock used in the simulations (Carlo and Lamberts, 2008; Melo et  
6 al., 2012b). The present study extended the amount of typologies used to describe the building stock but  
7 further work is required on this topic.

8 So far, the social and economic costs of energy conservation measures were not compared with the  
9 benefits obtained by these measures in the Brazilian energy conservation program. The ANN model  
10 proposed in this paper allows such analysis, providing a valuable tool in the definition of policies and  
11 negotiations with stake-holders.

12 The present paper demonstrates the importance of uncertainties in the energy performance of  
13 commercial buildings in Brazil. However, uncertainties in building usage and its inclusion in labelling  
14 programs require further investigation, not only in Brazil but also in the international context (Cantin et  
15 al., 2007; Masoso and Grobler, 2010; Nunes et al.; Yu et al., 2011). In the same line, the inclusion of  
16 further performance aspects, such as daylight usage and view to the outdoor environment, is essential to  
17 avoid misuse of the labelling program, such as the promotion of buildings with minimum or no  
18 fenestration leading to poor overall environmental indoor quality.

## 19 **5 Conclusions and implications for energy policy**

20 The main objective of this study was to investigate the use of artificial neural networks to estimate the  
21 energy consumption of commercial buildings to support building shell labelling programs. Based on the  
22 results presented in this paper, the following conclusions can be drawn:

- 23 • The development of the low-resolution model by applying the artificial neural network technique  
24 could represent the interaction between input and output data; with errors of  $\pm 16\%$  for a  
25 confidence level of 90% of the cases;
- 26 • The parameters of internal load density, patterns of use and infiltration presented a significant  
27 influence in the artificial neural network results, and should therefore be included in the labelling  
28 program;

- 1 • Sensitivity analysis shows that no single input parameter can be identified as the main  
2 responsible for the building energy performance, but rather the combination of different  
3 parameter play a role in the building performance;
- 4 • The range of performance defined by the best and worst building shells have large variation  
5 among the typologies evaluates, as well as the minimum energy consumption of the best  
6 building shell for each typology;
- 7 • The facade area and the shell-to-floor ratio play a significant role in the energy performance of  
8 the typologies analysed.

9 These results have some direct implications for energy policy:

- 10 • Countries adopting linear regression models in energy labelling of building shells should replace  
11 these models by ANN models, due to the simplicity and improved flexibility and accuracy of  
12 ANN.
- 13 • Policy makers involved in energy labelling of building shells should be aware that sometimes the  
14 shell plays a secondary role in the building energy performance. Building aspect ratio and usage  
15 may be dominant factors, and in this case any policies focused only on building shell properties  
16 will provide limited energy savings.
- 17 • Social, political, environmental and economic costs of different energy policies for energy  
18 conservation in buildings shall be compared to the actual gain in energy performance using ANN  
19 models of building shells such as the one presented in this paper.

20 Results of this work may have a profound impact in the building energy regulation in many countries,  
21 as artificial neural network may be applied to evaluate energy conservation measures improving the life  
22 quality of large amounts of people.

## 23 24 25 **Acknowledgements**

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28 Brasileiras S.A.



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35 15, 3133-3140.

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1

2 **Nomenclature**

3

4	$a_{roof}$	Roof absorptance of solar radiation [-]
5	$a_{wall}$	Wall absorptance of solar radiation [-]
6	$b_n$	bias of hidden node $n$
7	$b_s$	bias of the output node
8	$\bar{e}$	mean bias error - MBE
9	$E_{con}$	energy consumption [kWh/m <sup>2</sup> y]
10	$E_{max}$	maximum energy consumption used in the ANN training [kWh/m <sup>2</sup> y]
11	$E_{min}$	minimum energy consumption used in the ANN training [kWh/m <sup>2</sup> y]
12	$H$	number of nodes in the hidden layer
13	$I$	Infiltration [ACH]
14	ILD	Internal load density [W/m <sup>2</sup> ]
15	NETinput	as defined in Equation 3
16	PU	Patterns of use [h/day]
17	$R^2$	Coefficient of determination
18	$U_{wall}$	Wall thermal transmittance [W/(m <sup>2</sup> .K)]
19	$W_{i,n}$	weight values for each pair of nodes connecting the input and hidden layers
20	$W_{n,s}$	weight values for each pair of nodes connecting the hidden and the output layers
21	$X$	number of input nodes
22	$x_i$	input value $i$ of the ANN model
23	$x_{MAXi}$	maximum values of the input $i$ used in the ANN training
24	$x_{MINi}$	minimum values of the input $i$ used in the ANN training
25	$\sigma_e$	error standard deviation, also known as root-mean squared error – RMSE

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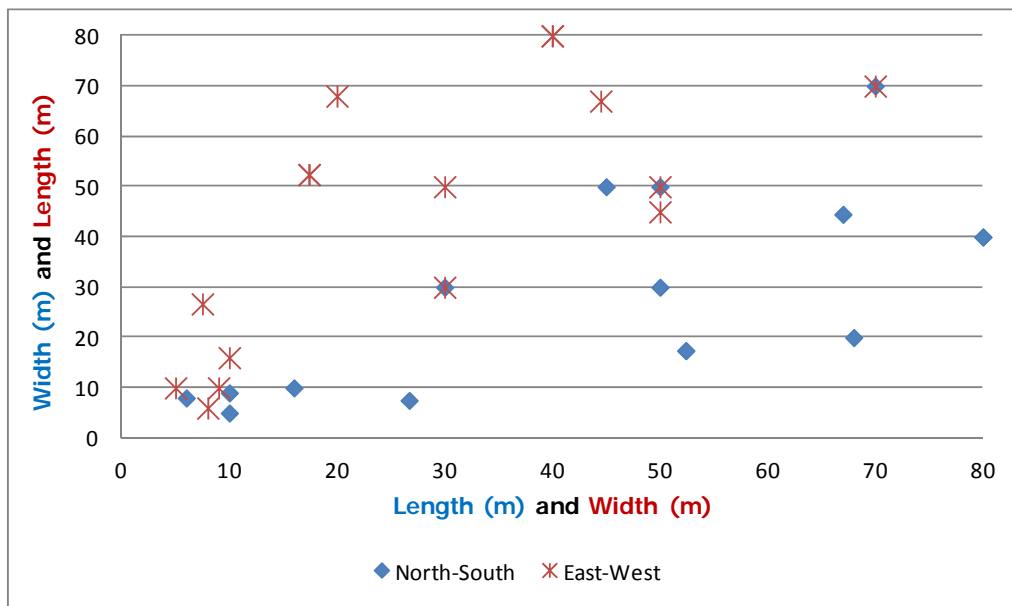
28 **Acronyms**

29	ACH	Air changes per hour [1/h]
30	ANN	Artificial neural network
31	ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
32	BES	Building Energy Simulation

33

- 1        **Figure captions**
- 2        Figure 1. Length and width for 16 typologies used in the simulations (as described in the appendix)
- 3        Figure 2 . ANN predictions compared to the reference data calculated using EnergyPlus. (A)
- 4                symmetry plot and (B) histogram of error in ANN calculation
- 5        Figure 3. Histogram of differences between EnergyPlus results and results by various ANNs that do
- 6                not take into account some input parameters
- 7        Figure 4. Example of sensitivity of different input parameter, for the case of a small office building
- 8        Figure 5. Average sensitivity of energy consumption calculated using the ANN model
- 9        Figure 6 . Calculated energy consumption of the best and worst performing shells of each of the
- 10               sixteen typologies
- 11        Figure 7 . Correlation between performance variation and building parameters
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Figure 1. Length and width for 16 typologies used in the simulations (as described in the appendix)

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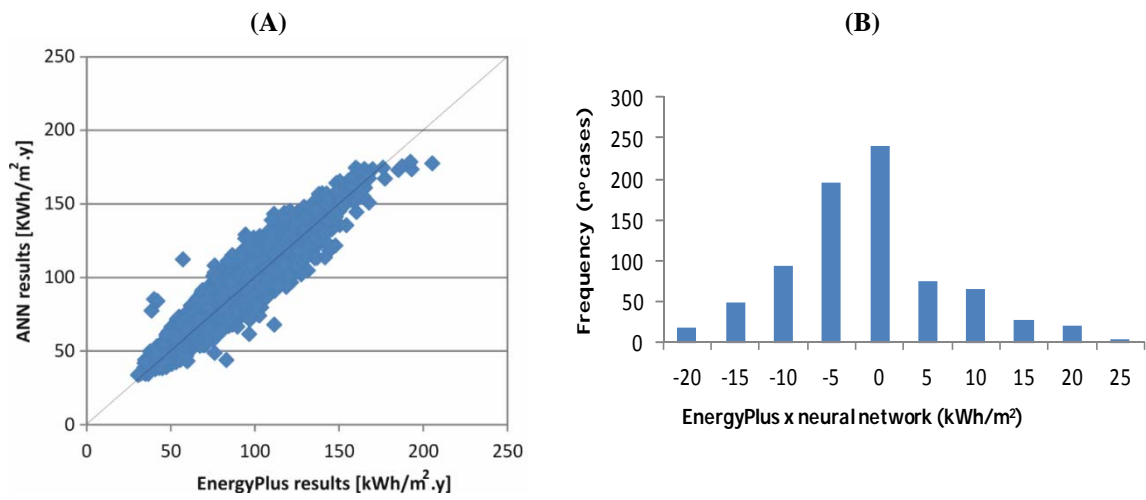


Figure 2. ANN predictions compared to the reference data calculated using EnergyPlus. (A) symmetry plot and (B) histogram of error in ANN calculation

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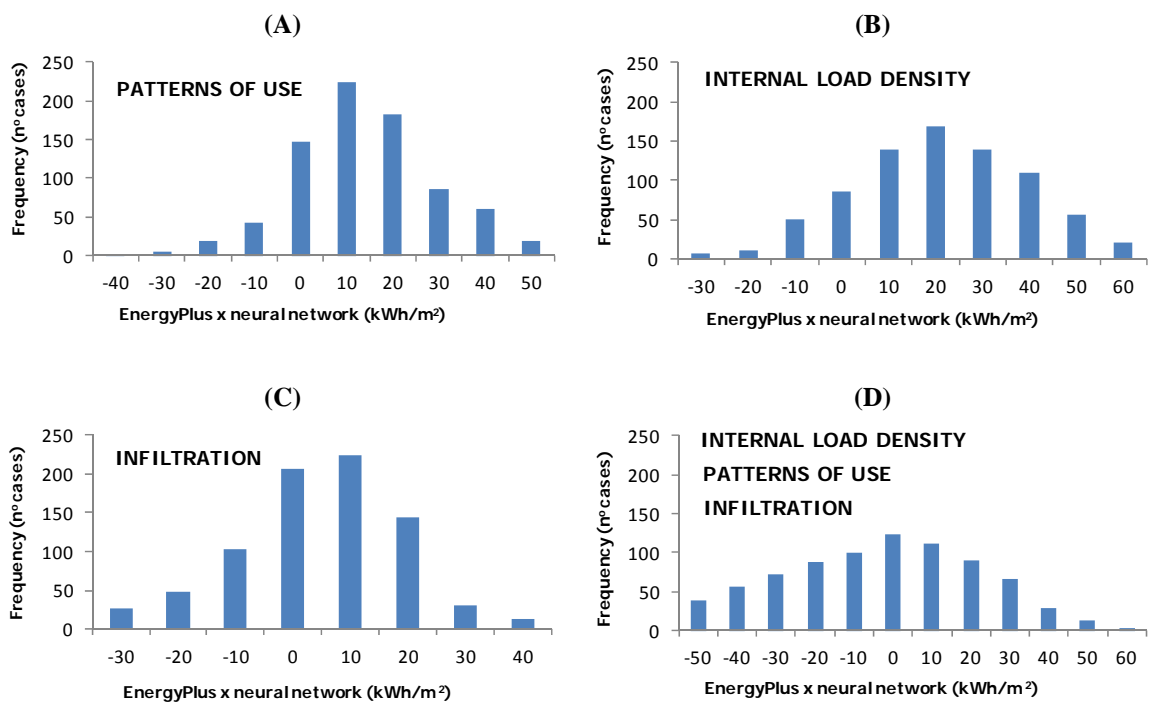


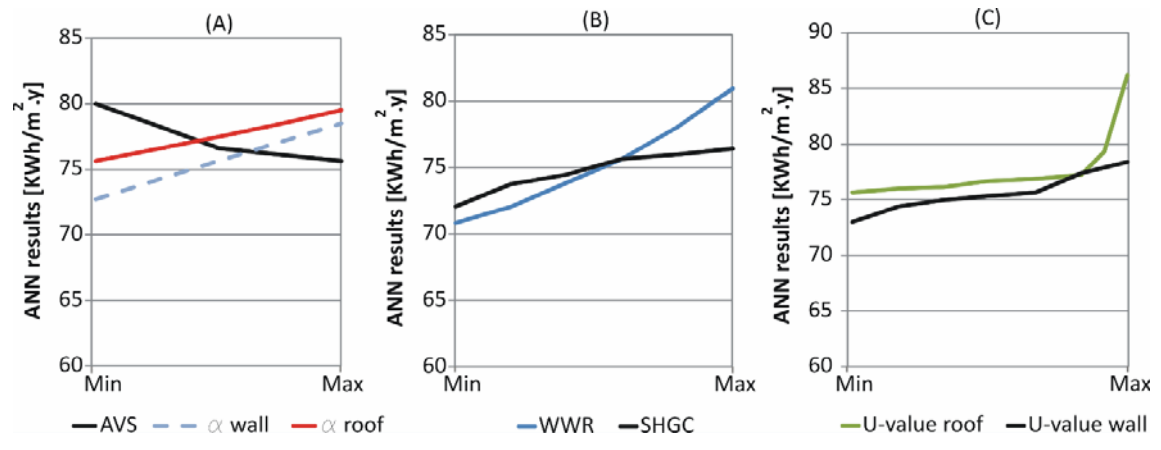
Figure 3. Histogram of differences between EnergyPlus results and results by various ANNs that do not take into account some input parameters

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Figure 4. Example of sensitivity of different input parameter, for the case of a small office building

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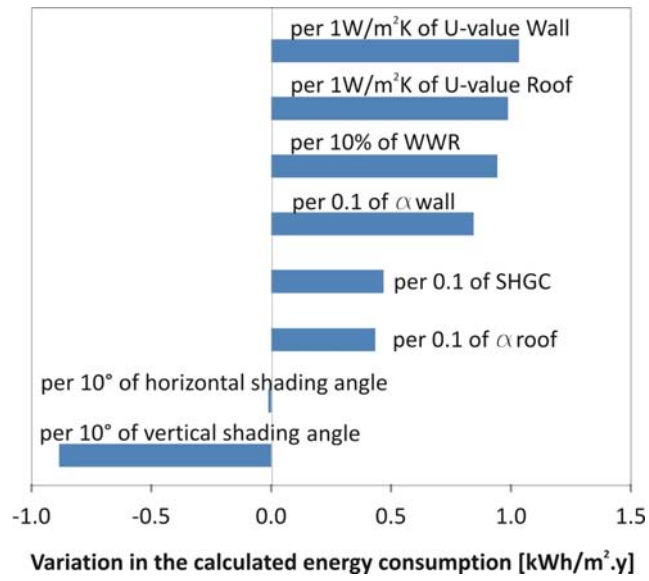
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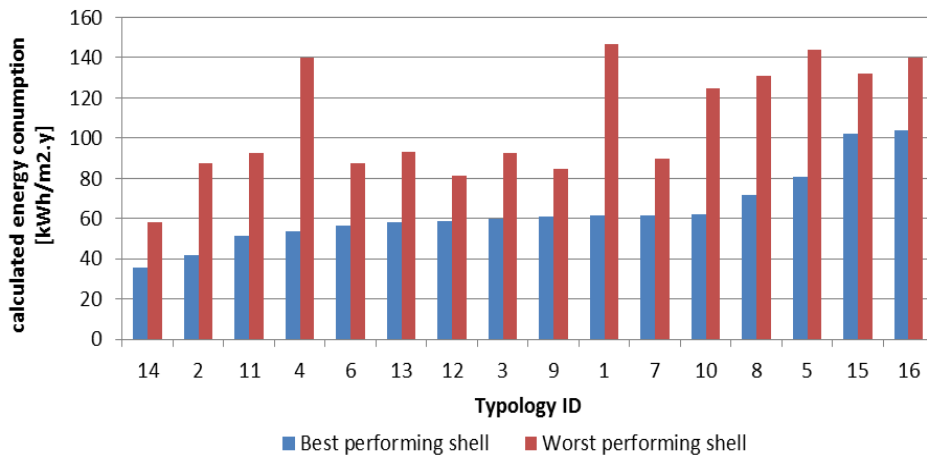
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Figure 5. Average sensitivity of energy consumption calculated using the ANN model

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3 Figure 6 . Calculated energy consumption of the best and worst performing shells of each of the  
4 sixteen typologies

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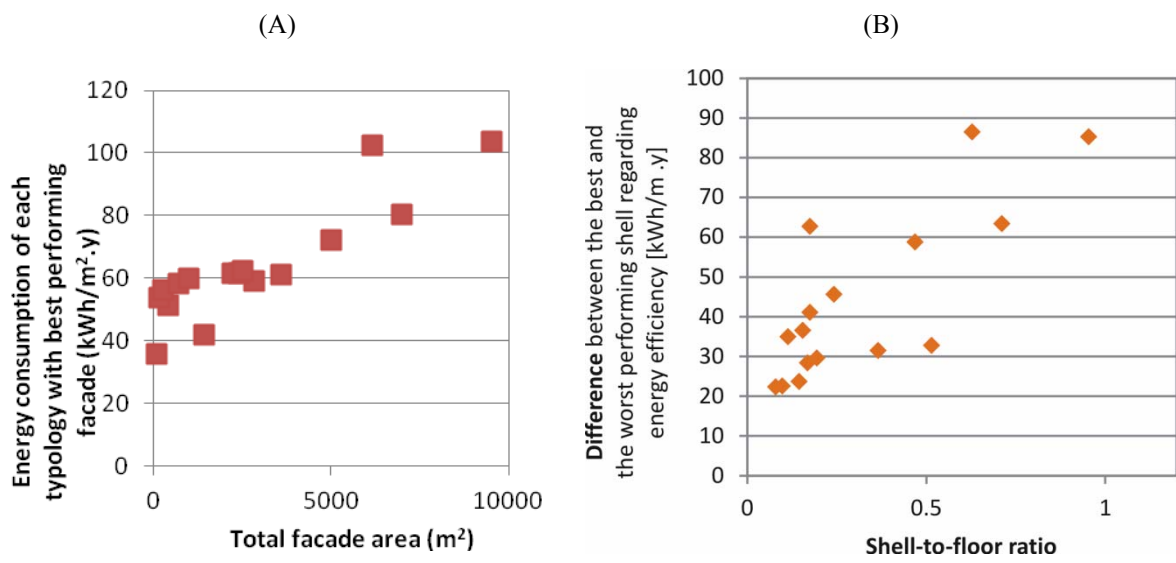


Figure 7. Correlation between performance variation and building parameters

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1 **Table captions**

2 Table 1 . Building properties and assumed values describing the existing building stock for Florianópolis,  
3 Brazil

4 Table 2 . Simulation parameters and correspondent uncertainty

5 Table 3. Error in ANN prediction for additional cases for validation.

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Table 2 . Building properties and assumed values  
describing the existing building stock for Florianópolis, Brazil

<b>Building property</b>	<b>Discreet values</b>
WWR - Window to wall ratio [%]	5; 15; 30; 45; 65; 90
SHGC - Solar heat gain coefficient [-]	0.87; 0.81; 0.76; 0.59; 0.49; 0.25
Uroof - Roof thermal transmittance [W/(m <sup>2</sup> .K)]	0.62; 1.03; 1.18; 1.75; 1.92; 2.25; 4.56
AVS - Vertical shading device coverage angle [°]	0 (no shading); 35; 45
AHS - Horizontal shading device coverage angle [°]	0 (no shading); 45
Uwall - Wall thermal transmittance [W/(m <sup>2</sup> .K)]	0.66; 1.61; 2.02; 2.28; 2.49; 3.7; 4.4
awall - Wall absorptance of solar radiation [-]	0.2; 0.5; 0.8
arof - Roof absorptance of solar radiation [-]	0.2; 0.5; 0.8
Orientation of the main facade [°], where North=0	0; 90

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Table 2 . Simulation parameters and correspondent uncertainty

<b>Parameters</b>	<b>Values</b>
I - Infiltration [ACH]	0.5; 1; 3
ILD - Internal load density [W/m <sup>2</sup> ]	20; 35; 40; 65
PU - Patterns of use [h/day]	11; 14; 24 (hotel)

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Table 3. Error in ANN prediction for additional cases for validation.

Building type	Energy consumption [kWh/m <sup>2</sup> ]		Difference [kWh/m <sup>2</sup> .y]
	EnergyPlus	ANN	
Small building	182	168	14 (-7%)
Large building	95	102	-7 (+7%)
Vertical building	46	55	-9 (+20%)
Non-conventional	58	49	9 (-15%)

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## Appendixes

### Appendix A . Typologies representing the building stock of Florianópolis, Brazil

Building type	Building dimensions (Width, length, ceiling height) [m,m,m]	Number of floors [-]	Exposed surface / indoor volume [1/m]	Typology ID
Small and large offices/stores.	6, 8, 2.7	1	0.95	1
	40, 80, 3	2	0.24	2
	9, 10, 2.7	4	0.51	3
	10, 16, 3.3	1	0.63	4
	5, 10, 3	3	0.71	5
	50, 50, 3.5	1	0.37	6
	45, 50, 3	5	0.17	7
	7.5, 26.7, 2.46	6	0.47	8
	30, 30, 3	10	0.14	9
	40, 80, 10	1	0.18	10
	44.5, 67, 5	2	0.17	11
	70, 70, 5	5	0.11	12
Hotels	17.4, 52.4, 3	6	0.08	13
	17.4, 52.4, 3	12	0.10	14
Vertical offices	20, 68, 2.7	13	0.19	15
	30, 50, 3.5	17	0.15	16

\* Ratio of exposed building surface (facades and roof) to the conditioned indoor volume

### Appendix B . Typologies considered for additional quality assurance test of ANN

Building type	Dimensions Width, length, ceiling height [m,m,m]	Number of floors [-]
Small building	5, 6, 3	2
Large building	30, 50, 5	3
Vertical building	40, 80, 3	12
Non-conventional	100, 200, 10	7
window to wall ratio of 50%, a roof thermal transmittance of 0.95 W/(m <sup>2</sup> .K) and...		

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## Appendix C . ANN weight values (input nodes to hidden nodes)

input node	hidden layer nodes								
	1	2	3	4	5	6	7	8	9
1	-0.12308	-0.35016	-0.40992	-0.48208	0.086147	0.215453	0.741669	-0.0943	-0.83535
2	0.004388	-0.11786	-0.17101	-0.21802	0.346246	-0.26864	-0.66445	0.172554	0.336566
3	0.186248	-0.33981	-0.17096	-0.10659	-0.32543	-5.93398	-0.21227	-0.21414	0.111231
4	0.072223	0.279413	0.121163	0.213017	0.394454	-0.35064	-0.1851	0.134382	0.42725
5	0.037709	0.087147	0.027861	-0.02397	-0.10409	-0.01142	0.192828	-0.14632	0.181567
6	0.192377	0.024764	-0.14441	-0.31155	-0.18266	-0.23567	0.581691	-0.16109	0.110236
7	-0.26023	-0.13304	-0.62842	-0.18306	-1.05263	-0.24523	0.381996	-2.40651	-0.08506
8	18.62549	1.563258	1.16034	0.675206	-21.9938	-0.26458	-24.8815	-2.27694	-19.047
9	0.095442	-0.48269	-0.20612	-0.2452	0.028968	0.0945	-0.55151	-0.10667	-0.56624
10	0.026898	-0.08773	-0.20437	-0.14106	0.191951	-2.9837	0.40572	-0.19156	0.292791
11	0.04762	-0.55983	-0.77358	-5.93024	-0.81317	-2.56719	-3.05493	-3.65517	-7.58972
12	-0.05211	-0.32534	-0.19708	0.122766	0.290045	0.489713	0.616344	0.579345	0.060928
13	-81.1039	-2.91337	-3.69507	1.00978	-4.33119	26.34617	-26.0436	1.651878	-10.188
14	11.06987	-25.2572	18.62168	-3.99185	7.052285	-14.2845	-9.10023	5.060556	18.44951
15	-6.74132	35.00231	-26.2364	7.390736	3.394253	-100.872	3.006375	-17.7776	14.53232
16	22.63756	-12.9089	-13.4423	-8.85356	-14.2736	-10.9504	-10.1224	6.403487	12.6688
17	0.731552	46.56242	-23.7549	5.069072	-0.92541	-12.6902	15.65485	-1.7385	-8.92484
18	-3.76618	0.523313	25.30659	1.598741	-0.62492	1.535674	10.11521	1.55289	-0.37837

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## Appendix D . ANN weight values (hidden nodes to output node)

Hidden layer	Output node
1	-2.433609
2	-1.948416
3	-2.697041
4	-1.766868
5	-1.174638
6	-1.699722
7	-0.771836
8	-1.915127
9	-0.927062

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## Appendix E . ANN bias of hidden nodes and output nodes

Layer	Node	Bias
Hidden node	1	-22.041482
	2	-3.471297
	3	-2.082993
	4	-0.291936
	5	0.783789
	6	7.535811
	7	22.135866
	8	-4.504219
	9	-14.056657
Output node	1	2.381588

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## Appendix F . ANN minimum and maximum values of input and output nodes

Layer	Node	Minimum	Maximum
Input node	1 (WWR)	5	90
	2 (SHGC)	0.25	0.87
	3 (Uroof)	0.62	4.56
	4 (AVS)	0	45
	5 (AHS)	0	45
	6 (Uwall)	0.7	4.4
	7 (I)	0.5	3
	8 (ILD)	20	65
	9 (awall)	0.2	0.8
	10 (arroof)	0.2	0.8
	11 (PU)	11	24
	12 (Orientation)	0	180
	13 (Ceiling height)	2.46	10
	14 (Length)	8	80
	15 (Number of floors)	1	17
	16 (Facade area)	75.6	9520
	17 (Roof area)	48	4900
	18 (Total conditioned floor area)	48	25152
	19 (Total non-conditioned floor area)	0	6400
Output node	Energy consumption	30.59	205.44

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## Appendix G . Input and output of the 3200 simulations using Energy Plus

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*To be included in the online version of the article as additional data for download*

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