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DEVELOPMENT OF A METHOD TO PREDICT BUILDING ENERGY CONSUMPTION THROUGH AN ARTIFICIAL NEURAL NETWORK APPROACH

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ABSTRACT

The main objective of this study is to develop a more accurate method to estimate the energy consumption of commercial buildings at the design stage. The study is based on the simplified model presented in the Regulation for Energy Efficiency Labelling of Commercial Buildings in Brazil. The first step was to evaluate the feasibility and relevance of more complex statistical modelling techniques, such as the neural network. The second step of the assessment consisted of applying the Latin Hypercube sampling technique to combine the effects of several input parameters. Therefore, results of this work may have a profound impact as artificial neural network may be applied in the future in the Brazilian regulation and many other countries.

INTRODUCTION

Building sustainability has been intensified with the increasing demand for sustainable certifications, such as Leadership in Energy and Environmental Design (LEED) and Building Research Establishment Environmental Assessment Method (BREEAM). Thus, many countries are realizing the importance of building more energy efficient buildings and are seeking certifications that increase the efficiency of their buildings (ASHRAE, 2010; California Energy Commission, 2001; Australian Building Codes Board, 2008).

Since 1970s, countries have been looking for solutions to improve energy efficiency in buildings and their systems. In 1984, Brazil initiated programmes focused on the assessment of thermal performance in order to inform consumers about the energy efficiency of equipment.

After several years of discussion and studies, the Regulation for Energy Efficiency Labelling of Commercial Buildings in Brazil (RTQ-C) was approved in 2009 (Brasil, 2009). This regulation reflects on the great improvement in the energy efficiency of buildings. The RTQ-C classifies a building level of energy efficiency based on three elements: the lighting system, the building envelope and the air conditioning system. The classification varies from A (most efficient) to E (least efficient). This classification can be based on two methods: the simulation method, which uses building energy simulation results, or the prescriptive method, which is based on a simplified model.

During the development of the simplified model, presented in Brazilian regulation, some limitations were found in the building shape and in the parameter wall thermal transmittance (Carlo, 2008).

The solution was to establish two simplified models. The first predicted the energy performance of the building envelope for each climatic zone in Brazil as a function of the building projection area. The second, found a high quality correlation between input and output data using the statistical method of multi linear regression, by removing the parameter wall thermal transmittance in the simplified model.

These limitations were analysed by Carlo and Lamberts (2010) and they identified that the simplified model has restrictions when applied to buildings with unusual volumetric conditions and high performance glazing with large window areas.

Yamakawa and Westphal (2011) observed the influence of the solar factor and opening area of facades in both methods proposed for evaluating the efficiency level in the RTQ-C. The results showed that the solar factor input data is not well evaluated in the simplified model. In addition, it was noted that there are discrepancies between the results of the efficiency level for the prescriptive method and the simulation method.

The study by Melo et al. (2012) looked at the accuracy of this simplified model in the RTQ-C. It was concluded that the simplified model presents results outside the limit when compared with the BESTEST (Building Energy Simulation Test) (ASHRAE Standard 140, 2004). Most cases exceeded the limit by 60%. Another limitation observed in this study was related to the efficiency level results based on both methods presented in the RTQ-C. The results showed that the final efficiency level in applying the simplified model is lower than the final efficiency level of the simulation method. It was also noted that the result presented by the simplified model is set as a consumption indicator, not as a result of the building energy consumption.

Based on these limitations and on the results presented in the previous studies, the main objective of this study is to develop a more accurate method to estimate the energy consumption of commercial buildings in the design stage.

METHODOLOGY

Statistical modelling technique

This section presents a comparison between two statistical modelling techniques, applied in the cases adopted, to develop the simplified model in the RTQ-C in Brazil: multiple linear regression and artificial neural networks (ANNs). The multiple linear regression method was used to develop the simplified model present in the Brazilian regulation.

The linear regression method is simple to develop and easy compared to computer simulation programs. Therefore, many studies have used this tool to determine building energy consumption (Signor, 1999; Ma et al., 2010). However, currently, there are other statistical methods for assessing the response of the development of simplified models, such as the ANN. This method has been outstanding among the other methods and there has been increased researcher interest. ANNs are based on the functioning of the human brain, specifically on neuron behaviour. According to Bezdek and Pal (1992), the main advantages of using the statistical method of neural networks are its quality compared to other methods, resistance to faults and noise, and the compact nature of the models with quick answers.

The same input data adopted to develop the simplified model presented in RTQ-C (Carlo, 2008) was used to realize the comparison between the two statistical modelling techniques. The average error, standard deviation and coefficient of determination were the results analysed in both methods. These results were obtained by comparing the results from computer simulation and the results from the simplified model equation. The EasyNN-Plus (EasyNN Plus, 2011) program was used to apply the artificial network method.

The structure of the neural network was classified as feed-forward, in which the output layer connects only to the previous layer. The methodology selected was that where 50% of cases are selected for training the neural network and 25% of cases are selected for the validation set. The other 25% of cases were selected to verify the performance of the network and these cases were not part of the training and validation. All cases were randomly selected by the EasyNN-Plus program.

The input parameters used in the development of the simplified model were considered to be the input layer for the application of the neural network. The building energy consumption (kWh/m^2 of the conditioned area) was considered to be the output layer. The input parameters and their respective values were considered to be independent variables and the energy consumption to be the dependent variable.

Analysis of combined effects of input parameters

This section presents a comparison of two sampling techniques applied in the cases adopted to develop the simplified model in the Brazilian regulation in Brazil: the changing of only one parameter for each new case and the Latin Hypercube method.

Among the steps in statistical analysis, the sampling techniques are the highlighted points. It is important to ensure that the sample used for the study is representative and can perform the statistical method adopted (Risso et al., 2010, Olsson et al., 2003, Xu et al. 2005). The choice of a low quality sample may be reflected in errors, compromising the results (De Wit and Augenbroe, 2002). It is essential to be especially careful and cautious with regard to the sample chosen.

For the development of cases of RTQ-C

The sampling technique where only one parameter is changed for each new case was taken to develop the simplified model presented in the Brazilian regulation. This technique allows the influence of each parameter in the simulation output data to be observed. However, it requires that several cases should be generated according to the number of parameters to be analysed, even if they do not influence the result. Furthermore, this technique obscures the influence of the interaction of two or more parameters in each simulation.

Adopting the Latin Hypercube method (MHL), it is possible to analyse the influence of the combination of different factors. This method allows a reduction in the number of cases generated, without a reduction in the quality of the results (McKay et al., 1979). The comparison between the two modelling techniques allows the behaviour and influence of these techniques on the development of a simplified model to be understood.

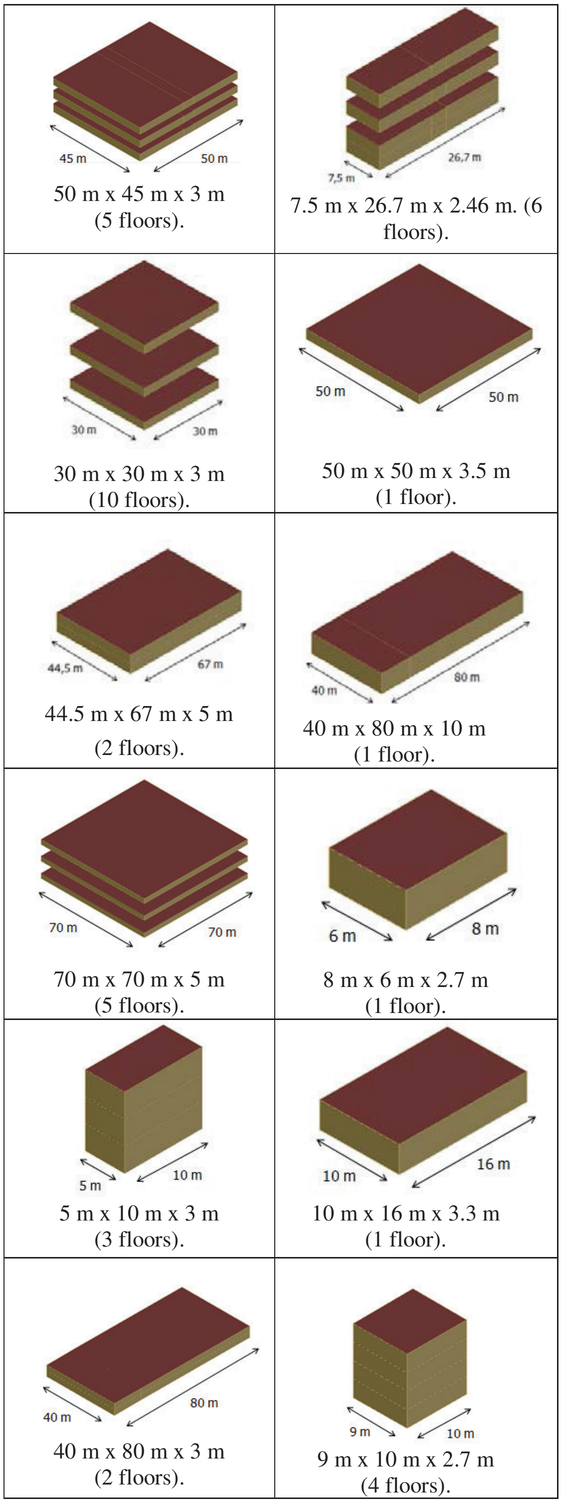
Therefore, after reviewing the results of both sampling techniques (changing one parameter at a time and the MHL), the statistical modelling technique of ANNs was applied. Therefore, the neural network method was applied to those cases generated to develop the simplified model presented in the RTQ-C and to those cases generated by the MHL.

Updated data base

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. Also, to achieve the goal of this study, different input data were assumed, varying the range from maximum and minimum values.

A total of sixteen typologies were adopted, taking into account small and large offices/stores (Figure 1), vertical offices (Figure 2) and hotels (Figure 3). All the input data and their values are presented in Table

1. The climate considered was the weather data of Florianopolis.



50 m x 45 m x 3 m (5 floors).

7.5 m x 26.7 m x 2.46 m. (6 floors).

30 m x 30 m x 3 m (10 floors).

50 m x 50 m x 3.5 m (1 floor).

44.5 m x 67 m x 5 m (2 floors).

40 m x 80 m x 10 m (1 floor).

70 m x 70 m x 5 m (5 floors).

8 m x 6 m x 2.7 m (1 floor).

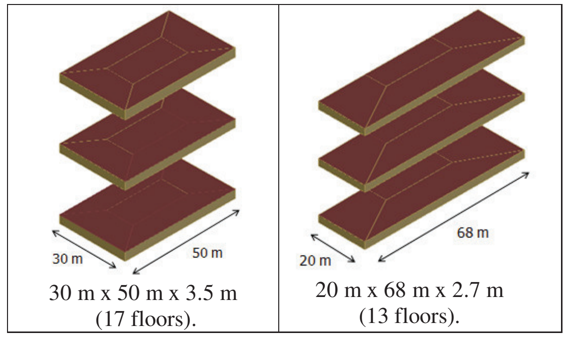
5 m x 10 m x 3 m (3 floors).

10 m x 16 m x 3.3 m (1 floor).

40 m x 80 m x 3 m (2 floors).

9 m x 10 m x 2.7 m (4 floors).

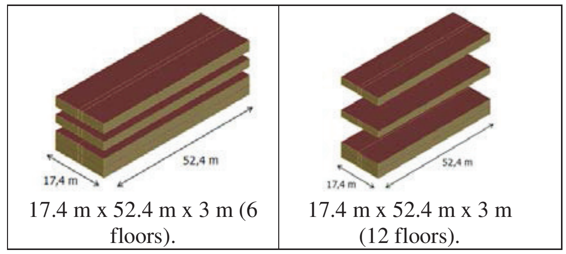
Figure 1. Small and large offices/stores.



30 m x 50 m x 3.5 m (17 floors).

20 m x 68 m x 2.7 m (13 floors).

Figure 2. Vertical offices.



17.4 m x 52.4 m x 3 m (6 floors).

17.4 m x 52.4 m x 3 m (12 floors).

Figure 3. Hotels.

Tabel 1. Values assumed for the parameters.

Parameter	Values assumed
Window to wall ratio (%)	5; 15; 30; 45; 65; 90
Internal load density (W/m^2)	20; 35; 40; 65
Walls thermal transmittance (W/(m^2.K))	0.66; 1.61; 2.02; 2.28; 2.49; 3.7; 4.4
Roofs thermal transmittance (W/(m^2.K))	0.62; 1.03; 1.18; 1.75; 1.92; 2.25; 4.56
Vertical brises	0 (no brise); 35; 45
Horizontal brises	0 (no brise); 45
Solar heat gain coefficient	0.87; 0.81; 0.76; 0.59; 0.49; 0.25
Infiltration (ACH)	0.5; 1; 3
Wall absorptance of solar radiation	0.2; 0.5; 0.8
Roof absorptance of solar radiation	0.2; 0.5; 0.8
Patterns of use (h/day)	11; 14; 24 (hotel)
Orientation (^{o} True North)	North–South; East–West
Air conditioning system (W/W)	Split – COP of 3.20

The MLH was selected for the elaboration of all cases. This method takes into account the influence of two or more new parameters in each case. The interaction between different parameters took place using a macro developed by Hoes (2007), which uses the programs SimLab (SimLab, 2011) and MatLab (MatLab, 2011). Based on this macro, 200 new cases were determined for each of the sixteen typologies. As a result, the total of new cases was 3200.

Based on all cases generated, the computer simulation program EnergyPlus, version 6.0 (DOE, 2010), was adopted to obtain the energy consumption for each case. The results have shown the influence of input data on the building energy consumption for each typology adopted.

Simplified model

The neural networks method was considered in developing the simplified model, adopting the Easy NN-Plus program. All the 3200 cases generated by the MLH were analysed, verifying the input data as the input layer (independent variables), and the output data (building energy consumption given in kWh/m^2) as the output layer. Certain parameters related to the building area were also considered to be the input layer. All parameters considered the input layer for the neural network training can be seen in Table 2.

Table 2. Input data.

Constructive parameters	Parameters related to the typology areas
WWR (%)	Ambient height (m)
SHGC	Length (m)
AVS (o)	Number of floors
AHS (o)	Façade area (m^2)
Uwall (W/(m^2.K))	Roof projection area (m^2)
Uroof (W/(m^2.K))	Conditioned floor area (m^2)
Infiltration (ACH)	Non-conditioned floor area (m^2)
ILD (W/m^2)	
Wall absorptance	
Roof absorptance	
Patterns of use (h)	

Based on the results obtained from the application of the neural network, the coefficient of determination (R^2), the mean error ($\bar{e}$) and the error standard deviation (σe) were calculated. The calculations were made evaluating the EnergyPlus results and the neural network results as both have their results in the same unit, kWh/m^2. The error frequency between the EnergyPlus results and the neural network results were observed through a histogram.

Validation

This section presents the application of the simplified model developed to assess the accuracy of the respective results.

Three different typologies were adopted to evaluate the new simplified model: a one floor small building of 5 m x 6 m x 3 m; a huge three-floor construction of 30 m x 50 m x 5 m, and a ten-floor vertical building of 40 m x 80 m x 3 m. Moreover, the accuracy of the new model was assessed by a non-conventional typology with seven floors and dimensions of 100 m x 200 m x 10 m. None of these typologies was considered for the development of the simplified model. Different values of input data, which were not taken into account to develop the simplified model, were also assumed; for example, a window to wall ratio of 50%, a roof thermal transmittance of 0.95 W/(m^2.K) and number of floors.

Based on these results, it was possible to verify the final error of the new simplified model when different typologies and input data values were taken into account.

RESULTS

Statistical modelling technique

According to Carlo (2008), the application of the statistical method of multiple linear regression achieved an R^2 of 0.99 for the typologies with projection area not exceeding 500 m^2, and R^2 of 0.99 for the typologies with projection area exceeding 500 m^2. With the application of the neural network, the R^2 was found to be 0.98 for the typologies with a projection area not exceeding 500 m^2, and 0.99 for the typologies with a projection area greater than 500 m^2.

It can be seen from Figure 4 that the energy consumption results from the EnergyPlus program and the neural network are almost the same for those typologies with a projection area not exceeding 500 m^2. However, analysing the consumption indicator results from the simplified model presented in the RTQ-C, there is a significant difference when compared to the EnergyPlus results (Figure 5).

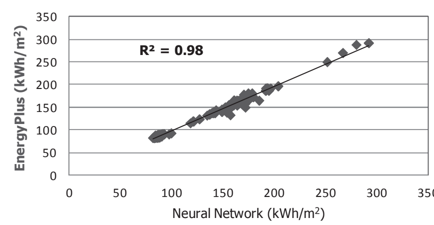


Figure 4. Coefficient of determination – typologies with projection area not exceeding 500 m^2.

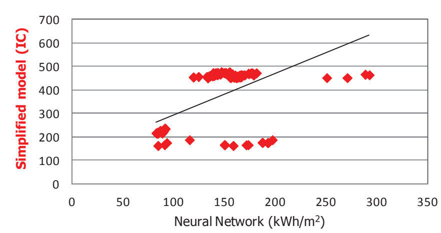


Figure 5. Simplified model versus neural network – typologies with projection area not exceeding 500 m^2

Analysing the results based on those typologies with a projection area exceeding 500 m^2, the same behaviour as previously can be observed. The results from EnergyPlus and the neural networks are similar, as shown in Figure 6. However, comparing the results from EnergyPlus and the simplified model, there is a large difference between the results (Figure 7).

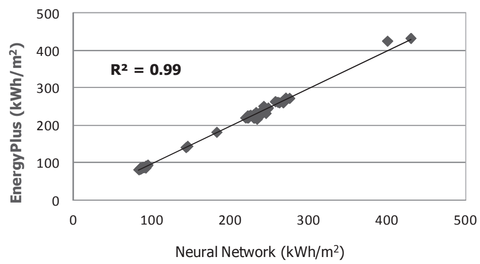


Figure 6. Coefficient of determination – typologies with a projection area greater than 500 m^2.

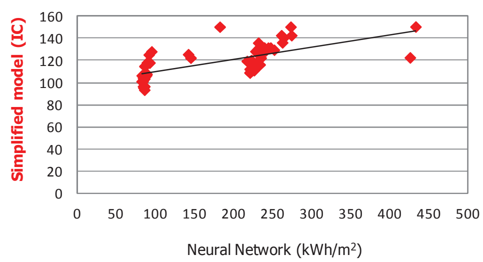


Figure 7. Simplified model versus neural network – typologies with a projection area greater than 500 m^2

The mean error and the error standard deviation based on the neural network results were analysed. It can be seen that the values found were 2.3 kWh/m^2 and 4.7 kWh/m^2, respectively, for typologies with a projection area not exceeding 500 m^2. For typologies with a projection area greater than 500 m^2 the results were 0.7 and 5.1 kWh/m^2, respectively. The values can be seen in Table 3.

Table 3. Application of neural network method.

Characteristics	TYPOLOGIES	
	Projection area ≤ 500 m^2	Projection area > 500 m^2
	NN	NN
R^2	0.98	.99
Mean errors (kWh/m^2.year)	2.3	0.7
Standard deviation (kWh/m^2.year)	4.7	5.1

The values of the standard deviation report that the mean error may be close to or distant from 4.7 kWh/m^2 for typologies with a projection area not exceeding 500 m^2. For typologies with a projection area greater than 500 m^2 the mean error may be close to or distant from 5.1 kWh/m^2.

Based on the results from this section, it can be noted that the neural network statistical method could accurately represent the energy consumption results obtained by the EnergyPlus program.

Even taking into account that the simulation method and the simplified model use different units (kWh/m^2 and IC (consumption indicator) respectively, it can be concluded that, in comparison to the multiple linear regression method adopted for the development of the simplified model presented in the RTQ-C, the neural network statistical method is more efficient in its representation of the interaction between input and output data. The behaviour of the simplified model is explained based on the same conclusions previously observed: the simplified model produces inaccurate results, and the statistical method of multiple linear regression adopted for the development of the simplified model was unable to understand the relationship between input data and building energy consumption.

Analysing the coefficient of determination results for the application of neural networks and the simplified model, it is noted that both have almost the same value. However, evaluating the mean error and the standard deviation for the statistical method of neural networks it is observed that this method presents a maximum standard deviation of 5.1 kWh/m^2 for the typologies with a projection area greater than 500 m^2 and 4.7 kWh/m^2 for typologies with a projection area not exceeding 500 m^2. For the simplified model results, it is possible to see that there is a significant difference between the IC and kWh/m^2 results.

Both methods have the same value of R^2. Nevertheless, it is noted that the statistical method of neural networks exhibits lower results for mean error and standard deviation.

It is important to evaluate the mean error and the standard deviation between the calculated and observed results before implying that the model has acceptable behaviour.

Analysis of combined effects of input parameters

Through the application of the neural networks method and its results, it can be concluded that this method was able to represent the results of energy consumption determined by computer simulation for each simplified model (based on the building projection area). Based on these results, it was decided to observe the behaviour of this statistical method in training all cases (buildings with different projection areas) in just one equation.

As a result, it was observed that it was possible to combine all cases in the same equation by using the neural network statistical method. The application of this methodology was possible for all cases generated by both sampling technique: changing one parameter for each new case and the MLH.

For those cases generated where only one parameter was modified for each new case, a value of 0.98 for the coefficient of determination was achieved. Analysing the mean error and the standard deviation, there is minimal difference between the computer simulation results and the neural network results. For those cases generated by the MLH, the coefficient of determination calculated was 0.96. The results for the mean error and standard deviation of errors were -0.2 kWh/m^2 and 5.3 kWh/m^2 respectively. These values can be seen in Table 4.

Table 4. Application of sampling techniques.

Characteristics	TYPOLOGIES Projection area ≤ 500 m² + > 500 m²	
	One parameter per case	Latin Hypercube
R^2	0.98	0.96
Mean error (kWh/m²)	-1.9	-0.2
Standard deviation (kWh/m²)	6.6	5.3

The results demonstrate that both sampling techniques could represent the energy consumption result obtained by computer simulation. But, a comparison between the sampling technique results shows that the MLH could better represent the behaviour of all the typologies analysed. This method resulted in a mean error of -0.2 kWh/m^2, and a standard deviation of 5.3 kWh/m^2.

Besides the MLH allowing the influence of an interaction of two or more parameters related to the output data to be investigated, this method also allows a reduction in the number of simulations required without losing the quality of the results. It was found that this method produces the best results of mean error and standard deviation even taking into account only a few cases.

The development of two simplified models to assess the energy efficiency of the building envelope in the RTQ-C was required, as the statistical method adopted was unsuccessful in covering different typologies in the same equation. However, based on the results of this section, the application of the neural network statistical method could produce almost the same results as computer simulation.

Simplified model

All the 3200 cases were considered for the development of the new simplified model. The ANN was considered as the statistical method. A total of 25% of cases (800 cases) were considered for the network validation and another 25% (800 cases) to verify the network performance. The other 50% (1600 cases) was selected for network training. The training and validation performance are presented in Figure 8.

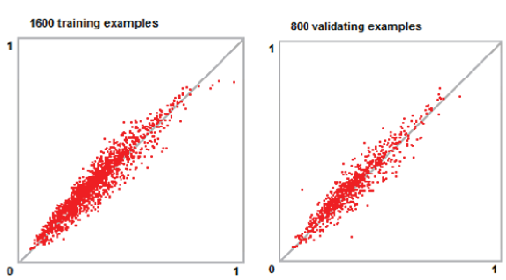


Figure 8. Training and validation.

The training and validation of the cases demonstrated a good performance as the results concentrated along the line. It can be seen that just two cases in the validation performance resulted in a great difference between the results from EnergyPlus and the neural network.

After training and validating of the neural network, the EasyNN-Plus program provides an output .csv file which allows analysis of all the cases that were selected to evaluate the performance of the network.

This file allows a comparison between the energy consumption results (kWh/m^2) from the neural network and the EnergyPlus program.

Based on these results, it was possible to calculate and analyse the mean error, the standard deviation, and the coefficient of determination. Moreover, it was possible to calculate the error frequency through a histogram (EnergyPlus x neural network).

The mean error and the standard deviation for the cases were -3.7 kWh/m^2 and 8.7 kWh/m^2, respectively. The standard deviation result shows that the values adopted to calculate the mean are 8.7 kWh/m^2 close or far from -3.7 kWh/m^2. The result for the coefficient of determination is 0.89, presented in Figure 9.

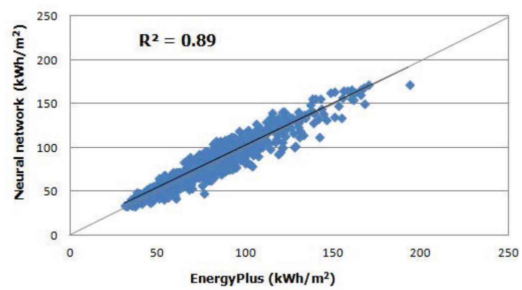


Figure 9. Coefficient of determination for the new simplified model.

Analysing the results through a histogram (Figure 10), it is noted that 241 cases from a total of 800 cases show a difference between the EnergyPlus and neural network energy consumption results of between -5 kWh/m^2 and 0 kWh/m^2. A total of 195 cases show a difference between -10 kWh/m^2 and -5 kWh/m^2 and a total of 140 cases between 0 kWh/m^2 and 10 kWh/m^2. The major difference between the EnergyPlus and the neural network results is in the range of -10 kWh/m^2 to 10 kWh/m^2 (84% of cases). Between the boundaries of -5 kWh/m^2 and 5 kWh/m^2 there are a total of 64% of cases.

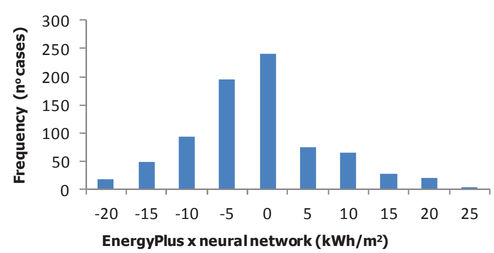


Figure 10. Histogram based on EnergyPlus and neural network results.

Based on the coefficient of determination and the histogram results, it can be concluded that the neural network statistical method could represent the relationship between input and output data, taking into account all the typologies of the same simplified model.

Validation

The energy consumption per m^2 results for all the four typologies adopted to verify the accuracy of the new simplified model were produced by the EasyNN-Plus program.

The model developed is kept in the Easy NN-Plus program and, based on the building characteristics, this program provides the results of energy consumption per m^2. The results are presented in Table 5.

Table 5. Validation of the simplified model.

	Consumption (kWh/m^2)		Difference (kWh/m^2)
	EnergyPlus	**Neural network**	
Small building	182	168	14
Huge building	95	102	-7
Vertical building	46	55	-9
Non-conventional	58	49	9

Based on the EnergyPlus program, a value of 182 kWh/m^2 was achieved for the small building. Based on the simplified model developed through the neural network, the value found was 168 kWh/m^2. The difference between the methods is 14 kWh/m^2.

The use of computer simulation for the huge building resulted in an energy consumption of 102 kWh/m^2. However, taking into account the simplified model the result was 95 kWh/m^2. A difference between EnergyPlus and the neural network results of -7 kWh/m^2.

For the vertical building analysis, the EnergyPlus result was 46 kWh/m^2 and for the simplified model was 55 kWh/m^2. A comparison between them showed a difference of 9 kWh/m^2.

Taking into account a non-conventional typology, the difference found between the two methods was also 9 kWh/m^2. A total of 58 kWh/m^2 for the EnergyPlus calculation and 49 kWh/m^2 for the simplified model.

Based on the results, it can be seen that the simplified model result shows a difference of approximately 15 kWh/m^2 lower when compared to the EnergyPlus results. Therefore, the network can enhance its accuracy with more detailed input data and information about each case. The simplified model developed through the neural network presented high quality learning when all the typologies were considered in the same model.

The importance of such work goes far beyond the Brazilian case, as most countries face similar challenges in the development of building energy simulation for regulatory purposes. Therefore, results of this work may have a profound impact as artificial neural network may be applied in the future in the Brazilian regulation and many other countries, with further impact in the energy consumption and life quality of large amounts of people.

CONCLUSIONS

The main objective of this study was to develop a method to estimate the energy consumption of commercial buildings in the design stage. The study emphasized the commercial buildings located in Florianópolis, Brazil. Analysing the simplified model presented in the RTQ-C in Brazil, the following conclusions can be drawn:

- The statistical method adopted to develop the simplified model presented in the RTQ-C was unable to understand the influence of input and output data. However, applying the statistical method of neural networks the results have shown almost the same result when compared to the EneryPlus results;
- The MLH reduces the number of cases that should be generated for a specific analysis, without affecting the quality of the results, when compared to the sampling technique of changing only one parameter per case, without affecting the quality of the results;
- The application of the statistical method of neural networks allows typologies with different projection areas in the same simplified model;
- The development of the simplified model by applying the neural network technique could represent the interaction between input and output data. The result of the mean error was -3.7 kWh/m^2 and the standard deviation was 8.7 kWh/m^2 ;
- The simplified model developed by the neural network presented a difference of approximately 15 kWh/m^2 lower than the EnergyPlus results for the typologies not considered in the development, even for typologies considered to be non-conventional;
- The results of this work may have a profound impact as artificial neural network may be applied in the future in the Brazilian regulation and many other countries, with further impact in the energy consumption and life quality of large amounts of people.

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INFLUENCE OF FIELDS DATA QUALITY ON THE MODELING OF RESIDENTIAL BUILDINGS WITH DYNAMIC SIMULATION TOOL

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ABSTRACT

To produce a realistic building reference's model, in order to work on a retrofitting project, input data have to be chosen with the field's information. The present work concerns French residential buildings of the pre-world-war-II family. This category is more and more subject to retrofitting project and represents more than 30% of the French building sector. In addition, the old buildings are characterised by difficulties to collect data.

The aim of this work is to identify the limits of modelling precision for energy simulation.

To achieve this objective, two buildings have been modelled, it consists on one house and one flat that were monitored and for which data have been recorded during a year. Moreover, for each input data, a field value and an uncertainty range are proposed. The output data analysis shows a hierarchical influence of the input data uncertainty.

INTRODUCTION

Dynamic thermal simulation of real building to work on retrofitting project is a common activity nowadays. Decisions on design are made thanks to these simulations. Different simulation tools are well known. The validations of these codes are published in the literature. Nevertheless, the question of the determination of the input data still exists for the user. Hopfe has shown the necessity to considerate the uncertainties of the model when decision making is based on simulation predictions (Hopfe, 2011).

The difficulties to assess some values and to be precise about stochastic scenarios can lead to a wide range of uncertainty on the input data. The results of the simulations depend on these sets of values coupled to uncertainties. So the comparison of simulations to real world outcomes may provide substantial differences.

Several authors investigate on the impact of the main uncertainties on the simulated energy consumption (Brohus, 2009) or on the indoor air temperature (Macdonald, 2001). Different methods of evaluation for these impact of uncertainties are available in the literature. Lomas compared differential sensitivity analysis, Monte Carlo analysis and stochastic analysis (Lomas, 1991). He concludes that stochastic analysis is the most complicated method to implement and can't be applied on all programs. The Monte Carlo analysis only gives the total sensitivity information and the differential sensitivity analysis gives both total and individual sensitivity with programs which can be assumed to operate as roughly linear. Macdonald tried the differential and the Monte Carlo analysis on ESP-r cases (Macdonald, 2001).

The aim of this paper is to identify the limits of modelling precision and therefore the limits in the comparison between simulation and real behaviour of traditional buildings.

A method to assess the modelling precision is applied to two different cases in this paper. To produce a realistic model of the reference cases for these buildings, field data can be collected. For that purpose, construction plans, surveys with the inhabitants, energy consumption and indoor temperature measurements, blower door tests and others actions could be used. The two buildings have been selected in a field measurements campaign (Cantin, 2010) of a previous project. Both are pre world war II French building, a flat and a house. This family of old building represents more than 30% of the French building sector and is a real stake for energy savings and retrofitting with heritage consideration. Another particularity, object of this paper, is the large uncertainties in the characteristics of these buildings. So, the buildings cases are presented, then the method to assess the local and global sensitivity and conclusions are made about the modeling of old buildings.

METHOD AND RESULTS

Data collection

The data to be collected via the different possible ways are listed in table 1. They are needed as input data for the simulation program.

For both cases, data have been collected during a year. It consists of a monitoring with timestep of an hour, an occupancy survey, punctual investigations such as infrared thermography, plans drawing with