USE OF NEURAL NETWORKS FOR EVALUATION OF ENERGY CONSUMPTION OF AIR CONDITIONING SYSTEMS

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Abstract. *This work presents a comparative study on the use of different artificial neural network configurations to predict the energy consumption of buildings. It was considered as main hypothesis that the variations in the energy consumption is mainly associated to the use of air conditioning equipment and, therefore, the climatic conditions of the buildings surrounding were considered as input parameters for the neural networks. Two buildings were studied: the University of São Paulo Museum of Contemporary Art, and the School of Economics and Administration building. For each building, secondary factors that could explain the variation in energy consumption were analyzed. The validation process indicates best results are obtained by Elman-type recurrent networks, with conjugate gradient learning method. Depending on building usage, different inputs and activation functions are required. In general, best forecast performances presented errors ranges of 10-20% for 80% of data.*

Keywords*: Neural networks, Electrical energy consumption, Air conditioning systems.*

1. INTRODUCTION

In the last decade the concern with the increase of energy consumption in Brazil intensified, due to the occurrence of blackouts in 2001 and possible rationing scenarios. A proper sizing and management of the power supply grid has became even more important, as well as the need for models for properly forecast of energy consumption.

Such models should be applied on a national basis but are also interesting to be applied on a smaller scale, as in predicting the energy consumption of an end-user like a commercial or public building. In the latter case, such models could be tool for the building manager to reduce their operational costs by choosing an energy contract that best suits the building needs and by avoiding penalties for exceeding contracted demand.

One of the main end-uses of electricity in commercial and public buildings is associated to air conditioning equipment. Since such consumption is weather-dependent, it is the main reason for the variation of energy consumption. This indicates that weather forecast must be an input for energy consumption prediction models.

The use of analytical models in this forecast process is very difficult because there is a great amount of variables to consider, and the need of knowing in detail properties and characteristics of the building facility and its components, which very often are not available (Hernandez & Fiorelli, 2008). A possible solution, when there is available previous data about building energy consumption, is the use of models that extrapolate the consumption for new situations based on such previous data.

One of these models is the artificial neural network (ANN), a generic denomination for several simple mathematical models that try to simulate the way a biological neural network (for instance the human brain) works. The main characteristic of such models, which is important for this study, is the capability of learning the "rule" that controls a physical phenomenon under consideration from previously known situations and to extrapolate results for new situations. Kovács (2006) and Hagan et al. (1996) present the fundamental concepts of ANN.

There are several works on ANN usage for forecasting energy consumption (for instance Kalogirou, 2000; Kalogirou & Bojic, 2000; Amjady, 2001; Ben-Nakhi & Mahmoud, 2004; Pao, 2006; Azadeh et al., 2008; Ekonomou, 2010), most of them using the feed-forward (also known as MLP, *multi-layer perceptron*) configuration for the neural network, since this is the most known and simple network arrangement.

Campoleone et al (2006) implemented a feed-forward ANN for forecasting the daily energy consumption of the Administration Building of University of São Paulo. It was assumed that consumption variations was basically due to air conditioning equipments, and therefore weather conditions (temperature, humidity and solar radiation were used as ANN inputs. The implemented network was trained using weather and consumption data from 2003 to 2004, and validation against data for the three first months of 2005 indicated that ANN predicts energy consumption within ± 10% error range, and that humidity and solar radiation has a second-order influence for the considered building.

Hernandez Neto & Fiorelli (2008) compared the simpler ANN model developed by Campoleone et al (2006) and detailed building HVAC design and simulation software (EnergyPlus) as forecasting tools for the energy demand. Results show that both models are suitable for energy consumption forecast for the Administration Building of University of São Paulo. The authors also carried out a parametric analysis for the considered building on EnergyPlus in order to evaluate the influence of several parameters such as the building profile occupation and weather data on such forecasting. Besides the second-order effect of humidity and solar radiation pointed out by Campoleone et al. (2006), such analysis showed that internal heat gains and equipment performance are more significant for the present case.

Considering the same building of Campoleone et al. (2006), Fiorelli et al. (2009) developed a comparative study on the use of different artificial neural network configurations to predict the daily energy consumption. It was implemented the following ANN configurations: MLP; Elman, Jordan and Hopfield recurrent networks; Kohonen self-organizing maps (SOM), and modular networks. The analysis indicated that the Elman configuration presented a better performance than the feed-forward for the considered building configuration, with a mean square error 10% lower than Campoleone et al. (2006).

Duarte & Fiorelli (2010) developed a similar study using a different type of building (a hotel located at São Paulo), and also concluded that Elman partially recurrent networks are better choice for the considered building. The resulting network was able to forecast 80% of consumption data within a ±11,4% error range.

In order to abroad the results of Campoleone et al. (2006), Fiorelli et al. (2009) and Duarte & Fiorelli (2010), this study analyzes two other types of public buildings located in the University of São Paulo campus: a museum (the Museum of Contemporary Art), and a faculty (the School of Economics, Administration and Accounting), shown in Fig. 1. The models are to be based on basic climatic data (temperature, relative humidity and solar radiation) and energy consumption historical data. It is analyzed the type of ANN that generates the best results and discussed the influence of the installation proper management in the forecasts, by comparing the results obtained in previous works for a university administrative building and a hotel.

(a) (b)

Figure 1. University of São Paulo Museum of Contemporary Art (a) and School of Economics (b).

2. BUILDINGS DESCRIPTION

2.1. School of Economics, Administration and Accounting (FEA)

The School of Economics, Administration and Accounting of University of São Paulo has six blocks and daily houses about 3190 undergraduate students, 530 graduate students, 190 professors e 120 administrative personnel. There is a significant quantity of personal computers and data projectors for classes (at least one pair computer/projector per classroom), as well as computers for professors and administrative personnel, and there is not any kind of lighting control.

Five blocks count on some type of air conditioning system (self-contained, split or chiller), and all blocks are relatively old (most of them from the 1970's), when proper energy usage in air conditioning systems was not a major concern. There is not a specific evaluation on this building energy use break-down. Hernandez Neto and Fiorelli (2008), analyzing another building in the campus, verified that the air conditioning system contributes with 30% to 40% of the total energy consumption.

2.2. Museum of Contemporary Art (MAC)

The Museum of Contemporary Art of the University of São Paulo has two blocks. The main block houses the collection and warehouse of the museum, and the annex houses administrative personnel and eventual exhibitions. Both blocks are climatized and have a major concern on controlling internal temperature in order to properly conserve the collection. Similarly to FEA, there is not a specific evaluation on building energy use break-down.

The museum is open to public from Tuesdays to Sundays. The number of visitors presents a high daily fluctuation. For example, during the week in which the inspections for this work were performed such number ranged 17 to 200 visitors. Besides the visitors, 114 employees work in three turns.

3. CLIMATIC DATA

Climatic data for 2006 to 2008 were provided by the "Água Funda" meteorological station of the IAG (Institute of Astronomy, Geophysics and Atmospheric Science of University of São Paulo). Such station hourly collects the following basic climatic data: dry bulb temperature T (ºC), relative humidity ϕ (%), total solar radiation G_s (MJ/m²), atmospheric pressure p_{atm} (MPa).

From such data it was evaluated the maximum, minimum and average daily values for the climatic parameters, which considered as inputs for the networks given that weather forecasts typically provide this kind of information. Figure 2 presents monthly averages for daily dry bulb temperatures and average solar radiation.

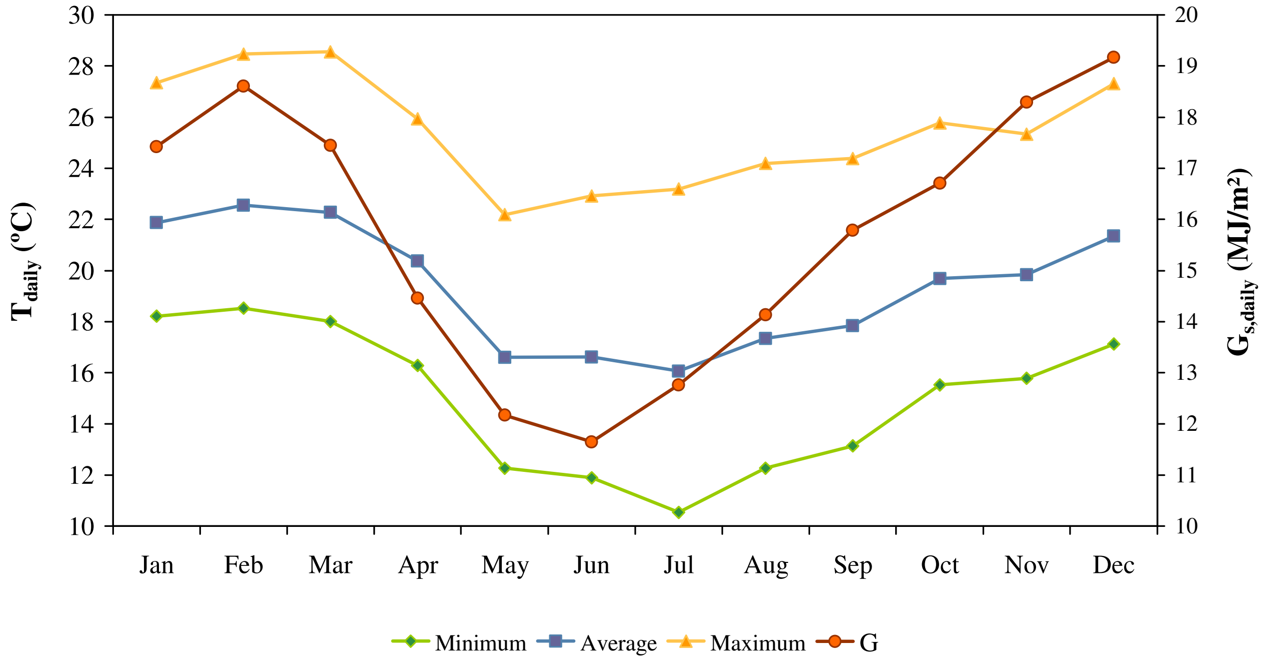

Figure 2. Temperatures and solar radiation profiles (monthly average)

4. ENERGY CONSUMPTION HISTORICAL DATA

The University of São Paulo (USP) started a program called PURE-USP (Permanent Program of Efficient Use of Energy) (Saidel et al., 2003) in 1997 to design and implement actions in order to reduce energy consumption. Among the several actions implemented by the program, an on-line measurement system for energy consumption that allows the development of building energy consumption profile database can be pointed out, which has become a very important tool for planning the retrofitting actions.

From such database it were collected 2006-2008 daily total electricity consumption data (C, kW) for FEA and the same data for 2006-2007 period for MAC. The data were analyzed and the following modifications were introduced in the database:

- **Exclusion of incoherent data:** in some days there was no consumption, indicating a measuring system malfunction; in other cases it were verified extremely high consumptions values (over 10 times the average consumption); such values were considered incoherent and excluded from the database.
- **Data classification:** energy consumption data were analyzed and it was verified, similarly to previous works of Campoleone (2006) and Arincibia (2009), a significant variation depending on it is a working day or weekend/holiday, as well as during the semesters and the vacations periods. In order to take it into account in the analysis, to each day it was associated variables to indicate its type. For FEA, data were classified as working day or weekend/holiday, as well as class period or vacations. For MAC, classifications were working day, weekend/holiday and mondays (when the collection area is closed to the public).

5. ANN IMPLEMENTATION

In order to implement an artificial neural network for energy consumption forecast in climatized buildings it is necessary to define the network inputs/outputs and arrangement, the neuron transfer function and learning rules.

Campoleone (2006) verified that inclusion of relative humidity and solar radiation has practically no impact on ANN performance. It was also verified by Campoleone et al. (2006), Fiorelli et al. (2009) and Duarte & Fiorelli (2010) that the day type (working day or weekend/holiday) must be taken into account depending on the building usage. Based on these conclusions, in this work it was defined as possible network inputs the maximum and minimum external temperatures and the day type.

Concerning to the aspects of ANN implementation, in this work it is analyzed several network configurations, namely:

- **ANN arrangements:** MLP, Elman, Jordan, Self-Organizing Maps, Modular Networks.
- **Network input data group:** A (T_{min}, T_{max})**,** B (T_{min}, T_{max}, day type)**,** C (T_{min}, T_{max}, day type, period of year type).
- **Transfer function:** T (Hyperbolic Tangent)**,** S (Sigmoidal).
- **Learning rules:** M (Momentum)**,** G (Conjugate Gradient)**,** L (Levenberg-Marquardt).

In the case of FEA, for learning process it was used 2006-2007 data, and validation was performed using 2008 data. Learning process for MAC was performed using 2006 data, and for validation process it were used data from the first half of 2007.

All network configurations were implemented using a spreadsheet (EXCEL™) with an ANN add-in (NeuroDimension, 2010), and the comparison parameter of the performance for the different network arrangements was the mean squared normalized error (*MSNE*), Eq. (7),

$$MSNE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{norm,i} - f_{norm,i}\left(x,w\right)\right)^2 \tag{1}$$

where $Y_{norm,i}$ represents the actual energy consumption value normalized to [-1,1], and $f_{norm,i}(x,w)$ is the network output, also normalized to [-1,1]. Normalization is used to ensure that networks with multiple outputs will be trained so that accuracy of each output is treated as equally important. Without normalization outputs with larger values, and therefore larger errors, would be treated as more important (MathWorks, 2009).

6. RESULTS

It was evaluated 90 different ANN configurations to each building. Tables 1 and 2 summarize the average *MSNE* results in terms of network arrangement, learning rule and transfer function for the different input data sets. In general, recurrent-type networks presented the best performances. Concerning transfer function there is a slightly better performance of conjugate gradient method, and for the considered transfer functions the results do not clearly indicate which is the best choice for the considered buildings.

Table 1. Result Analysis – FEA (*MSNE* in validation)

	Input data set			
ANN arrangement	A	B	C	**Average**
MLP	1,08	0,85	0,78	**0,90**
Elman	1,15	0,82	0,74	**0,90**
Jordan	1,03	0,86	0,84	**0,91**
Modular	1,10	0,86	0,89	**0,95**
SOM	1,10	0,78	1,15	**1,01**
Average	**1,09**	**0,83**	**0,88**	**0,93**

	Input data set			
Learning rule	A	B	C	**Average**
G (Conjugate Gradient)	1,01	0,77	0,72	**0,83**
M (Momentum)	1,02	0,83	0,77	**0,87**
L (Levenberg Marquardt)	1,24	0,90	1,15	**1,10**
Average	**1,09**	**0,83**	**0,88**	**0,93**

	Input data set			
Transfer function	A	B	C	**Average**
T (Hyperbolic Tangent)	1,13	0,79	0,76	**0,89**
S (Sigmoidal)	1,06	0,87	1,00	**0,98**
Average	**1,09**	**0,83**	**0,88**	**0,93**

Table 2. Result Analysis – MAC (*MSNE* in validation)

ANN arrangement	Input data set A	Input data set B	Input data set C	Average
MLP	2,00	1,17	1,21	**1,46**
Elman	0,99	1,06	0,97	**1,01**
Jordan	1,33	0,99	1,30	**1,21**
Modular	1,16	1,27	1,57	**1,34**
SOM	1,48	1,55	1,69	**1,57**
Average	**1,39**	**1,21**	**1,35**	**1,32**

Learning rule	Input data set A	Input data set B	Input data set C	Average
G (Conjugate Gradient)	1,53	0,93	0,95	**1,14**
M (Momentum)	0,99	0,96	0,96	**0,97**
L (Levenberg Marquardt)	1,66	1,73	2,14	**1,85**
Average	**1,39**	**1,21**	**1,35**	**1,32**

Transfer function	Input data set A	Input data set B	Input data set C	Average
T (Hyperbolic Tangent)	1,43	1,34	1,52	**1,43**
S (Sigmoidal)	1,35	1,08	1,18	**1,20**
Average	**1,39**	**1,21**	**1,35**	**1,32**

Table 3 ranks the best configurations for each case. It can be verified that most of then are recurrent-type networks, indicating that this is the best choice for this ANN application, and such result reinforces a similar conclusion of Fiorelli et al. (2009) and Duarte & Fiorelli (2010) for other building types (a university administration building and a hotel).

Figures 3 and 4 present a comparison of the actual energy consumption data profile and the ANN forecast. It can be verified that the forecasts qualitatively reproduce the actual observed behavior, but the ANN fail in adequately evaluates consumption peak values. It leads to higher error ranges than previous works, as shown in Figs. 5 and 6.

Such results, particularly for FEA, might be connected to an inadequate management of the building. For instance, during inspections for the development of this work it was verified unoccupied classrooms with lighting and air conditioning systems turned on, open windows during AC usage, and so on. It might also be connected other aspects that do not depend on weather conditions (for instance auditorium usage for special events, congresses, etc.).

One point that reinforces such consideration is that results for MAC are better than for FEA, and the inspection verified a better building management in MAC. Nevertheless, there is still an error in forecast, probably connected to special events and expositions occurring in the museum, which may lead to a higher AC consumption connected to a higher building occupation.

Table 3. Best ANN configurations for FEA and MAC

	FEA					MAC				
Ranking	ANN arrange-ment	Other configu-rations	MSNE in learning	MSNE in validation	Forecast Error Range	ANN arrange-ment	Other configu-rations	MSNE in learning	MSNE in validation	Forecast Error Range
1	Jordan	C,S,G	0,726	0,696	89,2%	Elman	C,T,M	0,809	0,815	19,0%
2	Modular	C,T,M	0,729	0,704	88,5%	MLP	B,T,M	0,924	0,854	14,4%
3	Elman	C,T,G	0,721	0,711	98,0%	Jordan	C,S,L	0,864	0,856	16,1%
4	Elman	C,S,G	0,710	0,714	98,8%	SOM	B,S,G	0,906	0,862	13,5%
5	MLP	C,S,M	0,740	0,714	97,3%	Modular	A,T,G	0,897	0,865	17,0%

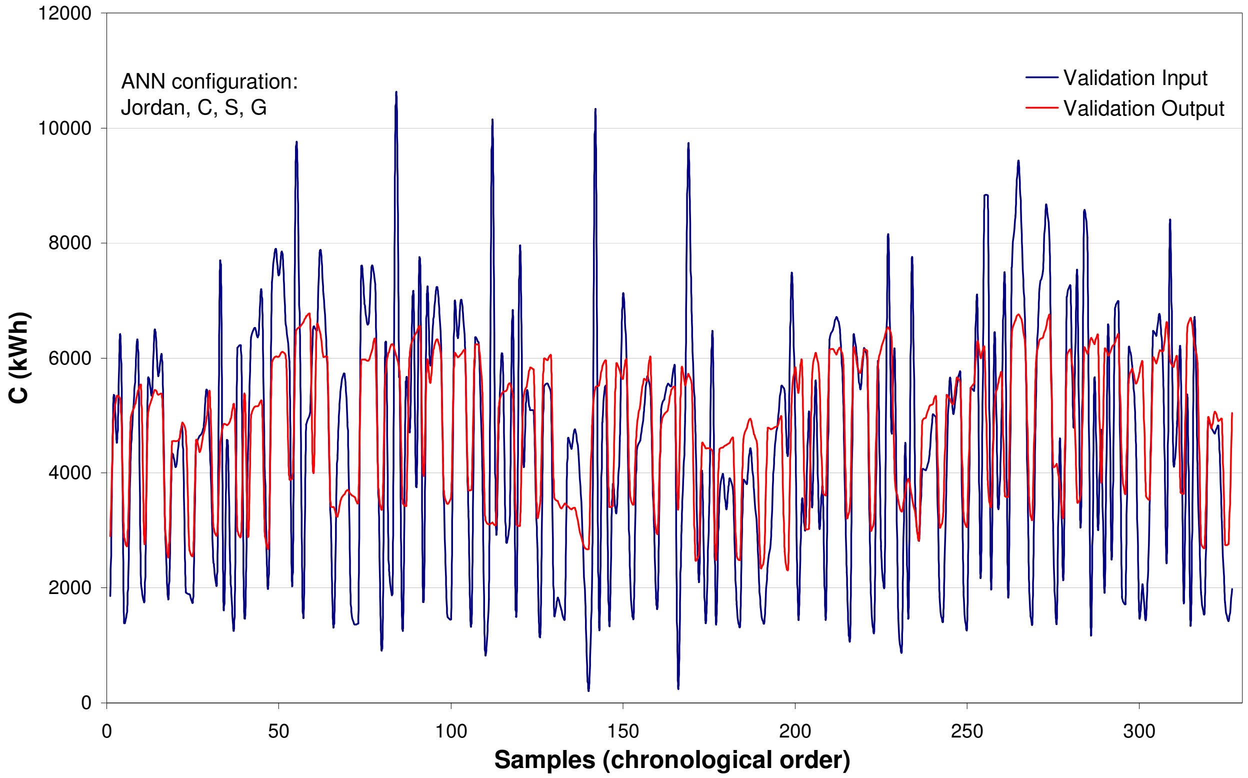

Figure 3. FEA ANN validation (Jordan, C, S, G)

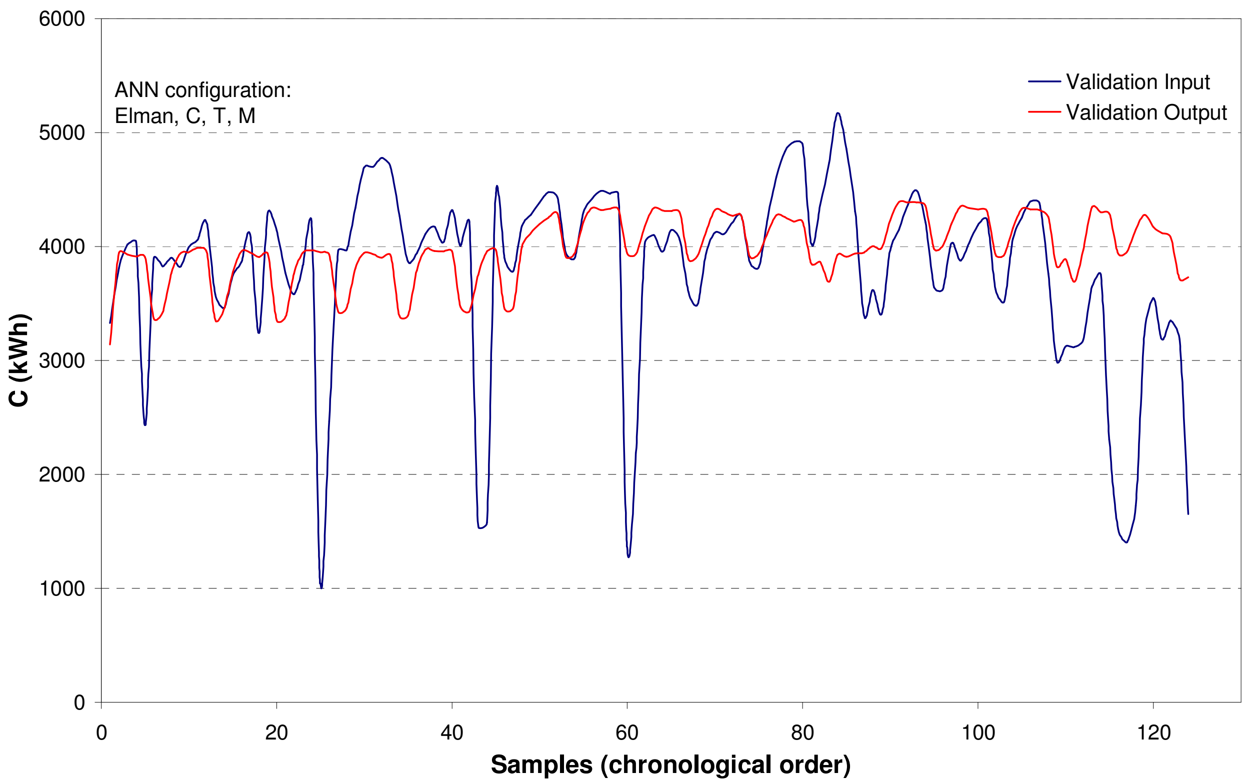

Figure 4. MAC ANN validation (Elman, C, T, M)

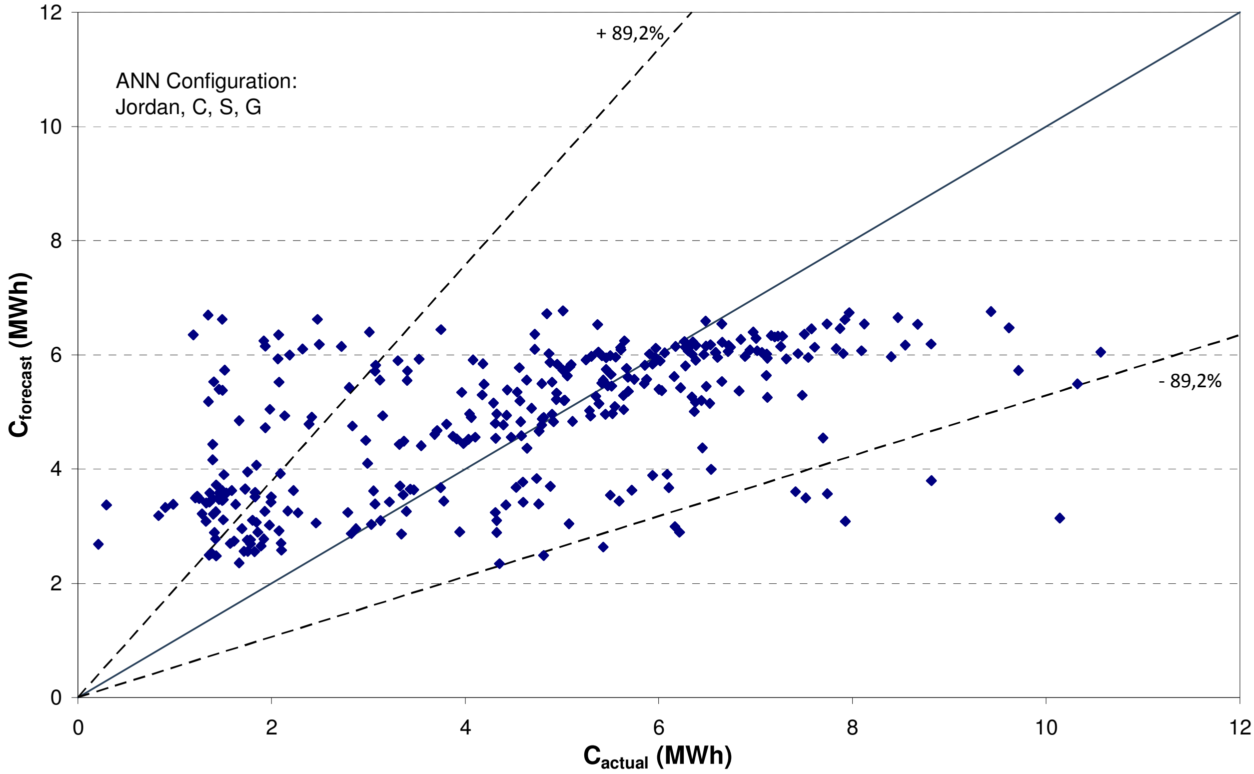

Figure 5. Error range for FEA (Jordan, C, S, G)

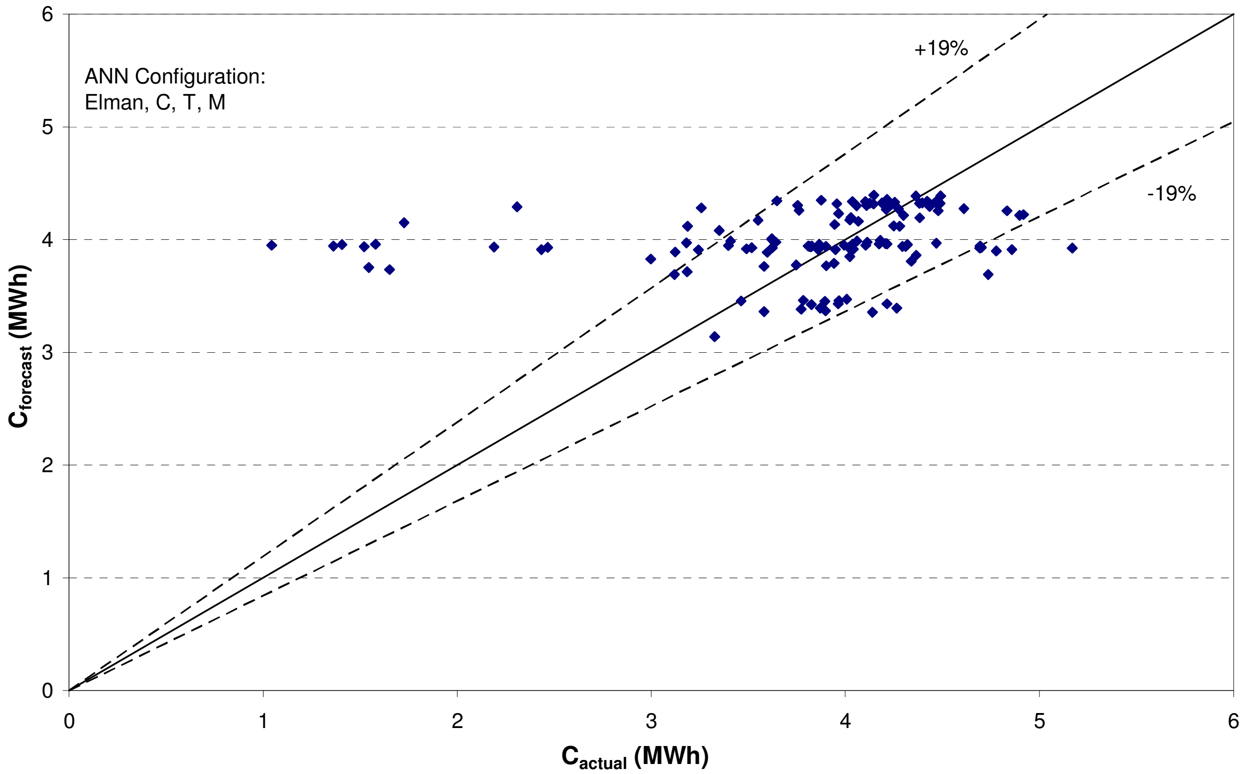

Figure 6. Error range for MAC (Elman, C, T, M)

6.1. Comparasion of results to previous works

Table 5 present a comparison of the results for FEA and MAC with previous works in terms of MSNE and error range. It can be verified that ANN performance is strongly dependant on building usage and characteristics.

Nevertheless, the recurrent-type ANN configuration presented the best performance for all comparable cases, particularly the Elman configuration. Such result indicates that this ANN configuration is the best option for building energy consumption forecast based on weather data.

Table 5. Comparison of results to previous works

Error Range (< 80%) — MSNE

Building Usage	**University Administration**	**University Administration**	**Hotel**	**University Faculty**	**University Museum**
Work	Campoleone (2006)	Arincibia (2009)	Duarte (2009)	FEA	MAC
ANN Configuration	MLP	MLP, Hopfield, Elman, Jordan, SOM, Modular	MLP, Hopfield, Elman, Jordan, SOM, Modular	MLP, Elman, Jordan, SOM, Modular	MLP, Elman, Jordan, SOM, Modular
Learning method/function	• M • linear	• M, G, L • S, T	• M • T	• M, G, L • S, T	• M, G, L • S, T
Best Average Performance	N.D.	Elman 0,92	↑ Elman 0,23 11% ↓	Elman 0,90	Elman 1,01
Best Absolut Performance	N.D.	Elman 0,89		Jordan 0,70 89%	Elman 0,81 19%

not comparable

7. CONCLUSIONS

This work presented a comparative study on the use of different artificial neural network configurations to predict the energy consumption of buildings. It was analyzed two types of public buildings located in the University of São Paulo campus: a museum and a faculty. The models were based on basic climatic data (temperature, relative humidity and solar radiation) and energy consumption historical data. It was analyzed the type of ANN that generates the best results and discussed the influence of the installation proper management in the forecasts, by comparing the results obtained in previous works for a university administrative building and a hotel.

The results indicates that best results are obtained by recurrent-type networks, with conjugate gradient learning method, and depending on building usage different inputs and activation functions are required. A possible explanation to the best performance of recurrent arrangements would be the feedback from the hidden layers to the network input neurons, which gives to this network higher generalization capacity and speed up learning process in comparison to feed-forward.

Nevertheless, for the considered buildings, it can be verified that the forecasts qualitatively reproduce the actual observed behavior, but the ANN fail in adequately evaluates consumption peak values. It leads to higher error ranges than previous works from the authors.

Such results might be connected to an inadequate management of the building. One point that reinforces such consideration is that results for MAC are better than for FEA, and the inspection verified a better building management in MAC. The results might also be connected other aspects that do not depend on weather conditions (for instance auditorium usage for special events, congresses, expositions, etc.).

8. ACKNOWLEDGEMENTS

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