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Mathematical modelling of the electric load profile of a low energy laboratory building in Spain

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Abstract

Energy saving and the integration of renewable energies are critical issues in Net Zero Energy Buildings (NZEB). In this context, the availability of methods for the prediction of the Electrical Load Demand (ELD) is extremely important mainly due to its relevance for an appropriate energy management, sizing of NZEB energy systems, and, especially, for the implementation of suitable energy control strategies, such as energy storage. This paper describes the development and assessment of an electricity demand short-term predictive Artificial Neural Network (ANN) model for a characteristic laboratory within an NZEB located at Almería (Southeastern Spain). As the model is aimed to be used as part of advanced building energy control schemes, some specific requirements, as a tradeoff between accuracy and simplicity, have been considered. The work presented in this paper contains both a description of the algorithms and reference data for an appropriate development of this kind of models. Moreover, a detailed discussion of the obtained ANN model which has been validated using real data obtained from the NZEB used as case-study has been included.

Keywords: *Net Zero Energy Buildings, Electrical Load Demand, Artificial Neural Network, Radial Basis Functions.*

1. Introduction

Nowadays, the concept of NZEB and energy efficiency measurement applied to buildings are receiving an extensive attention all around the world mainly due to their huge contribution to reduce climate change (Kolokotsa et al., 2001). Therefore, the prediction of ELD within the scope of NZEB is presently being widely studied since the optimization of the use of renewable energy sources by means of specific control systems requires an accurate knowledge of building energy consumption patterns, both for the peak and average loads and for the short and medium-term building rooms use dynamics (Castilla et al., 2014).

In this work, a bioclimatic building has been considered as a case of study. More specifically, this building is located at Almería (Spain) and it has been built to take advantage of the benefits provided by solar energy and natural ventilation for passive heating and cooling. In addition, it has a Heating, Ventilating and Air Conditioning (HVAC) system which uses solar thermal energy for active cooling of the rooms. Furthermore, a grid connected photovoltaic (PV) installation completes the building energy infrastructure to cope with the building electricity demands.

In literature, there are many studies that take into account the consumption of the whole building (Khosravani et al., 2016; Mena et al., 2014), several buildings or even the whole city (Ferreira et al., 2010), others are related to the power demand, wind speed, power forecasting and solar irradiance forecasting with different

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range of parameters (Ren et al., 2015). The approach presented in this paper takes into account one room (a laboratory) which can be observed in Fig.1, as a representative environment of the building. In this case, there are several factors that influence energy consumption such as weather variables, building's construction, building's occupants and their behavior, the use of artificial lighting, the use of the HVAC system, etc.

Artificial Neural Networks (ANNs) have been used to obtain predictive models for the power consumption. In addition, the modeling capabilities of Radial Basis Functions (RBFs) are influenced by the shape of basis functions, the number and placement of the centers, and the width (spread) of the basis function (Ferreira et al., 2012). The using of ANNs for forecasting has led to a tremendous increment in research activities in this field in the past years. As the interesting reader can check in the following works (Zhang el at, 1997; Mena et al, 2014).

In this work, an ANN for the prediction of the energy consumption of the laboratory has been considered. More specifically, it takes into account the energy consumption of artificial lighting, computers, and other equipment in the laboratory.

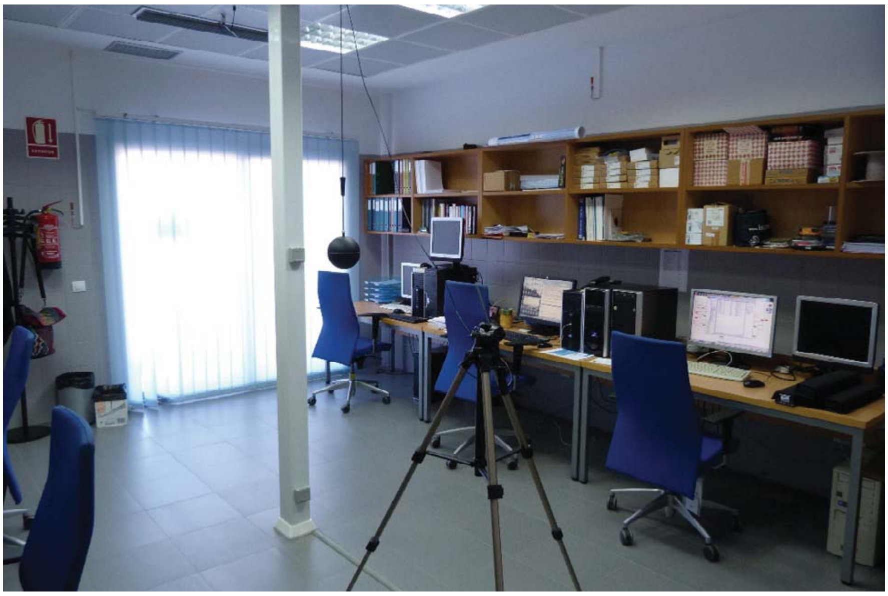

Fig. 1: Representative environment of the CIESOL building

The paper is organized as follows: Section 2 describes the scope of the work. The methodology used to obtain the ANN is presented in Section 3. In Section 4 the obtained results are briefly discussed. Finally, Section 5 includes the main conclusions and future works.

2. Scope of the work

The CIESOL building (http://www.ciesol.es) is a solar energy research center, see Fig. 2, which is located inside the Campus of the University of Almería in the southeast of Spain. This geographic location is characterized by having a typical desert Mediterranean climate, with an annual average number of 2965 hours of sunshine (climate values registered at the meteorological station of the Almería airport, located 3.5 kilometers far from CIESOL). This building is distributed into two different floors with a total surface of 1071.92 m^2. In addition, it was built following several bioclimatic criteria that affect to its architecture, as the use of photovoltaic panels to produce electricity and an HVAC system based on solar cooling.

This HVAC system makes use of a solar collector field, a hot water storage system, a boiler and an absorption machine with its refrigeration tower in order to produce heat or cold air as a function of the demanded necessities. Moreover, it has a wide network of sensors and actuators, and an appropriate data acquisition and measurement system. The availability of these data will allow to understand the behavior of each one of the bioclimatic strategies which are implemented in this building, the energy saving and CO_2 emissions reduction which can be obtained with them, and also, to perform energy scheduling tasks to optimize the use of renewable energies against conventional energy sources.

Fig. 2: CIESOL building

3. Methodology and experiments

ANNs can be seen as weighted directed graphs where the neurons are nodes and the directed edges (with weights in each) are connections between input and output neurons. They are used for non-linear mapping between the input data ***X*** and the output vector ***Y*** in order to model relations or detect patterns among them. ANNs are black-box models and, thus, their parameters and structure have to be determined from data.

3.1 Architecture and structure selection: RBF Neural Network

The ANN is an artificial intelligence technique that mimics the human brain's biological neural network in the problem solving processes. As humans solve a new problem based on the past experience, a neural network takes previously solved examples, looks for patterns in these examples, learns these patterns and develops the ability to correctly classify new patterns. In addition, the neural network has the ability to resemble human characteristics in problem solving that is difficult to simulate using the logical, analytical techniques of expert system and standard software technologies (Daosud et al., 2005). In this work an RBF neural network is used. As it can be observed in Fig. 3, an RBF ANN has three layers. The first layer represents the inputs to the network from the outside environment. The second layer, also denominated hidden layer, applies a non-linear transformation on the input set. This layer usually has a large number of neurons to achieve better results. Finally, the third layer, which usually has a single neuron, performs a linear combination over the outputs of the neurons from the previous layer, that is, the hidden layer. Hence, the output of this layer is the result provided by the neural network.

Therefore, the output of an RBF ANN can be expressed as:

$$y = \sum_{i=1}^{n} w_i f_i \cdot (\|c_i - x\|_2) \qquad \text{(eq. 1)}$$

where w_i is the weight associated with the i^{th} hidden layer node, f_i is the radial function, c_i is the center location and x is the input point. The modeling capabilities of this network are determined by the shape of the radial function, the number and placement of the centers, and the width (spread) of the function. Moreover, different options can be selected as radial function, such as radial linear function, radial cubic function, Gaussian function, thin plate spline function, multi-quadratic function, inverse multi-quadratic function or shifted logarithm function. However, the most used radial function is the Gaussian, see (eq. 2):

$$f_i(x) = e^{\left(-\frac{\|c_i - x\|_2^2}{2\sigma_i^2}\right)} \qquad \text{(eq. 2)}$$

where σ is the standard deviation, c_i is the center of the distribution, and x is the input point.

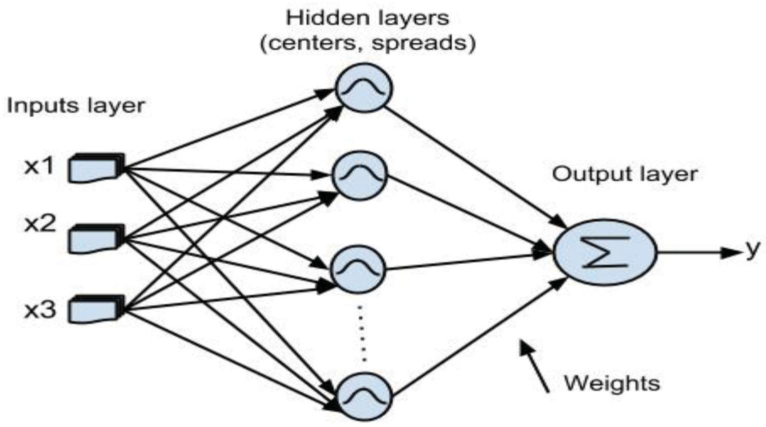

Fig. 3: RBF ANN simple diagram

In general, during the training process, the training error decreases. However, generalization error, that is, the accuracy of the used algorithm to predict the output for previously unseen input values, evolves as it is shown in Fig. 4. This problem is known as overfitting. Typically, the generalization error is estimated as the difference between the expected and the empirical error over a generalization data-set, which is a fixed set of data samples not from the training data-set. Therefore, the initial data-set should be partitioned into a training data-set and a testing data-set. Afterwards, the training data-set is split into two different data-sets: one to estimate the model, and the other to its validation. Hence, three different data-sets are used: training, generalization, and testing (Haykin 2005).

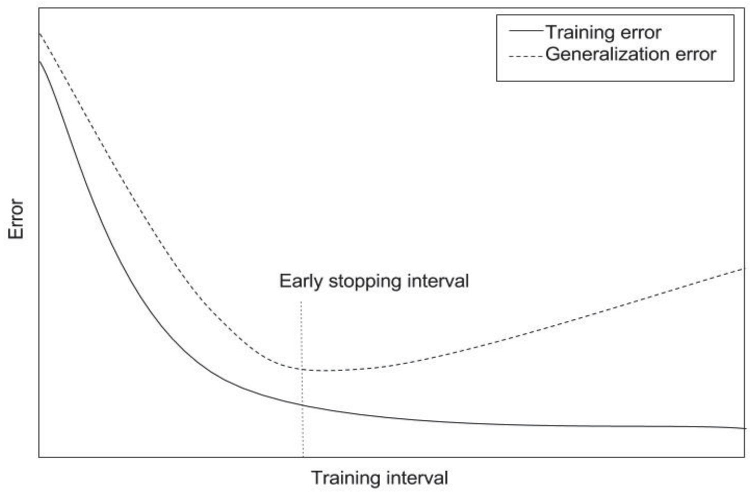

Fig. 4: Training error versus generalization error: early stopping interval (Haykin 2005)

3.2 Data-sets construction

To obtain the RBF ANN proposed in this paper, a set of historical data from the CIESOL building has been used. Concretely, the historic data-set comprises since the 11th of December 2013 to the 11th of February 2014, so it has a total length of 63 days, with a sample time of 1 minute, that is, 90720 points. These points were obtained from different measurement systems. Hence, to synchronize both of them, 60 points (1 hour) were removed from the historic data-set. Therefore, the final number of points was 90660 points.

Due to the sample time of the historic data, the power consumption signal had a random noise in it. Therefore, to remove this noise a smooth filter has been used. More specifically, the MATLAB *smooth* function has been applied to the data. This function smooths data using a 5-point moving average, that is, the

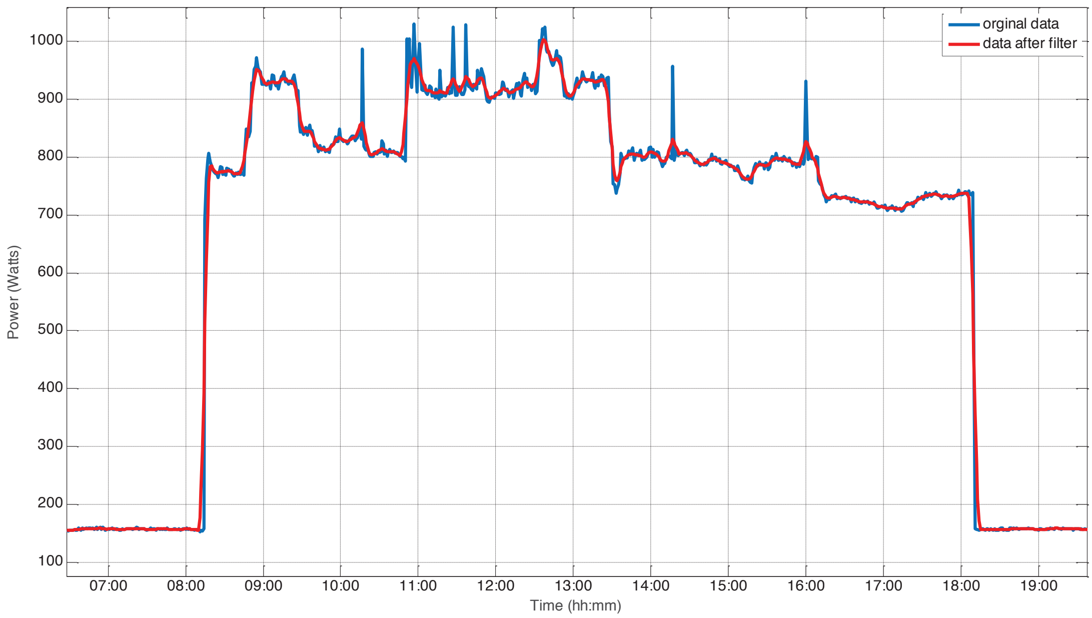

Fig. 5: Results provided by the smooth filter over the power demand signal

moving average filter smooths data by replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to a low pass filter. Hence, the response of the smooth function is given by the following difference equation:

$$y_s(i) = \frac{1}{2N+1}\left(y(i+N) + y(i+N-1) + \ldots + y(i-N)\right) \quad \text{(eq. 3)}$$

where $y_s(i)$ is the smoothed value for the ith data point, N is the number of neighboring data points on either side of $y_s(i)$, and $2N+1$ is the span (MathWorks Website, 2016). Fig. 5 shows a fraction of the data before and after the filter process has been applied.

3.3 ANN inputs and size

As has been pointed out within the Introduction Section, the output of the ANN model presented in this paper is the prediction of the power demand (excluding the HVAC system) of a representative laboratory of the CIESOL building, see Fig. 1. The original data-set has a total length of 63 days but, after removing the mistaken, unavailable, and unwanted data the size is reduced to 40 acceptable days that can be useful for modeling purposes, see Fig. 6. Figure. 7 shows the power demand of these 40 days in cyan color, and the average power demand in blue color. Finally, from this subdata-set only 23 days have been selected to be used for design the ANN.

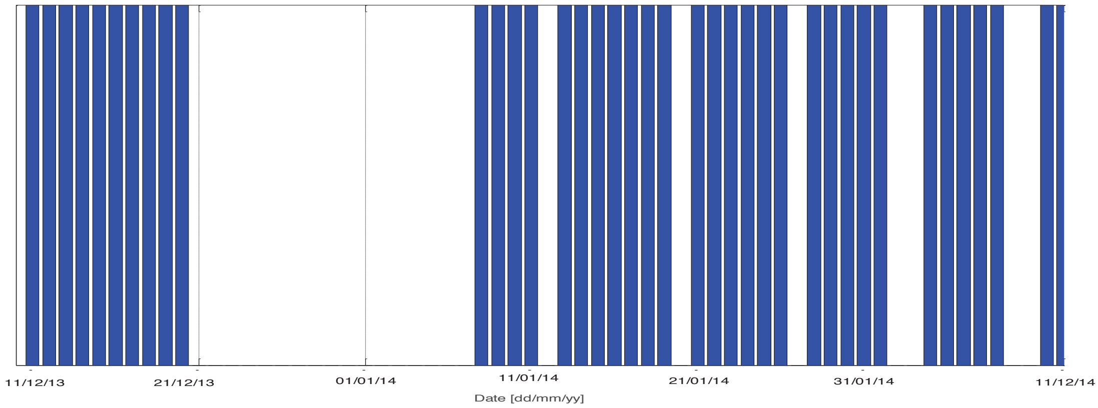

Fig. 6: Data used from the period

This subdata-set of 23 days has been divided into three different data-sets: training, generalization, and testing data-sets which contains the 12%, 8%, and 80% of total points respectively. These points have been selected randomly from the subdata-set of 23 days and, thus, the final size of training, generalization and testing data-set are 3974, 2650 and 26496 points respectively.

The ANNs proposed in this paper uses as inputs 2 lags of the power demand [W] of the laboratory, the CO_2 concentration inside the laboratory [ppm], the outside direct irradiance [W/m^2] and the number of people inside the modeled room [-]. The behavior of occupants have a major effect on the power consumption in the building (Virote and Neves-Silva, 2012). More specifically, they have a direct effect from their physical presence in the space, and an indirect effect derived from their social behavior and awareness of the power saving aspect (Oikonomou et al., 2009).

Moreover, the output of the ANNs is the prediction of the power demand in the laboratory. In Fig. 8 the three exogenous inputs data and the power demand of the period considered in this study are shown. The structure of the proposed ANN can be observed in Fig. 9.

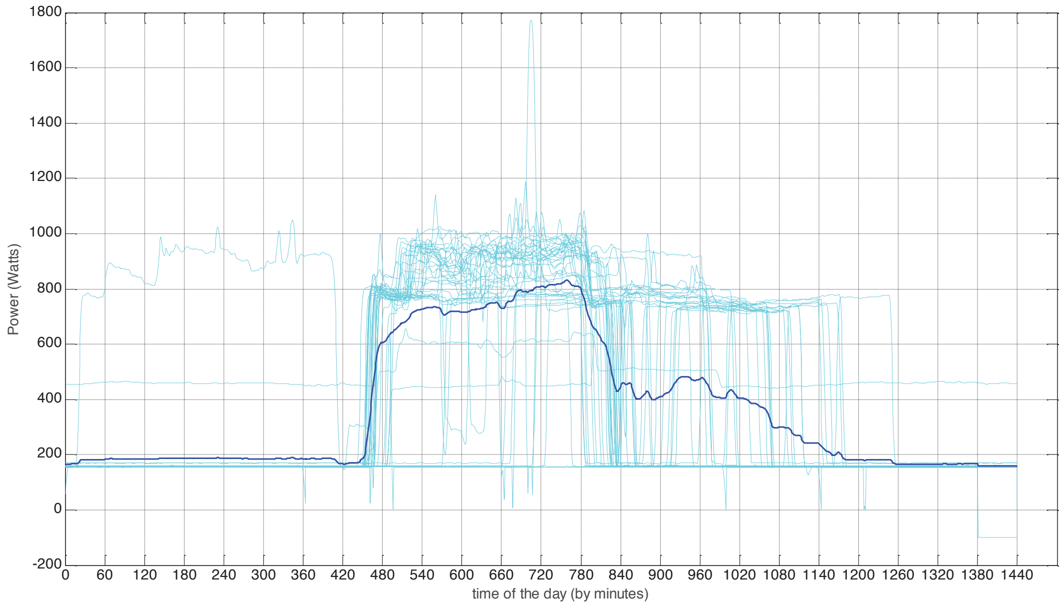

Fig. 7: Daily power of Laboratory with average of the period

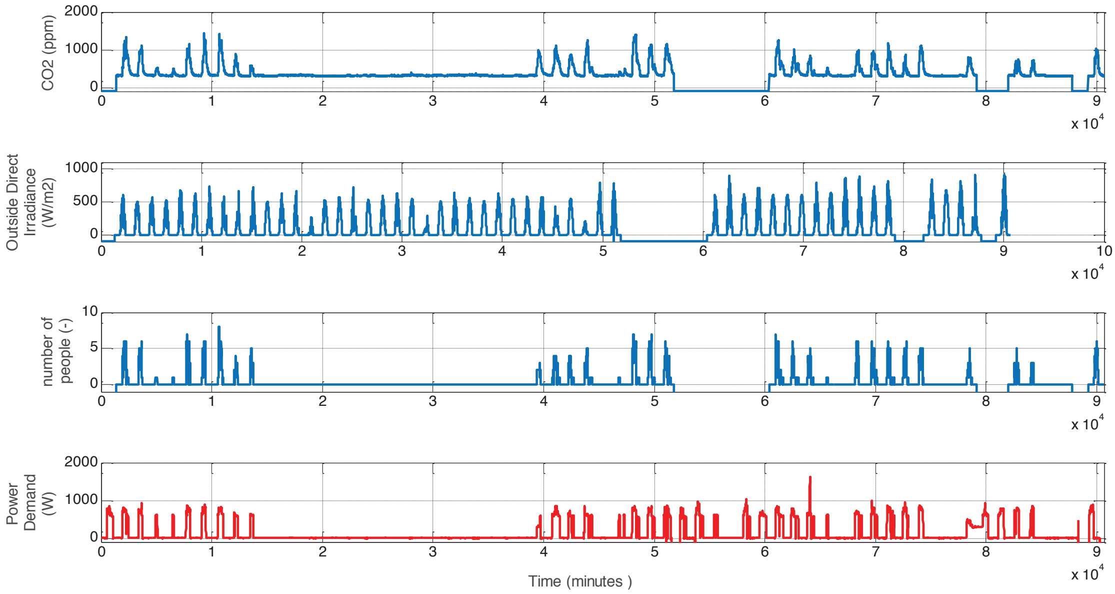

Fig. 8 The inputs and the output data

As different ANNs to predict the power demand of a representative laboratory have been obtained, each of them with different configurations, it is necessary to determine which of the proposed ANNs is the best one. For this aim, the Normalized Root Mean Square Error (NRMSE) has been used. This index is the percentage of the Root Mean Square Error (RMSE). In addition, this index has also been used to validate the proposed ANNs as a function of the prediction horizon (from 1st step and 16th step), see eq. 4, where λ is a weighting factor for each NRMSE:

$$rmseF = \frac{\lambda * NRMSE_{v-1st} + (1-\lambda) * NRMSE_{v-16th}}{2} \qquad \text{(eq. 4)}$$

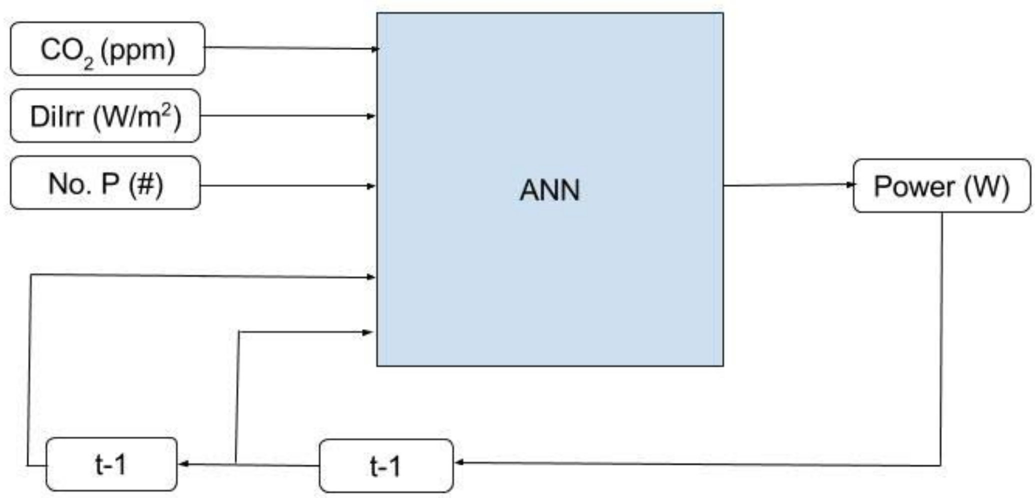

Fig. 9: Structure of the ANN proposed in this paper to predict the power demand in a laboratory of the CIESOL building

In the previous equation $NRMSE_{v-1st}$ and $NRMSE_{v-16th}$ are the NRMSE of the validation data-set for 1st step and 16th step prediction horizons respectively, and λ, in this case, has been fixed to 0.5.

The experiments had been run for all the combinations of these parameters:

- The number of the centers can be 3, 6, 9, 12 and 15.
- The τ parameter with values of 0.05, 0.01, 0.005 and 0.001, which is the termination criterion with early stopping, since an early stopping method with generalization data-set has been used.

In this work, the RBF ANN used to predict the power consumption of the laboratory has been trained using the Levenberg–Marquardt (LM) algorithm (T. Olofsson, 1998; D.W. Marquardt, 1963) which minimizes a modified training criterion (A. Ruano, et al, 1991; P.M. Ferreira and A.E. Ruano, 2000). This method has been successfully used in (P.M. Ferreira, 2012).

4. Results and discussion

In Table 1 a summary of the different models which have been obtained from training the ANN with real data from the bioclimatic building are shown. More specifically, the NRMSE index has been used to assess the performance on the different models. Moreover, validation results for one step ahead (using 1 minute interval) show an appropriate performance with a NRMSE less than 5% in the worst case. However, it does not happen with the worst case for 16 step ahead, which is higher. Thus, a final RMSE, which is the mean of the previous ones (1 and 16 steps ahead), has been calculated to select the most suitable model in both cases.

Finally, the results of the power demand for these 5 models in Table 1 are shown in Fig. 10, and the prediction of the 16 steps of the first model are shown in Fig. 11. In addition, the validation results of the 1st and 16th step prediction ahead for model number 1 can be observed in Fig 12.

The number of neurons that compose the hidden layer of the ANN, the small size of the data window and the parameters of the training algorithm for the experimental works carried out in this paper suggest that these values should be carefully studied, but anyway, many neurons were not needed to get satisfactory results.

Tab. 1: Results of the best five obtained models

Model number	Number of centres	NRMSE training	NRMSE generalization	NRMSE testing for 1 step ahead	NRMSE testing for 16 step ahead	Final RMSE
1	3	0.0099	0.0095	0.0097	0.2124	0.0555
2	3	0.0102	0.0105	0.0104	0.2125	0.0557
3	3	0.0103	0.0099	0.0103	0.2131	0.0558
4	3	0.0099	0.0095	0.0097	0.2172	0.0567
5	3	0.0102	0.0104	0.0103	0.2174	0.0569

Tab. 2: Statistical analysis of the best five obtained models

Model number		Mean Absolute Error (MAE)	Mean Relative Error (MRE)	Maximum Absolute Error (MaxAE)	Standard Deviation Error (SN)	Normalized Mean Absolute Error (NMAE)
1	1st step	1.1898	0.0855	58.4	3.8921	1.0298
	16th step	45.6813	6.1393	1041.6	84.8871	2.4538
2	1st step	1.2927	0.1060	94.0	4.1700	0.6938
	16th step	48.0858	8.1748	777.5	84.3525	3.1858
3	1st step	1.3399	0.1262	81.7	4.1145	1.0006
	16th step	49.2480	8.3953	1316.6	84.4973	2.5201

Model number		Mean Absolute Error (MAE)	Mean Relative Error (MRE)	Maximum Absolute Error (MaxAE)	Standard Deviation Error (SN)	Normalized Mean Absolute Error (NMAE)
4	1st step	1.1754	0.0838	57.8	3.8782	1.0333
	16th step	46.0759	6.3502	1060.8	86.7969	2.3949
5	1st step	1.1957	0.0953	105.1	4.1120	0.5983
	16th step	47.2486	10.4861	1077.7	84.7124	2.4327

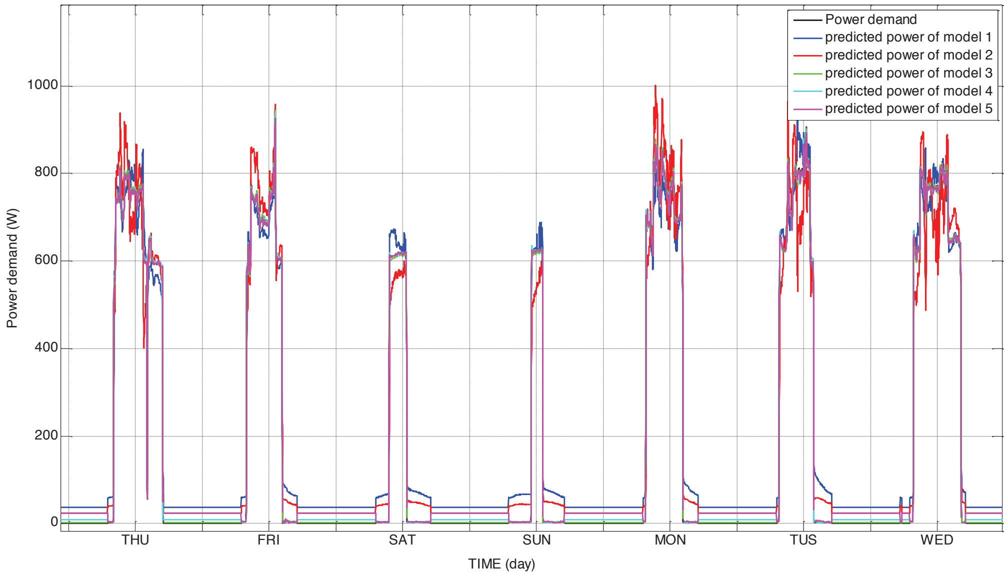

Fig. 10: Power demand prediction for one step ahead of the 5 obtained models

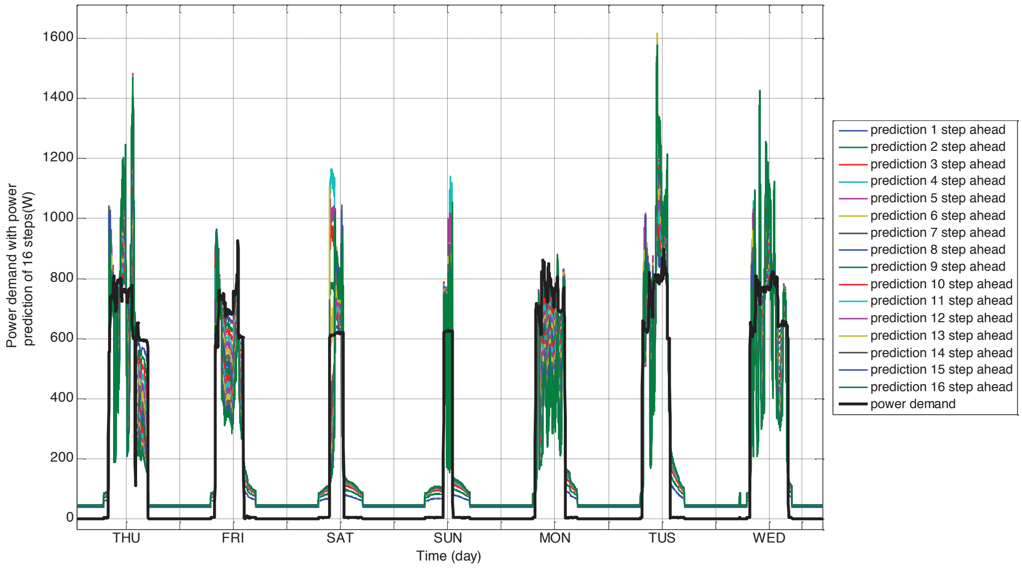

Fig. 11: Model 1 16 steps ahead power demand prediction

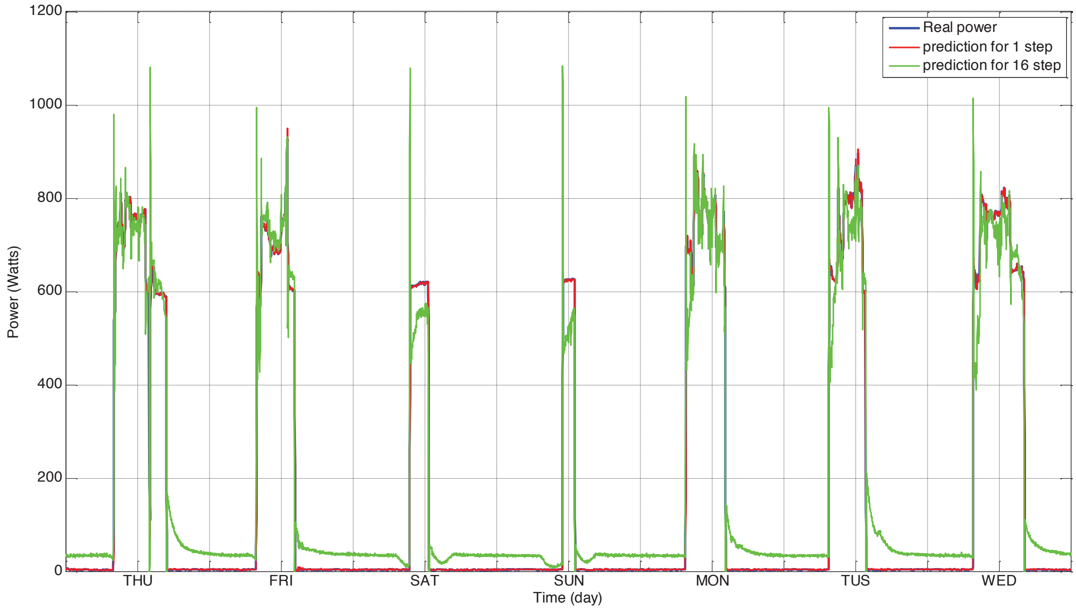

Fig. 12: Model 1 validation results

5. Conclusions and future work

The obtained RBF ANN shows optimistic results with a simple structure as a method for the prediction of electric load in one room. The main virtue of this ANN model is its simplicity, which is based on the fact that the developed tool is very simple and the resources for its application are tiny and available at modern automation systems. In particular, in order to apply it to a control system, only data from simple sensors and electric power measurements are required.

As a future work, another ANN will be developed in order to predict the HVAC power consumption used for cooling/heating the laboratory. Moreover, other future research line is the use of the ANN as the basis of a control system which, through the ANN model, will be able to maintain the thermal comfort of the users of building whereas the energy consumption necessary to reach this thermal comfort situation is minimized.

6. Acknowledgement

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