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The daily and hourly energy consumption and load forecasting using artificial neural network method: a case study using a set of 93 households in Portugal

Filipe Rodrigues [1,2], Carlos Cardeira[3], J.M.F.Calado[1,3]

[1] *IDMEC/ISEL - Instituto Superior de Engenharia de Lisboa, Instituto Politécnico de Lisboa, Departamento de Engenharia Mecânica.*

Rua Conselheiro Emídio Navarro, 1959-007 Lisboa, Portugal; e-mail: fmrodrigues@dem.isel.pt

[2] *MIT Portugal, Campus IST-Tagus Park Av. Professor Cavaco Silva, 2744-016 Porto Salvo, Portugal;*

e-mail: fmrodrigues@dem.isel.ipl.pt

[3] *IDMEC/LAETA, Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, 1049-001 Lisboa, Portugal; e-mail: carlos.cardeira@ist.utl.pt*

Abstract

It is important to understand and forecast a typical or a particularly household daily consumption in order to design and size suitable renewable energy systems and energy storage. In this research for Short Term Load Forecasting (STLF) it has been used Artificial Neural Networks (ANN) and, despite the consumption unpredictability, it has been shown the possibility to forecast the electricity consumption of a household with certainty. The ANNs are recognized to be a potential methodology for modeling hourly and daily energy consumption and load forecasting. Input variables such as apartment area, numbers of occupants, electrical appliance consumption and Boolean inputs as hourly meter system were considered. Furthermore, the investigation carried out aims to define an ANN architecture and a training algorithm in order to achieve a robust model to be used in forecasting energy consumption in a typical household. It was observed that a feed-forward ANN and the Levenberg-Marquardt algorithm provided a good performance. For this research it was used a database with consumption records, logged in 93 real households, in Lisbon, Portugal, between February 2000 and July 2001, including both weekdays and weekend. The results show that the ANN approach provides a reliable model for forecasting household electric energy consumption and load profile.

Keyword: Artificial Neural Networks; Levenberg-Marquardt; Energy forecasting; Hourly and daily energy; Boolean application.

1. Introduction

The increased of electricity demand, dioxide carbon emission and the energy resource scarcity are a worldwide concern. This paper seeks to contribute to the sustainable development concept, the rational use and storage of electric power.

The aim of this paper is to show the applicability of an Artificial Neural Network (ANN) approach to develop a simple and reliable method to forecast households' daily and hourly energy consumption for residential and small buildings.

Short-term forecasts, in particular, have become increasingly important since the rise of the competitive energy markets. Most forecasting models and methods have already been tried out on load forecasting, with varying degrees of success.

In contrast with the majority of the works published in this area, this work does not make use of temperature as a network input. Forecasting is made using only past load values and hour of the day. Our objective is to show that if an adequate

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training set is chosen, it is possible to obtain good results even without considering a huge amount of data like temperature or any other weather data.

The increasing use of renewable energy resources, namely the use of wind power in a larger scale, leads to issues of variable production rates that do not necessary fit to the demand of the consumers. Forecasting the consumers demand becomes of the utmost importance because some of the non-urgent consumer needs of energy (e.g. the turn on or off of the internal cycles of washing machines, air conditioning and fridge equipment) may be relatively shifted (delayed or anticipated) to achieve a better fit of the production profile to the consumption profile without compromising the comfort of the consumer and services level. The use of energy accumulators is always needed but their size can be reduced if a correct forecast of the energy consumption is available.

This work is dedicated to tackle the problem of energy consumption forecasts, using ANN, based in a 18 months long comprehensive set of data obtained from monitoring the energy consumption of 93 real households with a 15 mn granularity.

This paper is organized as follows: the second section presents the ANN architecture adopted; the third section explains the load forecasting models, their training processes and provides a deeper discussion about the results achieved. The last section presents the main conclusions and indicates some directions for future work.

2. State of the art

A number of researchers have compiled extensive surveys on load forecasting. Some of these surveys have been focused on neural networks for short term load forecasting (STLF) [1] [2], some other techniques used such as time series and regression models [3], as well as approaches based on exponentially weighted methods [5], while some other authors provided a general look at all types of load forecasting methodologies [5]. Artificial Neural Networks (ANN) have received a large share of attention and interest.

AlFuhaid *et al.*[6] use a cascaded neural network for predicting load demands for the next 24 hours.

Aydinalp [7] introduced a comprehensive national residential energy consumption model using an ANN methodology. They divided it into three separate models: appliances, lighting and cooling (ALC); Domestic hot water (DHW); and space heating (SH).

Becalli [8] describe an application based on ANN to forecast the daily electric load profiles of a suburban area, using a model based on a multi-layer perceptron (MLP), having as inputs load and weather data. Few years after, Beccali [8] used a forecasting model based on an Elman recurrent neural network to obtain lower prediction error rates assessing the influence of Air Conditioning systems on the electric energy consumption of Palermo, in Italy. The model estimates the electricity consumption for each hour of the day, starting from weather data and electricity demand related to the hour before the hour of the forecast.

Tso [10] presents three modeling techniques for the prediction of electricity energy consumption in two year seasons: summer and winter. The three predictive modeling techniques are multiple regressions, a neural network and decision tree models. When comparing accuracy in predicting electricity energy consumption, it was found that the decision tree model and the neural network approach perform slightly better than the other modeling methodology in the summer and winter seasons, respectively.

Despite the conditional demand analysis (CDA) method [11] is capable of accurately predict the energy consumption in the residential sector as well as others ([12] [13] [14] [15]) at the regional level and national level, however, considering households by households, it was shown that the CDA model has limited utility for modeling the energy consumption in the residential sector.

ANNs are reliable as a forecasting method in many applications, however load forecasting is a difficult task. First, because the load series are complex and exhibits several levels of seasonality: the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Secondly, there are many important exogenous variables that must be considered, especially weather-related variables. Most authors run their simulations using logged weather values instead of forecasted ones, which is a standard practice in electric load forecasting. However, one should take into account that the forecasting errors in practice will be larger than those obtained in simulations, because of the added weather forecast uncertainty [1].

The work described in this paper was carried out with the aim to achieve forecast approaches for daily and hourly energy consumption of a random household and prediction of several days' energy consumption, using ANNs and a Boolean metering system. The results achieve are encouraging revealing that ANNs are able to forecast daily and hourly energy consumption, as well as a reliable load profile.

To model the electric load profile, it has been used as ANNs training data, hourly and daily data measured at end-use energy consumptions. The energy consumption and electric load profiles have been recorded considering several weeks, including both weekdays and weekend.

3. Methodology

3.1. Designing Artificial Neural Networks

Selecting an appropriate architecture is in general the first step to take when designing an ANN-based forecasting system. In the current studies, the network architecture was built based on multilayer perceptron (MLP), full-connected, which is a feed-forward type of artificial neural network, and the training task was performed through a backpropagation learning algorithm.

The backpropagation learning algorithms, most common in use in feed-forward ANN, are based on steepest-descent methods that perform stochastic gradient descent on the error surface. Backpropagation is typically applied to multiple layers of neurons and works by calculating the overall error rate of an artificial neural network. The output layer is then analyzed to see the contribution of each of the neurons to that error. The neurons weights and threshold values are then adjusted, according to how much each neuron contributed to the error, to minimize the error in the next iteration. To customize its output, several backpropagation learning algorithms use the Momentum parameter. Momentum can be useful to prevent a training algorithm from getting trapped in a local minimum and determines how much influence the previous learning iteration will has on the current iteration.

In this study, it was used the learning Levenberg-Marquardt algorithm (Levenberg, 1944 and Marquardt, 1963) that works as a training algorithm with the capabilities of the pruning methodologies. Pruning is a process of examining a solution network, determining which units are not necessary to the solution and removing those units [16]. By doing the artificial neural network prune the model achieved has reduced complexity and the computational effort to run it, especially in real time, is reduced too.

While backpropagation is a steepest descent algorithm, the Levenberg-Marquardt algorithm is a variation of Newton's method. The advantage of Gauss–Newton over the standard Newton's method is that it does not require calculation of second-order derivatives. The Levenberg-Marquardt algorithm trains an ANN faster (10–100 times) than the usual backpropagation algorithms. The Levenberg-Marquardt algorithm, which consists in finding the update given by: $\Delta x = -[J^T(x)J(x) + \mu I]^{-1}J^T(x)e(x)$, (Eq. 1), where $J(x)$ is the Jacobian matrix, μ is a parameter conveniently modified during the algorithm iterations and $e(x)$ is the error vector. When μ is very small or null the Levenberg-Marquardt algorithm becomes Gauss-Newton, which should provide faster convergence, however for higher μ values, when the first term within square brackets of Eq. (1) is negligible with respect to the second term within square brackets, the algorithm becomes steepest descent. Hence, the Levenberg-Marquardt algorithm provides a nice compromise between the speed of Gauss-Newton and the guaranteed convergence of steepest descent [17].

Therefore, the Levenberg-Marquardt (LM) algorithm combines the robustness of the steepest-descent method with the quadratic convergence rate of the Gauss–Newton method to effectively identify the minimum of a convex objective function. LM outperforms gradient descent and conjugate gradient methods for medium sized nonlinear models. It is a well optimization procedure and it is one that works extremely well in practice. For medium sized networks (a few hundred weights say) this method will be much faster than gradient descent plus momentum and even allows to achieve a model with reduced complexity.

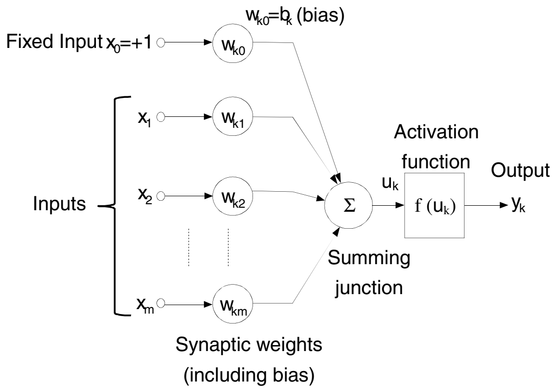
Since one hidden layer is enough to approximate any continuous functions [1], the MLP used in the current studies has three layers: an input layer, a hidden layer and an output layer. The number of neurons used in the input layer depends on the number of input variables being considered as inputs of the forecasting model, while the number of neurons in the output layer depends on the number of variables that one wants to predict with a specific model. Furthermore, the number of neurons in the hidden layer comes down by trial and error procedure to determine a workable number of hidden neurons to use. Selecting a few alternative numbers and then running simulations to find out the one that gave the best fitting (or predictive) performance allows to achieve the number of neurons in the hidden layer.

The activation function for the hidden and output neurons must be differentiable and non-decreasing [1]: as mentioned below in the current studies has been adopted the *linear* and the *hyperbolic tangent* functions. The activation functions are used to scale the output given by the neurons in the output layer.

As mentioned above, the ANN architecture was built with three-layer feedforward configuration as depicted in Figure 2. In order to achieve the desired performance for the forecasting model obtained, as well as during the artificial neural network training stage, following a trial and error procedure, the network was optimized by varying properties such as learning algorithm, scaling μ, and number of neurons, being the performance evaluated by maximizing the R^2 and minimizing the mean square error (MSE) values. Once defined the final architecture the selected learning algorithm was used during several training cycles to achieve the final connections weights and the bias values. The next step was concerned with test the performance of the model achieved. At this stage unseen data are exposed to the model.

The MATLAB neural network toolbox (*nntool*) has been used to train the feedforward ANNs. MATLAB provides built-in transfer functions that have been used for the hidden and output layers as follows: hyperbolic tangent sigmoid (*tansig*) for the hidden neurons; a pure linear function (*purelin*) for the output neurons.

Furthermore, the output of any neuron (Figure 1) is given by:



The output of an artificial neuron, mathematically, can be expressed by:

$$y_k = f(u_k) = f\left(\sum_{j=1}^{m} w_{kj} x_j + b_k\right)$$

or considering bias as input value $x_0=1$ and weight $w_{k0}=b_k$,

$$y_k = f(u_k) = f\left(\sum_{j=0}^{m} w_{kj} x_j\right)$$

The transfer function *f* can be selected from a set of readily available functions.

Figure 1 - Perceptron neurons

3.2. ANN energy consumption model

Designing ANN based models follows a number of systemic procedures. In general, there are five basics steps: (1) collecting data, (2) pre-processing data, (3) building the network, (4) train, and (5) test the model performance. After data collection, the available data has been pre-processed to train the ANN more efficiently.

ANNs models in this research used the following inputs: electric appliance, as well as apartment area and occupants for a total of 16 inputs. The trained model used the daily electricity consumption recorded data and inputs from a 93 household ‘‘training dataset’’. The number of people of each household has been selected relied with the apartment area as an example of the implication of this method.

This study creates a comprehensive residential energy consumption model using the ANN approach from an energy consumption database consisting of a set of 93 households, recorded in Lisbon (Portugal). Each household have a logged data around 6 to 8 week, including weekends. Since, ANNs are “data-driven” methods, they typically require large samples during the training stage and they must be appropriately selected. For this study, it was used a complete logged data acquired during six complete weeks at each household for training and validation. A total 93,744 records have been used (24 h x 7 days x 6 weeks x 93 households = 93,744 hours).

The mentioned collected data has been pre-processed before being ready to use during the ANN training and testing stages. It has been subjected to some form of pre-processing, that intends to enhance the forecasting model performance, such as “cleaning” the data (by removing outliers, missing values or any irregularities), since during the learning stage the ANN is sensitive to such defective data, degrading the performance of the model obtained.

This process begun with a network which had 3 neurons in its hidden layer, and repeated, increasing the number of neurons up to 30. The LM algorithm with 20 neurons in the hidden layer for network has produced the best results, and it is used for generating the outputs.

A three-layered feedforward neural network trained by the Levenberg-Marquardt algorithm has been adopted to deliver daily (average and maximum) and hourly energy forecast (one-step ahead forecasts: forecasts for next day’s total load; forecasts for hourly loads and define de load profile from a random day). The inputs to train the ANNs proposed in this paper are historical data load, electric appliance, occupancy and area apartment, which will be detailed below. At the training stage, several numbers of neurons in the hidden layer were tested. The best results were produced with twenty hidden neurons. The output layer has one neuron, which was set up to output load forecasts.

In an ANN the relation between inputs and outputs is driven from the data themselves, through a process of training that consists in the modification of the weights associated to the connections, using learning algorithms. In the learning process a neural network builds an input–output mapping, adjusting the weights and biases at each iteration based on the minimization of some error measure between the output produced and the desired output. Thus, learning entails an optimization process. The error minimization process is repeated until an acceptable criterion for convergence is reached.

Using the backpropagation learning algorithm, the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer. The standard backpropagation learning algorithm is a steepest descent algorithm that minimizes the sum of square errors.

The standard backpropagation learning algorithm is not efficient numerically and tends to converge slowly. In order to accelerate the learning process, two parameters of the backpropagation algorithm can be adjusted: the learning rate and the momentum. The learning rate is the proportion of error gradient by which the weights should be adjusted. Larger values can give a faster convergence to the minimum but also may produce oscillation around the minimum. The momentum determines the proportion of the change of past weights that should be used in the calculation of the new weights.

To avoid *overtraining* and *overfitting* it was used the *early stopping* method [18] to stop the training process. The generated data set was divided into three subsets: a training set, a validation set, and a test set. A training set is a portion of a data set used to train an ANN for the forecasting. The error on the validation set is monitored during the training process and the last set (test set) of parameters was computed to produce the forecasts.

The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The test set error is not used during the training, but it is used as a more objective measure of the performance of various models that have been fitted to the training data.

The evaluation of the ANN performance is based on the shape of the load profile distribution and following criterion: mean absolute percent error (MAPE); the standard deviation of error (SDE) and; serial correlation (linear correlation R and linear regression R^2), are defined as below.

The MAPE criterion is given by:

$$MAPE = \frac{100}{N}\sum_{j=1}^{N}\frac{|p_j - a_j|}{\bar{p}} \quad \text{(Eq.2)}$$

$$\bar{p} = \frac{1}{N}\sum_{j=1}^{N} p_j \quad \text{(Eq.3)}$$

Linear correlation coefficient is given by:

$$R = \frac{N\sum_{j=1}^{N}(p_j a_j) - \sum_{j=1}^{N} p_j \sum_{j=1}^{N} a_j}{\sqrt{\left[N\sum_{j=1}^{N} p_j{}^2 - (\sum_{j=1}^{N} p_j)^2\right] - \left[N\sum_{j=1}^{N} a_j{}^2 - (\sum_{j=1}^{N} a_j)^2\right]}} \quad \text{(Eq.4)}$$

Linear regression is given by:

$$R^2 = 1 - \sum_{j=1}^{N}(p_j - a_j)^2 \Big/ \sum_{j=1}^{N}(a_j)^2 \quad \text{(Eq.5)}$$

where p_j and a_j are respectively the forecasted and record load at hour j, $\bar{p}$ is the average price of the forecasting period and N is the number of forecasted hours.

The SDE criterion is given by

$$SDE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(e_j - \bar{e})^2} \quad \text{(Eq.6)}$$

$$e_j = p_j - a_j \quad \text{(Eq.7)}$$

$$\bar{e} = \frac{1}{N}\sum_{j=1}^{N} e_j \quad \text{(Eq.8)}$$

where e_j is the forecast error at hour j and $\bar{e}$ is the average error of the forecasting period.

Load consumption can rise to tens or even hundreds of times of its normal value at particular hours. It may drop to zero or near at other hours. Hence, the average load was used in Eq. (2) to avoid the problem caused by load to zero. In linear correlation (R) and regression (R^2) are statistical measure of how well the correlation or regression line approximates the real data points. An R or R^2 of 1 indicates that the correlation or regression line perfectly fits the data.

3.2.1. Daily energy consumption: average and maximum

In order to forecast daily energy consumption average and maximum, the inputs of the network were the daily average energy consumption of each electric appliance (lighting, refrigerator, chest freezer, cooking, dishwasher, washing machine, domestic hot water, cooling and heating systems, TV, VCR/DVD, computers and electronic entertainment) the apartment's areas and the occupants of a training households set (47 households).

To achieve the mentioned model the ANN approach use 16 neurons in the input layer, 20 neurons in the hidden layer and 1 neuron in the output layer (Figure 2). The variations in upper number of hidden neurons did not significantly affect forecasting accuracy [12] [19].

For the daily consumption forecast was used a total of 1,581 data, 50% of those data, making up the first subset, were used for ANN training and validation. The last 50% of the original data, making up the second subset, was used to evaluate the prediction capacity of the developed ANN model. The training data from the first subset was used for computing the ANN weights and biases, and the validation, from the second subset, was used to test the accuracy of the ANN model.

The first step for ANN training was take 85% of the data from first subset mentioned above for ANN training and validation. During training, the last 15% was used to evaluate the forecast capacity of the developed ANN model.

Hyperbolic tangent sigmoid function (HTSF) and pure line function (PF) were used as the transfer function in the hidden layer and output layer, respectively, and for the input layer it used PF.

The model was built, trained and tested using several networks each, putting through trial and error a different number of neurons (up to 30) in their hidden layer, using software tool (*nntool*) developed by Matlab. For each trial, the forecasting correlation and error values of the outputs were calculated and compared with the test set (logged data), as well the shape of the load profile distribution.

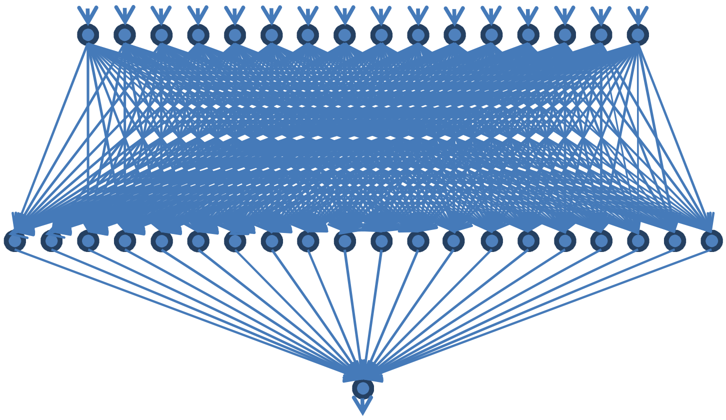


Figure 2 – ANN architecture used for daily energy average and maximum consumption.

3.2.2. Hourly energy consumption

In order to forecast the hourly energy consumption for a usual day, as mentioned above, it was used a network with three layers, which is shown in Figure 3. The inputs of the network were the hourly energy consumption of each household, including both weekdays and weekend and the output was the next hourly energy consumption.

To reduce the complexity of the training task, for the hourly consumption, a total of 3 week data, i.e., 32,760 data (504 hours x 65 households= 32,760 hours) were used. For each household it was used 504 hours, 2/3 of those data (336 hours), the two first weeks, making up the first subset, were used for ANN training and validation. The last 1/3 of the original data (168 hours), the last week, making up the second subset, was used to evaluate the prediction capacity of the developed ANN model.

The ANN model used Boolean input as an hourly meter system [20] for the forecast hourly load [21]. This method uses an input vector composed of Boolean variable and can take any configuration among 2^n different vectors containing Boolean values such as: 0000…0 = 01:00 h; 1000…0 = 02:00 h; 01000…0 = 03:00 h; 111…1 = 24:00 h. This model uses a concept of 11 data in the input layer: load energy (5 last hour load values and for 6^{th} hour the load 24 hours ago) and binary encoding for the time (0 to 24 hours) with n= 5; 20 neurons in the hidden layer and; 1 output (next hourly load) in the output layer.

The network training was performed by using LM backpropagation algorithms, HTSF were used as the transfer function in the hidden layer and output layer, and PF in input layer, also performed under software tool (*nntool*) developed by

Matlab. For this network, the forecasting correlation and error values of the outputs were calculated and compared with test set, as well the shape of the load profile distribution. The effectiveness of this approach is confirmed by forecast outputs obtained. In conclusion, the proposed artificial neural network shows a reliable performance for load forecasting.

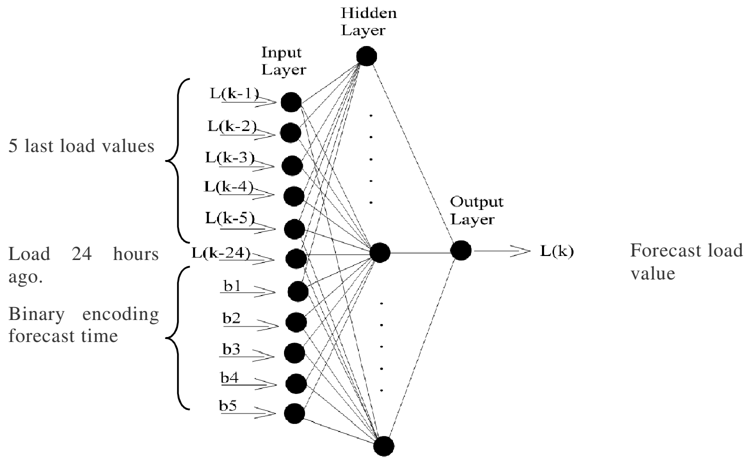


Figure 3 - Simplified ANN Architecture used to forecast hourly load

4. Results and discussion

4.1. Daily energy consumption: average and maximum

By analyzing the Table 1, Figure 4 and Figure 5, it is shown that the adopted model for predicting average and maximum consumption of housing allows good outcomes. Correlation values and linear regressions near unity validate the performance and adjustment of results. The values of the error (MAPE) and standard deviation (SDE) confirm sureness in the model adopted. These forecasting are reliable and satisfactory for power demanding and energy storage for each household.

The final results of this work are shown in the below Figure 4 and Figure 5, and illustrate the regularity in forecasting the average and maximum energy consumption for different households.

Daily Energy	R	R^2	MAPE	SDE
Average	98.9%	97.9%	4.2%	1.06
Maximum	93.5%	87.4%	18.1%	8.25

Table 1 - Statistical analysis of the forecasting error attained with the neural network approach for 46 households analyzed

The following figures show the modeling results of Portuguese household daily and maximum energy consumption (in the bottom, the horizontal axis, each number identified one household and vertical axis the daily consumption in kWh/day). The blue symbol (∗) represents the daily electric energy consumption, measured and recorded in a random day, and the red box (□) line represents the ANN forecast for the same day.

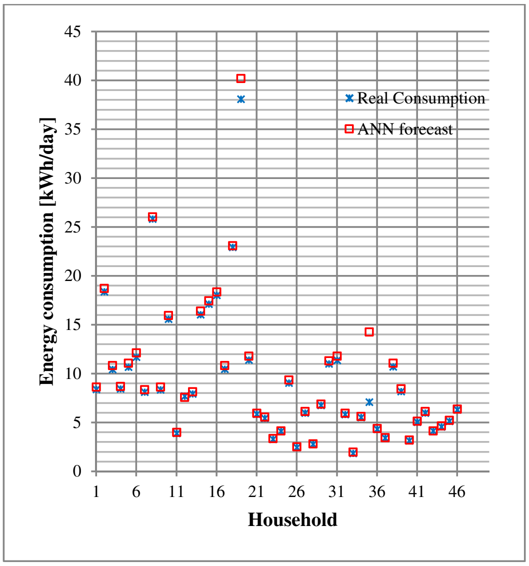


Figure 4 - Comparison of Daily Energy Demand [kWh] by Household.

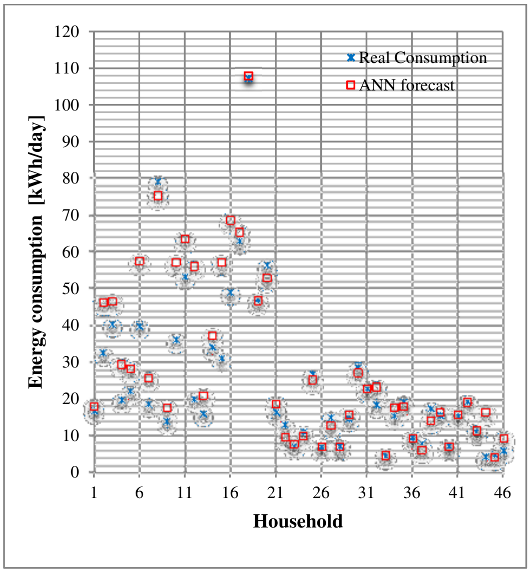


Figure 5 - Comparison of Maximum Consumption [kWh] for each household

4.2. Hourly Energy Demand

The ANN model used the Boolean input application, with 11 inputs, one hidden and one output layer, as shown in Figure 3, and for learning the neural network, that was adopted the Levenberg–Marquardt algorithm and a network which had 20 neurons in its hidden layer.

The ANN was trained using the first two weeks of data, one random household and tested for the next 3 day of 3th week. Figure 6 and Figure 7 show the forecast hourly load of random households. Evaluating those Figures and Table 2 it is found that for daily profiles which have a similar pattern the method proposed by [21][22] has a good performance for the first three days.

In test process, the forecasting correlation and error values of the outputs were calculated are:

	R	R^2	MAPE	SDE	R	R^2	MAPE	SDE
1st Day	98.8%	97.7%	16.0%	0,23	98.3%	96.6%	21.5%	0,17
2nd Day	99.6%	99.3%	10.0%	0,09	97.6%	94.5%	19.3%	0,21
3th Day	99.3%	98.6%	12.9%	0,14	97.9%	93.2%	23.5%	0,22

Table 2 - Statistical analysis of the forecasting error attained with the neural network approach for the households H64 (left) and H65 (right) analysed.

4.3. Results obtained in similar studies

The analysis of the current literature on the use of MLP neural networks with backpropagation forecasting a daily load curve with an advance of 24 hours, reveals a small number of papers mostly dedicated to large power systems operation as electric companies. These methods are able to provide good results and the use of temperature ensures an improved quality of forecasts [23] [24] [25] [26].

However, comparing the work shown in this paper with the existing works in the scientific literature, the approach followed in this work forecasts electric load for long periods ahead (i.e., over 24 hours), temperature and other weather data are not considered in these predictions and it was not used the group of days (weekday and weekend). The neural network used in this work is fed with actual load values available in order to forecast the next period. In [22] a 30 days forecast (following month) using data of 30 days (preceding month) is shown. The present approach shows a 3 days forecast using 15 days (two weeks) data with an ANN that is simpler providing results that present the same level of accuracy.

The figures show the modeling results of Portuguese household hourly energy consumption (in the bottom, the horizontal axis, each number identified one hour and vertical axis the energy consumption in kWh). The straight blue line represents the hourly load, measured and recorded in the first 3 days of the 3th week, and the discontinuous red line represents the ANN forecast for the same days.

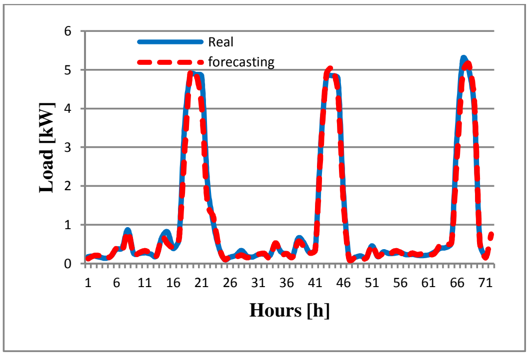


Figure 6 - Forecast Hourly load of Household nº 64 – first 3 days of 3th week

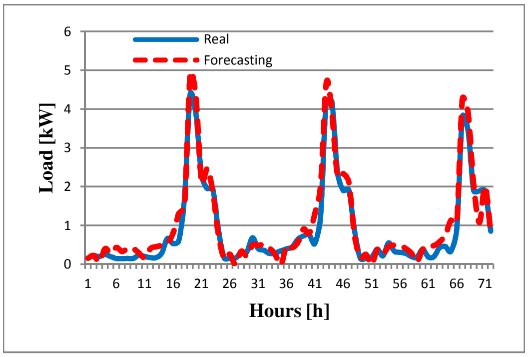


Figure 7 - Forecast Hourly load of Household nº 65 – first 3 days of 3th week

5. Conclusion

This paper introduced forecasting methods of daily and hourly energy consumption, by using an Artificial Neural Network (ANN). After identifying a faster algorithm, such as Levenberg-Marquardt, the research reveal that ANN are able to forecast daily and hourly energy consumption, as well the load profile with accuracy. This can be attributed to the amount of daily and hourly training data used to tuning the model [27].

The paper introduced the ANN technique for modeling energy consumption for a random day, the next hours (until 3th day), using a Boolean metering system. To determinate the electric load profile, the required input data are hourly and daily data logged end-use energy consumptions. The energy consumption and electric load profiles have been determined using several weeks, including both weekdays and weekend.

Forecast hourly and daily energy consumption can be useful to determine the required size of a storage energy system, delay and postpone energy consumption, and can be used at the renewable energy system early design stage. It can also help on the demand-side management (DSM), such as electricity suppliers, to forecast the likely future development of electricity demand in the entire sector of the community.

For future research, an important step is continuing this additional research enhancing forecasting capability on the load profile renewable energy production (micro production) to identify an accurate, effective and appropriate renewable energy production and energy storage.

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