Application and comparison of several artificial neural networks for forecasting the Hellenic daily electricity demand load

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GREECE

Abstract: This paper introduces an approach based on artificial neural networks in order to forecast the Hellenic daily electricity demand load. Several structures, learning algorithms and transfer functions were tested in order to produce a model with the best generalising ability. Actual input and output data collected from the Hellenic power network were used in the training, validation and testing process. Different factors such as economical, seasonality and weather conditions which indisputably affect the daily electricity demand load were taken into account in this approach. The produced results were compared with real electricity demand load records showing a great accuracy. The proposed approach can be useful in the studies of electricity providers, retailers and regulatory authorities aiming mainly in the uninterrupted supply of energy, maintaining at the same time a low cost.

Key-Words: Artificial neural networks, Climate factors, Daily electricity demand load, Economy factors, Feed-forward neural networks, Forecasting, Seasonality, Weather conditions

1. Introduction

Electricity demand load forecasting plays an important role in power system planning and operation. Basic operation functions such as unit commitment, economic dispatch, fuel scheduling and unit maintenance can be performed efficiently with an accurate forecast. Forecasting of daily electricity demand load is a recurrent, however not a routine, requirement in the management of utilities. The main reason of this daily electricity demand load treatment is related to the difficulties which occur in an accurate and reliable forecasting, due to the many different factors that are involved in the forecasting, such as multiple seasonality (corresponds to monthly seasonality and calendar effects, i.e., holidays and weekends) and weather conditions (corresponds to temperature, relative humidity and wind speed).

Various degrees of sophistication exist in the available methods of forecasting, ranging from linear regression [1] and complex econometric models [2] to complex fuzzy models [3], data mining procedures [4] and AutoRegressive Moving Average (ARMA) models [5]. Significant was also the use of artificial neural networks (ANN) in the electricity demand load forecasting where several studies were published referring to the short-term load forecasting [6], the mid-term load forecasting [7] and the long-term load forecasting [8], exploiting ANNs computational speed, ability to handle complex non-linear functions, robustness and great efficiency even in cases where full information for the studied problem is absent.

This study addresses the problem of forecasting the daily electricity demand loads of the Hellenic power network. A feed-forward (FF) ANN method is used, tested by developing several ANN models with different structures, learning algorithms and transfer functions in order the best generalizing ability to be achieved. Five years of actual input and output data, collected from the Hellenic power network, were used in the training, validation and testing process. A comparison among the developed neural network models was performed in order the most suitable network to be selected. Finally the selected ANN model was applied on the Hellenic power network for two different years (not included in the training) in order to validate its accuracy and the obtained results were compared with the real electricity demand load records.

The developed ANN model can be proved very useful in the studies of electric utilities and regulating authorities' electrical engineers, which concern electricity consumption and electricity prices forecasts.

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2. Artificial neural networks (ANN)

A typical three-layer feed-forward (FF) ANN is presented in Fig. 1, having four inputs and three outputs with each node to represent a single neuron. The name feed-forward implies that the flow is one way and there are not feedback paths between neurons. The initial layer where the inputs come into the ANN is called the input layer and the last layer where the outputs come out of the ANN, is denoted as the output layer. All other layers between them are called hidden layers [9].

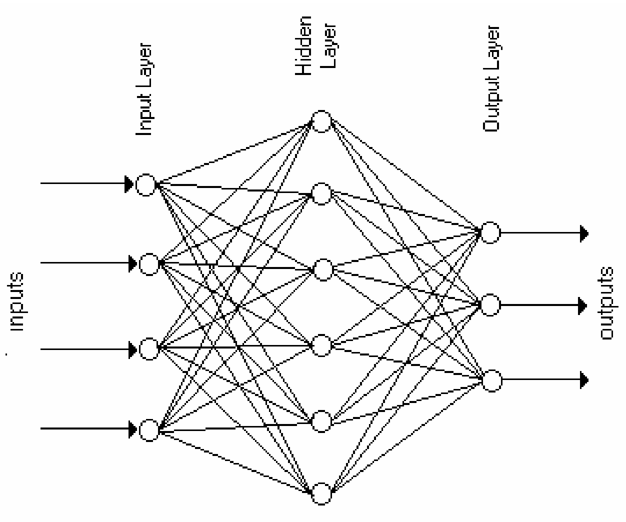

Fig. 1: Structure of a three-layer feed-forward neural network

Each neuron can be modeled as shown in Fig. 2, with n being the number of inputs to the neuron.

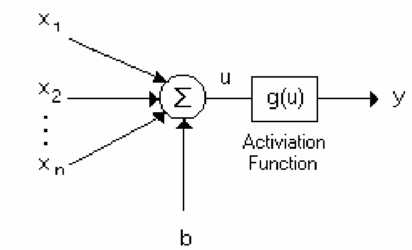

Fig. 2: A single artificial neuron network

Associated with each of the n inputs x_i are some adjustable scalar weights w_i (i=1,2,…,n), which multiply that inputs. In addition, an adjustable bias value, b, can be added to the summed scaled inputs. These combined inputs are then fed into an activation function, which produces the output y of the neuron, that is:

$$y = k\left(\sum_{i=1}^{n} w_i x_i + b\right) \qquad (1)$$

where:

k is a logarithmic sigmoid function $k(u)=\left(1+e^{-u}\right)^{-1}$, or a hyperbolic tangent sigmoid function $k(u)=\left(e^{u}-e^{-u}\right)\left(e^{u}+e^{-u}\right)^{-1}$ or a hard-limit function $k(u)=0 \; if \; u<0 \; and \; k(u)=1 \; if \; u \geq 0$.

3. Electricity Demand Load

A significant issue for electricity markets is the management of demand variability. In addition to placing stress on the physical transmission network, variability in electricity consumption is important for the financial aspects of the system, since it influences everything from the current spot price, to long term investment decisions in base and peaking load plants.

Fig. 3 indicates the real daily electricity demand loads for the year 2004 [10, 11]. Studying this figure it can be easily observed that the seasonality affects the demand load, something that is clearer the summer period. At the summer months is observed an important increase (almost 25%) which lasts approximately for 8 weeks. This increase reflects mainly in the influence of the air-conditioning and the irrigation at the total electricity load demand. A closer study of Fig. 3 reveals also seasonality during weekends and holidays, where the electricity load demand is quite smaller than the working days.

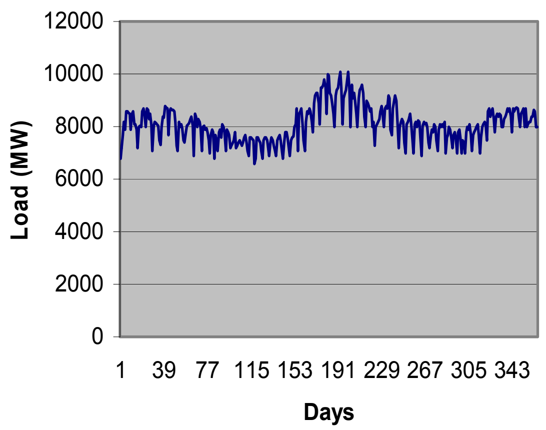

Fig. 3: The Hellenic daily electricity demand load during the year 2004.

Another crucial factor that affects electricity demand load is climate. Ambient temperature and relative humidity have a considerable effect for very obvious reasons.

Finally economy factors such as gross national product, gross domestic product and population can not be neglected in the electricity demand load forecasting, although they influence mainly long-term load forecasting. In this study a contribution

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factor has been used that has been estimated based on real data of all of the above three economy factors.

4. Design of the Proposed ANN

The goal is to develop a neural network architecture that could evaluate the Hellenic daily electricity demand load. Five parameters that play important role to the electricity demand load of a power network were selected as the inputs to the neural network, while as output the daily electricity demand load was considered. These data, which are presented in table 1, constitute actual collected data. More specifically, the daily ambient temperature T and the relative humidity H have been supplied from the National Meteorological Authority of Hellas [12]. The contribution factor F, which has been analyzed in section 3, was estimated based on real data provided by the Hellenic Ministry of Economy and Finance [13] and the National Statistical Service of Hellas [14]. The rest inputs parameters are the month of the year M and the day of the week W paying special attention and assigning weights for weekdays, weekends and holidays. Finally the output, i.e., the daily electricity demand load D_L has been provided from the Hellenic Public Power Corporation S.A. [10] and the Hellenic Regulatory Authority for Energy [11].

Table 1. ANN Architectures

Input Variables	Output Variables
- ambient temperature T - relative humidity H - the day of the week W - the month of the year M - contribution factor F	- electricity demand load D_L

As it has mentioned earlier each ANN model is determined according to its structure, the transfer function and the learning rule, which are used in an effort to learn the network the fundamental characteristics of the examined problem. The learning rules and the transfer functions are used to adjust the network's weights and biases in order to minimize the sum-squared error. The structure of the networks i.e. the number of hidden layers and the number of nodes in each hidden layer, is generally decided by trying varied combinations for selecting the structure with the best generalizing ability amongst the tried combinations. In general one hidden layer is adequate to distinguish input data that are linearly separable, whereas extra layers can accomplish nonlinear separations [15]. This approach was followed, since the selection of an optimal number of hidden layers and nodes for the FF network is still an open issue, although some papers have been published in these areas.

In this work, several FF ANN models were designed and tested. These were combinations of two learning algorithms, three transfer functions and several different structures selected among others due to their best generalizing ability in comparison with the all other tried combinations. The used learning algorithms were the Gradient Descent and the Levenberg-Marquardt, the transfer functions were the hyperbolic tangent sigmoid the logarithmic sigmoid and the hard-limit, while were used structures consisted of 1 to 3 hidden layers with 2 to 30 neurons in each hidden layer (table 2).

Table 2. Designed ANN Models

Structure	Learning Algorithm	Transfer Function
- 1 to 3 hidden layers - 2 to 30 neurons in each hidden layer	- Gradient Descent - Levenberg-Marquardt	- Hyperbolic Tangent Sigmoid - Logarithmic Sigmoid - Hard-Limit

5. ANN Training, Validation and Testing

The MATLAB neural network toolbox [16] was used to train the neural network models. One thousand eight hundred and twenty five values of each input and output data, referring to every one day of a five-year period, were used to train and validate the neural network models. In each training iteration 20% of random samples were removed from the training set and validation error was calculated for these data. The training process was repeated until a root mean square error between the actual output and the desired output reaches the goal of 1% or a maximum number of epochs, it was set to 11,000, is accomplished. Finally, the daily electricity demand load was checked with the number obtained from situations encountered in the training, i.e., the five-year period, and others which have not been encountered.

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6. Test Results

Table 3 presents the thirty best designed ANN models after their training validation and testing process. In order to evaluate the Hellenic daily electricity demand load, it was selected and used the model, which presented the best generalising ability, had a compact structure, a fast training process and consumed low memory. According to the training data of Table 3, model No. 7 (Levenberg-Marquardt - Hyperbolic Sigmoid - 5/16/21/1) was the selected one for the forecasting of the Hellenic daily electricity demand load.

The selected ANN model has been used in order to forecast the daily Hellenic electricity demand load for years 2005 and 2006. Figs 4 and 5 present a comparison of the actual daily electricity demand load and the produced ANN electricity demand load results for the years 2005 and 2006 respectively. It is obvious that the results obtained according to the proposed ANN method are very close to the actual ones (they have presented an average difference of 9%); something which clearly implies that the proposed ANN model is well working and has an acceptable accuracy.

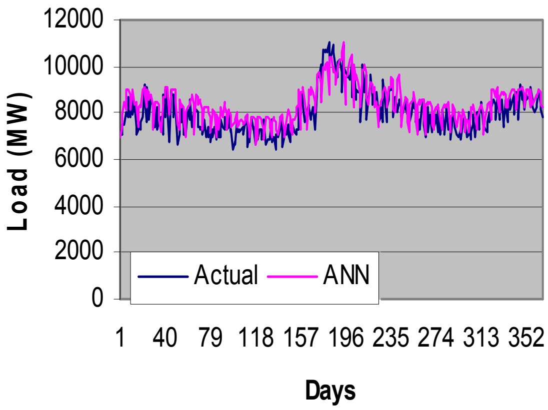

Fig. 4: Comparison of the actual daily electricity demand load and ANN results for the year 2005.

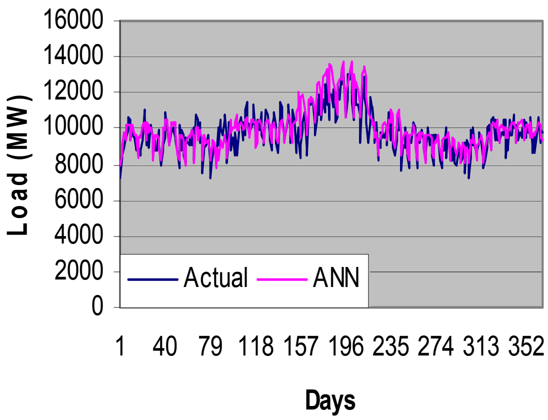

Fig. 5: Comparison of the actual daily electricity demand load and ANN results for the year 2006.

Table 3 Training data of the designed ANN models

No.	Structure	Epochs	Train Error	Validation Error
Gradient Descent - Hyperbolic Sigmoid				
1	5/14/22/1	10003	0.010	5.76 %
2	5/16/19/1	10238	0.010	8.27 %
3	5/11/24/1	8782	0.010	4.86 %
4	5/11/18/1	11000	0.023	18.03 %
5	5/9/25//1	11000	0.039	24.51 %
Levenberg-Marquardt - Hyperbolic Sigmoid				
6	5/15/20/1	10210	0.010	5.63 %
7	5/16/21/1	10891	0.010	4.32 %
8	5/10/23/8/1	9872	0.010	5.03 %
9	5/16/20/1	11000	0.083	30.29 %
10	5/5/21/1	11000	0.078	28.86 %
Gradient Descent - Logarithmic Sigmoid				
11	5/12/16/1	9912	0.010	8.62 %
12	5/9/14//13/1	11000	0.013	9.32 %
13	5/12/14/21/1	9792	0.010	12.37 %
14	5/19/25/1	11000	0.043	23.70 %
15	5/21//23/1	11000	0.021	12.42 %
Levenberg-Marquardt - Logarithmic Sigmoid				
16	5/9/11/1	9718	0.010	6.43 %
17	5/12/14/1	9639	0.010	5.58 %
18	5/10/15/7/1	10246	0.010	7.39 %
19	5/12/16/18/1	11000	0.026	12.38 %
20	5/21/15/1	11000	0.030	10.51 %
Gradient Descent - Hard-Limit				
21	5/5/10/1	11000	0.034	15.92 %
22	5/10/10/1	10304	0.010	6.79 %
23	5/10/15/1	9893	0.010	8.72 %
24	5/10/5/10/1	11000	0.041	14.95 %
25	5/10/15/10/1	11000	0.058	22.33%
Levenberg-Marquardt – Hard-Limit				
26	5/5/10/1	9702	0.010	5.50 %
27	5/10/10/1	10729	0.010	5.73 %
28	5/10/15/1	11000	0.032	17.26 %
29	5/10/5/10/1	11000	0.041	19.99%
30	5/10/15/10/1	11000	0.017	6.08 %

7. Conclusions

The paper describes an artificial neural network method for the forecasting of the daily Hellenic electricity demand load. Actual input and output data collected from the Hellenic power network were used in the training, validation and testing process. Economical factors, seasonality and weather conditions have been taken into account in this approach, since they affect significant the daily electricity demand load. The produced ANN results were compared with real daily electricity demand load records of the Hellenic power network showing a great accuracy. The proposed ANN approach can be useful in the studies of electricity providers, retailers and regulatory authorities aiming mainly in the uninterrupted supply of energy, maintaining at the same time a low cost.

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