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A NEURAL NETWORK SHORT TERM LOAD FORECASTING MODEL FOR THE GREEK POWER SYSTEM

A.G. Bakirtzis, V. Petridis, S. J. Kiartzis, M. C. Alexiadis

Department of Electrical and Computer Engineering
Aristotle University of Thessaloniki, Greece

A. H. Maissis

Public Power Corp.
Greece

Abstract : This paper presents the development of an Artificial Neural Network (ANN) based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation (PPC). The model can forecast daily load profiles with a lead time of one to seven days. Attention was paid for the accurate modeling of holidays. Experiences gained during the development of the model regarding the selection of the input variables, the ANN structure, and the training data set are described in the paper. The results indicate that the load forecasting model developed provides accurate forecasts.

Keywords : Load Forecasting, Artificial Neural Networks, Holiday Modeling.

1. INTRODUCTION

Short term load forecasting (STLF), with lead times from a few minutes to seven days, plays a key role for the economic and secure operation of power systems. Basic operations functions such as unit commitment, hydro-thermal co-ordination, interchange evaluation and security assessment require a reliable short term load forecast.

Forecast error in load predictions results in increased operating costs [1]. Underprediction of load results in a failure to provide the necessary reserves which translates to higher costs due to the use of expensive peaking units. Overprediction of load, on the other hand, results in an unnecessary increase of reserves and hence operating cost.

Various models for STLF have been proposed in the last few decades. Traditional STLF models can be classified in general, as regression models [2-3] or time series models [4-6]. An excellent discussion of traditional STLF models can be found in [1].

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Recently, with the developments of artificial intelligence, alternative solutions to the STLF problem have been proposed. Expert systems have been successfully applied to STLF [7-9]. This approach, however, presumes the existence of an expert capable of making accurate forecasts who will train the system. Neural networks [10-19] are a more promising area of artificial intelligence since they do not rely on human experience but attempt to learn by themselves the functional relationship between system inputs and outputs. This approach does not rely on an explicit adoption of a functional relationship between past load or weather variables and forecasted load. Instead, the neural network learns by itself the functional relationship between system inputs and outputs through a training process. Initially the neural network is trained by being presented with a sequence of past input - output patterns. After training, the neural network is presented only with inputs and it gives the prediction of the outputs.

This paper, describes the experiences we gained during the development of an ANN based STLF model for the Greek power system. The problems encountered and the solutions given are discussed. The developed model can provide daily load profile forecasts up to seven days ahead for both normal days and holidays. Results and statistics of forecasts for 1993 are also presented.

2. BASIC NEURAL NETWORK STRUCTURE

A fully connected three layer feedforward ANN was used in this development. The ANN has 63 input neurons, 24 hidden neurons and 24 output neurons representing next day's 24 hourly forecasted loads. The ANN inputs and outputs are described in Table I.

The first 48 inputs represent historical hourly load data for today and yesterday. Inputs 49-56 are maximum and minimum daily temperatures for today and temperature forecasts for the forecast day at two weather stations, one at North and another at South Greece. The last seven inputs, 57-63, represent the day of the week, bit encoded.

Other input variables were also tested but they did not improve the performance of our model. Temperature change and cooling/heating degree day variables [17] were tested without improvement in the forecast accuracy. This was attributed to the mild climatic conditions in Greece and the light air conditioning load: Graphical analysis of the load and temperature data showed an almost linear relationship

Table I. Definition of the basic ANN inputs and outputs

Inputs	Description
1-24	$\{L(d-1, h), \quad h = 1, 24\}$
25-48	$\{L(d-2, h), \quad h = 1, 24\}$
49-52	$\{T_{max}(d-1, W), T_{min}(d-1, W), W = N, S\}$
53-56	$\{\hat{T}_{max}(d, W), \hat{T}_{min}(d, W), \quad W = N, S\}$
57-63	Day of the Week
Outputs	**Description**
1-24	$\{\hat{L}(d, h), \quad h = 1,24\}$

d = day index
h = hour of day index
W = weather station index (N=North, S=South)
L = load
$\hat{L}$ = load forecast
T = temperature
T_{min} (T_{max})= minimum (maximum) temperature
$\hat{T}_{min}$ ($\hat{T}_{max}$)= minimum (maximum) temperature forecast

between peak load and temperature at the low and high temperature ranges.

Various tests were performed in order to identify the "optimum" number of hidden neurons. Neural networks with 10,...,80 hidden neurons were tested and it was concluded that the number of hidden neurons does not significantly affect the forecasting accuracy. It does, however, affect the training time, networks with a very small or a very large number of hidden neurons requiring more time to be trained. It was decided that a good practice is to choose the number of the hidden neurons equal to 24.

Another question raised during the selection of the ANN structure was the following: Should seven different ANNs be used, one for each day type (day of the week) without the day of the week input information or should we use only one ANN for all day types adding the day of the week as an input to the ANN? In order to answer this question two experiments were performed. In the first experiment a single ANN with the day of the week input information was trained using one year historical load and temperature data (365 input/output patterns). In the second experiment seven ANNs were trained using one year historical data (52 input/output patterns each). The forecast errors of both experiments averaged over all 1993 days, excluding holidays, for the Greek power system are shown in Table II. Table II shows that the use of a single ANN results in 10% lower yearly average forecast error. However since we believe that training each one of the seven ANNs of the second experiment with only 52 patterns does not give them enough capability to generalize, we performed a third experiment. In the third experiment each one of the seven ANNs was trained using five years historical data (5*52=260 input/output patterns). As shown in Table II the single ANN still gives slightly better forecast errors.

Table II. Comparative results of using a single ANN for all day types versus seven ANNs, one for each day type.

	Experiment A one ANN one year training		Experiment B seven ANNs one year training		Experiment C seven ANNs five years training	
Day of the week	average MW	error %	average MW	error %	average MW	error %
Monday	*89.76*	*2.33*	*99.05*	*2.58*	*97.54*	*2.53*
Tuesday	*94.15*	*2.41*	*103.60*	*2.66*	*90.55*	*2.33*
Wednesday	*77.20*	*2.01*	*85.20*	*2.20*	*73.92*	*1.94*
Thursday	*97.49*	*2.50*	*113.11*	*2.84*	*102.60*	*2.62*
Friday	*83.34*	*2.15*	*87.95*	*2.24*	*91.36*	*2.31*
Saturday	*81.09*	*2.24*	*87.61*	*2.40*	*81.50*	*2.25*
Sunday	*86.13*	*2.64*	*96.88*	*2.92*	*94.30*	*2.85*
Yearly Average	*87.39*	*2.34*	*96.12*	*2.55*	*90.19*	*2.40*

In addition, the maintenance of the parameters of a single ANN in the EMS on-line computers is much easier. It was therefore decided to use a single ANN for all day types.

3. NEURAL NETWORK TRAINING

The well known back propagation algorithm [20] was used for the ANN training. The selection of the training data set significantly affects the performance of the model.

Initially the ANN was trained using 365 input/output training patterns from the previous year. Holiday data, when encountered either as inputs or as outputs to the ANN, were excluded from the training data set. Once trained, the network parameters (weights and bias terms) were kept fixed for the rest of the current year and were updated once a year. However, improved performance of the model was observed (8% improvement) when the ANN parameters were updated every month and even better results (11% improvement) were obtained when the model parameters were updated on a daily basis (see Table III).

The ANN parameter updating is a new training of the ANN on the 365 most recent input/output patterns in which the model parameters are initialized to the most recently available ANN parameters. Since the training data sets of two consecutive days differ by only one input/output pattern daily model parameter updating is very efficient.

Although it would be preferable to have a fixed parameter on-line model it was felt that the average 2 min execution time required for parameter updating (on a 66 MHz PC) was worth the performance improvement obtained and daily parameter updating was implemented.

Table III. Effect of the frequency of the ANN parameter updating on forecast accuracy.

	Weight Updating Frequency		
	Yearly	Monthly	Daily
Av. error (MW)	*98.3*	*90.8*	*87.4*
Av. error (%)	*2.58*	*2.42*	*2.34*

The above described selection of the training data set gave satisfactory forecasts for regular days but resulted in high forecast errors for holidays when implemented along with the holiday forecasting model described in the next section. The holiday model requires holiday historical data extending further to the past and training the ANN with only the previous year data created a problem.

The problem was resolved by using "seasonal training" as follows:

The training data set consists of 90+6*30=270 input / output patterns created from the current year and the six past years historical data as follows (see Fig. 1): 90 patterns are created for the 90 days of the current year prior to the forecast day. Another 30 patterns are created for every one of the 6 previous years around that dates of the previous years that correspond to the current year forecast day. Holiday data are excluded from the seasonal training data set. After the basic training of the ANN for the first day of the year is performed, starting from random ANN parameters, the model parameters are updated on a daily basis by shifting the whole training data set of Fig.1 one day to the right. The new seasonal training method resulted in a slight (3%) improvement of the forecast error for regular days but drastically improved the forecast error of holidays when used along with the holiday model described next.

4. HOLIDAY LOAD FORECASTING

In Greece there are 13 fixed national and religious holidays and 5 movable religious holidays related to the Orthodox Easter. Special care is therefore needed for holiday load forecasting. There are two basic methods for holiday load forecasting. The first method uses a holiday forecasting ANN trained on a special - for each holiday - data set consisting of the specific holiday data from previous years together with weekend data [18]. In this study the second method for holiday modeling proposed by Papalexopoulos et al [17] was followed. In this method the basic ANN, used for normal day load forecasting, is also used for holiday load forecasting. However, if the basic ANN, trained with normal day data, is used in holiday load forecasting large errors will be observed since holiday loads are lower than normal loads. The basic ANN load forecasts must therefore be adjusted in order to obtain holiday load forecasts. This is achieved as follows [17]:

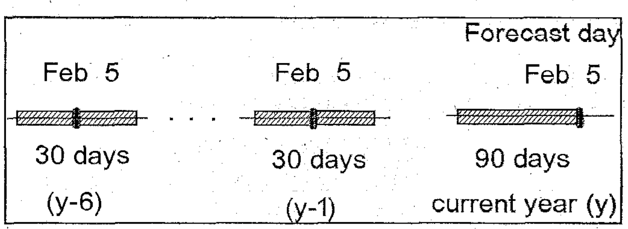

Figure 1. Training data set formation.

Each holiday load forecast is considered to have two components : a) a normal day component and b) a holiday effect adjustment. Therefore for a particular holiday,

$$\bar{L}_{holiday} = \bar{L}_{normal} - \Delta\bar{L}_{holiday} \qquad (1)$$

where $\bar{L}$ is a vector that contains 24 hourly loads.

The normal load component is computed by the basic ANN model that has been trained using normal data that do not include holiday loads. The normal load is

$$\bar{L}_{normal} = N(\bar{X}) \qquad (2)$$

where $\bar{X}$ is the ANN input vector of historical loads and temperatures and N is the neural network input / output mapping. The holiday effect adjustment , $\Delta\bar{L}_{holiday}$, for a particular holiday is computed using historical data of previous years as the average of the deviation of the basic ANN forecast from the measured load data of that holiday [17] :

$$\Delta\bar{L}_{holiday} = \frac{1}{m}\sum_{i=1}^{m}\left[N\left(X^i\right) - L^i\right] \qquad (3)$$

where $\left\{\left(X^i / L^i\right), i=1, m\right\}$ are historical input/output data of m past years for the holiday under consideration.

Fig. 2 illustrates the performance of the holiday adjustment logic on a particular holiday. The solid curve in Fig. 2 is the actual holiday load, which is in close agreement with the forecast, $\bar{L}_{holiday}$, obtained using (1) and (2). The correction curve $\Delta\bar{L}_{holiday}$ was computed based on past year data for the holiday using (3).

This holiday model provided good forecasts for isolated holidays. However, when consecutive holidays were encountered the forecast errors were rather high. High errors were also observed for the days following a holiday. The poor performance of the model in these situations was attributed to the fact that the ANN is trained with normal input / output data. When holiday loads exist in the input vector to the ANN the model has a tendency to underestimate the forecasted load.

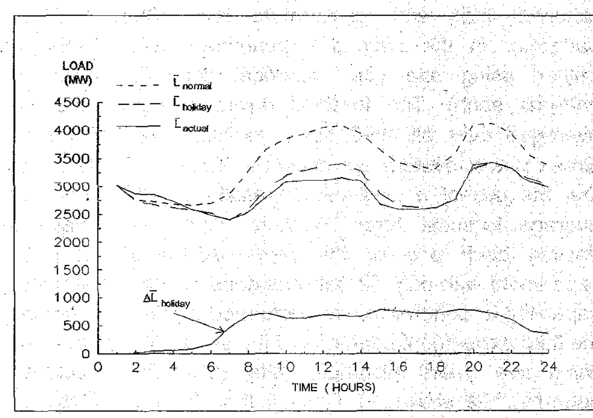

Figure 2. Demonstration of holiday adjustment logic

The method of Papalexopoulos et al [17] was extended to cover these situations as follows: When holiday loads exist in the ANN input vector they are increased by a holiday effect adjustment term before they are fed to the ANN. That is, the input/output mapping of the neural network trained to forecast normal data is now assumed to be of the form:

$$\overline{L}_{normal} = N(\overline{X}_{normal}) \qquad (4)$$

with

$$\overline{X}_{normal} = \overline{X} + \Delta\overline{X}_{holiday} \qquad (5)$$

where $\overline{X}$ is the ANN input vector of historical loads and temperatures and $\Delta\overline{X}_{holiday}$ is the holiday effect adjustment of the input vector affecting holiday load terms only. The holiday effect adjustment is again computed using historical data of previous years for the holiday under consideration as follows:

Let $\overline{X} = [\overline{L}_1, \overline{L}_2, \overline{T}]$ (6)

be the ANN input vector where $\overline{L}_1$ and $\overline{L}_2$ represent today's and yesterday's loads and $\overline{T}$ the temperature input variables.

If we assume that today is a holiday while yesterday was a normal day the holiday effect adjustment of the input vector will have the form :

$$\Delta\overline{X}_{holiday} = [\Delta\overline{L}_{1,holiday}, \overline{0}, \overline{0}] \qquad (7)$$

where $\Delta\overline{L}_{1,holiday}$ is computed from :

$$\Delta\overline{L}_{1,holiday} = \frac{1}{m}\sum_{i=1}^{m}\left[N(X_1^i) - L_1^i\right] \qquad (8)$$

where $\{(X_1^i / L_1^i),\ i = 1,m\}$ are historical input / output data of m past years for the holiday under consideration.

If many concecutive holidays are encountered, the procedure must be repeated until an input / output pattern (X_i, L_i) is encountered with all normal input loads.

Fig. 3 illustrates the performance of the new holiday adjustment logic on a day following a holiday. The solid curve represents the actual load of three consecutive days. The second day (today) is a holiday. The load of the third day (tomorrow) is to be forecasted based on an ANN whose inputs are the loads of the two first days along with other temperature variables. If the actual loads of days 1 and 2 are used as inputs to the ANN, the load forecast is the long dashed curve $\overline{L}_a$ which greatly underestimates the demand. If today's load is adjusted, using (5), to $\overline{L}_{1,normal}$ and then used as input to the ANN, the load forecast $\overline{L}_b$ (short dash) is very close to the actual load (solid line).

5. WEEKLY FORECASTING AND TWELVE - NOON FORECASTING

Like the 24 hour forecast, one week ahead load forecasts are required for unit commitment, hydrothermal co-ordination and transaction evaluation. The "weekly forecasting" model provides this capability.

The basic next 24 hour load forecasting model assumes that the forecasting is executed at twelve midnight, where all

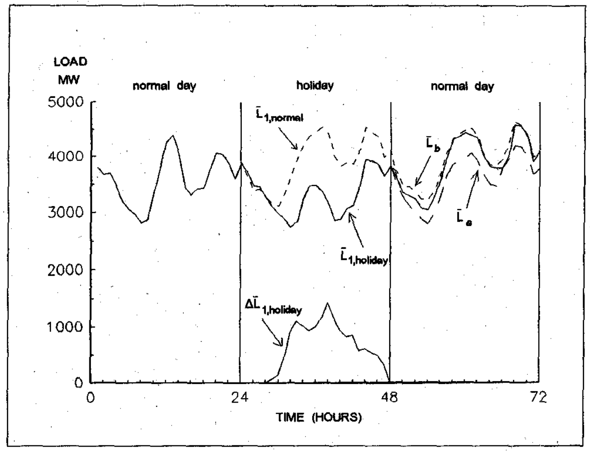

Figure 3. Demonstration of new holiday adjustment logic.

current day loads are available. The system operators at the PPC dispatch center forecast next day's loads at noon when all generation scheduling functions take place. The "twelve-noon forecasting" model forecasts next day's load pattern with incomplete current day load information.

5.1 Weekly forecasting

The weekly load forecasting model produces hourly loads up to 168 hours in future. For this purpose besides the basic next-24 hour forecasting model six additional ANN models are used for 2 to 7 day ahead forecasts. The structure of these models is similar to the structure of the basic model shown in Table I. The changes required in Table I to represent these new models are the following: Inputs 53-56 should be changed to $\{\hat{T}_{max}(d+k, W), \hat{T}_{min}(d+k, W),\quad W = N,S\}$ and the outputs should be changed to $\{\hat{L}(d+k, h),\quad h = 1,24\}$ where k is the forecast lead time in days.

5.2 Twelve - Noon Forecasting

The twelve-noon forecasting model has 51 inputs, where today loads from 1 p.m. - 12 p.m., which are not available at the time of forecast, are omitted. Otherwise the structure of this model is similar to the basic model shown in Table I. As expected, the forecast error of this model is higher than the one of the basic 24 hour ahead forecasting model.

6. RESULTS

This section presents the results and the statistics of forecasts obtained from the application of the developed STLF model on the Greek Power System for 1993. The Greek Power System has a summer peak load of about 5.5 GW (1993) and is supplied by the Public Power Corporation

Table IV. Error duration curve (hours) for 1 to 7 days ahead forecasts and for the 12-noon model.

	Lead Time (days)							12 noon
Load (MW)	1	2	3	4	5	6	7	forecasting
100	2978	3832	4363	4551	4739	4942	4850	3590
200	642	1212	1654	1993	2129	2334	2400	1206
300	161	363	567	741	879	932	1088	407
400	56	91	180	235	309	308	448	145
500	19	22	60	103	105	61	181	55
600	9	4	33	41	26	18	64	34
Av. Error (MW)	87.7	108.0	124.1	133.4	139.5	144.5	149.5	106.7
Av. Error (%)	2.35	2.89	3.32	3.57	3.74	3.87	4.00	2.85

Table V. Average 1993 forecast errors for normal days, holidays and the two days following a holiday.

	normal days	holidays		2 days following holidays	
		Papalexopoulos et al [17]	Proposed model	Papalexopoulos et al [17]	Proposed model
Aver.Error (%)	2.24	3.77	3.56	5.35	4.00
Aver.Error (MW)	83.62	116.48	112.08	193.17	134.31

(PPC). Load and temperature historical data were available since 1985.

Fig. 4 gives the 24 hour ahead absolute forecast MW error duration curve for all hourly loads in 1993, including holiday loads. The time axis of Fig. 4 represents the number of hours the forecast error is greater than the MW value read on the curve. The numerical values used for the formation of the error duration curve are also given in the first two columns of Table IV. As observed in Table IV the hourly load forecast error is greater than 200 MW for 642 hours during 1993 or 7% of the time. The average error is 87,7 MW. Table IV gives the absolute forecast error duration curve data and average MW forecast errors for one to seven days ahead forecasts as well as for the 12-noon forecasts. As expected, the forecast errors increase with the forecast lead time.

Table V gives the average absolute errors in MW and in per-cent for the 24-hour ahead forecasts of all days in 1993 separated in three groups: a) normal days, b) holidays and c) two days following a holiday.

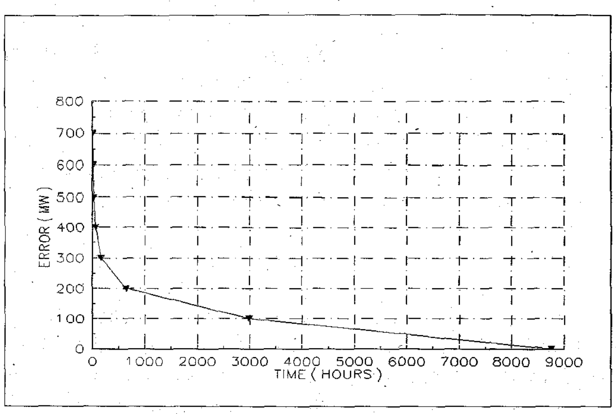

Figure 4. Absolute hourly load forecast error duration curve for 1993.

For the last two groups a comparison of the results obtained using the holiday model of Papalexopoulos et al [17] and our extended model (section 4) is made. It is observed that a significant (30%) improvement in the forecasts of the days following a holiday is achieved by the new holiday model. The slight improvement in the forecasts of holiday loads is due to the better forecasts of consecutive holidays.

7. CONCLUSION

This paper presented a neural network based short term load forecasting model designed for the Greek Public Power Corporation. A single neural network with 24 outputs was used for the load forecasting of all day types, thus requiring minimal effort for the maintenance of the model parameters in the EMS on-line computers. Models for 2 to 7 days ahead forecasts as well as 12-noon forecasts were developed. A "seasonal" training of the neural network was used with daily model parameter updating. An improved holiday forecasting model was developed which reduced the forecast errors of consecutive holidays and the days following a holiday. Test results show that the developed ANN-STLF model produces accurate load predictions for both normal days and holidays.

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BIOGRAPHIES

Anastasios G. Bakirtzis was born in Serres, Greece, in February 1956. He received the Dipl. Eng. degree from the Department of Electrical Engineering at the National Technical University of Athens, Greece, in 1979 and the M.S.E.E. and Ph.D. degrees from Georgia Institute of Technology, Atlanta, in 1981 and 1984 respectively. He has worked (1984) as consultant to Southern Company. Since 1986 he joined the Department of Electrical and Computer Engineering at the Aristotle University of Thessaloniki, Greece, where he is an associate professor. His research interests are in power system operation and control, reliability analysis and in alternative energy sources.
Dr. Bakirtzis is a member of IEEE and the Society of Professional Engineers of Greece.

Vasilios Petridis received the diploma in Electrical Engineering from the National Technical University in Athens, Greece, in 1969. He obtained the M.Sc. and Ph.D. degrees in electronics and systems from King's College, University of London, in 1970 and 1974 respectively. He has been consultant of the Naval Research Center in Greece, Director of the Department of Electronics and Computer Engineering and Vice-Chairman of the Faculty of Electrical and Computer Engineering in the Aristotle University of Thessaloniki. He is currently professor in the Department of Electronics and Computer Engineering in the Aristotle University of Thessaloniki, Greece.
Author of three books on control and measurement systems and over fifty research papers. His reseach interests include control systems, intelligent and autonomous systems, artificial neural networks, genetic algorithms, robotics and industrial automation.

Spyros J. Kiartzis was born in Thessaloniki, Greece, in January 1969. He received the Dipl. Eng. degree from the Department of Electrical Engineering at the Aristotle University of Thessaloniki in 1992. Since 1992 he is a Ph.D. student in the Department of Electrical and Computer Engineering at the Aristotle University of Thessaloniki. His research interests are in artificial intelligence applications in power systems. Mr. Kiartzis is a member of IEEE and the Society of Professional Engineers of Greece.

Minas C. Alexiadis was born in Thessaloniki, Greece, in July 1969. He received the Dipl. Eng. degree from the Department of Electrical Engineering at the Aristotle University of Thessaloniki in 1994. Since 1995 he is a Ph.D. student in the Department of Electrical and Computer Engineering at the Aristotle University of Thessaloniki

Albert H. Maissis received the diploma in Electrical Engineering from the National Technical University in Athens, Greece, in 1961. He obtained the DEA and Doctorat d' Etat es Sciences degrees in Electrical Engineering from the University of Paris, in 1968 and 1973 respectively. From 1964 till 1967 he has worked as a professional engineer in the private sector. From 1968 till 1974 he has been researcher in the University of Paris. Since 1975 he has joined the Public Power Corp. (PPC), Greece, where he has been involved in statistical analysis and design projects in the Department of Transport Exploitation.