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Peak Load Forecasting Using Optimal Linear Combinations of Artificial Neural Networks

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Abstract: A new approach for daily Peak Load forecasting using combinations of trained Artificial Neural Networks (ANNs) is presented in this study. Two different methods constrained and unconstrained are used to identify various combinations of ANNs for peak load forecasting. In this study, a set of neural networks are trained with different architecture and with different learning parameters. The neural networks are trained and tested for the actual peak load data of Chennai city (Tamilnadu-India). A set of better trained ANNs are selected to develop various combinations using these two methods instead of using a single best trained neural network. Obtained test results using the combinations of ANNs prove its validity.

Key words: Artificial neural network, peak load forecasting, optimal linear combination

INTRODUCTION

Load forecasting has always been a vital part in power system planning, operation and in a deregulated electricity market. Particularly, daily peak load forecasting is very important for generation scheduling. In the recent years, many studies have been reported and many models have been developed for load forecasting using the computational intelligence methods such as fuzzy systems and artificial neural networks (Papadakis *et al*., 1998; Desouky and ElKateb, 2000; Bakirtzis *et al*., 1995; Rahman and Hazim, 1993). Especially, several ANN approaches have been studied and successfully employed in many load forecasting applications because of its ability to learn complex and non-linear relationships through a training process with the use of historical data and weather information (Peng *et al*., 1992; Lu *et al*., 1993; Alex *et al*., 1994; Lee and Park, 1992; Al Fuhaid *et al*., 1997; Drezga and Rahman, 1998; Dash *et al*., 1993).

In this study, a number of neural networks are trained with different architecture and with different training parameters for the given input and output relationships. Of these trained networks, ten neural networks with best performance are selected for various combinations to develop a combination module for load forecasting application rather than using only the single best trained ANN. The Optimal Linear Combination of these trained networks is achieved by two different methods, such as, Constrained and Unconstrained methods. Using the selected ten neural networks, nine different combinations can be obtained for the combination module with the above two methods and all the combinations are tested and the results of these combinations are compared themselves and with the conventional ANN (single best trained network) with best performance.

The developed combination module with various combinations is proposed to achieve Medium Term Load Forecasting (MTLF) (Desouky and El Kateb, 2000; Matsui *et al*., 2001) where the objective is to predict daily peak load for the month of May 2005 (summer) for the power system of Chennai city (Tamilnadu State-India).

ARCHITECTURE OF ANN

A three layer feed forward ANN with a sigmoid function is selected for ANN modeling (Peng *et al*., 1992; Lu *et al*., 1993; Alex *et al*., 1994; Lee and Park, 1992). The back propagation algorithm is adopted to train the ANN. Using past experience and heuristics, the structure and the input variables (Drezga and Rahman, 1998) are selected. Figure 1 shows the general architecture representation of ANN and Table 1 shows different input variables selected for ANN.

With these input variables selection, a number of ANNs are trained with different architectures and with different training parameters. Of these trained networks, based on the error measures (performance) the best networks are selected and these are combined together to develop various combinations for the combination module to improve the accuracy of prediction. The daily peak load forecasting has been applied for Chennai city with the help of these selected network structures and by using

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Table 1: Selected input variables

Input variables	Index	
Peak load of previous day	L(d-1)	(1)
Temperature of previous day (mean, max, min)	T(d-1)	(2-4)
Relative humidity of previous day (mean, max, min)	RH(d-1)	(5-7)
Wind speed of previous day (max)	WS(d-1)	(8)
Peak load of previous week	L(d-7)	(9)
Temperature of previous week (mean, max, min)	T(d-7)	(10-12)
Relative humidity of previous week (mean, max, min)	RH(d-7)	(13-15)
Wind speed of previous day (max)	WS(d-7)	(16)
Temperature of previous day (mean, max, min)	T(d)	(17-19)
Relative humidity of previous day (mean, max, min)	RH(d)	(20-22)
Wind speed of previous day (max)	WS(d)	(23)
Day index	d	(24)

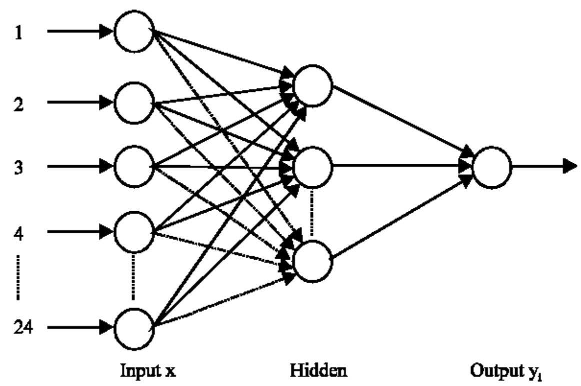

Fig. 1: Representation of ANN Architecture

the combination module with various combinations. The Mean Absolute Percent Error (MAPE) and Root Mean Squared Error (RMSE) are the error measures used to analyze the results (Desouky and El Kateb, 2000; Alex *et al.*, 1994; Drezga and Rahman, 1998; Matsui *et al.*, 2001). They are defined by (1) and (2).

$$\text{MAPE} = \left(\frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - d_i|}{d_i}\right)\times 100 \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - d_i)^2} \quad (2)$$

Where, y_i is the predicted load and d_i is the actual (desired) load for a day i and N is the total number of test data.

COMBINING OUTPUTS OF ANNS

In this study, the Optimal Linear Combination (OLC) (Sherif and Bruce, 1995) problem is formulated for a set of n-trained neural networks. There are n-trained artificial neural networks for the given input-output relations.

x = The input to all the neural networks
y_j = The predicted output for the input x (j = 1,2,...n)

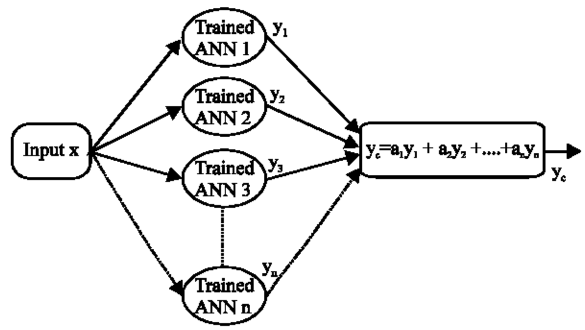

Fig. 2: Block diagram representation of combining n-trained neural networks

d = The desired output for the given input x and
e_j = $d-y_j$ is the error of the jth neural network for the given input x,
y_c = $a_1y_1 + a_2y_2 + ... + a_ny_n$ is the linear combination of the outputs of n-trained neural networks for a given input x and the corresponding error for the input x is given by $e_c = d-y_c$.
a_j = The combination weight associated with ANN's outputs (j = 1,2,...n).

Figure 2 shows the general block diagram representation of combining the n-trained neural networks. The input x is applied to the all n-trained ANNs. The outputs $y_1, y_2, ... y_n$ are predicted and obtained from the n-trained ANNs and then given to the combining module. This combining module follows the EP based algorithm given below and produces the combined output y_c.

The problem is to find good values for the combination weights a_j (j = 1,2,...n), using the optimal linear combination of the outputs of n-trained ANNs. The OLC is defined by the optimal combination weights vector that minimizes the expected loss;

$$\int_s l\left(d_c\left(X^c : a\right)\right)dF_X^c, \quad (3)$$

Where, s is the support of F_x^c and l is a loss function. The input x is as an observation of a random variable X^c from a multivariate distribution function F_x^c. Although various loss functions could be followed, here the loss function is restricted to squared-error loss, $l(e_c) = (e_c)^2$. The objective is then to minimize the Mean Squared Error (MSE) of y_c:

$$\text{MSE}\left(y_c(x:a)\right) = E\left(e_c(x:a)^2\right) \quad (4)$$

In this study, two different computational methods are pursued to achieve the optimal linear combination of weights for n-trained neural networks by minimizing the MSE and so that to obtain the required performance measures (1, 2) for the selected load forecasting problem.

IMPLEMENTATION

Unconstrained method

$$a = Z^{-1} \times b \tag{5}$$

Where Z is a n×n matrix and b is a n×1 vector and

$$Z_{ij} = \frac{1}{|N|} \sum_{k=1}^{|N|} y_i(x_k) \times y_j(x_k) \text{ for all i, j} \tag{6}$$

$$b_i = \frac{1}{|N|} \sum_{k=1}^{|N|} d \times y_i(x_k) \text{ for all i} \tag{7}$$

Constrained method

$$\sum_{j=1}^{N} a_j = 1 \tag{8}$$

$$a = \frac{C^{-1} \times \vec{1}}{\vec{1} \times C^{-1} \times \vec{1}^t} \tag{9}$$

Where, C is a n×n matrix and $\vec{1}^t$ is a n×1 vector with all components equal to 1

$$C_{ij} = \frac{1}{|N|} \sum_{k=1}^{|N|} c_i(x_k) \times c_j(x_k) \text{ for all i, j} \tag{10}$$

$|N|$ is the cardinality of N and $y_i(x_k)$ is the output of the ith ANN for the kth input in the data set N.

TEST RESULTS

The entire research of this selected problem is carried out in AMD Sempron 1.4 GHz processor. The programs for the two methods are coded in MATLAB 6.5 software. Initially, the neural networks with the different architecture and with different training parameters have been selected for this problem. For the case of architecture, the number of hidden neurons has been varied from the range of one neuron to 80 neurons, so that 50 different neural networks in terms of architecture are modeled and created for training. These neural networks are trained with different learning rates and it has been varied from 0.1 to 1.5 with step 0.1. Totally, 1200 networks are obtained and they are trained with different architecture and with different learning rates. The number of iterations has also been varied from 500 to 20,000 and finally it is set to 10,000 for all the networks.

Table 2: Performance of different combinations of ANNs using constrained and unconstrained methods

		Constrained method based combination module		Unconstrained method based combination module	
Combination modules	Combinations of networks	MAPE (%)	RMSE (MW)	MAPE (%)	RMSE (MW)
Module 1	ANN 1,2	2.6609	47.7422	2.6862	48.2882
Module 2	ANN 1,2,3	2.6168	46.7431	2.6299	46.8374
Module 3	ANN 1,2,3,4	2.5849	45.9535	2.5442	46.3520
Module 4	ANN 1,2,...5	2.4705	44.7253	2.5148	45.2085
Module 5	ANN 1,2,...6	2.4631	42.8240	2.4508	42.9212
Module 6	ANN 1,2,...7	2.4228	38.9026	2.4199	39.3800
Module 7	ANN 1,2,...8	2.3841	32.7146	2.3802	32.6255
Module 8	ANN 1,2,...9	2.3463	29.0600	2.3431	29.1891
Module 9	ANN 1,2,...10	2.2803	27.9112	2.3041	28.1753

All these neural networks are trained for the months from January to April 2005 (four months and 120 input data sets). The data set of May 2005 (test data) is selected to test the trained networks. It is understood that the better neural networks are obtained for the hidden neurons that are varying from 5 to 48 and for the learning rate 0.1 to 0.3. Based on the performance measures given in (1) and (2), the first ten ranked (top 10) neural networks are selected to develop different combinations for the combination module to obtain combined output and the performances of different combinations are studied and they are tabulated in Table 2.

It is found that when more number of networks included in the combination, the performance of the combination is also improved, that is the accuracy of load forecasting is increased. The results produced by the combination module of different combinations, using the above said two different methods are compared with each other and with the best conventional neural network (single best trained ANN) with respect to the performance measures MAPE and RMSE.

Table 3 shows the details of selected neural networks with the tested results. From Table 3 it is understood that the conventional ANN, that is the single best-trained network with the structure of 24-19-1 and with the learning rate of 0.1 produced the best performance values of MAPE and RMSE as 2.92 and 48.86 MW, respectively. The ANN with the structure 24-05-1 and the learning rate of 0.3 produced the least performance values among the selected 10 networks as 3.56 and 58.25 MW for the given set of test data of the month of May 2005.

Table 2 and 3 gives the details of results produced by the combination module obtained with different

Table 3: Best selected networks

Networks	Topology i/p-hid-o/p	Learning rate	May 2005 MAPE (%)	RMSE (MW)
ANN 1	24-19-1	0.1	2.9213	48.8646
ANN 2	24-24-1	0.1	3.1654	50.2625
ANN 3	24-30-1	0.1	3.1821	51.7516
ANN 4	24-12-1	0.1	3.1936	51.6732
ANN 5	24-17-1	0.1	3.6062	51.5811
ANN 6	24-14-1	0.3	3.2155	51.6046
ANN 7	24-48-1	0.2	3.2598	53.1741
ANN 8	24-18-1	0.2	3.2974	56.8239
ANN 9	24-32-1	0.1	3.4901	58.9749
ANN 10	24-05-1	0.3	3.5627	59.2510
			Iteration:	10,000

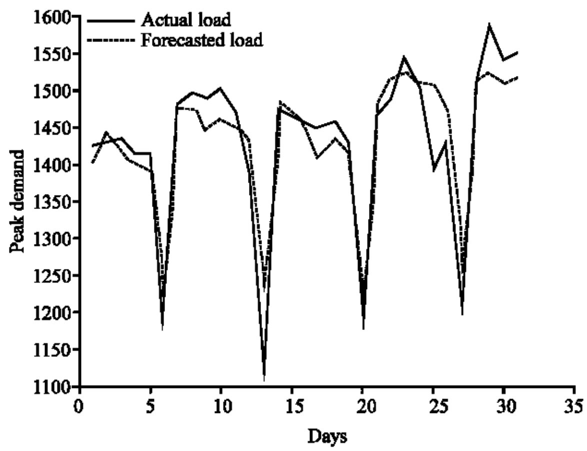

Fig. 3: Variation between actual and forecasted loads for May 2005 using constrained method based combination module 9

combinations, using the referenced techniques and the first 10 ranked conventional ANNs. In comparison with the results in terms of performance measures, all the combinations of networks produce better performance than the best conventional ANN. And among the two methods, the Constrained method based combination module has shown a bit of higher accuracy in prediction (i.e., the error measures MAPE and RMSE are remarkably reduced from the values of 2.9213% and 48.8646 MW to 2.2803% and 27.9112 MW, respectively) than the Unconstrained method based combination module which also produces a good performance (i.e., the error measures MAPE and RMSE are considerably reduced from the values of 2.9213% and 48.8646 MW to 2.3041% and 28.1753 MW, respectively) than the single best trained network for the selected problem.

Figure 3 and 4 show the variations between the actual and forecasted loads using the Constrained and Unconstrained based combination modules (Module 9), in which all the selected 10 networks are combined together to produce combined output (forecasted output).

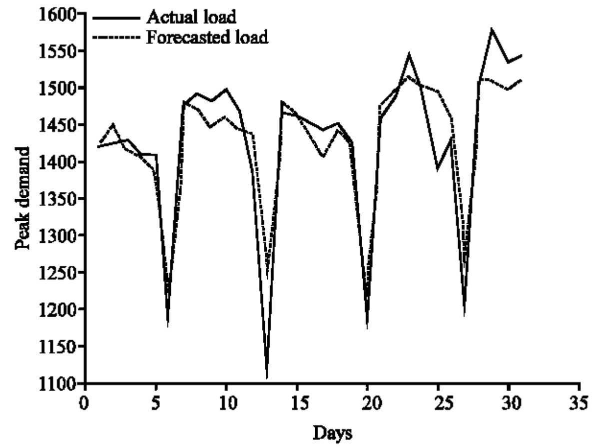

Fig. 4: Variation between actual and forecasted loads for May 2005 using unconstrained method based combination module 9

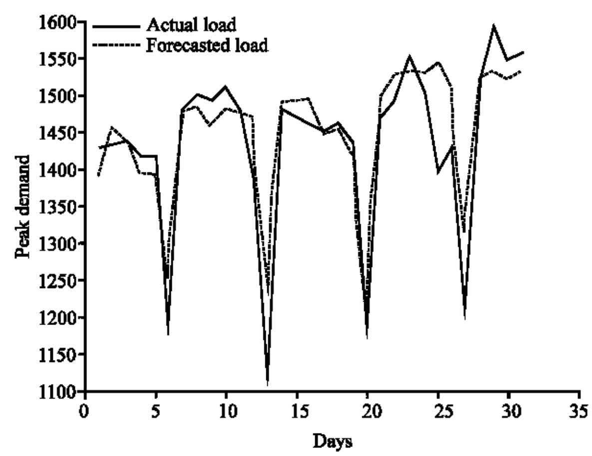

Fig. 5: Variation between actual and forecasted loads for May 2005 using the single best trained ANN with the structure 24-19-1

Figure 5 shows the variations between the actual and forecasted loads using the single best trained ANN with the structure 24-19-1 and with a learning rate of 0.1.

CONCLUSION

This study proposes a new approach for daily peak load forecasting using constrained and unconstrained methods based combinations of ANNs. A group of neural networks is trained and some of the networks with best performance are selected for combining the outputs. Two different approaches are discussed and applied to develop the different neural network combinations for the optimal linear combination module that combines the outputs of the selected networks. The obtained results indicate that the proposed method of approach for combination modules can provide power system engineer with the reason of forecasting results. The proposed combination modules using the referenced methods can forecast peak load demand (MTLF) more accurately than the single best trained network and other conventional methods.

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