Short-Term Load Forecasting using Artificial Neural Network

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***Abstract* - Artificial Neural Network (ANN) Method is applied to forecast the short-term load for a large power system. This paper presents a neural network based approach for short-term load forecasting that uses the most correlated weather data for training and testing the neural network of weather data determines the input parameters of the neural networks. Inputs to the ANN are past loads and the output of the ANN is the load forecast for a given day.**

Keywords* - *Neural network, load forecasting, Correlation analysis

I. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development.[1]

In achieving this goal, the knowledge of future power system load is the first prerequisite;[2] therefore short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes.[1] [2]

Short-term load forecasting (STLF) refers to forecasts of electricity demand (or load), on an hourly basis, from one to several days ahead. The short-term load forecasting (one to twenty four hours) is of importance in the daily operations of a power utility. It is required for unit commitment, energy transfer scheduling and load dispatch. With the emergence of load management strategies, the short term load forecasting has played a greater role in utility operations. The development of an accurate, fast and robust short-term load forecasting methodology is of importance to both the electric utility and its customers.

Many algorithms have been proposed in the last few decades for performing accurate load forecasting. The most commonly used techniques include statistically based techniques like time series, and regression techniques, and computational intelligence method like fuzzy systems, ANNs and neuro-fuzzy systems.[3]

For developing the forecasting models, the historical hourly loads and temperature observations from the Australian Energy Market Operator (AEMO) & Bereau Of Meteordology (BOM) for Sydney/NSW for the years 2006 to 2010 was used. The weather information includes the dry bulb, wet bulb temperatures, dew point & humidity affect the forecasting accuracy and are included in the model. To ascertain the forecasting accuracy, the developed models were tested on the data for the years 2006-2010.

II. LOAD DEMAND PATTERN

The most factors affects the system's load level such as trend effects, cyclic-time effects, weather effects, random effects like human activities, load management and thunderstorms. Thus the load profile is dynamic in nature with temporal and annual variations .In this paper, a system was develop as shown in Fig. 1 with inputs parameters such as dry bulb temperature, dew point, wet bulb temperature, humidity, hour of day, day of the week, a flag indicating if it is a holiday/weekend, previous day's average load, demand from the same hour the previous day, demand from the same hour and same day from the previous week and day of the week to forecast day ahead load demands (output) for the Australian market using artificial neural networks.

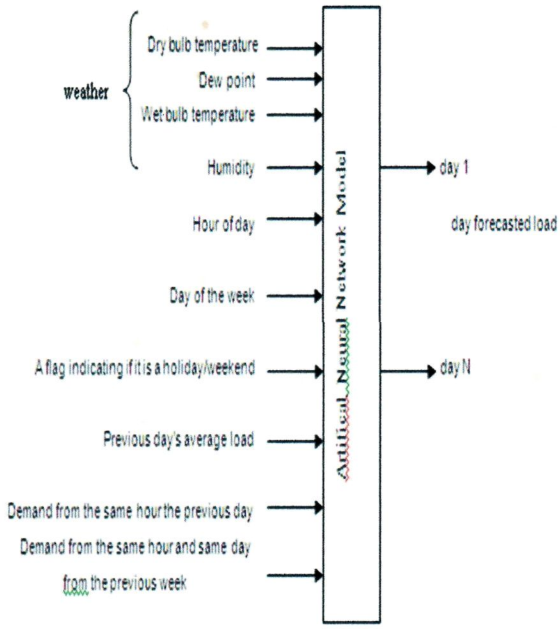

Fig. 1 : Input-output schematic of system

III. NEURAL NETWORK MODEL

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain.

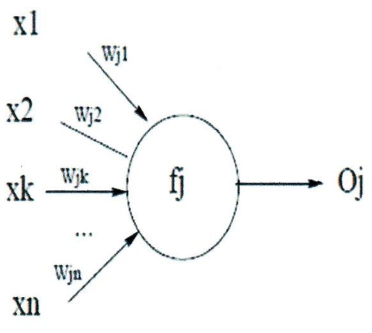

Fig. 2. Mathematical model of an ANN neuron.

A. STLF Modeling

ANN-based methods are a good choice to study the STLF problem, as these techniques are characterized by not requiring definite models to represent the complex relationship between the load and the factors that determine it. This part discusses the ANN model and the procedure used here for STLF.

A. Modeling

1. Neuron model ANNs are made up of a number of simple and highly interconnected Processing Elements (PE), called neurons, as depicted in Fig. 2. Its mathematical model is expressed as

$$Oj = fj \sum_k (wjk - xk) \quad (1)$$

Where Oj is the output of a neuron, fj is a transfer function, wj is an adjustable weight that represents the connection strength and x is the input of a neuron.

2. Network Architecture The three-layer fully connected feed-forward neural network illustrated in Fig. 3 is used. it includes an input layer, one hidden layer and an output layer. Signal propagation is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer. The input variables are come from historical data corresponding to the factors that affect the load. The outputs are the required forecasting results, for this case are m = 336, i.e., half hour of the week. The number of inputs, the number of hidden nodes, transfer functions, scaling schemes, and training methods affect the forecasting performance and hence need to be chosen carefully.

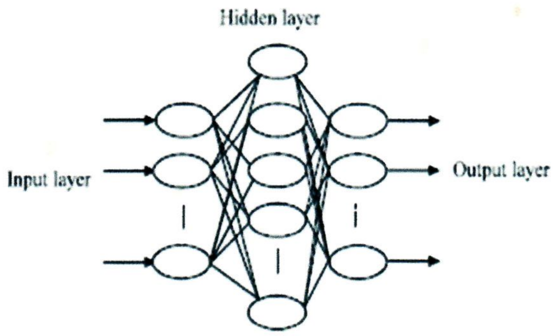

Fig.3 : Schematic of feed forward neural network

3. Training when training an ANN with a set of input and output data, we wish to adjust the weights in the ANN, to make the ANN give the same outputs as seen in the training data. Usually, multi-layer feedforward neural networks are trained in a supervised manner. Back-propagation is used as the training method here.

The Levenberg-Marquardt algorithms is used to train the developed network since it provides a good compromise between fast convergence and a low computation cost .

Training stops when the performance has been minimized to the goal, the performance gradient falls below a minimum gradient, the maximum number of epochs is reached, or the maximum amount of time has been exceeded. The error function used in the back-propagation training process is the sum-squared error, i.e.,

$$E = \frac{1}{2}\Sigma p \Sigma j (tpj - Opj)^2 \quad (2)$$

where *tpj* and *Opj* are the target output and the actual output *j* for input pattern *p*, respectively.

To get the best performance the data is divided into training data and testing data. The data of 4 years is divided into two groups for training and testing. In these model 75% of the total data are used for training and 25% data is used for testing.

IV. METHODOLOGY

A. *Forecasting procedure*

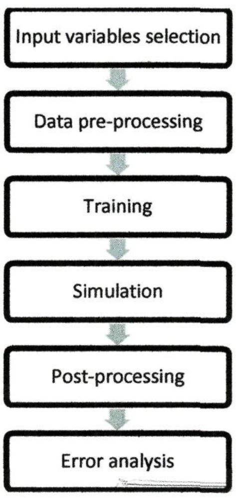

Fig.4 : ANN-based demand forecasting procedure.

The STLF procedure for the chosen ANN model is shown in Fig. 4.

1. Input Variable Selection Input variables such as load, day type, temperature and load of the previous day of the forecasting day are chosen.

2. Data Pre-processing Improperly recorded data and observation error are cannot be avoided. Hence, bad and abnormal data are identified and discarded or adjusted using a statistical method to avoid contamination of the model

3. Training Each layer's weights and biases are initialized when the neural network is set up. The network adjusts the connection strength among the internal network nodes until the proper transformation that links past inputs and outputs from the training cases is learned. The ANN training algorithm is shown in Fig. 5.

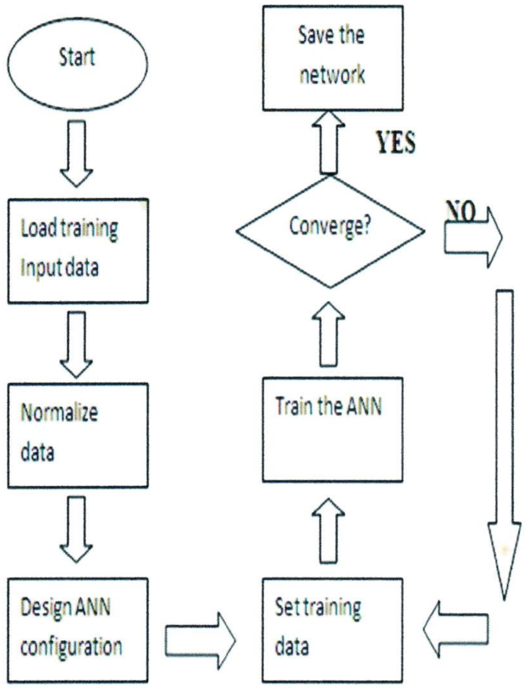

Fig.5 ANN Training algorithm

4. Simulation Using the trained neural network, the forecasting output is simulated using the input patterns. The ANN testing algorithm is shown in Fig. 6.

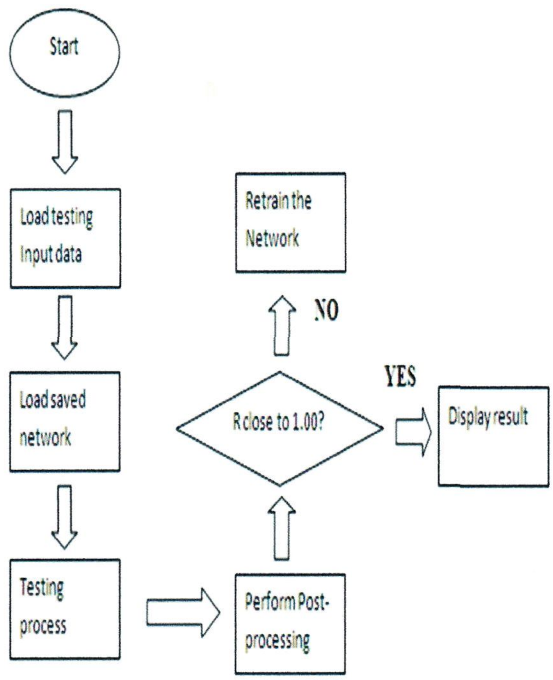

Fig.6 ANN Testing algorithm

5. Post-Processing The neural network output need de-scaling to generate the desired forecasted loads. If necessary, special events can be considered at this stage.

6. Error Analysis As characteristics of load vary, error observations are important for the forecasting process. Hence, the following Mean Absolute Percentage Error (MAPE) ε are used here for after-the-fact error analysis:

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N} \frac{(\,|Xt - Xf\,|)}{Xt} * 100 \qquad (3)$$

where Xt is the actual load and Xf is the forecasted load.

V. DISCUSSION AND RESULT

This section presents the results and the statistic of forecasts obtained from the application of the develop STLF model on the Australian market. The assessment of the prediction performance of the different soft computing models was done by quantifying the prediction obtained on an independent data set. The mean absolute percentage error (MAPE) was used to study the performance of the trained forecasting models for the testing years. MAPE is defined as follows:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{P\ actual\ i - P\ predicted\ i}{P\ actual\ i}\right)$$

Where P *actual i* is the actual load on day and P *predicted i* is the forecast value of the load on that day. Where N represents the total number of data .The mean absolute percentage error (MAPE) results are shown in table 1. Thus, structures of ANN with the backpropagation learning algorithm were tested used with various numbers of neurons.

TABLE 1
COMPARISON OF FORECASTING RESULTS FOR VARIOUS NEURON

No of neuron	10	20	30
Mean Average Percent Error (MAPE) (%)	2.33	2.24	1.99
Mean Average Error (MAE) (MWh)	205.88	198.47	176.20
Daily Peak MAPE (%)	2.86	2.52	2.24

From table 1,the better results were obtained as the number of neurons increases to 30 neurons. But when the 10 neurons were used, the values of MAPE, MAE and daily peak MAPE which are 2.33%, 205.88Mwh and 2.86%, the result was worse than those cases with 20 and 30 numbers of neurons. The values that were found when use 20 neurons which are 2.24%, 198.47Mwh and 2.52% respectively, and the values that were found when use 30 neurons which are 1.99% , 176.20Mwh and 2.24% respectively. The results obtained from testing the trained neural network on data of a day over a one-week period are presented below in graphical form. Each graph shows a plot of both the „predicted" and „actual" load in MW values against the day. The mean average percent error MAPE (%) between the „predicted" and „actual" loads for each week presented in the fig 7,8,9,10 and 11 for the first month.

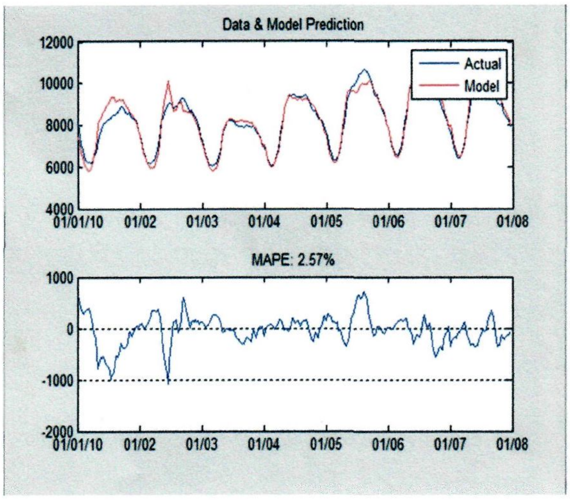

Figure 7 Comparison of actual load and forecasted load for 1st week

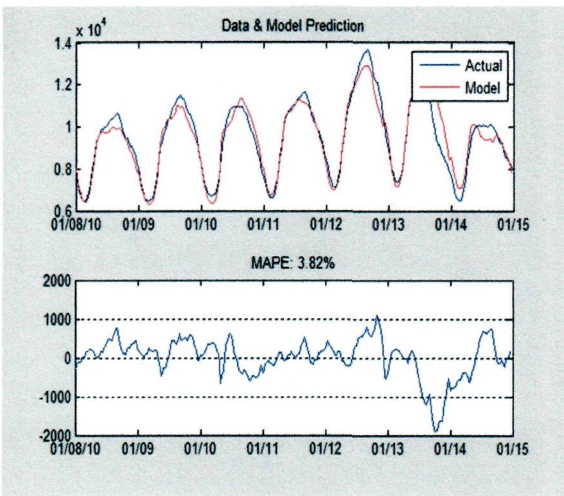

Figure 8 Comparison of actual load and forecasted load for 2nd week

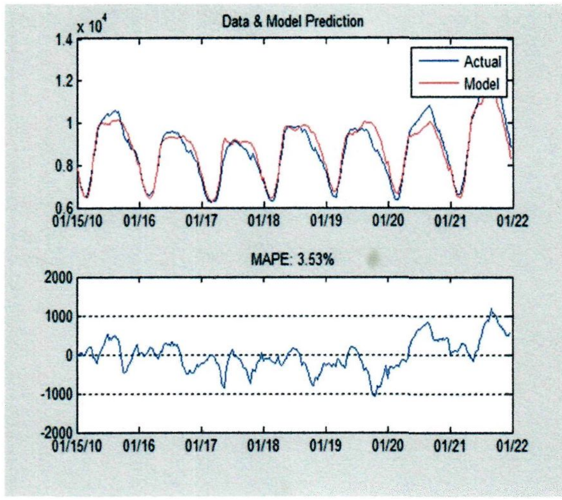

Figure 9 Comparison of actual load and forecasted load for 3rd week

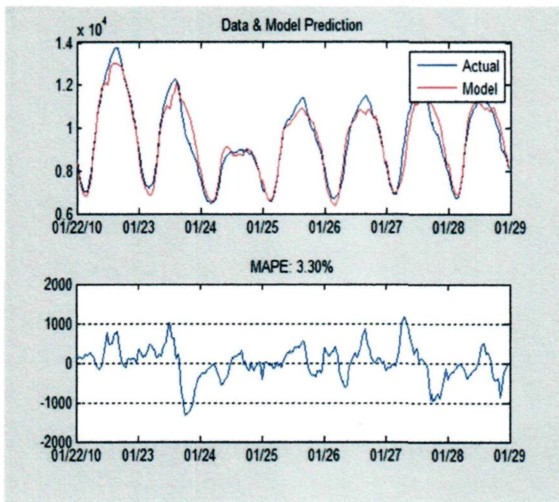

Figure 10 Comparison of actual load and forecasted load for 4th week

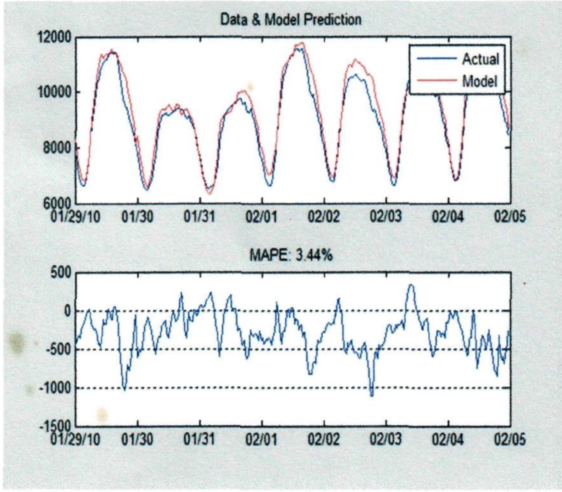

Figure 11 Comparison of actual load and forecasted load for 5th week

VI. CONCLUSION AND RECOMMENDATION

The result of one day ahead short term load forecast for Australian market shows that has a good performance and reasonable prediction accuracy was achieved for this model. It's forecasting reliabilities were evaluated by computing the mean absolute error between the exact and predicted values. The results suggest that ANN model with the developed structure can perform good prediction with least error and finally this neural network could be an important tool for short term load forecasting.

Future studies on this work can incorporate additional information such as customer class, price and season of the years into the network so as to obtain a more representative forecast of future load

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