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Forecast and Analysis of Short Term Electric Load of New South Wales Region using ANN

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***Abstract*—This paper reveals the use of Artificial Neural Networks (ANN) for short term electrical load forecasting on a given load bus ahead of its actual load occurrence using feed-forward ANNs and by considering humidity, dew point, day of the Year, hour of the day, dry bulb, wet bulb and holiday indicator as variables for predicting the value of electrical load. The historical load data from New South Wales Region (obtained from Australian Energy Market Operations [6]) along with data related to thermodynamics of air and temperature (obtained from Bureau of Meteorology [7]) is used for forecast and analysis. The Analysis is done using Neural Network toolbox of Matlab.**

Keywords—artificial neural networks; short term load forecasting ; Matlab implementation

I. INTRODUCTION

Electrical Load Forecasting is of vital importance in making decisions like purchasing and generation of electric power, infrastructure development, load switching, planning generation schedule etc. However in recent days with the deregulation of the energy industries load forecasting has become even more important. In short term load forecasting, the time period of forecast ranges from a leading time of 1 hour to a maximum of 7 days. Short term load forecasting can be used to estimate load flows which can act as a preventionary measure to protect system from overloads. Though a large number of traditional as well as modern techniques have been applied for forecasting purposes but amongst them ANN is the most widely accepted technique due to its ability to do nonlinear curve fitting.

II. INPUT VARIABLE SELECTION

A. Load influencing factors

The electric load on any load bus depends on several factors and generally these factors are generally related directly or indirectly to either the comfort of human beings or to the living habits and economy of the customers. Thus the following input variables for feeding the network are considered:

- Electricity Price
- Dew Point
- Dry Bulb
- Humidity
- Wet Bulb
- Holiday Indicator
- Day of the Year
- Hour of the Day

B. Creating Input Matrix for Matlab Implementation

The five year data corresponding to each input variable is collected for every half an hour, which gives 48 entries for a single day and a total of 87648 entries corresponding to each of these input variables for a time range of 5 years. The next step is preprocessing and scaling of data in which bad and abnormal data values are discarded using statistical methods and then data is scaled down in the range [0, 1] by normalizing it. Thus an input matrix of dimensions 8*87648 is created.

II. TARGET VARAIBLE SELECTION

The output data is divided into 4 binary classes:

- **Full Load**: If electrical load is greater than 75% of the maximum value of the load.
- **Heavy Load**: If load lies in the range 75% to50% of the maximum value of load.
- **Medium Load**: If load lies in the range 50% to 25% of the maximum value of load.
- **Light Load**: If load is less than 25% of the maximum value of load.

Thus the target matrix of dimensions 4*87648 is created for training the neural network.

III. TRAINING THE NETWORK

The feed forward neural network is trained using back propagation algorithm with mean squared error as the performance measure and tansig as the activation function. The number of neurons in the hidden layer and the training function are varied to find the optimum performance of the network. Neural Network Toolbox in Matlab gives an option of 17 training functions and each of them are tested corresponding to a fixed number of neurons in the hidden layer keeping all other factors constant to find which training function suits network the best. The best performance is shown by Levenberg-Marquardt back propagation training function (TRAINLM in Matlab toolbox) as shown in the figure (fig.1) and fig.2 shows the performance of the network for TRAINLM function with 10 number of neurons in the hidden layer during train, validation and testing. The MSE performance index is found to be 0.034363.

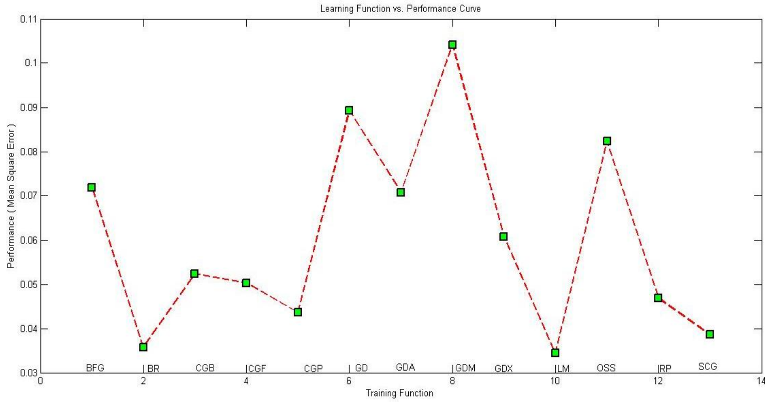

fig.1: Performance of network for different training functions

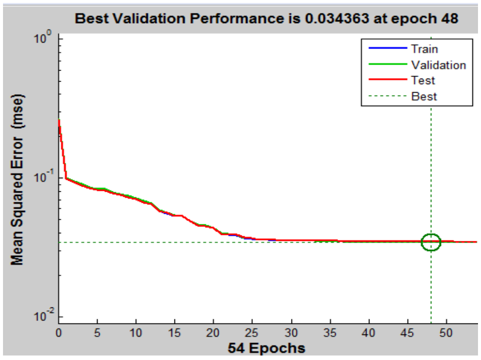

fig.2: Performance of TRAINLM function

The performance of network is also dependent on the number of neurons in the hidden layer, hence the network is also tested for its performance by varying the number of neurons and optimum number of neurons are found as shown in fig.3. The best performance is found for 19 number of neurons in the hidden layer with MSE = 0.02962.

IV. TEST AND ANALYSIS OF THE NETWORK

The five year data is taken as input and is divided into 3 parts i.e. 60% for training, 20% for validation and 20% for testing. A neural network with 8 inputs, 1 hidden layer with 19 number of neurons and 4 output variables is used for analysis. The tangent sigmoid is chosen as the transfer function of the hidden layer as well as for the output layer. TRAINLM is used as the training function which uses back propagation to train the network. This particular architecture of the neural network is chosen on the basis of several tests and analysis as shown above and when this network was tested on a fresh data of one year satisfactory results were obtained. The forecast was done with an accuracy of 82.78% and with MSE of 0.029628. Thus our model predicted the true class of load 14503 times out of total 17472 test cases.

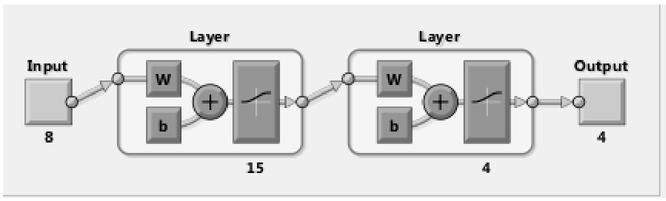

fig.3: The Neural Network Architecture for 15 number of neurons in the hidden layer

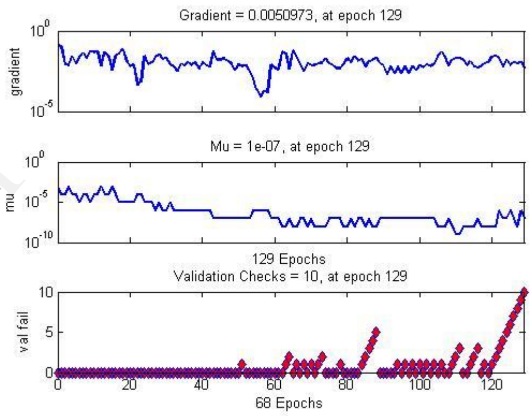

fig.4: The variation in various performance measures during training

V. CONCLUSION

The ANN based model for forecasting the short term electric load was implemented using Matlab. The historical load and temperature data from the New South Wales region Australia was used for testing and analysis and satisfactory results were obtained. However better results can be obtained if load forecasting is done for smaller regions along with their accurate temperature and weather information. The accuracy can also be increased by using a larger dataset for training the network.

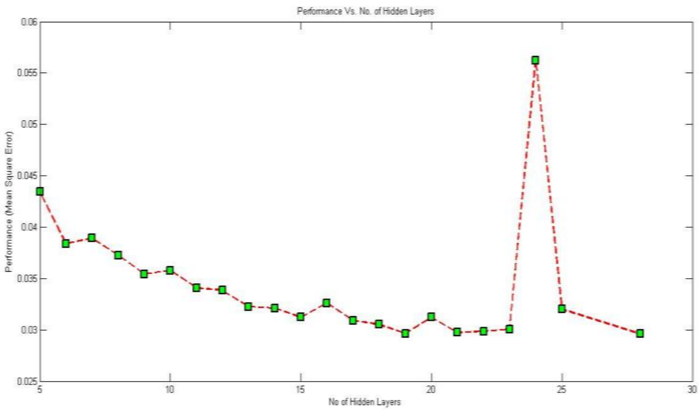

fig.1: Performance of network for different number of neurons in hidden layer

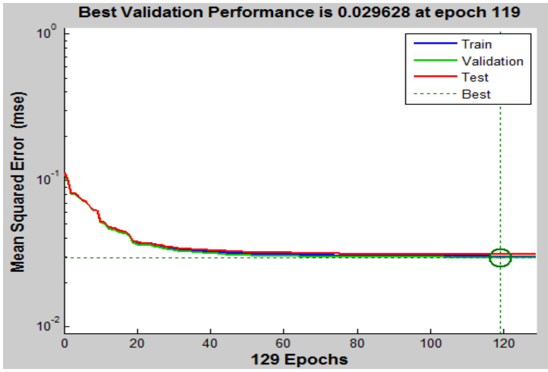

fig.2: Performance for 19 number of neurons in hidden layer

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