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SHORT TERM LOAD FORECASTING USING ARTIFICIAL NEURAL NETWORK TECHNIQUE

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Abstract: Electricity is indispensable and of strategic importance to national economies. Consequently, electric utilities make an effort to balance power generation and demand in order to offer a good service at a competitive price. For this purpose, these utilities need electric load forecasts to be as accurate as possible. This paper proposes artificial neural network based short term load forecasting. The main reason for using Artificial Neural Networks, over other techniques, in the development of the short term Load and Price Forecaster is their ability to learn complex relationships through a training process with historical data. Historical load data were obtained from Australian Energy Market Operator website and weather data were obtained from Australian Bureau of Meteorology for the same period to train neural network. It is trained using back propagation algorithm and tested. Error was calculated as MAPE (Mean Absolute Percentage Error) and with error of about 2.05% this paper was successfully carried out.
Keywords: Load forecasting, artificial neural network, Multilayer perceptron, MAPE

I. INTRODUCTION

Short-Term Load Forecasting (STLF) is basically aimed at predicting system load with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power systems. With the worldwide deregulation of the power industry, load forecasting is becoming even more important, not only for system operators, but also for market operators, transmission owners, and any other market participants, so that adequate energy transactions can be scheduled, and appropriate operational plans and bidding strategies can be established. Thus, load forecasting has also become an important component of energy brokerage systems. In this new context, high forecasting accuracy and speed are required not only for reliable system operation, but also for adequate market operation, as both under-forecasts and over-forecasts would result in increased operational costs and loss of revenue. [1-2]. There is a 3-7% increase of electric load per year for many years. The increase of load depends on the population growth, local area development, industrial expansion etc. The taxonomy of load forecasting can be considered as Spatial forecasting & Temporal forecasting. Forecasting future load distribution in a particular region, such as a county, a state, or the whole country is called Spatial forecasting. Temporal forecasting is dealing with forecasting load for a specific supplier or collection of consumers in future hours, days, months, or even years. The temporal forecasting can be broadly divided into 4 types – long term, medium term, short term and very short term. The long term forecast (5 to 20 years) is required as the building of power plant requires many years. The forecast ranging from few months to 5 years is termed as medium term forecasting. Thus long and medium term forecasts help in determining the capacity of generation, transmission or distribution system expansions and the type of facilities required in transmission expansion planning, annual hydro thermal maintenance scheduling etc. Typically the short term load forecast covers a period of one week. The forecast calculates the estimated load for each hour of the day, the daily peak load and the daily/weekly energy generation. [3] The introduction of deregulation in the electricity industry made short term load forecasting much more important.

Because of its great economic importance and the high complexity of electric power systems, short term load forecasting has been subjected to constant improvements in which numerous techniques have been used [4, 5, 6]. Different techniques for load forecasting: Time series models (load is modeled as a function of its past observed values), multiplicative auto-regressive models [7], dynamic linear [8] or non-linear models [9], threshold auto-regressive models [10], methods based on Kalman-filtering [11], Box – Jenkins transfer functions [12, 13], ARMAX models [14, 15], optimization techniques [16], non-parametric regression [17], structural models [18] and curve – fitting [19] procedures. The most popular ones are linear regression ones [20]. Artificial Intelligence techniques include Expert Systems [21], Fuzzy inference [22] and Fuzzy – neural models [9, 23]. In the section 2 data of load, flow of work & training of artificial neural network using matlab is described. In section 3 results of work are described.

II. METHODOLOGY

A. Data

There are two sets of data namely load profile data and weather data. Load data is obtained from Australian Energy Market Operator website & weather data is obtained from Australian bureau of Meteorology website for same period. Both data are of New South Wales. Load data consist half hourly measurement of load for period of year 2006 to 2010. Weather data consist of dry bulb, wet bulb, dew point temperature & humidity. Data is arranged as shown in figure

1 to train neural network.

	A	B	C	D	E	F	G
1	Date	Hour	DryBulb	DewPnt	WetBulb	Humidity	SYSLoad
2	01/01/2006	0.5	23.9	21.65	22.4	87.5	8013.278
3	01/01/2006	1	23.9	21.7	22.4	88	7726.892
4	01/01/2006	1.5	23.8	21.65	22.35	88	7372.858
5	01/01/2006	2	23.7	21.6	22.3	88	7071.833
6	01/01/2006	2.5	23.7	21.6	22.3	88	6865.44
7	01/01/2006	3	23.7	21.6	22.3	88	6685.927
8	01/01/2006	3.5	23.6	21.65	22.3	89	6548.628
9	01/01/2006	4	23.5	21.7	22.3	90	6487.837
10	01/01/2006	4.5	23.5	21.7	22.3	90	6449.178
11	01/01/2006	5	23.5	21.7	22.3	90	6388.278
12	01/01/2006	5.5	23.75	21.7	22.4	88.5	6395.48
13	01/01/2006	6	24	21.7	22.5	87	6494.333
14	01/01/2006	6.5	24.7	21.75	22.75	84	6715.202
15	01/01/2006	7	25.4	21.8	23	81	7062.48
16	01/01/2006	7.5	27.35	22.05	23.75	73.5	7532.117
17	01/01/2006	8	29.3	22.3	24.5	66	8037.868
18	01/01/2006	8.5	32.15	18.85	23.6	48.5	8623.735
19	01/01/2006	9	35	15.4	22.7	31	9169.365
20	01/01/2006	9.5	36.65	14.5	22.85	27	9600.79
21	01/01/2006	10	38.3	13.6	23	23	10005.31
22	01/01/2006	10.5	39.15	13.4	23.2	22	10264.63

Sheet1 Sheet2 Sheet3
Ready 100%

Fig. 1. Arrangement of data set

B. Flow of work

The data set is imported from an Access database using the auto-generated function. A list of Australian holidays that span the historical date range is imported from an Excel spreadsheet. The function genPredictors generates the predictor variables used as inputs for the model. The dataset is divided into two sets, a training set which includes data from 2006 to 2009 and a test set with data from 2010. The training set is used for building the model. The test set is used only for forecasting to test the performance of the model on out-of-sample data. The next few cells builds a Neural Network regression model for load forecasting given the training data. This model is then used on the test data to validate its accuracy. Neural network is initialized with two layers and 20 hidden layer neurons. Network is trained with Levenburg-Marquardt algorithm. Once the model is build forecast is performed on independent test set. A plot is created to compare the actual load and the predicted load as well as compute the forecast error. In addition to the visualization, quantify the performance of the forecaster using metrics such as mean average error (MAE) & mean average percent error (MAPE). Sequence of work is described in below figure2.

Importing Load & Weather Data

Importing list of holidays

Creating Predictor Matrix

Separating Dataset to Create Training & Test set

Training neural network

Forecasting Load by neural network Model

Comparing Forecast Load & Actual Load

Generating Weekly Chart

Figure: 2 sequence of work

C. Neural network training

Neural network is trained using training sets. The input variables to the neural network are:

- 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
- Load from the same hour the previous day
- Load from the same hour and same day from the previous week

The outputs of input layer are used as input of hidden layer. Hidden layer consist of 20 neurons with log sigmoid as activation function. The outputs of hidden layer are used as inputs for this layer. It consists of single neuron, with linear activation function. From total number of samples 70% were used for training, 15% were used for validation and 15% were used for testing. Neural network training tool is shown in figure 3. Neural network performance and regression plot are shown in figure 4 and figure 5.

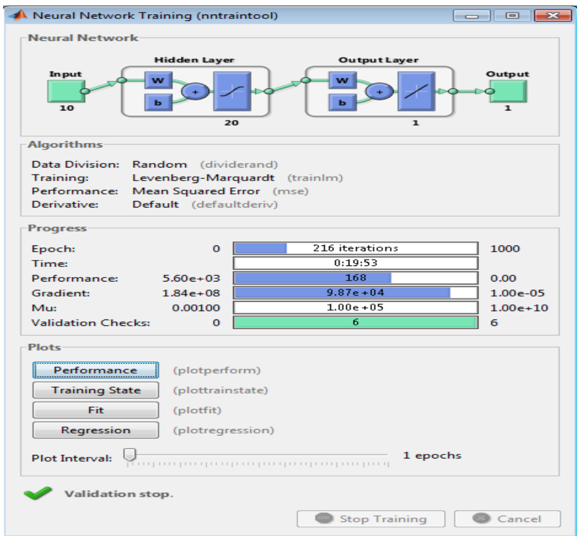

Fig. 3. Neural network training tool

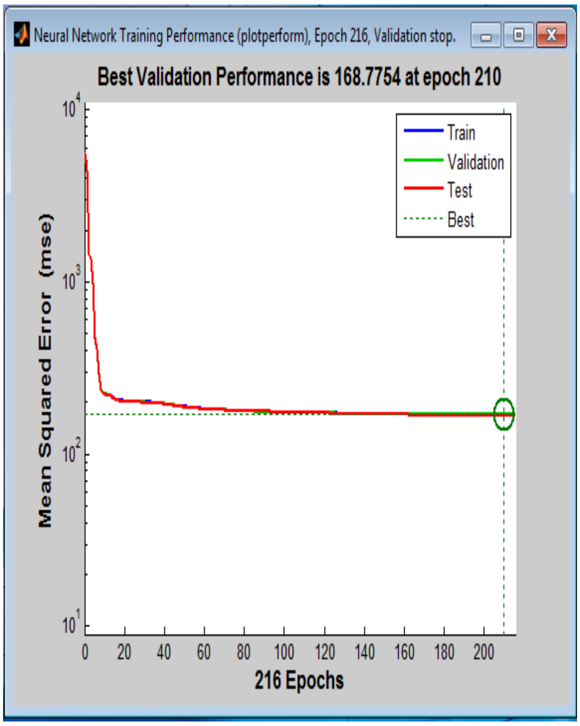

Fig. 4. Neural network performance plot

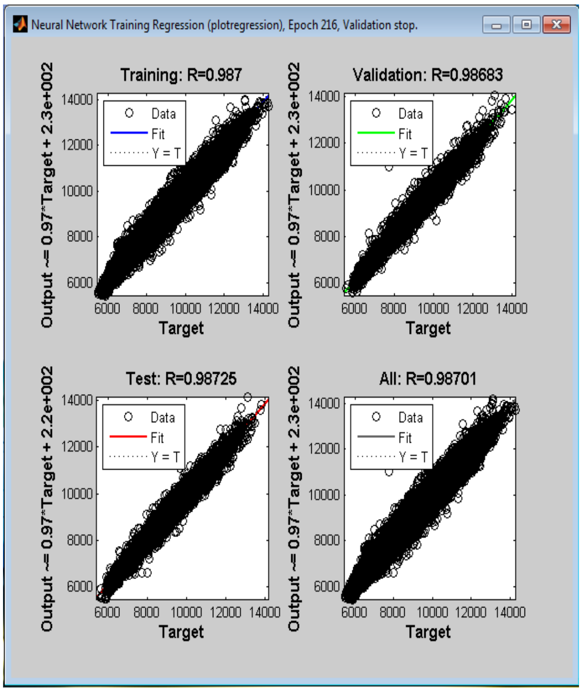

Fig. 5. Neural network regression plot

The best performance achieved for validation is at epoch 210. The R (correlation coefficient value) values for training, validation and testing are 0.987, 0.9868 & 0.9872 respectively. The overall R value is 0.987 resulting in very close prediction.

III. RESULTS

Results include comparison of actual load and forecast load as shown in figure 6. Mean percentage absolute error is 2.05% which is good for overall forecast. Mean absolute error is 179.87 MWh.

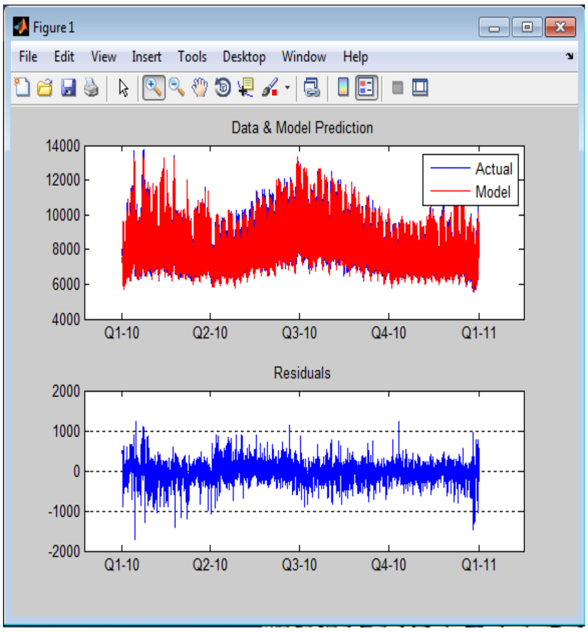

Fig. 6. Comparison between actual load & predicted load

Figure 7 shows one of the weekly chart and figure 8 shows one of the daily chart of comparison between actual and predicted load.

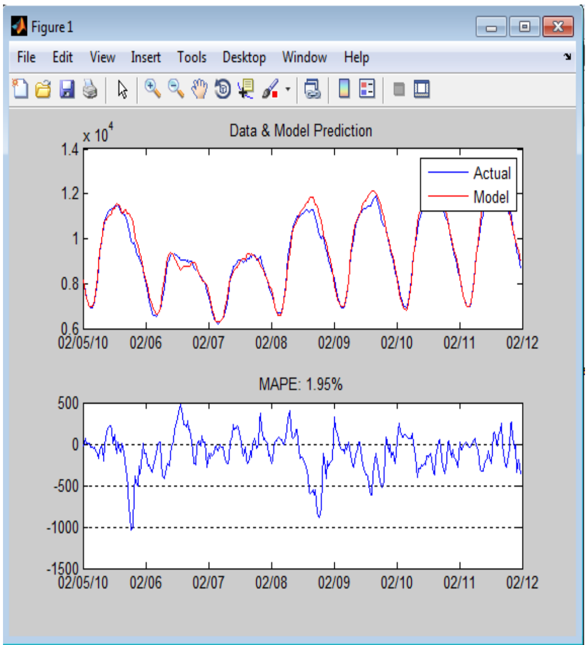

Figure: 7 Comparison between actual load & predicted load weekly

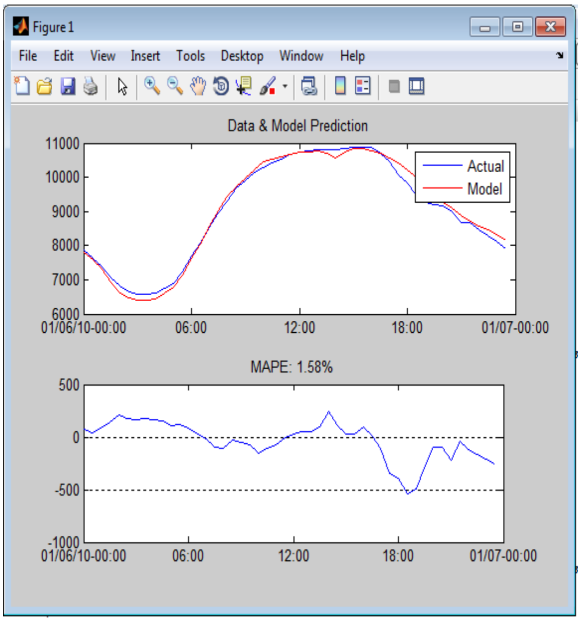

Fig. 8. Comparison between actual load & predicted load daily

IV. CONCLUSION

In present work short term load forecasting is done using artificial neural network. Neural network is trained using past data of system load, temperature, humidity and list of holidays. The dataset is divided into two sets, a training set which includes data from 2006 to 2009 and a test set with data from 2010 onwards. The training set is used for building the model. The test set is used only for forecasting to test the performance of the model. Results reveal that mean absolute percentage error of forecasted load is 2.05%. Further this work can be converted into price forecasting by using past data of price of electricity and natural gas.

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