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A Comparative Analysis of Neural Network based Short Term Load Forecast for Seasonal Prediction

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ABSTRACT

Accurate load forecasting has always been an important issue for efficient and reliable operation of the power system. Load forecasting shows non linear characteristics due to several influencing factors. In this paper, comparison of Back Propagation (BP) and Levenberg Marquardt (LM) neural network (NN) based forecast model is presented for seasonal prediction. The historical load and weather data of four year is used as input of forecast model. To enhance the forecast accuracy of model, type and hour of day, day of week, dew point and correlated historical load data is treated as input of model. The forecast model is used to predict the 168 hours ahead load demand of winter, spring, summer and autumn season. The mean absolute percentage errors (MAPE), Convergence and regression analysis of NN training are used to measure the NN performance index. To avoid the over fitting problem in NN training process, the load data sets is divided into training and validation data sets. The real time load and weather data of power grid is used to validate the model. LM based forecast model outperforms than the BP model in terms of forecast accuracy, convergence rate and training of the network.

INTRODUCTION

Prediction of future load demand of consumers is known as load forecasting. It has quite an important part to play in energy management as it can be helpful for achieving a better energy planning for the power system. An energy management system is vital for achieving a supply of power that is not only reliable and inexpensive but also secure. This requires that it possesses, as an integral part, load forecasting that is accurate. Over the past 10 years, extensive research has been carried out in regards to the accurate forecast of electrical loads. This has been spurred on by its many applications in load flow analysis, power system scheduling and various kinds of contingency analyses. By accurately forecasting electrical loads, the power system operation, planning, and maintenance can be performed quite effectively (Ruzic *et al*., 2003).

There has been a significant increase in the demand for accurate load forecasting due to the negative effect that over and underestimation of load demand can affect to the operation of a power system. In case, if the load demand is underestimated, the energy system will experience an extremely negative effect in regards to the demand response. Moreover, it is quite difficult to control the conditions of an overload particularly when there is no large backup power supply is available. On the other hand, an unexpected over-production cost of energy could be the case with overestimation (Wei and Ying, 2007). Scheduling, maintenance and day to day operation of the power system are applications that depend on accurate load forecasting.

The measure of the correctness of the predictability of the future load demand is an important part in the operation of a power system, planning and energy policy decisions making (De Felice and Xin, 2011). Adequate planning can result in the savings of millions of dollars as a survey was conducted for UK power system (Young, 1986). In the modern era of technology, it is vital that the supply of power is uninterruptible and that is the reason accurate load forecasting has been receiving more and more attention from researchers. Millions of dollars could be saved by even a slight increase in accuracy that could result from the application of an enhanced system for energy management (Chakhchoukh *et al*., 2011). Uncertain load demand, sudden weather changes, type of day, historical load data requirement and the type of prediction model affect the forecasting accuracy.

In the research area of load forecasting in recent years, a more comprehensive research has been carried out for implementation in energy management systems for smart buildings, micro and smart grids. There are various methods used to perform load forecasting in the short term. Generally, there are two classifications for the load forecasting methods. They are as below:

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- Statistical methods (parametric method).
- Artificial intelligence methods (non-parametric method).

Statistical methods employed to determine future loads include the autoregressive moving average (Drezga and Rahman, 1998), linear regression, general exponential method (Christiaanse, 1971) and stochastic time series models (Amarawickrama and Hunt, 2008). If the weather and load demand behavior is under the normal conditions, there will be smaller forecast errors when using the statistical method. However, a large forecasting error could be caused if there is a sudden variation in sociological (social or cultural events) or meteorological (like humidity, dry blub, dew point or temperature) parameters. This is a major disadvantage when using the statistical method for load forecasting.

Artificial neural network (ANN) based forecast models and non-parametric methods have gained much interest from researchers from the middle of the 1990's. ANN considered as a power computational tool for prediction and load forecasting problem. ANN shows more better results when compared to methods that have been applied earlier for load forecasting (Hanmandlu and Chauhan, 2011). The NN has the capability of solving, under uncertainty and prediction patterns, the relationship between input and output, and decision-making that is complex. A variety of ANN techniques have been employed for short term load forecasting. These techniques include the quasi Newton network (Saini and Soni, 2002), multilayer feed forward NN (Malki *et al*., 2004), Bayesian regulation (Niu *et al*., 2012), radial basis function network(Gontar and Hatziargyriou, 2001) and the adaptive neural network (Zhao-Yang *et al*., 2001).

The paper is organized as follows : Section II examines the impact of ANN model inputs on STLF and STLF NN model inputs. Section III presents the weight update rule of Levenberg-Marquardt (LM) training algorithm. The forecast results of NN STLF model and convergence analysis of LM and BP training techniques are discussed in section IV.

Neural Network Based Load Forecast Model:

The neural network containing the neurons between the input and output layer is called multilayer neural network and neuron layer between the input and output layer is referred as hidden layer as shown in figure 1. The single layer network are not able to learn the complex relationship between input and output but multilayer network (MNN) have the ability to learn the complex relationship.

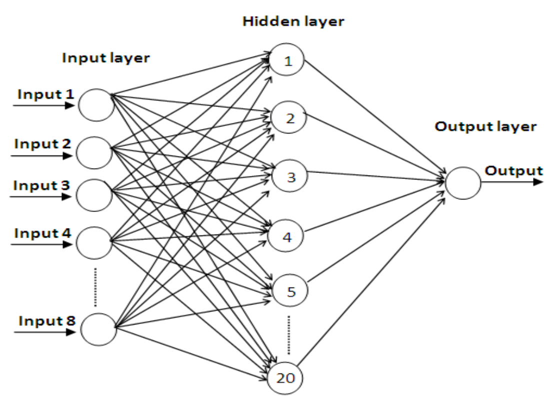

Fig. 1: ANN forecast model architecture.

Characteristics of Load Curve:

The figure 2 shows, the graph of input load demand (MW) of five years (2005-09) new-ISO England grid. The load trend can be analyzed with load demand graph and this type of analysis can be useful for energy policy making decision (Huaiwei and Niebur, 2003). Seasonality trend can be easily observed in load profile of ISO-new England grid data as demand repeats according to season of year.

The load demand in summer season is about double than the winter season. This great demand change is due to weather variation throughout the year.

Neural Network Inputs:

The most important task for short term load forecast problem is to select input variables of forecast model. There is no general rule followed for input selection of STLF but better selection can be carried out by engineering expertise or based on field experience (Drezga and Rahman, 1998). As H. Liao *et al*., stated that Independent components analysis can be very helpful to determine the inputs which significantly influences the load forecast accuracy (Huaiwei and Niebur, 2003).

Australian Journal of Basic and Applied Sciences, 7(11) Sep 2013, Pages: 419-428

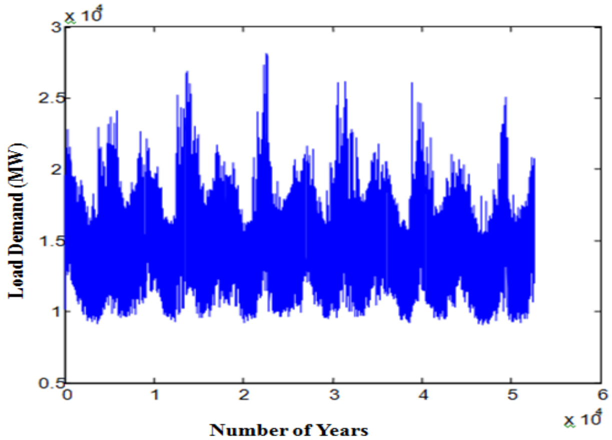

Fig. 2: (2005-09) five year load profile of grid.

Load Data Analysis:

The ANN proposed model is trained by Levenberg-Marquardt training algorithm for 24 and 168 hours ahead for ISO-New England grid. The load data set is divided into two sets: first data set is used for training purpose of network and second data set for testing of forecasting results. A four year 2005-2008 24-hourly load and weather data is used to train the network called training data set and 2009 hourly load data is considered as test data set. The inputs of ANN model for hourly load forecasting is shown in figure 3.

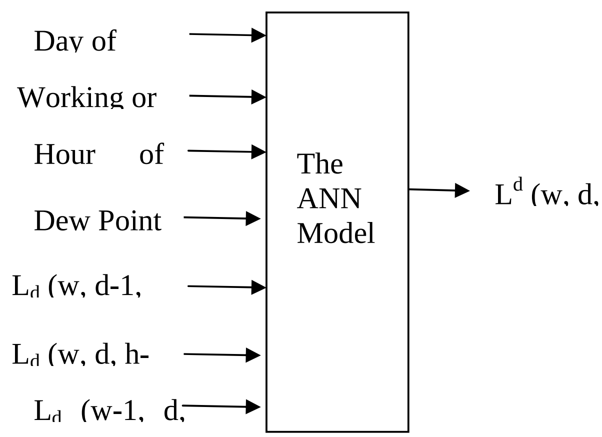

Fig. 3: ANN forecast model inputs for STLF.

Where L_d (w,d,h) represents load demand of particular hour of the same day and same week.

- L_d (w, d, h-1): load demand of the pervious hour of the same day and week
- L_d (w, d-1, h) represents load demand of same hour of pervious day of the same week
- L_d(w-1,d,h) represents load demand of same hour of the same day of the previous week

Type of the Day:

Type of day either on or off day (weekends or special occasion) like Eid, Christmas celebration, national and cultural celebration days of a country, which affect on electrical load demand (Kwang-Ho *et al*., 2000).

Day Pointer D(K) and Hour Pointer H(K):

Other inputs are day of week (Monday is day first and Sunday is seventh day), hour of the day. Figure 4 shows that the load demand from Monday to Sunday. It depicts that, in working days the load demand is much higher than the off days (Saturday and Sunday) due higher social activities. This weekly pattern is repeated more or less throughout the month as shown in figure 5.

Australian Journal of Basic and Applied Sciences, 7(11) Sep 2013, Pages: 419-428

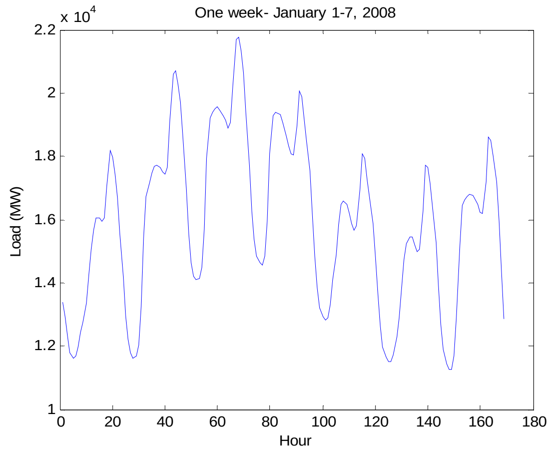

Fig. 4: Load profile of January 1 to 7, 2008.

Proposed ANN Model:

The multilayer preceptoron model is used for forecasting the load demand. The network structure is 6-20-1, 6 nodes in the input layer, 20 nodes in hidden layer and one node in output layer because the network output is one.

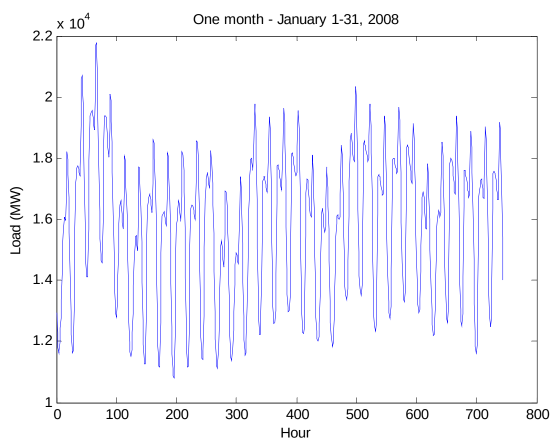

Fig. 5: Load profile of ISO New England grid of January 2008.

Levenberg Marquardt Training Method for ANN:

The Levenberg Marquardt NN training algorithm as fellows (Yuan *et al*., 2010).

$$O_p\left(w_{ij}+d_{wij}\right)=Op\left(w_{ij}\right)+\nabla O_p\left(w_{ij}\right)^T dw_{ij}+1/2*dw_{ij}{}^T\nabla^2 O_p\left(w_{ij}\right)dwij \tag{1}$$

Where $\nabla O_p(w_{ij})$ and $\nabla^2 O_p\left(w_{ij}\right)$ are the gradient vector and hessian matrix of the error function.

dw_{ij} is

$$dw_{ij}=-\left[\nabla^2 Op\left(w_{ij}\right)\right]^{-1}\nabla O_p\left(w_{ij}\right) \tag{1}$$

And hessian matrix as fellows

$$\nabla^2 O_p\left(w_{ij}\right)=J^t J+S \tag{2}$$

Where J is jocobian matrix, which contains the primary derivative of network error which is relative to weight and errors. By traditional directional propagation algorithm it can be calculated and where S represents the 2nd order derivative information in $\nabla^2 O_p(w_{ij})$. If the S is ignored then equation will be Gauss Newton method. We can also obtain results for Hessian matrix by following approximation.

$$\nabla^2 O_p(w_{ij}) = J_t J + \mu I \quad (3)$$

To get modulus weight and approximation of hessian matrix LM method is applied.

$$\nabla W = \left(J^t J + \mu I\right)^{-1} J^t O_p \quad (4)$$

To control the size of trust region μ scalar quantity is used and I is unit identity matrix (Reynaldi *et al*., 2012).

RESULTS AND DISCUSSION

The accuracy of load forecasting is measured in term of error. The mean absolute percentage error (MAPE) is calculated as:

$$MAPE = 1/M\sum_{i=1}^{m} | P_i - P_o | / P_i \quad (5)$$

Where P_i is the actual load, P_o is forecasted load and actual load P_i is in the denominator.

In order to access the prediction accuracy of forecasting model the mean absolute percent error (MAPE) a is calculated.

Normally, each season has 2 month for typical season such as: December and January are considered as winter; March and April as spring; July and August are seen as summer; and September and October as the autumn season (Niu *et al*., 2012). Comparison of 168 hours ahead seasonal load forecast of year with back propagation (BP) and Levenberg Marquardt (LM) training method of NN is shown in figure 6, 7,8 and 9. Analysis shows that MAPE of forecast model is less in morning time and as the time is passed of a day, the MAPE becomes higher. One of the reasons is due to social activities of certain population in day time. In the ANN model, the type of day (working or off day) is considered as an input of the system because its effects on the load demand. At different events celebrations like, Eid-ul-Fitar, Eid-ul-Azha, New Year night or other public events increase the load uncertainty of the system.

In table 1, the Levenberg Marquardt NN training algorithm shows relativity small MAPE than the Back propagation of 168 hours ahead forecast model. The LM NN training algorithm shows higher forecast accuracy and network performance.

168 hours ahead seasonal forecast of LM based forecast model shows that, the winter season load forecast produce less error than the other seasons due to the enhanced training of the neural network with respect to other seasons forecast training. The seasonal results also represents that, the forecast error of summer season produce the highest error for BP and LM based forecast model than the other seasons as shown in figure 10. This means that, due to occurrence of over fitting and low generalizing capability the of network leads to poor training of network. Consequently the forecast error of autumn seasons was increased than the other seasons. Analyzing the seasonal forecast results shows that, LM based forecast model give lower forecast MAPE than BP model for seasonal prediction which is one main objective of forecasting problem.

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Performance Analysis of LM and BP Trianing Methods:

A large set of training data has been employed to train the model for NN forecasting; however, only a small number of data pattern has been employed for updating the weights. The input data for training is based on the similar day or corelation method which is one of the more suitable methods utilised for neural network learning. Otherwise it may cause the large foreacasting error and negtive affect on power system. A large amount of training data could result in a lenghty training period and slow convergence and that could negatively effect the accuracy (Hush, 1989).

The relationship between the Mean square error and the number of epochs of the back propagation training technique for the STLF model is presented in Figure 11. The validation performance that was the best for the technique of back propagation was 1106 in 719 epochs for STLF networks; this was a rather high result. The training, validation and testing values were seen to be moving at the same time towards the convergence of the STLF model as is also presented in Figure 13.

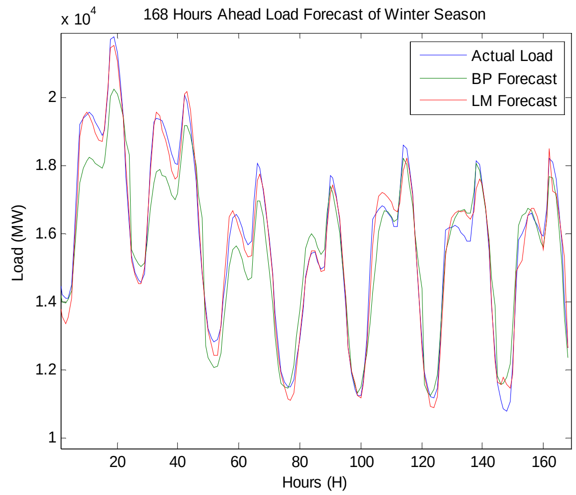

Fig. 6: 168 hours ahead winter load forecast using LM and BP method.

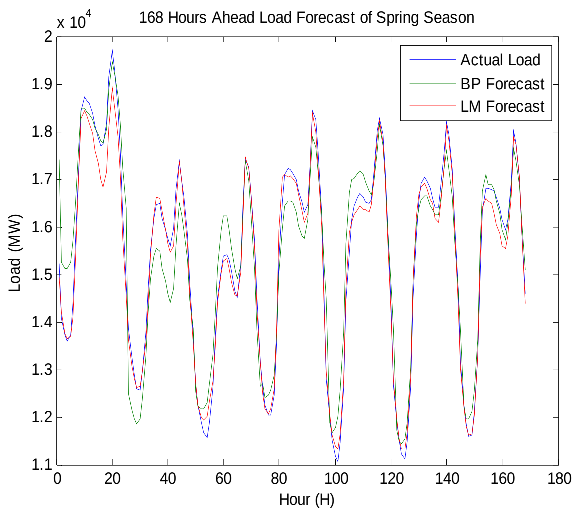

Fig. 7: 168 hours ahead spring load forecast using LM and BP method.

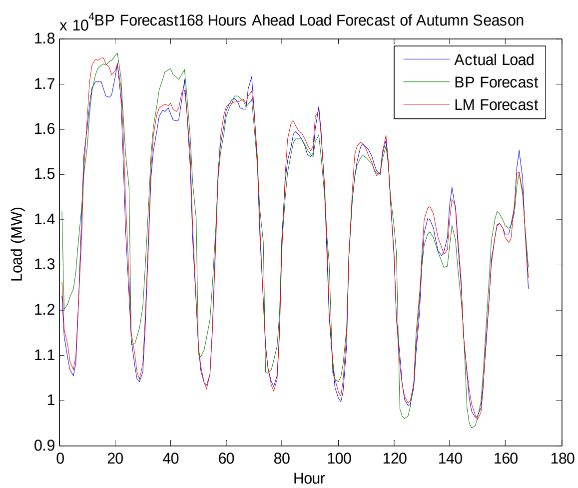

Fig. 8: 168 hours ahead autumn load forecast using LM and BP.

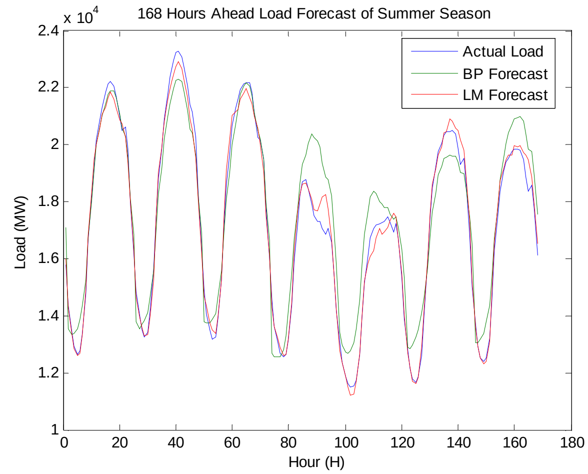

Fig. 9: 168 hours ahead summer load forecast using LM and BP.

Table 1: MAPE comparison of LM and BP NN for 168 hours ahead forecast model.

Season	*Forecast Date*	*Forecast Horizon (Hours)*	*BP MAPE (%)*	*LM MAPE (%)*
Winter	January 1st to 7th 2009	168	4.30	2.72
Spring	March 1st to 7th 2009	168	4.08	3.16
Summer	July 1st to 7th 2009	168	4.66	3.82
Autumn	September 1st to 7th 2009	168	4.50	2.91

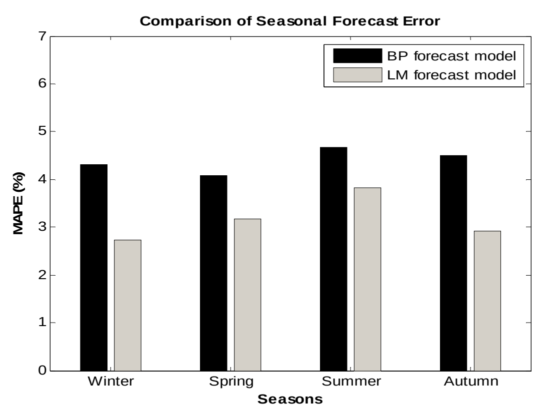

Fig. 10: Seasonal error comparison of LM and BP method.

The regression analysis of the LM training of the ANN technique for the STLF model with given inputs is shown in Figure 9. In order to measure the overall performance of the STLF model, the training process was performed multiple times so that the confidence interval of the training, testing, and validation could be analysed. 5% of the estimated data was not statistically significant for the NN as was indicated by the confidence interval of 95% for the model. The 95% confidence interval indicated the degree of confidence, in the NN training process, that the network has adjusted itself in regards to its error. In the validation process, the confidence interval is employed to measure the network generalization capatbilty. This allows for the independent measure of performance both during and after the training process. The prime objective here has been to decrease the forecasting error which is the problem in load forecasting and this can be achieved through a notable increase in the confidence interval range.

In table 2, training, testing, validation and overall performance of training algorithm is shown.

Table 2: Comparison of regression analysis of NN training techniques.

Training Technique	*Training*	*Testing*	*Validation*	*All*
BP	0.9046	0.9051	0.9022	0.9043
LM	0.9524	0.9517	0.9529	0.9523

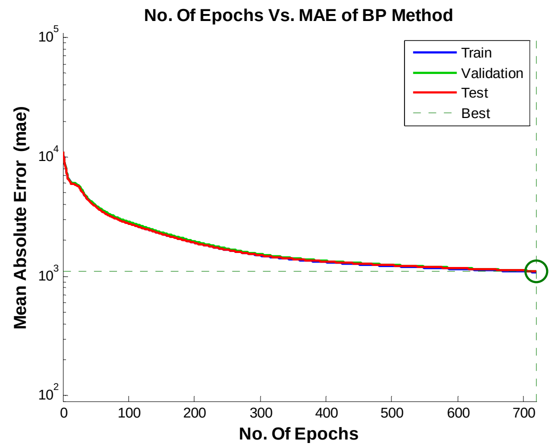

Fig. 12: Number Of Epochs vs. Absolute error of BP training method.

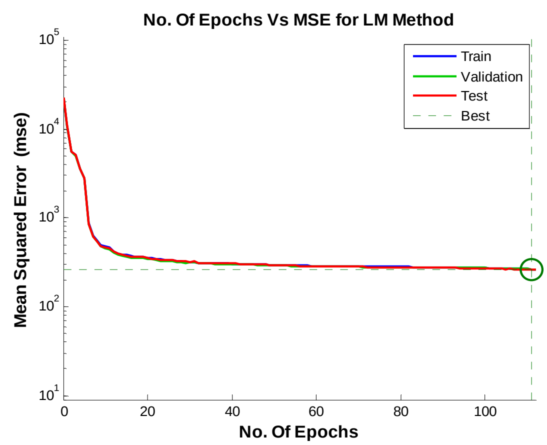

Fig. 13: Number Of Epochs vs. Mean Absolute error of LM training.

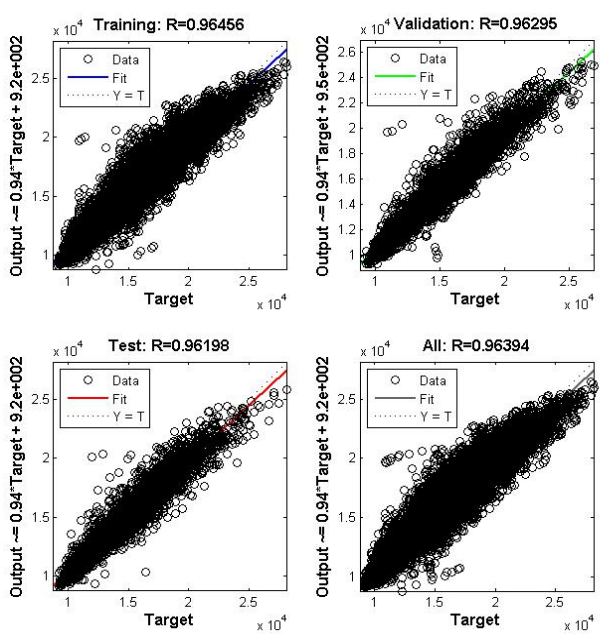

Fig. 14: Regression analysis of LM based NN forecast model.

Australian Journal of Basic and Applied Sciences, 7(11) Sep 2013, Pages: 419-428

In table 2, results shows that the LM techniques having better capability to reduce the error during the training and better generalization. The reason of better forecast results of LM training is due to faster training and convergence speed. The local minima arise during the training process in which neuron get trap in shallow valley which ultimately effect the forecasting accuracy. BP trained network having more chances to get trap in the local minima due to slow training speed of the network. LM training method shows faster training performance which avoids the NN to get trap in to the local minima.

It can be analyzed from load forecast results show that, the training algorithm and inputs having affect on the model output. Levenberg Marquardt (LM) training method shows overall better results than the Back propagation (BP).

Conclusion:

This paper demonstrated the ability of neural network for short term load forecasting using Back propagation (BP) and Levenberg Marquardt (LM) training method with weather inputs. The pervious load demand, type of day, day of weak and dew point are considered as an input of neural network. LM based NN forecast model shows better results than the BP NN in terms of MAPE, daily peak error, convergence rate and overall training performance of neural network. LM training shows the strong training capability of the network which avoids the neural network to trapped into the local minima. LM NN based model regression analysis shows that, the network achieves 95% of confidence interval for network training, testing, validation and overall NN performance. Consequently LM NN model proves that the higher forecast accuracy than BP due to strong generalization capability over a large data which increase the accuracy.

Future research focus on enhancement of forecast accuracy by including the more weather parameters such as: temperature, humidity information, wind speed, cloud cover, rainfall, and human body index.

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