Electricity Prices Forecasting Using Multilayered Perceptron Network with Levenberg-Marquardt

Sharifah Safiah Binti Syed Ab Ghani
Faculty of Electrical Engineering
Universiti Teknologi MARA Malaysia
40450 Shah Alam, Selangor, Malaysia
e-mail: sssag24@yahoo.com

Abstract— **In competitive electricity markets in most country, price forecasting is becoming increasingly relevant to power producers and consumers. Price forecasts provide crucial information for power producers and consumers to develop bidding strategies in order to maximize benefit. In this paper, a Multi-layer Perceptron (MLP) based neural network model to forecast price profile in electricity market has been presented. Publicly available data acquired from the Australia electricity market were used for training and testing the Artificial Neural Network (ANN). The results obtained through the simulation show that the proposed algorithm is efficient, accurate and can be used to forecast electricity prices.**

Keywords: Multi-layer Perceptron (MLP), Artificial Neural Network (ANN), price forecasting.

I. INTRODUCTION

Nowadays in electricity markets, forecasting becomes more and more important. Accurate estimating price is the most essential task and the basis for any decision making and developing biding strategies[1]. All over the world, the electricity industry is converging toward a competitive framework and a market environment is replacing the traditional monopolistic scenery for the electricity industry. In this competitive electricity industry, forecasting electricity prices is an important problem. In particular, accuracy in forecasting these electricity prices is very critical, since more accuracy in forecasting reduces the risk of under/over estimating the revenue from the generators for the power companies and provides better risk management [2].

The structure of the Australian National Electricity Market (NEM) has generators offering energy to buyers (retailers) via a wholesale spot market. They are required to submit generation supply curves to a system operator twenty-four hours ahead of dispatch. A supply curve is created for each of the forty-eight half-hours in a day. This indicates how much energy each generator is willing to generate from each generating unit as the pool price varies. The system operator decides which generators should be dispatched when the spot price exceeds their offer price and determines the price every five minutes. Expected load (demand) is matched with the industry supply curve for a particular half-hour, with the price offered by the last generator dispatched forming the five-minute price. A time-weighted average of the five-minute prices sets the half-hour pool price[3].

Electricity prices depend on factors such as load, distribution networks, status of generators, market policies and etc. The uncertainties in these factors introduce high volatility into the prices and cause difficulties in forecasting. Yet, being able to forecast the price precisely is of interest to both producers and buyers. Since, relation between price and its influencing variables is non-linear, therefore ANNs are well suited for this problem because of their ability to model the complex and non-linear relationship involved in price forecasting [4].

Neural networks method are simple, but powerful and flexible tools for forecasting, provided that there are enough data for training, an adequate selection of the input–output samples, an appropriate number of hidden units and enough computational resources available. Also, neural networks have the well known advantages of being able to approximate any nonlinear function and being able to solve problems where the input–output relationship is neither well defined nor easily computable, because neural networks are data driven[1]. The layered feedforward neural networks are specially suited for forecasting, implementing nonlinearities using sigmoid functions for the hidden layer and linear functions for the output layer.

There are a lots of method have been reported for price prediction of the electricity market. Most of these methods are basically short-term load forecasting methods. Artificial intelligent based technique is the most well known technique that has been used in the literature to forecast electricity prices. S. Kumar et al. proposed a wavelet transform (WT) based neural network model to forecast price profile in deregulated market [4]. On the other hand, D.C Sansom has proposed a back propagation neural network model. The resulting price forecast are described by four different measures, the MAE, load weighted mean, cross-correlation and direction. There is also a study provides a method for predicting hourly prices in the day-ahead electricity market using Recursive Neural Network (RNN) technique, which is based on similar days approach [10].

Some work that has used Levenberg-Marquardt is to forecast solar radiation. Nian Zhang propose a predictive model that is based on recurrent neural networks trained with the Levenberg-Marquardt Back Propagation learning algorithm to forecast solar radiation using the past solar radiation and solar energy [11]. In this study, Levenberg-Marquardt Back Propagation (LMBP) has been used for the ANN training to increase the speed of convergence and forecasted the electricity price. The detail explanation on this technique will be provided in the section of methodology.

II. SCOPE OF WORK

This paper proposes a technique to forecast the electricity prices by using MLP network with Levenberg-Marquardt Back Propagation (LMBP). The model is developed using a commercial programming software, MATLAB from MathWorks. The parameters that are used as the input to the model are based on the Australia electricity market. The data input consist of 17520 data of input and output patterns and use as Training Data sets in the training process. Each training presentation contains four input layers. The input layers are system load, time, humidity and temperature. There is one output node which provides corresponding value of electricity price.

III. METHODOLOGY

The method used in this paper to model the electricity prices is Multilayered Perceptron Network (MLP). Figure 1 shows a flowchart detailing the step in MLP Neural Network procedure. The methodology involves collecting data for the ANN model, selecting data for training, testing and validation process, developing programming code for the MLP neural network based LMBP, setting the MLP neural network parameter using LMBP, training the neural network, testing the data and plotting the performance.

Detail explanation about the MLP neural network and Lavenberg-Marquardt technique will also be provided in this section.

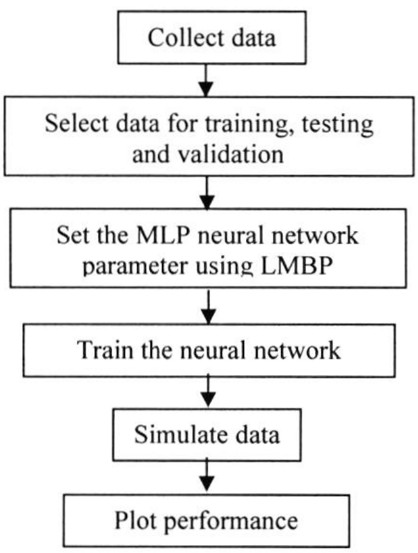

Figure 1: Step in MLP Neural Network Training Procedure

A. *Forecasting With Artificial Neural Network*

Artificial neural networks comprise of two different network structures i.e. Feedforward Neural Network (FNN) and Recurrent Neural Network (RNN). ANNs are mathematical models based upon the functioning of the human brain, indeed ANNs are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [5]. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent. ANNs are composed of three different layers input, hidden and output layers each of which are composed of a certain number of neurons, that relationship between inputs and outputs is vague (black box models). But ANN can be used to approximate practically any function (even non-linear ones). This means that ANNs can approximate the best function to a set of data, which is especially important when the functions are complex.

Multilayer perceptrons are the best known and most widely used kind of neural network. Networks with interconnections that do not form any loops are called feedforward. In feedforward networks, units are often arranged in layers: an input layer, one or more hidden layers and an output layer. The units in each layer may share the same inputs, but are not connected to each other. Typically, the units in the input layer serve only for transferring the input pattern to the rest of the network, without any processing. The information is processed by the units in the hidden and output layers.

B. *Multilayered Perceptron Networks*

MLP network is a feed forward neural network with one or more hidden layers. Cybenko (1989) and Funahashi (1989) have proved that the MLP network is a general function approximator and one hidden layer networks will always be sufficient to approximate any continuous function up to certain accuracy. A MLP network with two hidden layers is shown in Figure 2. The input layer acts as an input data holder that distributes the input to the first hidden layer. The outputs from the first hidden layer then become the inputs to the second layer and so on. The last layer acts as the network output layer.

A hidden neuron performs two functions that are the combining function and the activation function. The output of the j-th neuron of the k-th hidden layer, is given by:

$$v_j^k\ (t) = F\left(\sum_{i=1}^{nk-1} w_{ij}^k v_i^{k-1}(t) + b_j^k\right);$$

$$\text{for } 1i \leq j \leq n_k \qquad (1)$$

and if the m-th layer is the output layer then the output of the l-th neuron of the output layer is given by:

$$\hat{y}_l(t) = \sum_{i=1}^{n_{m-1}} w_{ij}^m\, v_i^{m-1}\ (t);$$

$$\text{for } 1 \leq l \leq n_o \qquad (2)$$

where n_k, n_o w's, b's and $F(.)$ are the number of neurons in k-th layer, number of neurons in output layer, weights, thresholds and activation function respectively.

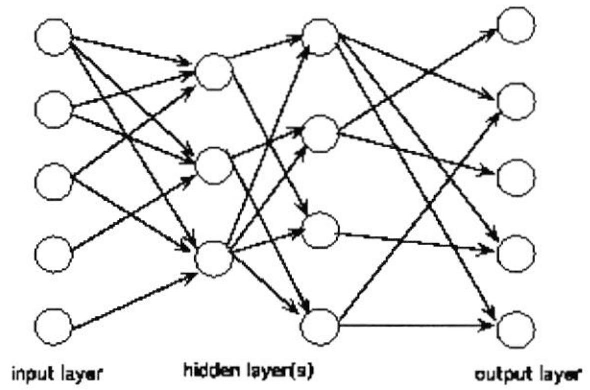

Figure 2: Multilayered perceptron networks

In this study, the network with a single output node and a single hidden layer was used, i.e $m = 2$ and $n_o = 1$. With these simplifications the network output is:

$$\hat{y}(t) = \sum_{i=1}^{n_1} w_i^2 v_i^1(t) = \sum_{i=1}^{n_1} w_i^2 F\left(\sum_{j=1}^{n_r} w_{ij}^1 v_j(t) + b_j^1\right) \tag{3}$$

Where n_r is the number of nodes in the input layer. The activation function F (.) is selected to be

$$F(v(t)) = \frac{1}{1 + e^{-v(t)}} \tag{4}$$

The weights w_i and threshold b_j are unknown and should be selected to minimised the prediction errors defined as

$$\varepsilon(t) = y(t) - \hat{y}(t) \tag{5}$$

Where $y(t)$ is the actual output and $\hat{y}(t)$ is the network output.

C. Details of Levenberg-Marquardt

The training method for the new ANN models is Levenberg-Marquardt back propagation (LMBP), which is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. This method is an improve Gauss-Newton method that has an extra regularization term to deal with the additive noise in the training samples. In comparison to LMBP, conventional back propagation methods are often too slow for practical problems. Neurons in the hidden and output layer have non linear transfer function as the "tangent sigmoid" (tansig):

$$f(x) = \frac{2}{1 + exp(-2x)} - 1 \tag{6}$$

The weighted input received by a tansig node are summed and passed through this function to produce an output. The tansig function generates output between -1 and +1 and its input in the same range. It will limit the ANN input and target output. Mean standard deviation and minimum to maximum normalization selected:

$$X_{normalized} = \frac{X_{actual} - X_{min}}{X_{max} - X_{min}} \times 2 - 1 \tag{7}$$

This normalization method has also the advantage of mapping the target output to the non-saturated sector of tansig function. This process helps to improve the accuracy of both the training and forecasting modes. Beside that LMBP gave faster convergence with fixed momentum and learning rate.

The performance of MLP networks is trained using TRAINLM Levenberg-Marquardt back propagation. TRAINLM is a network training function that updates weight and bias status according to Levenberg-Marquardt optimization. TRAINLM supports training with validation and test vectors if the network's NET.divideFcn property is set to a data division function. The training will stop when any of these conditions occurs:

i. The maximum number of EPOCHS (repetitions) is reached.
ii. The maximum amount of TIME has been exceeded.
iii. Performance has been minimized to the GOAL.
iv. The performance gradient falls below MINGRAD.
v. MU exceeds MU_MAX.
vi. Validation performance has increased more than MAX_FAIL times since the last time it decreased (when using validation).

The ANN models have the output layer. In the model of price forecasting the output is the electricity price, so the output layer has only one neuron. The number of hidden layers and the number of neurons in each layer are selected whereas the best results are obtained. In order to evaluate performance of the ANN models, LMBP method has been used for the ANN training to increase the speed of convergence.The MSE (Mean Squared Error) calculated over training and testing data sets. MSE is a network performance function. Its measures the networks performance according to the mean of squared errors.

IV. TEST DATA

In this project, a data set was taken from the Australia electricity market consist of 17520 data. The first 12264 data samples were used for training and the next 2628 data samples were used for validation. Other 2628 data samples were used for testing. The function was used is 'dividerand' which to separate input and target vectors into three sets: training, validation, and testing. The MSE (Mean Squared Error) calculated over training and testing data sets. MSE is a network performance function. It measures the networks performance according to the mean of squared errors.

The value of momentum and learning rate used in the training process using Lavenberg-Marquardt technique are 0.9 and 0.01 respectively. The training process stop when the network performance on the validation vectors fails to improve or remains the same.

V. RESULTS

The model has been tested using Australia electricity market – [12] data from January-December 2010. The neural network was set up to produce electricity price forecasts for every half an hour. The neural network are trained using Levenberg-Marquard back propagation. Price forecasts for 48 hours, seven-days and 28 to 31 days ahead were performed. The performance of the price forecasts using different number of hidden layer and the iteration are described by MSE.. Table 1 shows a different value of hidden layer size used in the model will give a different value of MSE.

The smallest MSE i.e. 0.069434, is obtained with 15 hidden layer sizes with the number of iteration equal to 345. The performance of this value can be seen in the performance plot in Figure 3.

TABLE I. MEAN SQUARED ERROR VALUE

Hidden Layer	Iteration	MSE
8	124	0.076395
8	183	0.073864
9	156	0.078955
9	292	0.071115
10	61	0.076616
10	37	0.074351
11	143	0.075433
11	556	0.08045
12	37	0.07223
12	15	0.17143
13	280	0.081076
13	21	0.076097
14	202	0.080648
14	103	0.072274
15	345	0.069434
15	25	0.097882

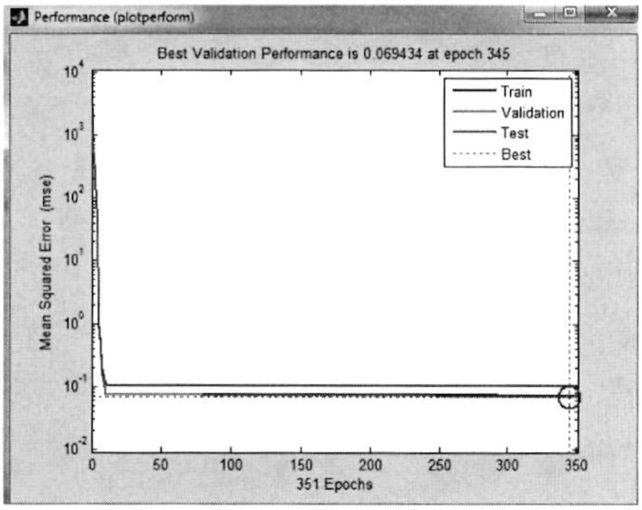

Figure 3: Best validation performance with hidden layer size.

The ANN parameters with the best MSE were use to get the value of actual output. The data was chosen randomly to get the value of actual output price. Table II shows the comparison between the two values which is the target price value and the ANN output value.

TABLE II. VALUE OF TARGET PRICE AND ANN OUTPUT

No. of data	Time	Target	ANN Output
1	100	92	91.9389
2	1000	81	58.4949
3	2000	63.5	63.6505
4	3000	71.5	71.7369
5	4000	79	79.1914
6	5000	87	85.4716
7	6000	48.5	48.0863
8	7000	84.5	84.8585
9	8000	61.5	61.7021
10	9000	81	80.6514
11	10000	84.5	84.2812
12	12000	70.5	70.5693
13	14000	57	57.0630
14	17000	53.5	53.3587

Figure 4 shows that the forecasted prices obtained from the MLP with LMBP model has a very good correlation with the actual data from the real electricity market. This concludes that the MLP with LMBP model able to forecast electricity prices with good efficiency and accuracy.

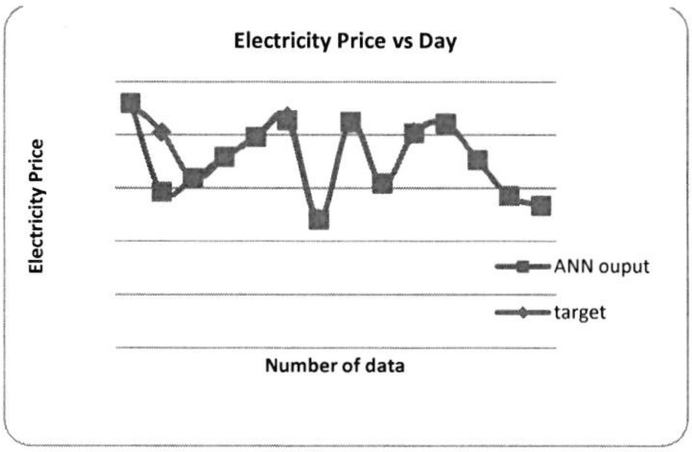

Figure 4: The different between target and ANN output value.

VI. CONCLUSION

This paper proposes a multilayered perceptron network approach combined with the Lavenberg-Marquardt Back Propagation (LMBP) technique for faster convergence to forecast every half an hour average electricity price of the Australia electricity markets. The results present a very small difference between the forcasted prices and the actual data. This shows that the MLP-LMBP technique is able to forecast electricity prices accurately. Thus this technique could be used by generating companies to forecast electricity prices accurately in estimating their investment profitability and also by the consumers to plan their consumption and buying strategy.

VII. FUTURE WORK

For the future work, it is required to obtain as much as data possible for the analysis and to better understand the effectiveness of this method to forecast the electricity price. It also required other method such as wavelet transform, General Regression Neural Network (GRNN). The result can be compare with method.

REFERENCES

[1] M. Zarezadeh, "Electricity price forecasting in Iranian electricty market applying Ariftificial Neural Network" ,in *Electric Pewer Conference 2008.EPEC 2008*

[2] J.P.S. Catalao, S.J.P.S. Mariano, V.M.F. Mendesb, L.A.F.M. Ferreira(2007). "Short-term electricity prices forecasting in a competitive market: A neural network approach",

[3] M. Stevenson, "Filtering and forecasting spot electricity prices in Austalian electricity market" School of France Economics, University of Technology of Sydney Australia, 2001.

[4] S.K Angarwal, L.M Saini, A. Kumar, "Electricity price forecasting in Ontario electricity market using Wavelet Transform in Artificial Neural Network Based Model" in *International Journal of Control, Automation, and System,* 2008.

[5] S. Haykin, "Neural Networks: a comprehensive foundation", Prentice Hall, New Jersey, 1999.

[6] M.Y Mashor, "Hybrid Multilayered Perceptron Networks" , *International Journal Of System Science, volume 31, number 6,* 2000.

[7] MATLAB Neural Network Toolbox R2010a.

[8] H. Y. Yamin, S. M. Shahidehpour, and Z. Li, "Adaptive short-term electricity price forecasting using artificial neural networks in the restructured power markets," *Electrical Power and Energy Systems*, vol. 26, pp. 571-581, 2004.

[9] D.C Sansom and T.K Saha "Neural network for forecasting electricity pool price in a deregulated electricity supply industry" Department of Computer Science and Electrical Engineering University of Queensland.

[10] P.Mandal, T.Senjyu, N.Urrrasaki, A.Yona, and A.K Srivastara. " Price forecasting Day-Ahead electricity market using recursive neural network", *Power Engineering Society General Meeting 2007.*

[11] Nian Zhang: Behera, P.K ; "Solar radiation prediction based on recurrent neural networks trained by Levenberg-Marquardt Back Propagation learning algorithm", *Innovative Smart Grid Technologies (ISGT), 2012 IEEEPES, Jan. 2012.*

[12] Matlab Central File Exchange Electricity Load forecasting for Australia Market Case Study.