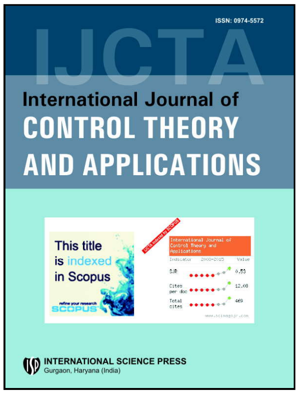

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Artificial Neural Network Based Electricity Price Forecasting Using Levenberg-Marquardt Algorithm

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Abstract: In the framework of deregulated electricity markets, generation Companies and load service entities need accurate electricity price forecasting to decide strategies to broadcast 'sell' and 'buy' bids for selling and buying of power in the power trading markets. An accurate price forecasting tool is the prime requirement in the present deregulated electricity market to maintain constant balance between demand and supply. This paper presents an artificial neural network with Levenberg-Marquardt learning algorithm for accurate electricity price forecasting with a minimum mean square error of 0.0267. The result obtained from this Levenberg-Marquardt learning algorithm is compared with one of the commonly used algorithms called momentum back propagation algorithm. It is found that converge rate of the forecasting technique increases with the application of Levenberg-Marquardt learning algorithm as it reduces 98.8 % of the epochs taken by the artificial neural network using the momentum back propagation algorithm.

Keywords: Electricity price forecasting; Artificial neural network; Levenberg–Marquardt algorithm; Mean square error.

1. INTRODUCTION

After undergoing enormous changes after 1990s the electricity industry now a day's evolving into a distributed and competitive industry in which market forces used to drive the price of electricity and so reduce the net cost through increased competition [1,5]. In the current deregulated scenario, the electricity price forecasting is become a crucial requirement for generation Companies (GENCOs) as they must set up bids for the spot market in the short term; they have to define contract policies in the medium term; and in the long term, they must have to define their expansion plans [1,6]. The electricity market equilibrium is primarily influenced by both generation and load side uncertainties. So electric price forecasting is equally important for load service entities (LSEs) too as a requirement of maintaining constant balance between demand and supply [1-2,4,28]. Electric price forecasting is necessary for the Independent Power Producers (IPPs) or market players for deciding the strategies to broadcast 'sell' and 'buy' bids for selling and buying of power in the power trading markets [7]. Electricity price forecasting has also been a major issue in power system operational planning such as feasibility studies of new generation plants, design of new systems, energy management optimization and price based unit commitment [7,9].

Deregulation brings electricity prices uncertainty, placing higher needs on forecasting therefore price forecasting tools are essential requirement for all market players for their survival under deregulated environment [2,10,11]. So the forecasting of electricity load and price has emerged as one of the major research area in electrical engineering [2, 28]. In the last few decades various techniques have been used in price forecasting, in general, hard and soft computing techniques could be used to predict electricity prices [10]. The hard computing techniques are including auto regressive integrated moving average, wavelet- auto regressive integrated moving average, and mixed-model approaches [10, 14-16]. Here an exact model of the system is needed, and the solution is usually found using algorithms that consider the physical phenomena that govern the process. These techniques can be very accurate but they require a lot of information and the computational cost is also very high [10]. The soft computing techniques are including neural networks, fuzzy neural networks, weighted nearest neighbors, adaptive wavelet neural network and hybrid intelligent system approaches [9, 10, 18-24]. Here an input–output mapping is learned from historical examples so there is no requirement for modeling the system. Hence, these techniques can be much more efficient computationally and as much accurate as the hard computing techniques, if the correct inputs are considered [10,25]. Among these methods, the artificial neural networks (ANN) are used to be most suitable tool as it can map the complex interdependencies between electricity prices, historical loads and other varying factors [1,7,10]. Various ANN learning technique using different algorithm for electric price forecasting have been proposed in the last few decades. Among them the most common training algorithm is the back propagation (BP) algorithm in which the input is passed layer through layer until the final output is calculated and it is compared to real output to find the error. The error is then propagated back to the input and adjusted the weights and biases in each of the layer. There are various standard BP learning algorithm present in the literature, among them momentum back propagation (MOBP) or steepest descent back propagation algorithm is mostly used because it minimizes the sum of square errors, but it is not efficient computationally and tends to converge very slowly. So in order to achieve a higher converge rate which is 10–100 times faster than the usual BP algorithm the Levenberg–Marquardt (LM) algorithm is used [1,12,13,26]. Apart from the high converge rate; the LM algorithm is also well suited to neural network training. The mean square error (MSE) is used to be the key performance index in the LM algorithm [26].

In this paper we have implemented ANN for electric price forecasting using LM algorithm. The ANN is employed with three different hidden layers and performances of the ANN with all three hidden layers in terms of gradient, regression and MSE are compared. The best result of the ANN with LM algorithm is compared with the result obtained from the same configured ANN using MOBP algorithm in terms of gradient, regression and MSE. The applied LM learning algorithm is presented in the next section. Results and relevant discussions are also presented in the following sections and the paper is concluded in the last section.

2. LEVENBURG-MARQUARDT ALGORITHM [26]

The LM learning algorithm is an approximation to the Newton's method. The Newton's update for optimizing a performance index F(x) is

$$X_{K+1} = X_k - A_k^{-1} g_k \tag{1}$$

Here $A_k \equiv \nabla^2 F(x)\big|_{x=x_k}$ and $g_k \equiv \nabla F(x)\big|_{x=x_k}$

Now let us assume that the F(x) is a sum of square function

$$F(x) = \sum_{i=1}^{N} v^T(x)\, v(x) \tag{2}$$

So, the j^{th} element of the gradient could be

$$\left[\nabla F(x)\right]_j = \frac{\partial F(x)}{\partial x_j} = 2\sum_{i=1}^{N} v_i(x)\frac{\partial v_i(x)}{\partial x_j} \tag{3}$$

So, the gradient can be written in matrix form

$$\nabla F(x) = 2J^T(x)v(x) \tag{4}$$

Where J(x) is a Jacobian matrix.

$$J(x) = \begin{bmatrix} \frac{\partial v_1(x)}{\partial x_1} & \frac{\partial v_1(x)}{\partial x_2} & \cdots & \frac{\partial v_1(x)}{\partial x_n} \\ \frac{\partial v_2(x)}{\partial x_1} & \frac{\partial v_2(x)}{\partial x_2} & \cdots & \frac{\partial v_2(x)}{\partial x_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial v_N(x)}{\partial x_1} & \frac{\partial v_N(x)}{\partial x_2} & \cdots & \frac{\partial v_N(x)}{\partial x_n} \end{bmatrix} \tag{5}$$

Now the Hessian matrix has to be determined. The k, j element of the Hessian matrix could be

$$\left[\nabla^2 F(x)\right]_{k,j} = \frac{\partial^2 F(x)}{\partial x_k \partial x_j} = 2\sum_{i=1}^{N}\left\{\frac{\partial v_i(x)}{\partial x_k}\frac{\partial v_i(x)}{\partial x_j} + v_i(x)\frac{\partial^2 v_i(x)}{\partial x_k \partial x_j}\right\} \tag{6}$$

Now Hessian matrix could be expressed as

$$\nabla^2 F(x) = 2J^T(x)J(x) + 2S(x) \tag{7}$$

Here

$$S(x) = \sum_{i=1}^{N} v_i(x)\nabla^2 v_i(x) \tag{8}$$

Now, if the S(x) is assumed to be small then the Hessian matrix is approximated as

$$\nabla^2 F(x) \cong 2J^T(x)J(x) \tag{9}$$

Again substituting (9) and (4) in to (1), the Gauss-Newton method can be obtained as

$$\begin{aligned} X_{k+1} &= x_k - \left[2J^T(x_k)J(x_k)\right]^{-1} 2J^T(x_k)v(x_k) \\ &= x_k - \left[J^T(x_k)J(x_k)\right]^{-1} J^T(x_k)v(x_k) \end{aligned} \tag{10}$$

From this, it is proved that the advantage of Gauss-Newton method over the standard conventional Newton's method is that the calculation of second-order derivatives does not required. The problem with the Gauss-Newton method is that the matrix $H = J^T J$ could not be invertible. This problem can be overcome by using the following modification in the approximate Hessian matrix.

$$G = H + \mu I \tag{11}$$

In order to make this matrix invertible, let the eigenvalues and eigenvectors of H are to be $\{\lambda_1, \lambda_2, ..., \lambda_n\}$ and $\{Z_1, Z_2, ..., Z_n\}$. Then

$$Gz_i = [H + \mu I]z_i = Hz_i + \mu z_i = \lambda_i z_i + \mu z_i = (\lambda_i + \mu)Z_i \tag{12}$$

So the eigenvalues of G are as same as the eigenvectors of H. The eigenvalues of G are $(\lambda_1 + \mu)$ and G could be made positive definite by increasing μ until $(\lambda_1 + \mu) > 0$ for all i. So the matrix will be invertible. This leads to LM learning algorithm.

$$X_{k+1} = X_k - \left[J^T(x_k)J(x_k) + \mu_k I\right]^{-1} J^T(x_k)v(x_k)$$

or

$$\Delta x_k = -\left[J^T(x_k)J(x_k) + \mu_k I\right]^{-1} J^T(x_k)v(x_k) \tag{13}$$

This LM algorithm has a useful feature that, as μ_k increased it approaches the steepest descent algorithm with a small learning rate

$$x_{k+1} \cong x_k - \frac{1}{\mu_k}J^T(x_k)v(x_k) = x_k - \frac{1}{2\mu_k}\nabla F(x) \tag{14}$$

The equation (14) is for large μ_k, if the μ_k decreased to zero then the algorithm becomes Gauss-Newton. The algorithm begins with $\mu_k = 0.01$. If a step did not yield a smaller value for F(x) then the step is to be used repeated with μ_k multiplied by some factor $\delta > 1$. So the F(x) should decrease as a small step is taken in the direction of steepest descent method. If a step produces a smaller value for F(x), then μ_k is to be divided by for next step. Thus the algorithm could approach Gauss-Newton to provide faster convergence and the algorithm gives a suitable compromise between the speed of the Newton's method and guaranteed convergence of the steepest descent method.

3. ARTIFICIAL NEURAL NETWORK IMPLEMENTATION

The data were obtained from the Bihar State Power Holding Company Limited, Bihar, India. The per day electricity price from the period of January, 2010 to September, 2015 has been taken as input and two weeks ahead electricity price is forecasted in the this study. LM learning algorithm has been employed to the ANN to perform the electricity price forecasting in MATLAB R2013a (License number: 724504). The ANN is executed with different number of hidden layer: 1, 2, 3 and the electricity price forecasting have been conducted. The performances of the model with all three hidden layers in terms of gradient, regression and MSE are compared and discussed in the later sections. The accuracy of the employed model is indicated by the MSE. The MSE is defined as:

$$MSE = \sum_{i=1}^{N} \frac{\frac{|A_i - F_i| \times 100}{A_i}}{N} \tag{15}$$

Here, A_i is the actual value of the load, F_i is the forecasted value of the load and N is the total number of values predicted [3].

4. RESULTS

In this study ANN with LM learning algorithm has been used for electric price forecasting. The ANN is employed with three different hidden layers (1 hidden layer, 2 hidden layers, and 3 hidden layers) and the performances of the ANN with all three hidden layers in terms of gradient, regression and MSE are compared. The MSE, gradient, regression and training performances with the different hidden layers of the employed ANN using LM learning algorithm are given in table 1. The MSEs against epoch with different hidden layers of the ANN using this algorithm are also shown in the fig. 1. Using this LM learning algorithm training state of the ANN with 1 hidden layer, 2 hidden layers, and 3 hidden layers are also shown fig. 2. From these performance analysis of the ANN using LM learning algorithm the best configured ANN in this case is evaluated and in the last part of this section best results of the ANN using LM learning algorithm is compared with the result obtained from the same configured ANN using the MOBP algorithm in terms of the gradient, regression and the MSE.

Table 1
Performances of the ANN with Different Hidden Layers Using LM Learning Algorithm

Sl. No.	*Number of hidden layers*	*MSE*	*Gradient*	*Regression*	*TP* [a]
1	1 hidden layer	0.0267	0.020927	R= 0.99999	Best at Epoch 12
2	2 hidden layers	0.0848	0.001997	R= 0.99989	Best at Epoch 64
3	3 hidden layers	0.0691	0.0017853	R= 0.99992	Best at Epoch 86

[a.] TP: Training Performance

It is clear from figure 1 and table 1 that a very low MSE is achieved in a low epoch in the modeled ANN using 1 hidden layer. It is also evident from fig. 2 that the goal for learning data set of the ANN with LM learning algorithm is achieved in 12 epochs, 64 epochs and 86 epochs with 1 hidden layer, 2 hidden layers and 3 hidden layers respectively. The gradient found decreasing with the number of hidden layers. The regression is found very high and almost same in this applied LM learning algorithm irrespective of the number of hidden layers. Increasing the number of hidden layer found increasing in the number of epoch taken by the ANN in this LM learning algorithm. Here the ANN took 64 epochs and achieved a MSE of 0.0848 and regression of R=0.99989 with 2 hidden layers. The maximum 86 epochs is taken by the ANN with 3 hidden layers where the regression of R=0.99992 and a MSE of 0.0691 is achieved. The minimum MSE of 0.0267 in the ANN using this LM learning algorithm is achieved in a minimum epoch of 12 with the best regression of R=0.99999 with 1 hidden layer.

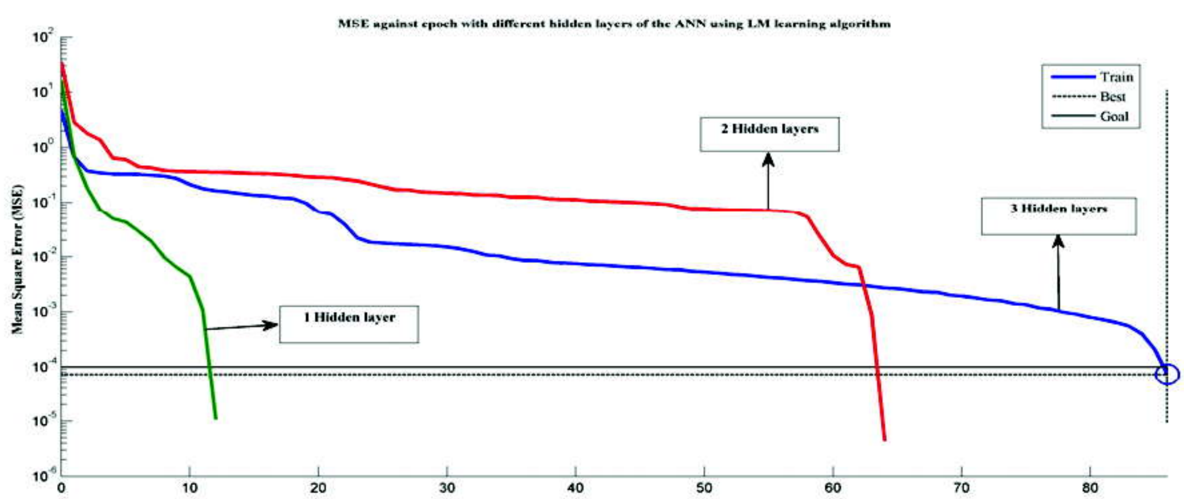

Figure 1: MSE against epoch with different hidden layers of the ANN using LM learning algorithm

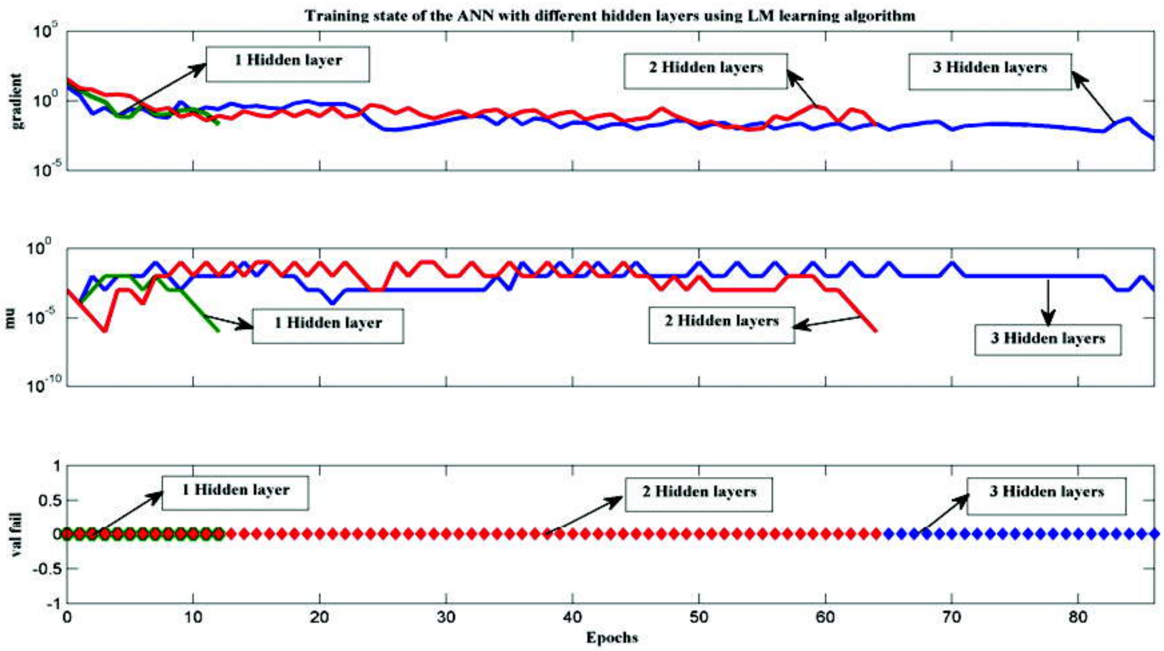

Figure 2: Training state of the ANN with different hidden layers using LM learning algorithm

So, here if the cost factor, converge rate and the complexity of the system needs to take into consideration then single hidden layers is to be considered as optimum number for the ANN using LM learning algorithm. Now this result of the ANN using LM learning algorithm is compared with the ANN using MOBP algorithm. The reduction of the MSE with respect to epoch using MOBP algorithm and LM learning algorithm are shown in the figure 3 and figure 4 respectively. A minimum MSE of 0.0267 is achieved in only 12 epoch using LM learning algorithm whereas it is not even achieved in 1000 epoch using the MOBP algorithm. After the 1000 epoch the ANN only produce a minimum MSE of 0.3260 using MOBP algorithm. So, as compared to MOBP algorithm 98.8 % epoch can be reduced by using this LM learning algorithm in the ANN with a production of more accuracy in the computing processes. This validate the efficiency of the applied LM learning algorithm in electricity price forecasting. The figure 5 and figure 6 shows the regression in MOBP algorithm and LM learning algorithm respectively. In the MOBP algorithm the regression found is R=0.88286 where as in the LM learning

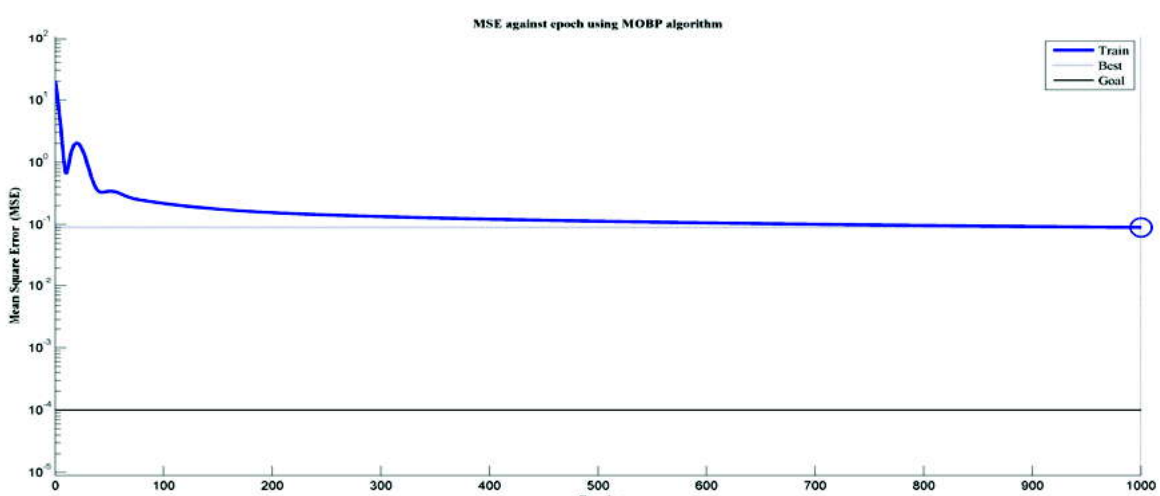

Figure 3: MSE against epoch using MOBP algorithm

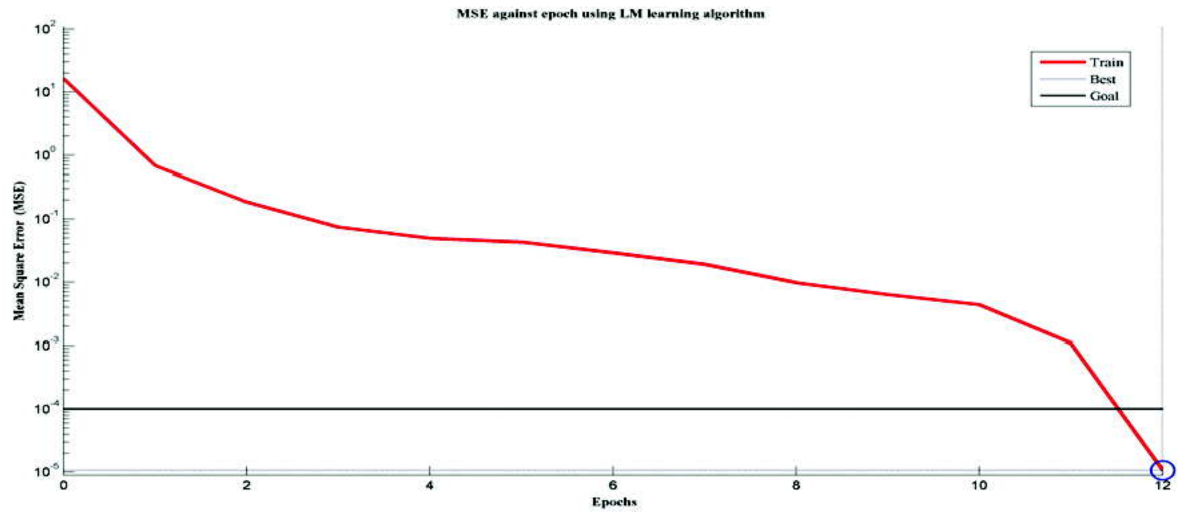

Figure 4: MSE against epoch using LM learning algorithm

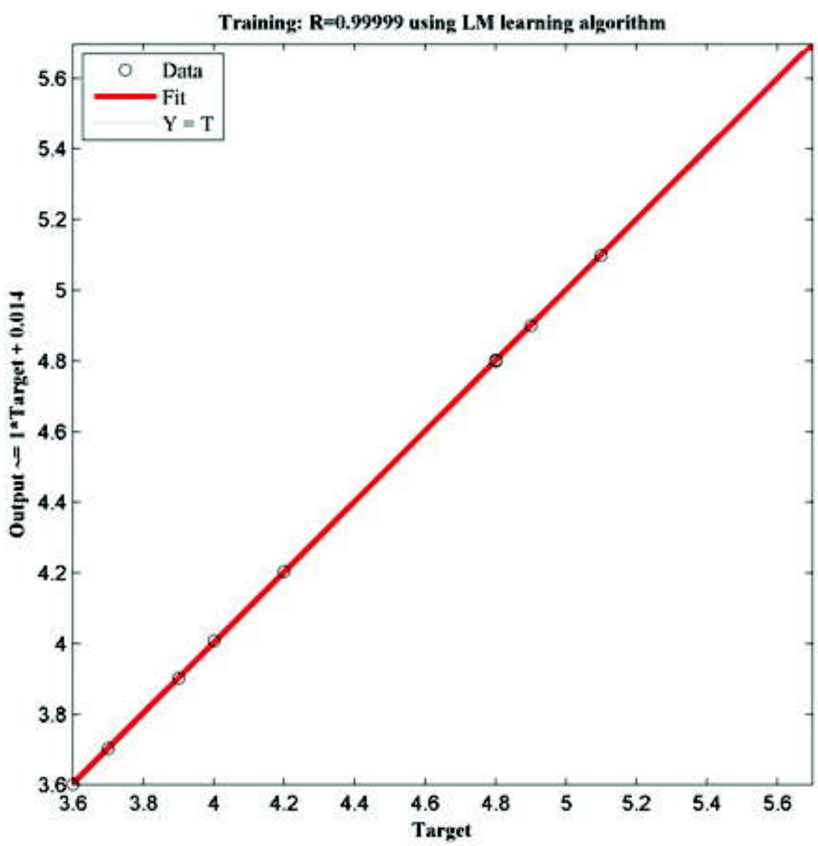

Figure 5: Regression in MOBP algorithm

algorithm the regression found is R=0.99999, which is far better than the MOBP algorithm. The decrease in the gradient with respect to epoch using the MOBP algorithm and using the LM learning algorithm are shown in figure 7 and figure 8 respectively. A minimum gradient of 0.020927 is achieved in only 12 epoch using LM learning algorithm and using the MOBP algorithm the ANN produces a minimum gradient 0.054047 after the 1000 epochs.

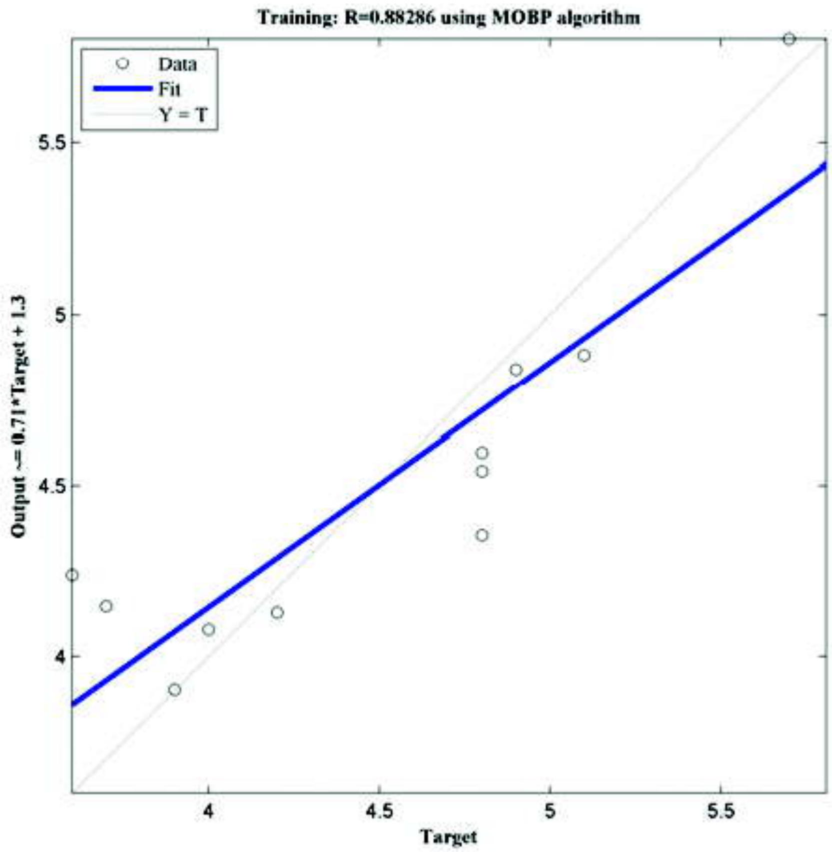

Figure 6: Regression in LM learning algorithm

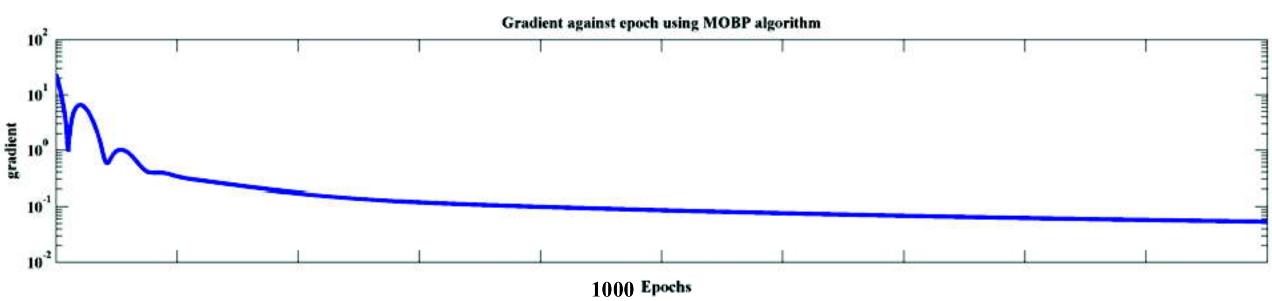

Figure 7: Gradient against epoch using MOBP algorithm

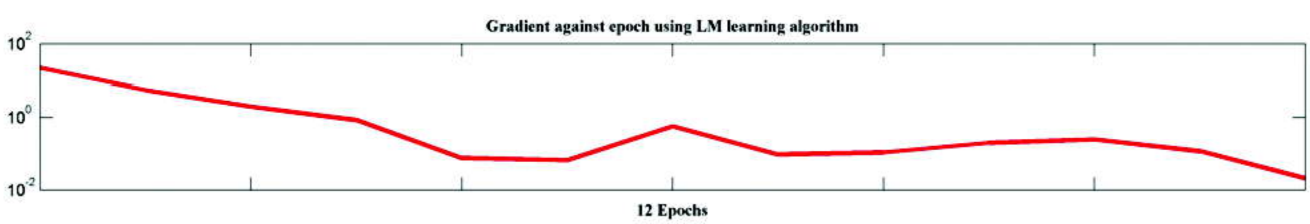

Figure 8: Gradient against epoch using LM learning algorithm

So over all it is found that the ANN using LM learning algorithm is not only achieved a high accuracy as compared to MOBP algorithm but it also reduces 98.8 % of the epochs taken by the ANN using the MOBP algorithm. This reflects that a significant improvement in converge rate of the ANN can be achieved using this LM learning algorithm

5. CONCLUSIONS

With the deregulation of electricity prices, a tough competition was introduced into the markets which lead to the rise in bidding and tendering process. It is evident in the literature that even if 1% increases in the mean absolute error of forecasting it caused millions of overpayment for operating costs [27]. Accurate electricity price forecast can help to build up cost effective risk management plans for each participating stakeholders in the present electricity market. The GENCOs and LSEs as main market participating stakeholders can be able to reduce their risks and maximize their profits further under the deregulated environment with the help of accurate price forecasting technique [27]. The slow converge rate in a forecasting technique is basically due to are two main reasons, the first one is that its step sizes should be adequate to the gradient. Logically a small step sizes should be taken where the gradient is steep so as not to rattle out of the required minima because of the oscillation. So, if the step size is a constant, it needs to be chosen small enough. Then, in the place where the gradient is gentle, the training process could be very slow. The second reason is that the curvature of the error surface may not be the same in all the directions, such as the Rosen brock function. In this study ANN with different hidden layers using LM learning algorithm is deployed for electricity price forecasting and a minimum MSE of 0.0267 in only 12 epochs.

In this study the results of the ANN using LM learning algorithm is compared with the ANN using MOBP algorithm. It is found that the ANN using LM learning algorithm is not only achieved a high accuracy as compared to MOBP algorithm but it also takes only 1.2% of the epochs taken by the MOBP algorithm to achieved that high accuracy. This reflects that a significant improvement in converge rate of the ANN can be achieved using this LM learning algorithm. Overall it is found that if we have to consider the cost factor, converge rate and the complexity of the system the ANN using LM learning algorithm is very effective and accurate for electricity price forecasting.

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