

Wind Speed Prediction using Levenberg-Marquardt Back Propagation Neural Network

Arpita Yadav*, Kapil Sahu**

M. Tech Student, Sanghavi Institute of Management & Science, RGTU, Indore, Madhya Pradesh, India*

Assistant Professor, Sanghavi Institute of Management & Science, RGTU, Madhya Pradesh, India**

arpitayadav11@gmail.com*, kapil.sahu@sims-indore.com**

Abstract

Several fields of science and technology are adopting Artificial Intelligence as an effective tool in complex and overwhelmingly large data analysis. One such field is prediction problems where statistical prediction prove to be too complex to handle or are not highly accurate. In this paper, we devise a model for wind speed prediction based on the use of Artificial Neural Networks (ANN). Wind speed prediction plays an extremely critical role in generation of renewable generation of power and reducing the dependence on fossil fuels. Here the Levenberg-Marquardt algorithm is used which employs back propagation and hence attains lesser time of convergence and overall average error. The performance metrics chosen are Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

Keywords:-

Artificial Neural Network (ANN), Back Propagation, Levenberg-Marquardt Algorithm, Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

I.Introduction

Neural Networks have started affecting numerous areas of science and technology where human intervention has not been competent enough to process data and predict outcomes with high accuracy or within constrained time limits or both. One such area has been the prediction of wind speed which is a crucial factor in deciding or predicting the amount of wind power that can be generated by wind power stations. Prediction of wind power is challenging yet instrumental at the same time. This is because wind speed changes continuously with time due various natural parameters, leading to uncertainty in availability of amount of wind power that can be generated using it. If we integrate this wind power system directly to the existing power system, it will lead to a number of issues in terms of attaining good power quality, power system stability, frequency of generated power, rated terminal voltage, optimizing spinning reserve capacity, uncertainty in wind power in to unit commitment and reducing power dispatching issues in the grid power balance, and, then we have planning and economic problems including, economic load dispatching. Therefore present researchers are focussing on accurate prediction models using artificial neural networks.

II. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are computing systems or technique that are inspired by the learning architecture of human brain to discover the relations between the input and target variables of a system. Human brain consists of a large set of structural constituents, known as neurons, which form a well-connected network to respond to an input signal to perform all its computations / calculations in a certain complex task such as image and voice recognition task and they do this with incredible speed and accuracy. Neurons are simple processing units, which has the ability to store experimental data and which work as parallelly distributed processor. The speed of human brain is several thousand time faster than traditional computer because in brain unlike traditional computer as whole information is not passed from neuron to neuron they are rather encoded in the neuron network. This is reason why neural network is also named as connectionism. The mathematical model of artificial neural networks can be understood using the following figure

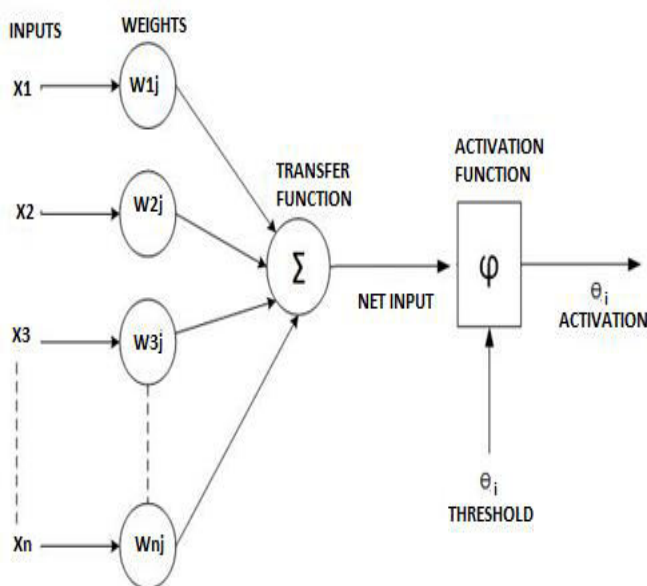


Fig.1 Mathematical model of a neural network

The relation between the inputs, weights, bias and output of an artificial neural network can be given by:

$$\sum_{i=1}^n X_i W_i + \Theta$$

Where X_i represents the signals arriving through various paths, W_i represents the weight corresponding to the various paths and Θ is the bias. The above diagram exhibits the derived mathematical model of the neural network. It can be seen that various signals traversing different paths have been assigned names X and each path has been assigned a weight W . The signal traversing a particular path gets multiplied by a corresponding weight W and finally the overall summation of the signals multiplied by the corresponding path weights reaches the neuron which reacts to it according to the bias Θ . Finally it's the bias that decides the activation function that is responsible for the decision taken upon by the neural network.

The soul of the above model lies in the fact that the system so developed tries to mimic the working of human brain in terms of the following:

- 1) It works in a complex parallel computation manner
- 2) High speed of performance due to the parallel architecture.
- 3) It learning and adapt according to the modified link weights.

Work on ANN has been inspired right from its inception by the acknowledgement that the human brain computes in an entirely different way from the conventional digital computer.

III. Back Propagation in ANN

Back propagation in artificial neural networks is based on the fact that the feeding back the errors of each iteration can reduce the errors in much lesser time and result in a steep descent of error. depicts the working of a backpropagation network in the form of flow chart. From the chart, it is clear that after the initiation of training initial values of weights are to be assumed. Then input data is processed in sets. After all sets of input data are processed, then error is calculated. If the error is within tolerant range, then network weights are saved and training is ended. If the error is not in the range of tolerance range than check for number of epochs. If epochs exceeded maximum value, then show failure message and end training else retrain network until required results are obtained.

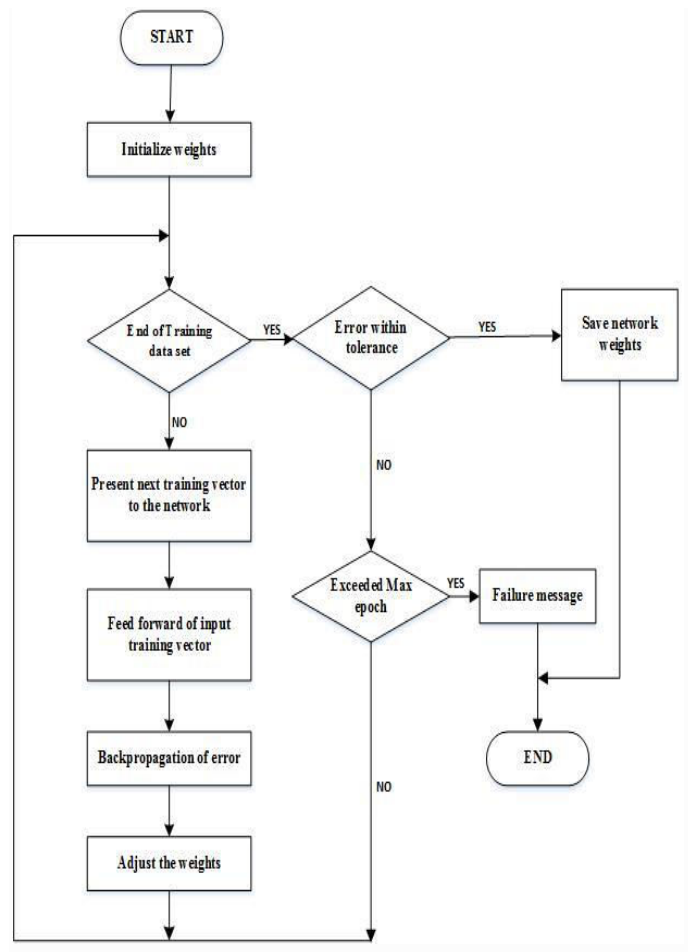


Fig.2 Flowchart of Back Propagation

IV. The Levenberg–Marquardt (LM) Algorithm

Reducing error function is the main reason for using this algorithm. Levenberg-Marquardt algorithm is a very efficient technique for minimizing a nonlinear function [11] [12]. The algorithm contains many different variables like in present study we have output data (wind speed), weight in between neurons and error function, which govern the efficiency and success rate of network.

Levenberg-Marquardt algorithm is fast and has stable convergence [3]. This algorithm was developed to approach 2nd order training speed w/o calculating the Hessian matrix. When the performance function is in the form of a sum of squares, then the Hessian matrix and the gradient can be approached and calculated as,

$$H = J_k^T J_k$$

$$g = J_k^T e$$

Where J_k is the Jacobian matrix for kth input set, which contains first order derivatives of the network errors with respect to the weights and biases, e is representing network errors. Hence computing Jacobian matrix through a backpropagation technique that is far less complex than computing the Hessian matrix [4].

The Levenberg –Marquardt algorithm is actually a blend of the steepest descent method and the Gauss–Newton algorithm. The following is the relation for LM algorithm computation,

$$W_{k+1} = W_k - [J_k^T J_k + \mu I]^{-1} J_k^T e_k$$

Where, I is the identity matrix, W_k is the current weight, W_{k+1} is the next weight and e_k is the last error, μ is combination coefficient [4] [5].

It tries to combine the advantages of both the methods hence it inherits the speed of the Gauss–Newton method and the stability of the steepest descent method. The combination coefficient μ is multiplied by some factor (β) whenever a step would result in an increase in error e_{k+1} and when a step reduces e_{k+1} , μ is divided by β . In this study, we used $\beta = 10$. When μ is large the algorithm converts to steepest descent while for small μ the algorithm converts to Gauss-Newton.

V. Performance Metrics

Since errors can be both negative and positive in polarity, therefore its immaterial to consider errors with signs which may lead to cancellation and hence inaccurate evaluation of errors. Therefore we consider mean square error and mean absolute percentage errors for evaluation. Mean Square Error is defined as:

Mean Square Error can be defined as:

$$MSE = [\sum_{i=1}^n (X - X')^2] / n$$

Mean Absolute Error (MAE) is defined as:

$$MAE = [\sum_{i=1}^n (X - X') / X'] / n$$

Mean Absolute Percentage Error is defined as:

$$MAPE = [\sum_{i=1}^n (X - X') / X'] / n \times 100\%$$

Here, X is the predicted value and X' is the actual value and n is the number of samples.

VI. Results and Discussions

The results obtained from the proposed work are discussed here.

Data is collected for the weather station of “The Electric Reliability Council of Texas (ERCOT)” located at Texas, USA.

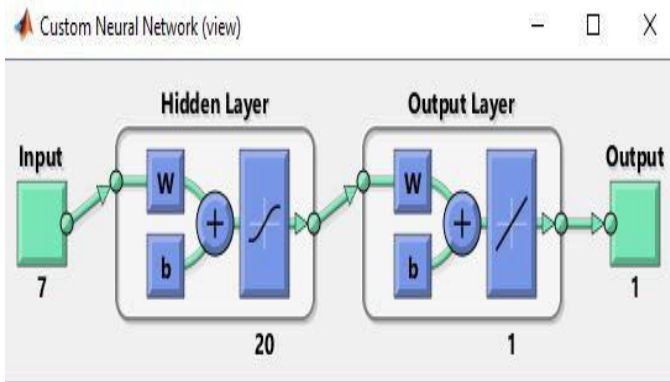


Fig.3 Designed Neural Network

Fig.4 Neural Network During Training

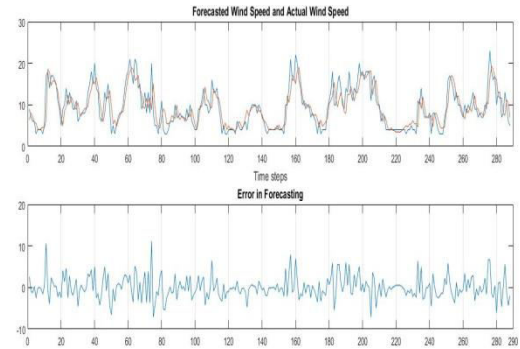


Fig.5 Predicted and Actual Values

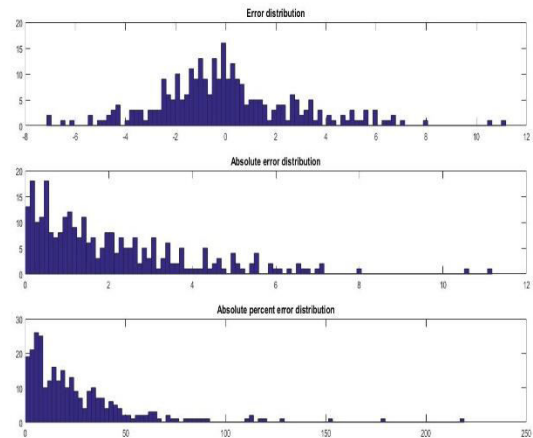


Fig.6 Error Histogram

The screenshot shows the 'Neural Network Training (nntraintool)' interface. It includes a diagram of the neural network (7 input, 20 hidden, 1 output nodes). Below the diagram, the 'Algorithms' section lists: Data Division: Random (dividerand), Training: Levenberg-Marquardt (trainlm), Performance: Mean Squared Error (mse), and Calculations: MEX. The 'Progress' section shows: Epoch: 0 / 35 iterations / 1000, Time: 0:00:05, Performance: 5.85e+03 / 6.63 / 0.00, Gradient: 1.03e+04 / 4.02 / 1.00e-07, Mu: 0.00100 / 0.00100 / 1.00e+10, and Validation Checks: 0 / 6 / 6. The 'Plots' section has buttons for Performance (plotperform), Training State (plottrainstate), Fit (plotfit), and Regression (plotregression). A 'Plot Interval' is set to 1 epochs. At the bottom, there is a green checkmark and the text 'Opening Regression Plot', along with 'Stop Training' and 'Cancel' buttons.

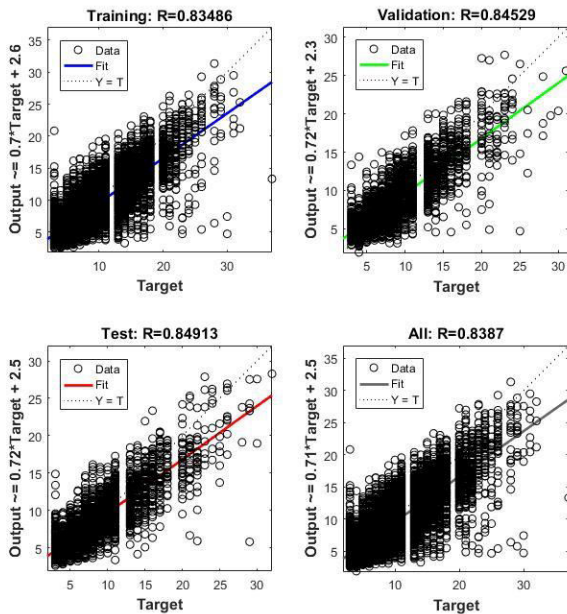


Fig.7 Regression Analysis

VII. Conclusion:

From the previous discussions, it can be concluded that the proposed technique efficiently employs the Levenberg-Marquardt (LM) algorithm to predict wind speed value. The back propagation mechanism attains reduction in error in minimalistic epochs and predicts with an average MAPE of 14% (approx.) The MAE attained is 2.02km/hr and the MSE obtained is 6.391. The regression curve also augments the obtained results. As a standard convention, 70% data is utilized for training, 15% is utilized for testing and rest 15% is utilized for validation. Finally the overall regression is also analysed.

References

- [1] Tarlochan Kaur, Sanjay Kumar, Ravi Segal, "Application of Artificial Neural Network for Short Term Wind Speed Forecasting". 2016 Biennial International Conference on Power and Energy Systems: Towards Sustainable Energy (PESTSE), 2016.
- [2] Rohan Singh, KishanBhushan Sahay, ShubhankarAseet Srivastava, "Short-Term Wind Speed Forecasting of Oak Park

Weather Station by Using Different ANN Algorithms", *Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, IEEE, 2015

[3] P. Ramasamy, S.S. Chandel, Amit Kumar Yadav, "Wind speed prediction in the mountainous region of India using an artificial neural network model", *Renewable Energy* 80, Elsevier, pp. 338-347, 2015.

[4] Anirudh S. Shekhawat, "Wind Power Forecasting using Artificial Neural Networks". *International Journal of Engineering Research & Technology*, Volume 3, 2014.

[5] KannaBhaskar and S.N. Singh, "AWNN - Assisted Wind Power Forecasting using Feed-Forward Neural Network". *IEEE Transactions on Sustainable Energy*, Volume 3, pp. 306-315, 2012.

[6] UlasEminoglu, "A New Model for Output Power Calculation of Variable-Speed Wind Turbine Systems". *Intl. Conference on Optimization of Electrical & Electronic Equipment (OPTIM)*, pp. 141 – 146, 2015.

[7] Ministry of New and Renewable energy, Government of India, "Annual Report 2015-16", <http://mnre.gov.in>, 2016.

[8] Renewables 2015 Global Status Report, 2015.

[9] Global Wind Report, Annual Market Update, by Global Wind Energy Council (GWEC), 2015.

[10] Wen-Yeou Chang, "A Literature Review of Wind Forecasting Methods", *Journal of Power and Energy Engineering*, pp. 161-168, 2014.

[11] X. Zhao, S.X. Wang, and T. Li, "Review of Evaluation Criteria and Main Methods of Wind Power Forecasting". *Energy Procedia*, Volume 12, pp. 761-769, 2011.

[12] S.S. Somam, H. Zareipour, O. Malik, and P. Mandal, "A Review of Wind Power and Wind Speed Forecasting Methods with Different Time Horizons". *North American Power Symposium*, Arlington, pp. 26-28, 2010.