

Day-Ahead Wind Energy Forecasting Using Feed Forward Neural Network

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Abstract Wind energy injection is intermittent in nature and is one of the most affecting factors in maintaining deviation limits. This paper proposes an artificial neural network-based day-ahead short-term wind energy forecasting using feed forward neural network. Different training algorithms were studied, and mean absolute percentage error of each has been calculated. The results show that Levenberg–Marquardt back propagation provides a better accuracy than other training algorithms.

Keywords Wind energy forecasting · ANN · Feed forward neural network
MATLAB

1 Introduction

Wind energy is one of the most promising sources for electricity generation. The utilization of wind energy has become increasingly popular due to its free availability and environmental friendly. Renewable energy sources are growing remarkably since the last two decades among which wind energy is the fastest growing source of energy. Also renewable energy sources are considered as best alternate source for conventional energy.

The factor to be considered in wind energy is its reliability as wind is uncertain. Wind speed is the most difficult weather parameter to forecast. The intermittent behavior of wind speed causes difficulty in forecasting wind generation [1]. To deal with such challenging nature of wind generation, also increasing wind energy

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penetration and to overcome its impact, a realistic forecast is vital and prerequisite for reliable operation. Moreover, real-time wind generation and operational availability of wind mills are also crucial part for more accurate wind energy forecasting. For better operation of power system, a good forecasting has to be made by transmission system operator [2]. A physical approach for wind forecasting technique uses wind pattern along with wind turbine power curve for forecasting output power of wind. Mathematical model can be used by forecaster based on physical approach [3]. Physical models can be used which considers terrain, obstacles, temperature, and pressure to estimate wind power generation.

Currently, various methodologies have been developed to predict the wind power and wind speed. Methodology like time series modeling such as ARMA and ARIMA provide a good forecasting. To forecast for short- and medium-term interval of time artificial neural network (ANN) has proved very useful. ANN provides accurate result with minimum errors.

ANN is inspired from biological nervous system. ANN is composed of highly interconnected processing elements working in union to solve specific problems. ANN is used in specific applications such as pattern recognition and data classification through learning process. Thus, ANN is an information processing system. In this information processing system, the elements called neurons which process the information. ANN consists of many nodes and connecting synapses. Nodes operate in parallel and communicate with each other through connecting synapses [4]. The signals are transmitted by connected links. This links possess an associated weight, which are multiplied with incoming signal. The output signal is obtained by applying activation to the net input. In recent years, ANN is used for forecasting and for solving complex problems. The advantage of ANN includes modeling of both linear and nonlinear systems by means of learning with training data [5].

Transmission system operator currently uses day-ahead wind energy forecast to predict the power to be delivered for each time blocks of the next day. This forecast ensembles day-ahead commitments of generation resources [6]. By using day-ahead forecasting, it helps the system operator to meet with the demand of power.

Due to variability and uncertainty in wind power generation, it becomes difficult for power system operator to maintain the balance between generation and demand. A reliable prediction of day-ahead forecast helps the power system operator to make good decision in critical situation and also to maintain grid stability of the system.

Development of wind generation has increased in state of Gujarat. It has 52 pooling station for wind generation. Wind farms are located at the coastal regions, and also offshore wind projects are being developed. As wind energy injection is intermittent in nature, an accurate forecasting should be made.

Section 2 describes wind generation characteristics, wind pattern of one region. Section 3 presents the methodology implemented in wind energy forecasting. Section 4 shows the forecast values and is compared with actual values and Sect. 5 provides conclusion.

2 Wind Generation Characteristics

Gujarat has a good wind potential. The wind installed capacity of Gujarat is 4086 MW as on July 2016 and currently ranks 3rd in installed capacity across India. Various wind farms which is located at coastline of Gujarat produce large amount of wind power. So it gives challenge to system operator to meet between generation and demand. The power obtained from renewable energy sources should be used instantly at the time it is produced. Initially, it is needed to understand the behavior of wind generation before developing wind energy forecasting methodology. Annual-, month-, day-wise scenarios of actual wind generation as well as seasonal scenario need to be observed to identify the behavior of wind generation. Wind generation is also affected by heavy rain. Sudden rise and fall of wind may lead to wide variation in wind generation.

Seasonal variation of Gujarat also affects wind generation. Gujarat has primarily three seasons: winter, from November to March; summer, from March to June; and monsoon, from July to September. As Gujarat has a long coast line, sea breezes and it influences the wind characteristics in this region.

Wind power output depends on weather parameters such as wind speed, temperature, pressure, humidity, and air density [7]. The wind power equation is given by

$$P = 0.5 \rho A v^3 \quad (1)$$

where ρ is air density in kg/m^3 , A is the swept area of turbine blade, v is the wind speed in m/s , and P is the power in W . Weather parameters play important role in wind energy forecasting model. Wind speed is one of the major parameters to be considered as a slight variation in wind speed causes change in wind power. Wind power curve depends on three key points: cut-in speed, speed below which turbine not produce power; rated speed, speed at which rated power of turbine is produced; and cutoff speed, defined as the speed beyond which the turbine is not allowed to deliver power. The production of wind power depends humidity, and the relative humidity of air depends on amount of water vapor in air, which determines air density. Temperature and pressure directly influence wind power as they are related to air density. Also geographic location also affects wind generation, if wind power plant are installed where the availability of wind speed, temperature, pressure, humidity is not available at desired range wind power plant will not give a better output.

Wind generation trend remains same during particular season, but it does not mean that the same pattern will be followed the entire season. Wind generation may have change of pattern on hourly basis.

Figure 1 shows the wind pattern of one region of Jamnagar, Gujarat. From the figure, a wide variability in wind energy of three days can be seen.

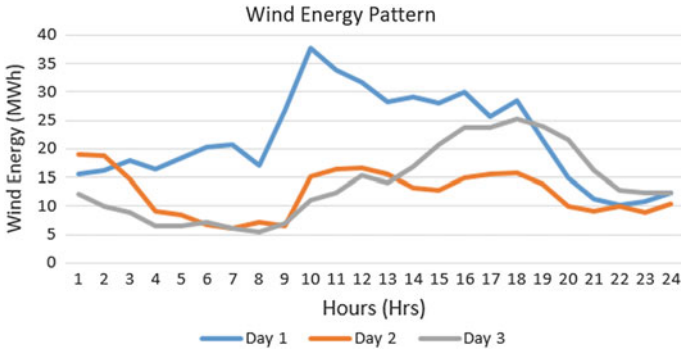
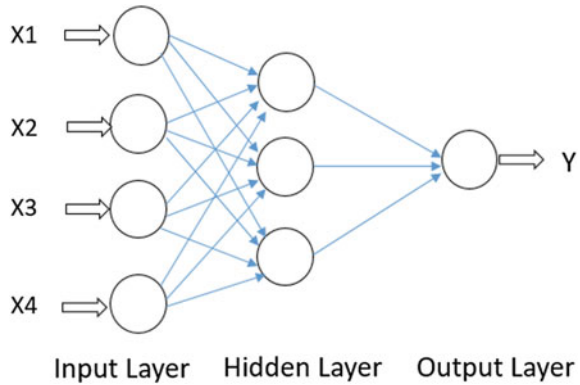


Fig. 1 Wind energy pattern of three days

Fig. 2 Three-layer feed forward neural network



Wind energy pattern also changes from one region to another as it is related to wind speed. Due to this type of variability, it becomes difficult to manage grid operations.

3 Methodology Implemented

ANN-based methods are good choice to study forecasting problems. ANN has ability to learn from the past data which is very useful for future prediction. Various ANN techniques like feed forward neural network (FFN), radial basis function neural network (RBFN), and Elman recurrent neural network can be used for forecasting.

In this paper, wind energy forecasting is done using feed forward neural network. Feed forward neural network is formed by interconnection of several layers. A three-layered feed forward neural network is shown in Fig. 2.

FFN often has more than one hidden layers followed by output layer. Multiple layers allow network to learn nonlinear relationship between input and output.

Analysis was done on one of pooling stations of Gujarat. The wind farm of WWIL is considered for forecasting. The wind farm has installed capacity of 319 MW. It is connected to Tebhda substation. Wind power and weather data were provided by SLDC GETCO. Location of wind farm is at Jamnagar, so hourly weather dataset was provided.

Various weather data which affect the wind power are to be considered. Weather dataset is considered as the input data, and generated wind power is given as Target data. After specifying, the inputs and target data were normalized to a range of [-1, 1]. Normalization is to bring data in a uniform scale. It is helpful for better training performance. The equation of normalization used is as below:

$$pn = \min pn + (\max pn - \min pn) \times (p - \min p) / (\max p - \min p)$$

After normalization, feed forward neural network has to be created by specifying number of inputs and target data and hidden layer. Various parameters such as training algorithm, learning rate, number of epochs are to be specified. The neural network is then trained by using different types of training algorithm.

Short-term wind energy forecasting procedure is as below:

Weather parameters are comprised of wind speed, temperature, pressure, humidity. The parameters selected as weather data are related with wind power. From Eq. (1), wind power is related with cube of wind speed and is also related with air density. Air density is related with pressure and temperature, so all these parameters are used in weather data. Wind power data are considered for the investigation. Hourly dataset of months of July and August was used for detail study. A multilayered feed forward neural network consisting of input layer, hidden layer, and output layer is used. The number of neurons in hidden layer is selected on a trial-and-error basis. Two types of training algorithms are used and compared. The neural network is trained on hourly dataset of months of July and August, and prediction was made for day ahead. The network is trained using Levenberg–Marquardt algorithm. The LM algorithm tries to reduce mean square error, i.e., minimizing the performance function in form of sum of squares.

$$MSE = \frac{1}{n} \sum_{q=1}^n (Tq - Aq) \tag{2}$$

Tq = target value

Aq = actual value

The second algorithm used for training the network is gradient descent with momentum back propagation. Gradient descent with momentum depends on two parameters: 1. learning rate which is similar to simple gradient descent and 2. the momentum constant in which the value is to be set between 0 and 1.

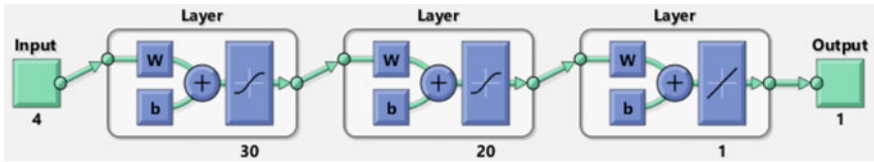


Fig. 3 Developed network

Another algorithm is gradient descent back propagation. The weights and biases are updated in the direction of negative gradient of performance function. The learning rate is multiplied times the negative of the gradient to determine the changes to the weights and biases [8].

The network is ready for training; during the training, weights and bias are adjusted. After training, the neural network was tested on new dataset, and error has been computed.

The network is developed and trained using MATLAB R2015a. Figure 3 shows the feed forward neural network consisting of four input parameters followed by two hidden layers, and one output layer has been created. First hidden layer consists of 30 neurons, and second hidden layer consists of 20 neurons. The output layer consists of single neuron. The transfer function of first layer and second layer in ‘tansig’ i.e. hyperbolic tansigmoid. It is selected as it gives high convergence. The output layer has transfer function ‘purelin.’

Error analysis can be computed by mean absolute percentage error (MAPE) and is given by

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{Z_{ai} - Z_{pi}}{Z_{ai}} \tag{3}$$

where

Z_{ai} is actual value

Z_{pi} is forecasted value

n is number of periods

4 Result and Discussion

Feed forward neural network has been developed, network was first trained on hourly data of two months, and prediction was made for day ahead. Three types of training algorithm were considered: LM back propagation, gradient descent with momentum back propagation, and gradient descent back propagation. MAPE for all the three training algorithms is obtained.

1. Training algorithm: LM back propagation

Levenberg–Marquardt back propagation was implemented on the developed neural network. The learning rate was set at 0.01. Parameters were divided into random division consisting of training samples used for analysis is 70%, validation and testing of network at 15% each (Fig. 4).

The best validation performance is at 0.033959 at epochs 5 as LM back propagation is fastest and gives a stable convergence.

Figure 5 depicts the regression analysis on the test data. Regression analysis clarifies in terms of training, testing, and validation of the developed model. It can also be seen from Fig. 5 test and validation have a value greater than 0.96.

Also the actual and predicted plots of wind power generation using feed forward neural network trained with LM back propagation on hourly basis are shown in Fig. 6. MAPE with LM back propagation is 13.08%.

2. Training algorithm: gradient descent with momentum back propagation

In this algorithm, learning rate was same and momentum constant of the parameter was considered as 0.8. Data division was random as above case. The best validation performance was obtained at 0.0035504 at epoch 286 (Fig. 7).

Regression analysis was also done as shown in Fig. 8. MAPE obtained is 28.75%. The validation of the trained algorithm obtained is $R = 0.92479$, and testing result is $R = 0.96434$.

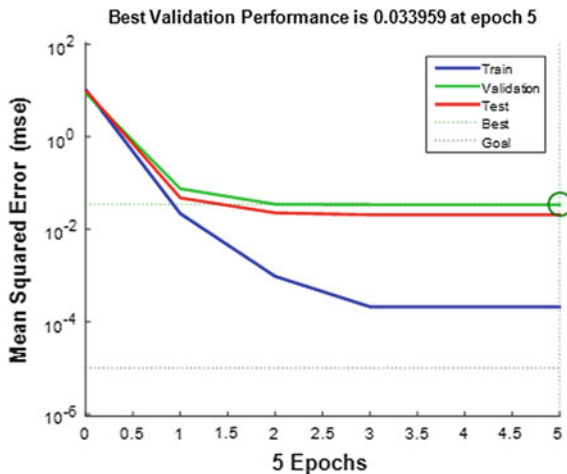


Fig. 4 Performance plot

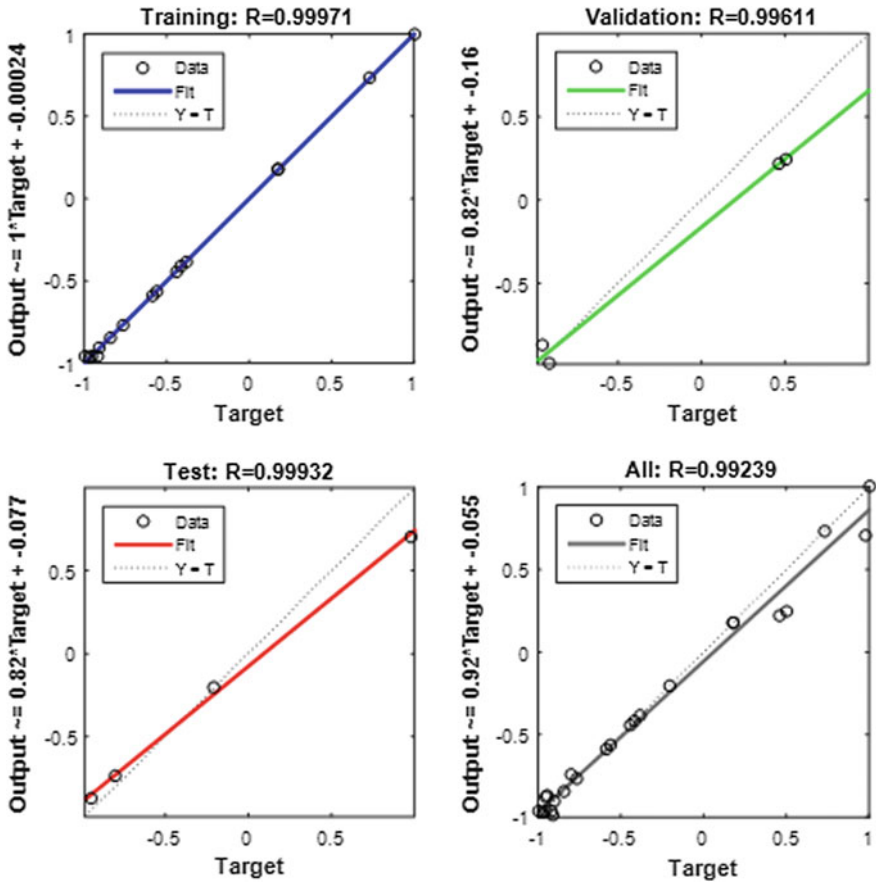


Fig. 5 ANN regression analysis

Figure 9 shows actual and predicted outputs of wind power generation using GDM back propagation. MAPE obtained is 28.75%.

3. Training algorithm: gradient descent back propagation

Gradient descent back propagation combines learning rate with momentum training. The momentum constant was taken as 0.8. The training algorithm took 115 iterations. Data division was random, i.e., 70% data were used for training, rest 15% for testing and validation. The learning rate was same as previous case. In Fig. 10, performance plot best validation is obtained at 0.07787 at epoch 98.

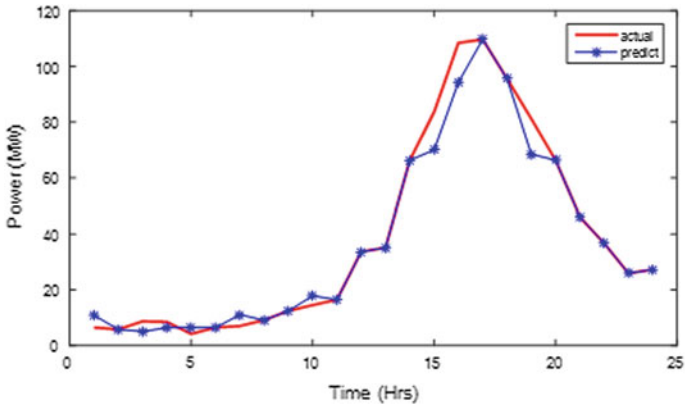
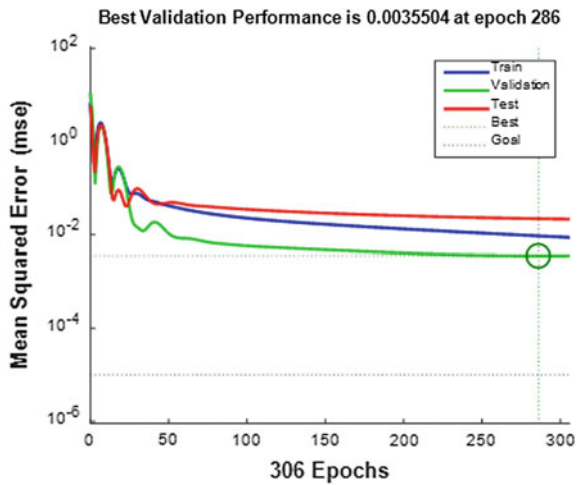


Fig. 6 Comparison of actual and predicted wind power using LM back propagation

Fig. 7 Performance plot



Regression plot is shown in Fig. 11. The testing and validation value for regression analysis is more than 0.95.

Figure 12 depicts actual and predicted results of wind power generation with GD back propagation. MAPE of above algorithm is 18.89%.

Table 1 indicates the comparison of various training algorithm.

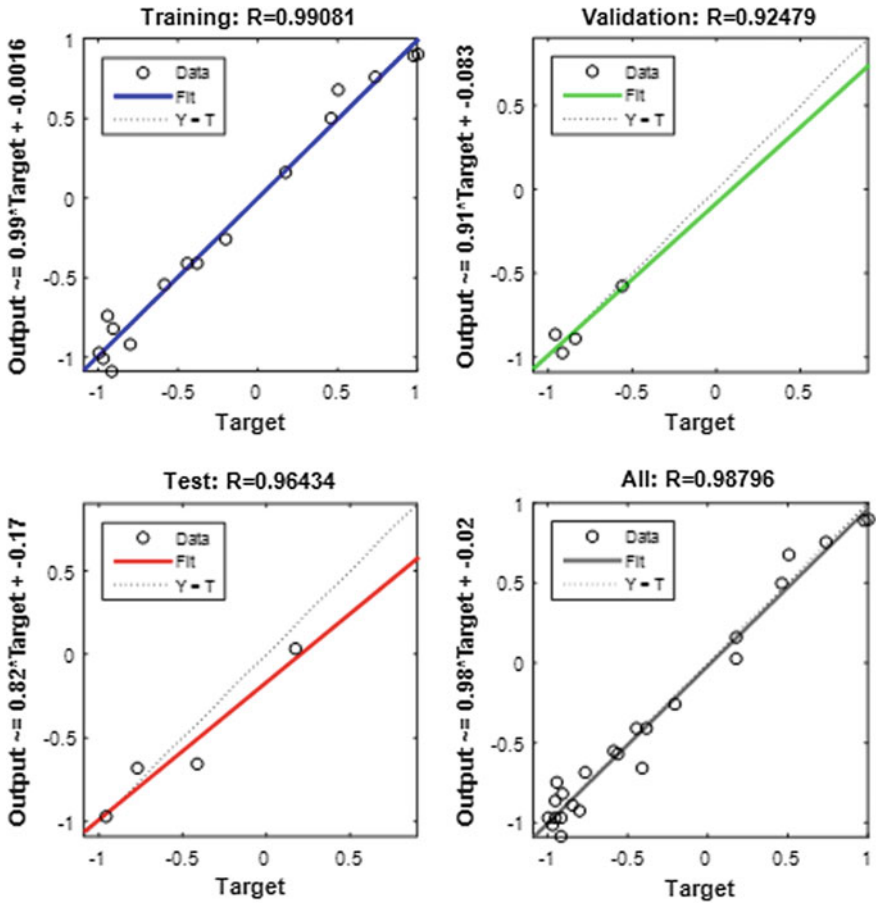


Fig. 8 ANN regression analysis

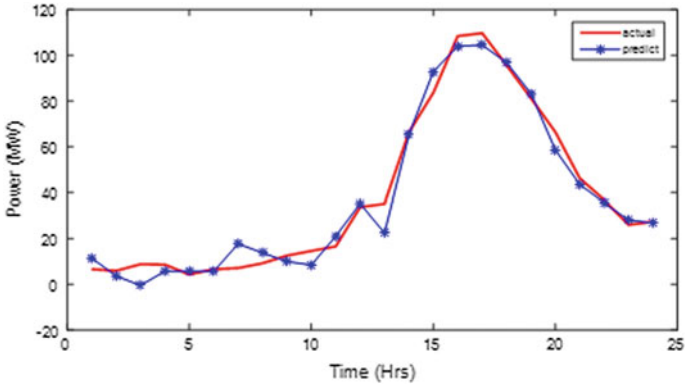


Fig. 9 Comparison of actual and predicted wind power using gradient descent with momentum back propagation

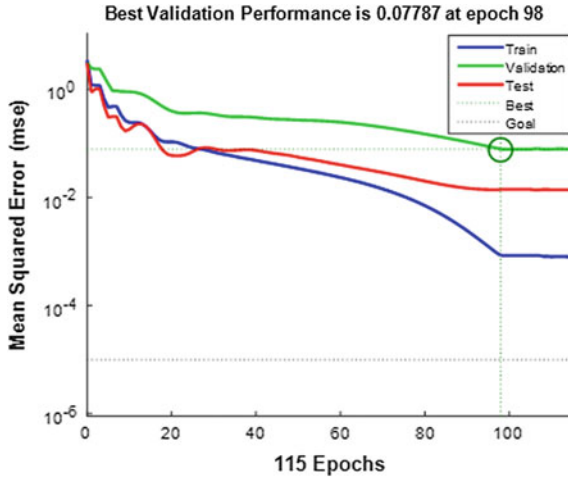


Fig. 10 Performance plot

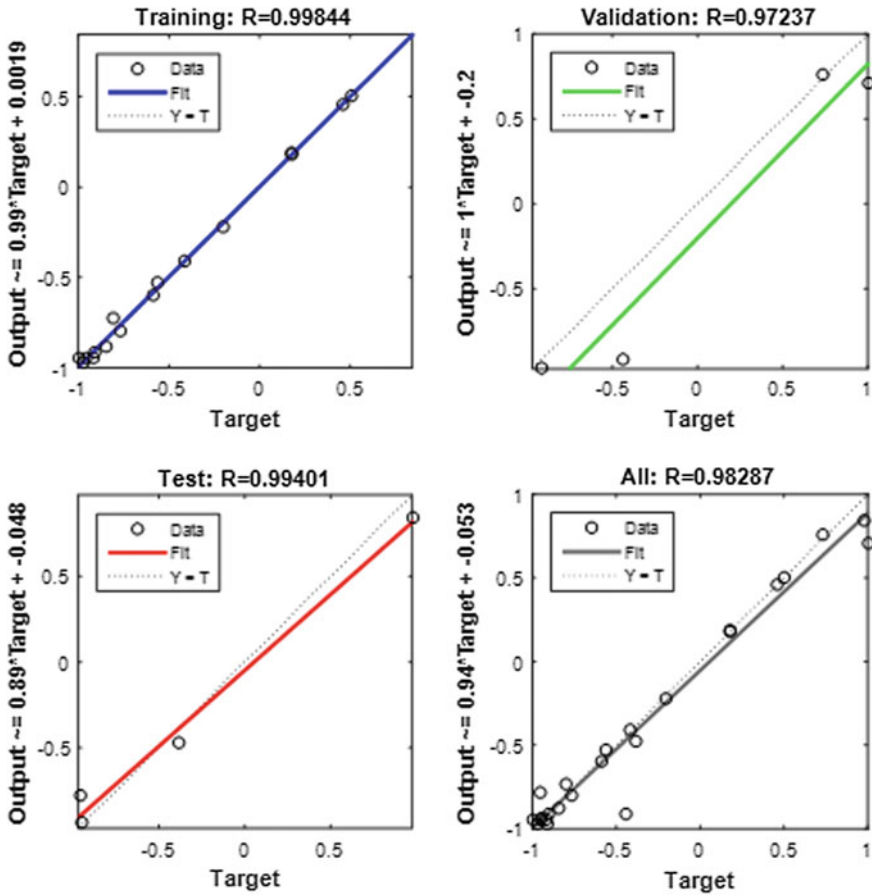


Fig. 11 Regression analysis

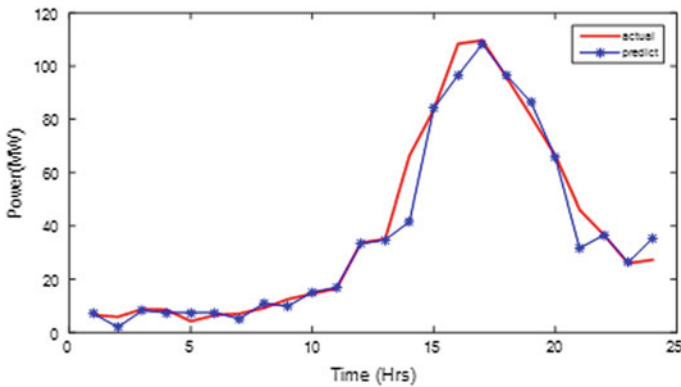


Fig. 12 Comparison of actual and predicted wind power using gradient descent back propagation

Table 1 Comparison of different training algorithm

Training algorithm	MAPE (%)
LM back propagation	13.08
Gradient descent back propagation	18.89
Gradient descent with momentum back propagation	28.75

5 Conclusion

The developed feed forward neural network is capable for providing day-ahead wind energy forecasting. The network is able to forecast on hourly wind power. From Table 1, it is seen that LM back propagation provides accurate forecasting with least deviation between actual and forecasted value. The developed model gives a desirable accuracy. The predicted results show that ANN is an excellent tool, and by using different algorithm, it can provide a better forecasting.

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References

1. Ahmed Ouammi, Hanane Dagdougui, Roberto Sacile, "Short Term of Wind Power by an Artificial Neural Network Approach" IEEE 2012.
2. Priyadarshini S, Booma J, Dhanarega A. J, Dhanalakshmi "A very short term wind power forecasting using back propagation algorithm in neural networks", Vol 10, No. 6, April 2015 APRN Journal of engineering and applied sciences.
3. Anirudh S. Shekhawat "Wind Power Forecasting using Artificial Neural Networks.", Vol. 3 Issue 4 April 2014 IJERT.
4. Introduction to Neural Networks using MATLAB 6.0 by S N Sivanandam, S Sumathi, S N Deepa.
5. K. G. Upadhyay, A.K Choudhary, M.M. Tripathi "Short term wind speed forecasting using feed forward Neural Network" Vol 3 No. 5 2011 pp 107–112.
6. Debra Lew, Michael Milligan, Gary Jordan and Richard Piwko "The value of Wind Power Forecasting", 2nd Conference on Weather, Climate and the New Energy Economy Jan 26 2011.
7. Vicky Jain, Alok Singh, Vibhor Chauhan and Alok Pandey "Analytical Study of Wind Power Prediction using Feed Forward Neural Network" ICCPEIC pp 303–306.
8. Neural Network Toolbox, MATHWORK Inc. Mark H Beale, Martin T. Hagan, Howard B. Demuth.