Error Evaluation of Short-Term Wind Power Forecasting Models

Upma Singh and M. Rizwan

Abstract Inconsistency and randomness of wind power impose massive challenges to large-scale wind power production. An accurate production of the wind power for the upcoming hours is imperative, in order that accurate planning and scheduling of the wind power production from conventional units can be accomplished. In the present work, we have proposed three intelligent forecasting models using fuzzy logic, artificial neural network (ANN) and adaptive-neuro-fuzzy inference system (ANFIS) approaches. These models can efficiently incorporate the uncertainty and nonlinearity linked with climatic parameters. To implement these models, the forecasting has been done using historical data of various stations. The performance of these intelligent forecasting models are estimated with statistical indicators and observed that the results obtained using ANFIS forecasting model are found quite accurate. Consequently, ANFIS model can be useful for accurate forecasting of wind power and for efficiently utilizing the wind resources.

Keywords ANN · ANFIS · Fuzzy logic (FL) · Renewable energy resources · Wind power

1 Introduction

With the rising industrial and agricultural activities, especially in developing countries like India, enhancing the demand of electricity and also conventional energy sources are in limited amount, so we have to be more responsible in using natural resources in more effective way [1–3]. As rising industrial and agricultural activities also increase environment pollution, hence it is a matter of concern for all growing and developed countries to focus on natural resources [4, 5]. Wind power is growing source of electricity and can significantly ease the problems of global environmental

U. Singh (✉) · M. Rizwan
Delhi Technological University, Maharaja Surajmal Institute of Technology, Delhi, India
e-mail: upma@msit.in

M. Rizwan
e-mail: rizwan@dce.ac.in

S. Smys et al. (eds.), *Inventive Computation and Information Technologies*, Lecture Notes in Networks and Systems 336, https://doi.org/10.1007/978-981-16-6723-7_41

pollution [6, 7]. Wind power depends on weather conditions and having intermittent nature may leads to irregularity and uncertainty in wind power output. Also, the conventional sources of energy are also diminishing at a very fast rate. Therefore, it is extremely important to look toward renewable sources such as hydro, wind, solar and biomass [8–11]. Alarmingly, the availability of wind data is scarcely available due to finite spatial coverage, limited length of record and high cost of instrumentation. On account of, inaccessibility of the measured data, forecasting of wind energy is significantly important at the surface of earth. In this regard, it is imperative to construct intelligent systems or models on the basis of easily accessible meteorological data-set to forecast global wind power.

The wind power is clean and world-wide distributed having low cost of power generation [12]. Wind energy-model varies from mathematical models to hybrid models namely persistence model, Kalman filter, ARMA model, etc., have been grown for predicting wind power. Latest research carried out represents that the mathematical models presented in the literature are not providing satisfactory results for all situations is universally accepted, primarily due to highest simplicity of parameterization [13]. As illustrated in literature several techniques for example, linear predictors, exponential smoothing models and gray predictors, etc., have developed and presented for the purpose of wind energy estimation. All these models utilize historical data for modeling, but because of the intermittent nature of wind they cannot yield precise prediction of wind power [14–17].

Presently, with the improvements in the artificial intelligent technique various algorithms like artificial neural network, WPT (wavelet packet transform) and SVM (support vector machines) have been employed for forecasting of wind power [18, 19]. Furthermore, an intelligent hybrid forecasting model relying on Markov model and least square support vector machine has also been integrated for forecasting of wind power. But these techniques are not reliable for real-time implementations due to over computational complexity associated with them which many times reduces the reliability of forecasting [20]. In another research work radial basis function network (RBFN), adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) approaches were utilized to compare 1-h ahead prediction of wind power. It was found in that fuzzy logic based algorithm works well even when mathematical model of the network is not obtainable [21]. To enhance the quality of wind power interval prediction, a fuzzy interval prediction model (FIPM) is developed. To optimize the FIPM gravitational search algorithm is used. The experimental output represents that FIPM model gives better performance than traditional forecasting models [22, 23]. In other paper to predict the wind energy output, two-hidden layer neural network is used. By utilizing proper data in combination with a back-propagation algorithm, neural-network model is prepared. Simulation output shows that predicted wind power is in better agreement with the experimentally measured values [24]. The long short term memory (LSTM), rectified linear unit activation function and Adam-optimization algorithm are investigated to perform daily to monthly estimation with the help of recurrent neural network process. It was investigated that a univariate single-layer recurrent neural network architecture is preferred for wind speed estimation and multilayer recurrent neural network model may be considered for improving the prediction accuracy over a longer period [25].

In recent study, to estimate the performance of wind power of china's 29 provinces and cities from 2011 to 2018, adaptive neuro-fuzzy approach is utilized, and it is found that ANFIS shows a vital improvement in accuracy [26]. Therefore, it has been seen that, a hybrid adaptive neuro-fuzzy model provides better accuracy in forecasting of wind power in comparison with standalone model [27]. For this aim, three modeling techniques, Support Vector Machines, ANFIS and Multi-Nonlinear Regression were utilized. After evaluating the performance, it was seen that modeling based on Subtractive-Clustering provides better outputs than Grid-Partitioning [28]. In other research, Weibull probability density function for estimating the wind speed and power has been used in particular Dakhla and Taza cities [29]. In the present paper, three forecasting models (Fuzzy logic, ANN and ANFIS) have been developed for forecasting of wind power by using wind speed and air density taken as input parameters keeping in view of aforesaid literature. These three wind power forecasting models demand limited amount of dataset.

This paper is structured in seven sections as a concise introduction related to the topic with meticulous literature study has been described in Sect. 1. Section 2 presents the determination of input variables Sect. 3 deliberates the study area and collection of data-set Sect. 4 presents implementation of the fuzzy logic based system for the forecasting of wind power. Section 5 describes the implementation of ANN based model for forecasting of wind power. ANFIS implementation is outlined in Sect. 6. Section 7 deliberates results and discussion. Finally, Sect. 8 presents concluding remarks.

2 Determination of Input Parameters for the Wind Power Forecasting Model

The meteorological input parameters that affect the wind turbine output are identified as wind direction, dew point temperature, speed of the wind, temperature, relative humidity, rainfall, air density and pressure, etc. The meteorological parameter, air density is associated with the change in temperature and relative humidity. However, the other parameters like dew point temperature, pressure and rainfall may impact on the production of wind turbine output, but these factors are not likely to be considered so significant so these meteorological factors are not taken into consideration. Though, the effect of wind speed and air density on wind turbine output production is considered more significant. Thus, speed of wind and air density factor (derived from the Eq. 1) is chosen as input features for developing the wind power forecasting model. The equation of air density parameter is represented as follows:

$$\text{Air Density} = D\left(\frac{B - 0.3783e}{760}\right)\left(\frac{273.15}{T}\right) \tag{1}$$

where, e is the vapor pressure of moist air in torr, B is the barometric pressure in torr, T is the absolute temperature in Kelvin and D is the density of dry air at standard atmospheric temperature (25 °C) and pressure (100 kPa) ($D = 1.168$ kg/m^3) [30].

3 Study Area and Collection of Data-Set

As described in previous section, factors that affect the wind turbine output are wind speed, relative humidity and temperature. To attain the aim, a continuous record of all meteorological parameters is needed, which is rarely available. The required data-set was collected from NIWF (National Institute of Wind Energy) and IMD (Indian Meteorological Department), Pune, which is 10 years averaged data for the period January 2008–June 2018 for the study area, New Delhi, Rajasthan, Maharashtra and Chennai [31, 32]. Before applying the data-set to the forecast models as input, the whole data-set were analysed and pre-processed. The normalization of the data-set is done and defined in the range of 0.1–0.9, so as to bypass the convergence problems during operation for four weather stations such as New Delhi, Rajasthan, Maharashtra and Chennai that show different climatic conditions. Approximately, 70% data-set are utilized for training and 30% data-set are utilized for testing purposes.

4 Implementation of Fuzzy Logic Based Model

Fuzzy-systems are comparable to human-decision making having capability to generate reliable and accurate results from imprecise information. In the paper, main motive is to forecast wind power with the help of two input variables, i.e., wind speed and air density. Both parameters are utilized as input to fuzzy logic system and output variable is wind power. Hence, there are two input variables which are utilized to forecast wind power as an output. Later on, input and output variables are normalized by examining all the parameters behavior and stated in the range from 0.1 to 0.9 to prevent or by pass convergence problem throughout the operation. Membership functions are of many types such as trapezoidal, bell shape, triangular and Gaussian membership function and these are designated using trial and error strategy.

To develop the forecasting model, triangular membership function has been selected for input as well as output parameters. Prior to developing the fuzzy rules, we have done partitioning the all parameters range into five regions namely very low, low, medium, high and very high.

The proposed forecasting model use if–then rules. To acquire rule base forecasting, accuracy is checked by using a distinct set of past data. If it is inadequate, then we can change the shape of the membership functions and number of membership functions. Hence, error range is reduced by nearly four percent using fuzzy logic model. The modeling takes into account the uncertainties exhibit in the environment caused by

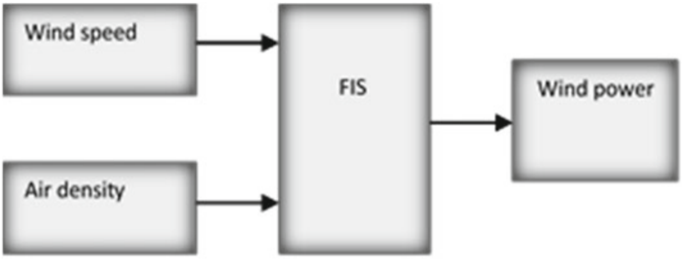

Fig. 1 Fuzzy inference system based model for the forecasting of wind power

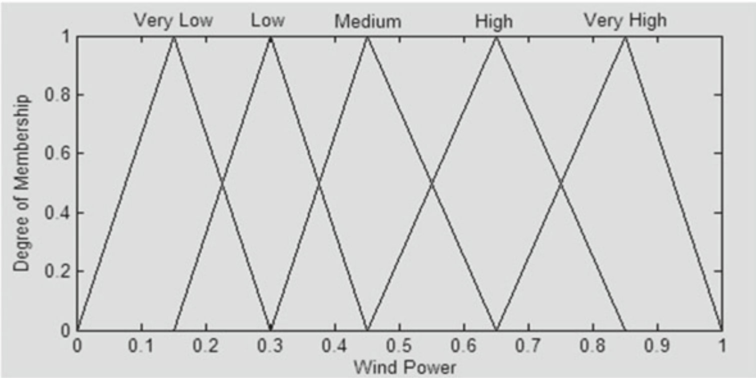

Fig. 2 Fuzzy membership function of air density and wind speed

varying weather conditions [33]. Figure 1 represents fuzzy inference system based model for the forecasting of wind power.

Figure 2 displays the membership functions linked with each of the variables. To specify the shape of all membership function, membership function editor is employed. Fuzzy membership is a curve that represents how each point in the input space is mapped to membership value or degree of membership between 0 and 1. So, forecasting results are accomplished using triangular membership function.

The proposed fuzzy logic based forecasting model is depicted in Fig. 3. Rule editor is used to modify and view the rules, which describes the system performance shown in Figs. 4 and 5 represents fuzzy rule viewer, which is useful in viewing the inference process of the fuzzy system. By adjusting the input values, correspondent output of each fuzzy rule can be viewed.

The display of the fuzzy inference plot comprises of a figure window with seven small plots nested in it. The two small plots across the top of the figure shows the antecedent and consequent of the first rule. Each column is a variables, and each rule is a row of plots.

Also, the first two columns of the plots represents the membership functions referenced by the antecedent or if–part of each rule. The third column of the plots

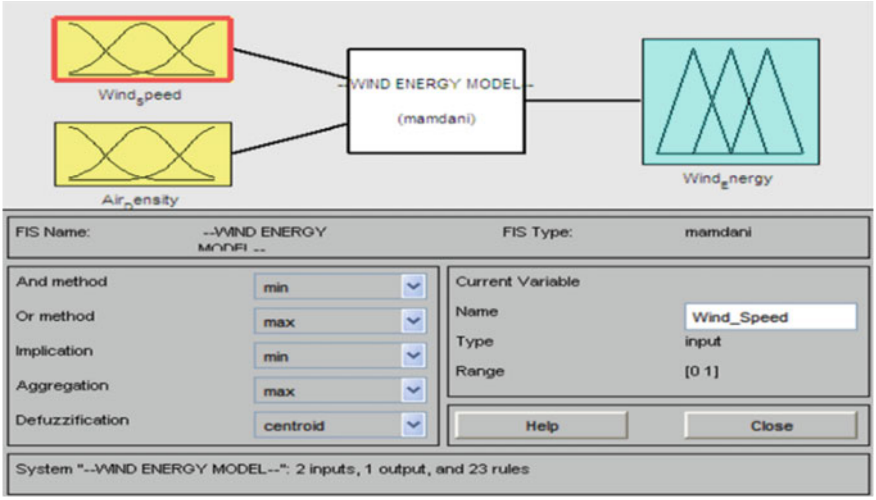

Fig. 3 Fuzzy logic based forecasting model

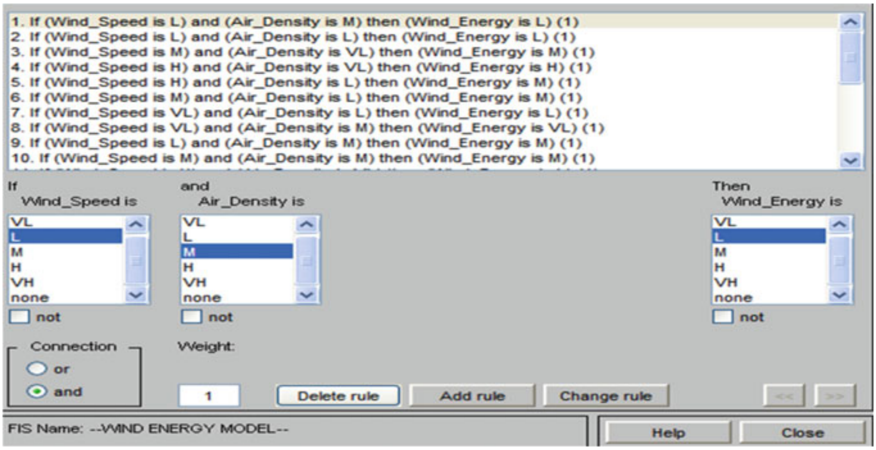

Fig. 4 Rule editor for fuzzy logic based model

represents the membership functions referenced by the consequent, or then–part of each rule. The last plot in the third column shows the aggregate-weighted decision and the bold vertical line on it shows the defuzzified output.

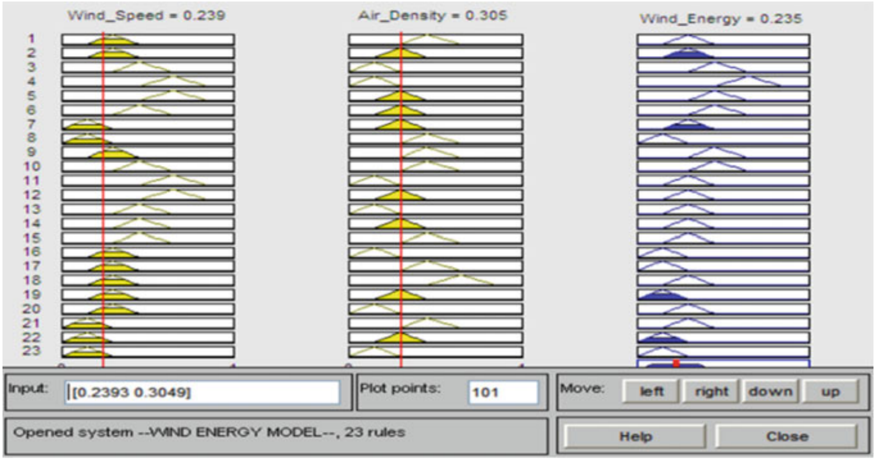

Fig. 5 Fuzzy rule viewer for the forecasting of wind power

5 Implementation of ANN Based Model

In this section, forecasting technique using ANN tool is implemented to estimate the produced energy from wind turbine with the help of neural network trained by using past data. An artificial neural network is used in forecasting, on account of its ability of approaching nonlinear mapping between numbers of inputs and outputs and dig out unidentified data or information within the huge available data. ANN is distributed in data storage and computing in terms of structure. Hence, model developed by artificial neural network retain robustness and capability of solving troublesome problems. This section uses excellent nonlinear mapping ability of neural network to forecast wind energy at distinct stations namely New Delhi, Rajasthan, Maharashtra and Chennai by utilizing the data-set of wind speed and air density.

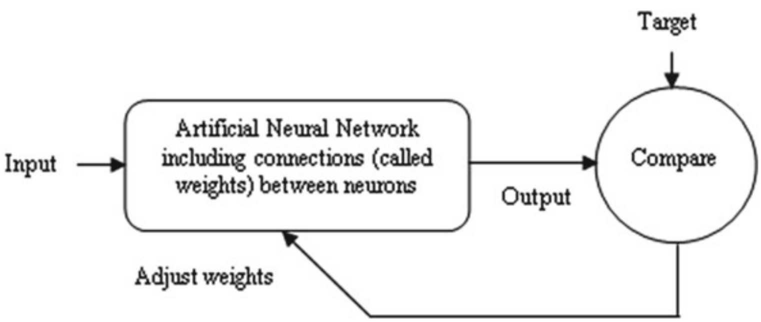

Fig. 6 Operating scheme of artificial neural network

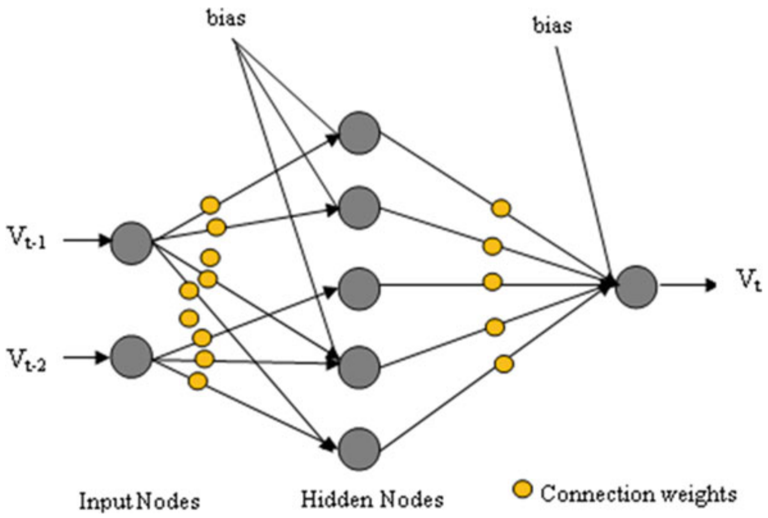

Fig. 7 Architecture of a feed-forward neural network having 2-input nodes, 5-hidden nodes and 1-output node

The basic operating scheme of artificial neural network is represented in Fig. 6. For development of the model all data has been divided into two parts, i.e., training data-set and testing data-set, for this 70% data-set is utilized for training and 30% data-set is utilized to test the model.

Figure 7 presents the architecture of a feed-forward neural network having 2-input nodes, 5-hidden nodes and 1-output node. In this network, the information (data) will enter through the input nodes to output nodes by means of hidden nodes. Here, the first layer having two input parameters (i.e., wind speed and air density), a hidden layer has tansigmoid function "tansig" which is expressed by the equation represented as:

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

where, input is represented by x. The output layer having linear activation "purelin" transfer-function which would solve hard problems. To implement a neural network algorithm, neural network toolbox has been used in Matlab. The network output is shown below:

$$y = \sum_{J=1}^{n} w_{ij} x_{ij} + \theta_i \tag{3}$$

where w_{ij} is connection weights directed from j neuron to i neuron at the hidden-layer, θ_i is the i neuron bias, x_{ij} is the j_{th} neuron incoming signal at the input-layer.

Table 1 The ANN model properties

ANN model parameters	Type or value
Input number	2
Output number	1
Number of hidden layers	1
Number of hidden-neurons	8
Transfer-function of output layer	Purelin
Transfer-function of hidden layer	Tansig
Training cycles, epochs(e)	30
Learning rate	0.01
Optimization method	Feed-forward back-propagation
Scaling method	Normalization

Artificial neural networks have a built in capability to adapt their synaptic weights with respect to the varying atmosphere condition. It also has ability to carried out tasks that a linear program cannot [34, 35].

It produces good results by using enormous amount of data. ANNs learns with the help of examples and they can be programmed to carry out a specified task. Neural networks are also fault-tolerant; therefore, these networks handles insufficient and noisy data [36]. They also has ability to handle nonlinear problems so, they can be used in forecasting problems once trained [37]. Feed-forward back-propagation network is applied in this proposed work and for training and adaptation of the neural network TRAINLM training function with LEARNGDM adaptive learning function has been utilized to develop the forecasting model (Table 1).

6 Implementation of ANFIS Based Model

From the previously implemented techniques, it is observed that neural network is a flexible and powerful approach for modeling several real world problems, but it has few limitations, such as if input data-set are ambiguous or highly uncertain than fuzzy system like adaptive neuro-fuzzy inference system may be a favorable approach. In addition, ANN also involves huge data-set to train, selecting adequate number of hidden-units, input and output samples.

In the given segment, ANFIS tool has been utilized in the Matlab software to train and test by utilizing "anfisedit" function in the command to forecast wind power.

In 1993, Jang first evolved the ANFIS method and successfully implemented its principles to several problems. Neuro-fuzzy system is used in wide range of scientific applications due to its several features such as accurate and fast learning, robust generalization capabilities, easy to implement, great explanation possibility with fuzzy rules. By combining the advantages of neural network and fuzzy logic, adaptive neuro- fuzzy inference system can solve any kind of nonlinear and complex problems efficiently. Neuro-fuzzy is basically the rule based fuzzy modeling. Fuzzy-rules are molded via the process of training. The training process is done by utilizing a data-set. The neuro-fuzzy designs a fuzzy inference system and based on the training dataset, parameters of membership- functions are designed.

In neuro-fuzzy system, neural networks take out automatically fuzzy-rules from the numerical data and membership functions get adaptively adjusted with help of learning action. It has multi-layered feed-forward architecture. This architecture is generally comprised of five layers in which first and forth layer encompass adaptive nodes whereas, other layers comprises of fixed nodes [38]. Process of fuzzification is carried out in the first layer having adaptive neurons. Second layer having fixed neurons, represent incoming signals. Third layer consists of fixed neurons (nodes) wherein every node is stable marked as M shows fuzzy rules. The forth layer having adaptive neurons showing the rule inference and the fifth layer which is output layer marked as "$\sum$", i.e., summation neuron. On the basis of previous past data as utilized for earlier models, adaptive neuro-fuzzy model has been constructed to forecast wind energy [39, 40]. By adopting the given procedure neuro-fuzzy model has been constructed. First of all, given past data is partitioned into two sections one for training purpose (70% of data-set) and other section utilized for testing operation (30% of data-set). In neuro-fuzzy system, there are M^n fuzzy-rules where, membership function is denoted by "M" and number of inputs are denoted by "n." In this model, 5 membership functions and 2 inputs are selected. Therefore, number of fuzzy-rules are 25. For each input variable, 5 membership functions are formed. To train FIS, two distinct optimization methods (back-propagation and hybrid) are used. For developing the model gauss2mf membership function is used because it gives superior outcomes in contrast to other membership functions for the given data-set. While output membership function is selected to be linear as shown in Fig. 10. In this model, the grid partitioning is selected to generate FIS as the forecasting accuracy obtained is more compared to the subtractive clustering. The parameters of the neuro-fuzzy model are given in Table 2. Later on, neuro-fuzzy model has been checked and validated after the successful training operation by using the testing data. Validation of the proposed model was done using statistical indicators. Using the above procedure ANFIS model was evolved. It is essential to indicate that the number of input sets and the number of rules to be composed increases if the number of variables utilized to execute the forecasting increases. The neuro-fuzzy system comprises of hybrid and back-propagation leaning algorithms that reduces the error between forecasted and observed data. To develop the model, both algorithms are used to compare the outcomes of them. Minimization of error was achieved by using learning process.

Figure 8 shows the flowchart of training and testing neuro-fuzzy model. Training error in ANFIS is given in Fig. 9. Figure 11 shows ANFIS architecture comprises of five layers. It is a feed-forward neural network, which comprises of fuzzification-layer, rule-layer, normalization-layer, defuzzification-layer and a summation neuron. All the nodes are adaptive nodes in the first layer. Output of neuro-fuzzy model structure is shown in Fig. 12 (Fig. 10).

Table 2 The ANFIS model properties

ANFIS model parameters	Type or value
Input number	2
Output number	1
Type of fuzzy inference system	Sugeno
Number of input membership function	5 5
Input membership function type	gauss2mf
Output membership function type	Linear
Optimization method for training FIS	Grid partition
Optimization method	Hybrid; back-propagation
Training epoch numbers	500

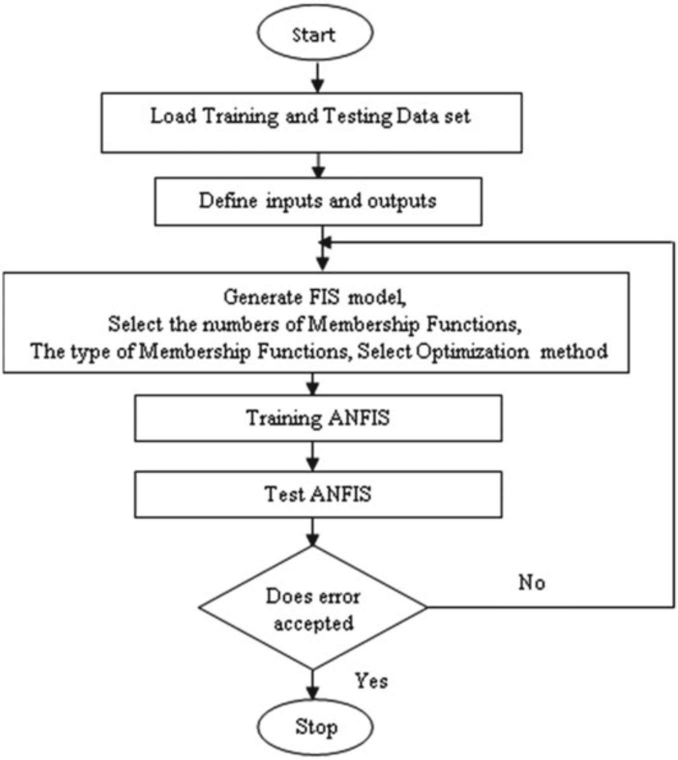

Fig. 8 Training and testing ANFIS method flowchart

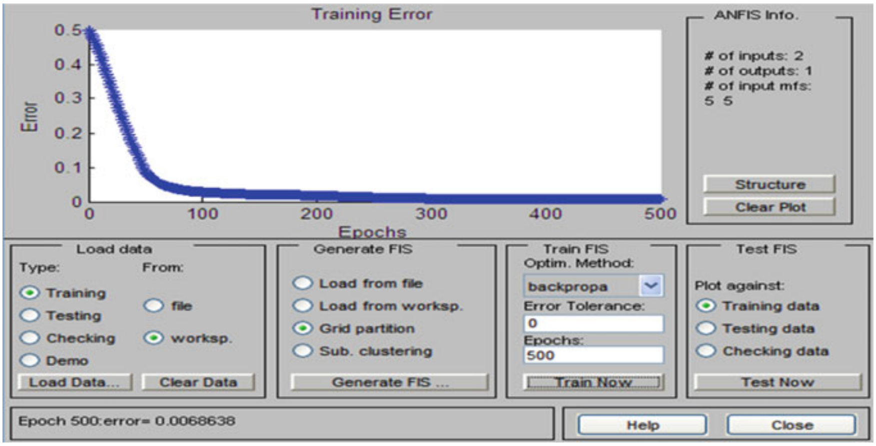

Fig. 9 Training error in ANFIS

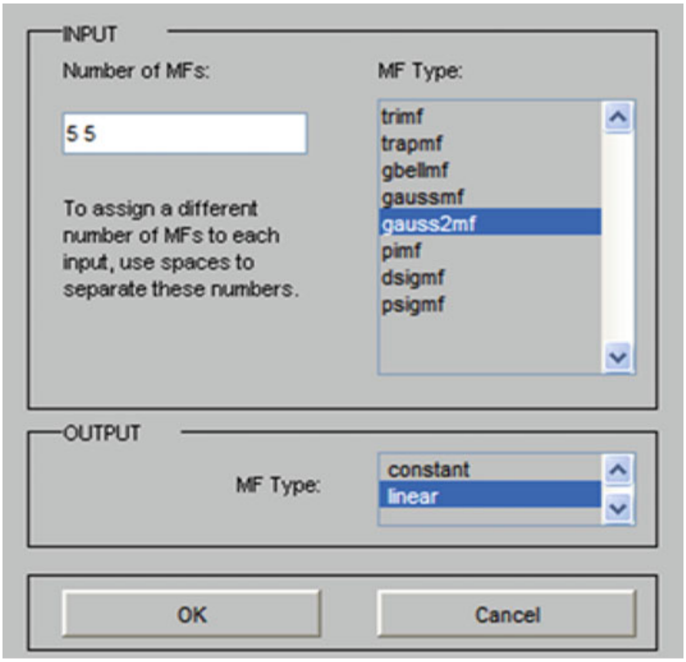

Fig. 10 Initial ANFIS generation

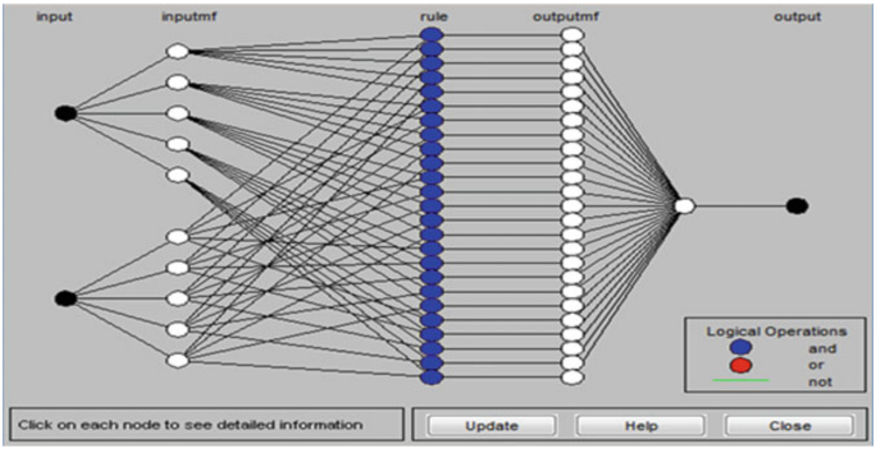

Fig. 11 ANFIS model structure

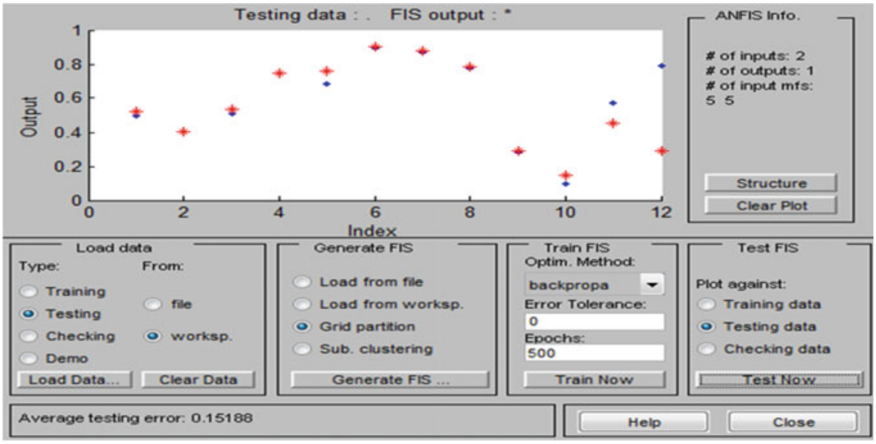

Fig. 12 Output of ANFIS model structure

7 Results and Discussions

In this research work, the FL, ANN and ANFIS based methodologies are employed for developing forecasting models to estimate wind turbine output. The meteorological input parameters, wind speed and air density considered in implementing the models to estimate the wind turbine output power. For developing the all three models, normalized data has been utilized.

Figures 13, 14 and 15 depict the month by month comparison between forecasted wind power using fuzzy logic, neural network and neuro-fuzzy techniques and those calculated from the measured data, respectively.

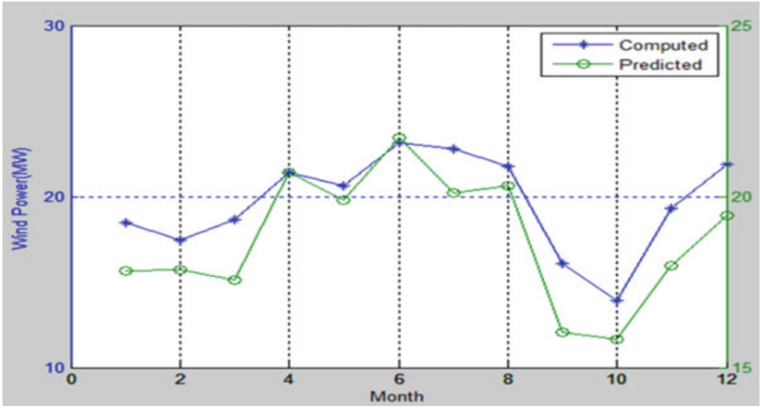

Fig. 13 Predicted values of wind power in comparison with computed power with FL

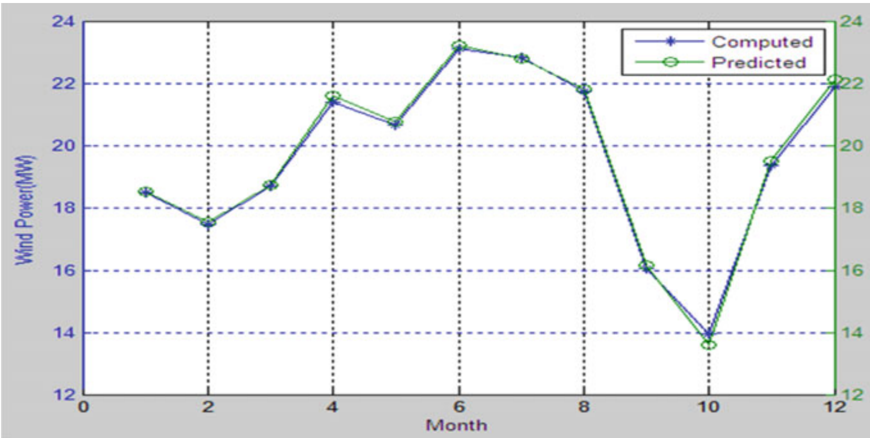

Fig. 14 Predicted values of wind power in comparison with computed power with ANN

As we can infer from Fig. 15 that mostly forecasted data are overlapping and substantially near to the computed data. Therefore, it can be inferred that the proposed neuro-fuzzy model gives better results than the other two forecasting models. The forecasted wind power in comparison with computed values of wind power with FL, ANN and ANFIS techniques are displayed in Table 3. From Table 3, it is quantifies that ANFIS hybrid intelligent system provides best results for forecasting of wind power. Hence, neuro-fuzzy based model provides a stipulated mathematical arrangement that makes it an excellent adaptive approximator. Additionally, neuro-fuzzy system delivers good learning ability and minimizes convergence error for a network of same complexity and displays supremacy to the ANN technique and other techniques of same complexity.

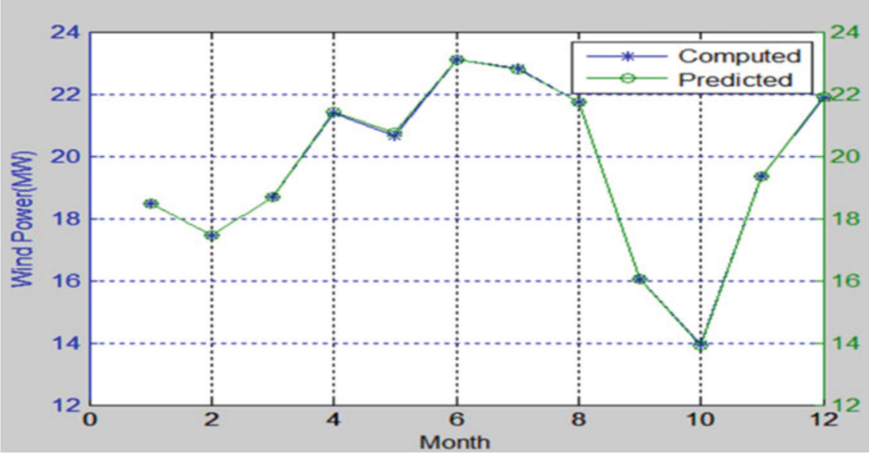

Fig. 15 Predicted values of wind power in comparison with computed power with ANFIS

Table 3 Monthly mean forecasting wind power in comparison with computed power

Months	Wind power (computed), MW	Wind power (forecasted), MW		
		FLs	ANNs	ANFISs
Jan	18.491	17.83	18.49	18.52
Feb	17.542	17.85	17.46	17.54
Mar	18.584	17.57	18.68	18.73
Apr	21.471	20.69	21.42	21.57
May	20.552	19.89	20.77	20.77
Jun	23.021	21.74	23.10	23.19
Jul	22.802	20.11	22.80	22.80
Aug	21.816	20.31	21.73	21.82
Sep	16.143	16.04	16.07	16.14
Oct	13.640	15.83	13.92	13.58
Nov	19.362	17.98	19.35	19.48
Dec	21.361	19.45	21.90	21.11

There are many assessment measures to estimate the performance of all given models on the basis of various widely used statistical indicators such as absolute relative error (ARE), standard deviation of error (SDE), the sum squared error (SSE), the mean absolute percentage error (MAPE).

It can be inferred with the help of statistical indicators results for forecasting of wind power, ANFIS based forecasting generates minimum errors when compared to the other intelligent forecasting models. Hence, ANFIS model provides quite favorable results than fuzzy logic and ANN models. Table 4 summarizes performance

Table 4 Performance of the developed models for wind power forecasting based on diferent statistical indicators

Model	Statistical Indicators			
	ARE	MAPE	SSE	SDE
FL	4.60	14.225	0.0540	0.0543
ANN	0.07	0.0838	2.331e−006	3.964e−004
ANFIS	0.034	0.0227	2.0417e−007	1.2822e−004

evaluation of FL, ANN and ANFIS models for the forecasting of wind power with regard to statistical indicators.

The MAPE, SSE and SDE criterion are stated below:

$$\mathrm{MAPE} = \frac{100}{N} \sum_{h=1}^{N} \frac{\left| \widehat{p}_h - p_h \right|}{\overline{p}} \tag{4}$$

$$\overline{p} = \frac{1}{N} \sum_{h=1}^{1} p_h \tag{5}$$

where, N is the number of forecasted hours, $\overline{p}$ is the average wind power of the forecasting period, $\widehat{p}_h$ and p_h are the forecasted and actual wind power at hour h.

$$\mathrm{SSE} = \sum_{h=1}^{N} \left(\widehat{p}_h - p_h \right)^2 \tag{6}$$

$$\mathrm{SDE} = \sqrt{\frac{1}{N} \sum_{h=1}^{N} (e_h - \overline{e})^2} \tag{7}$$

$$e_h = \widehat{p}_h - p_h \tag{8}$$

$$\overline{e} = \frac{1}{N} \sum_{h=1}^{N} e_h \tag{9}$$

where $\overline{e}$ is the average error of the forecasting period and $e_h$is the forecast error at hour *h*.

From the results of Table 4, it has been observed that the forecasting results of all three intelligent models based on statistical indicators shows that ANFIS model gives better performance than the other two models (fuzzy logic and ANN).

8 Conclusion

For effective wind power harnessing, the reliable and precise wind resource evaluation plays a significant role. In this study, FLs, ANNs and ANFISs based models are developed and analyzed for forecasting of wind power at four distinct places. These models have two input variables, i.e., wind speed and air density and one output variable, i.e., wind power. A comparative study was also conducted to validate functioning of all intelligent models is determined by using statistical indicators. ARE, MAPE, SSE and SDE, respectively, are 4.60, 14.225, 0.0540 and 0.0543% for fuzzy logic, are 0.07, 0.0838, 2.331e−006 and 3.964e−004% for ANN, are 0.03, 0.0227, 2.0417e−007 and 1.2822e−004% for ANFIS. The results demonstrated superior performance of ANFIS model in contrast to the other two intelligent forecasting models (FLs and ANNs). Hence, ANFIS based model could be important tool to forecast wind power. The forecasting of wind power would be practically utilized for optimization, real-time power dispatch, power smoothening, selection of appropriate energy storage and requirements of additional generating stations. Such forecasting would be useful for handling demand and supply for power building in a smart-grid environment, which may reduce the problems of power fluctuations generated from wind based energy systems. For the development of smart energy management system, this work will help the stakeholders such as designer, operation engineer, service provider, utility, technocrats and power engineer.

References

1. Z. Jinhua, Y. Jie, W.U. Wenjing, L.I.U. Yongqian, Research on short-term forecasting and uncertainty of wind turbine power based on relevance vector machine. Energy Procedia **158**, 229–236 (2019)
2. W.Y. Chang, A literature review of wind forecasting methods. J. Power Energy Eng. **2**(04), 161 (2014)
3. H.P. Oak, S.J. Honade, ANFIS based short term load forecasting. Int. J. Current Eng. Technol. **5**(3), 1878–1880 (2015)
4. Prabhas, K., Vishavdeep, J.: Review: wind power forecasting & grid integration. Int. J. Adv. Res. Electr. Electron. Instrum. Eng. **5**(9), (2016)
5. R. Sharma, D. Singh, A review of wind power and wind speed forecasting. J. Eng. Res. Appl. **8**, 1–9 (2018)
6. S. Wagh, P.V. Walke, The hybrid solar and wind power extraction for domestic purposes: a review.Int. J. Res. Advent Technol. **5**(3) (2017)
7. L. Suganthi, S. Iniyan, A.A. Samuel, Applications of fuzzy logic in renewable energy systems—a review. Renew. Sustain. Energy Rev. **48**, 585–607 (2015)
8. S. Sukhdev, K. Naresh, Wind power forecasting: a survey. Int. J. Eng. Res. Gener. Sci. **4**(3) (2016)
9. A. Ahmed, M. Khalid, A review on the selected applications of forecasting models in renewable power systems. Renew. Sustain. Energy Rev. **100**, 9–21 (2019)
10. A. Ul Haque, J. Meng: Short-term wind speed forecasting based on fuzzy artmap. Int. J. Green Energy **8**, 65–80 (2013)
11. A. Kumar, M.Z.U. Khan, B. Pandey, S. Mekhilef, Wind energy: a review paper. Gyancity J. Eng. Technol. **4**(2), 29–37 (2018)

12. M.H. Baloch, J. Wang, G.S. Kaloi, Stability and nonlinear controller analysis of wind energy conversion system with random wind speed. Int. J. Electr. Power Energy Syst. **79**, 75–83 (2016)
13. W. Li, X. Jia, X. Li, Y. Wang, J. Lee, A Markov model for short term wind speed prediction by integrating the wind acceleration information. Renew. Energy **164**, 242–253 (2021)
14. P.K. Chaurasiya, V. Warudkar, S. Ahmed, Wind energy development and policy in India: a review. Energ. Strat. Rev. **24**, 342–357 (2019)
15. S.P. Mishra, P.K. Dash, Short term wind speed prediction using multiple kernel pseudo inverse neural network. Int. J. Autom. Comput. **15**(1), 66–83 (2018)
16. K. Gunavardhan, A convollution neural network based deep learning neural network forecast model for wind energy prediction. Int. J. Adv. Sci. Technol. **28**(19), 141–150 (2019)
17. A.P. Marugán, F.P.G. Márquez, J.M.P. Perez, D. Ruiz-Hernández, A survey of artificial neural network in wind energy systems. Appl. Energy **228**, 1822–1836 (2018)
18. A.A. Helen, A. Ojokoh Bolanle, O. Falaki Samuel, Comparative analysis of rainfall prediction models using neural network and fuzzy logic. Int. J. Soft Comput. Eng **5**, 4–7 (2016)
19. V. Vanitha, Adaptive neuro-fuzzy inference system based short term wind speed forecasting. Int. J. Innov. Technol. Explor. Eng. **9**(5), 1–6 (2020)
20. L. Yang, M. He, J. Zhang, V. Vittal, Support-vector-machine-enhanced markov model for short-term wind power forecast. IEEE Trans. Sustain. Energy **6**(3), 791–799 (2015)
21. M. Godinho, R. Castro, Comparative performance of AI methods for wind power forecast in Portugal. Wind Energy **24**(1), 39–53 (2021)
22. M. Shahzad, U. Naeem, R. Sadiq, E. Muhammad, Fuzzy logic based algorithm for wind energy prediction, in *International Symposium on Recent Advances in Electrical Engineering (RAEE)*, vol. 4, pp. 1–6, IEEE (2019)
23. W. Zou, C. Li, P. Chen, An inter type-2 FCR algorithm based T-S fuzzy model for short-term wind power interval prediction. IEEE Trans. Industr. Inf. **15**(9), 4934–4943 (2019)
24. G. Grassi, P. Vecchio, Wind energy prediction using a two-hidden layer neural network. Commun. Nonlinear Sci. Num. Simul. **15**(9), 2262–2266 (2010)
25. S. Pasari, A. Shah, U. Sirpurkar, Wind energy prediction using artificial neural networks, in *Enhancing Future Skills and Entrepreneurship* (Springer, Cham, 2020), pp. 101–107
26. F. Dong, L. Shi, Regional differences study of renewable energy performance: a case of wind power in China. J. Clean. Prod. **233**, 490–500 (2019)
27. P.A. Adedeji, S. Akinlabi, N. Madushele, O.O. Olatunji, Wind turbine power output very short-term forecast: a comparative study of data clustering techniques in a PSO-ANFIS model. J. Cleaner Prod. **254**, 120135 (2020)
28. İ Mert, F. Üneş, C. Karakuş, D. Joksimovic, Estimation of wind energy power using different artificial intelligence techniques and empirical equations. Energy Sour. Part A: Recovery Util. Environ. Effects **43**(7), 815–828 (2021)
29. Y. El Khchine, M. Sriti, N.E.E.K. Elyamani, Evaluation of wind energy potential and trends in Morocco. Heliyon **5**(6), e01830 (2019)
30. F. Ji, X. Cai, J. Zhang, Wind power prediction interval estimation method using wavelet-transform neuro-fuzzy network. J. Intel. Fuzzy Syst. **29**(6), 2439–2445 (2015)
31. A. Mani, *Handbook of Solar Radiation and Wind Data for India* (Allied Publishers, New Delhi, 2019)
32. Solar Radiation and wind data Handbook, SEC & IMD Pune (2018)
33. O. Badran, E. Abdulhadi, Y. El-Tous, Fuzzy logic controller for predicting wind turbine power generation. Int. J. Mechan. Mater. Eng. **6**(1), 51–66 (2011)
34. P. Devyani, C. Krishna Teerth, A study on short term wind power prediction using machine learning approach. Int. J. Adv. Res. Electric. Electron. Instrum. Eng. **7**(5) (2018)
35. F. Farivar, T. Negar, M.A. Rosenet, Short-term wind speed forecasting using artificial neural networks for Tehran. Int. J. Energy Environ. Eng. **7**, 377–390 (2016)
36. F. Gökgöz, F. Filiz, Deep learning for renewable power forecasting: an approach using LSTM neural networks. Int. J. Energy Power Eng. **12**(6), 416–420 (2018)
37. M.H. Baloch, G.S. Kaloi, Z.A. Memon, Current scenario of the wind energy in Pakistan challenges and future perspectives: a case study. Energy Rep. **2**, 201–210 (2016)

38. C. Wan, Z. Xu, P. Pinson, Z.Y. Dong, K.P. Wong, Optimal prediction intervals of wind power generation. IEEE Trans. Power Syst. **29**(3), 1166–1174 (2013)
39. S. Qin, F. Liu, J. Wang, Y. Song, Interval forecasts of a novelty hybrid model for wind speeds. Energy Rep. **1**, 8–16 (2015)
40. Q. Chen, K.A. Folly, Wind power forecasting. IFAC-Papers OnLine **51**(28), 414–419 (2018)