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An Intelligent Power Prediction Method for Wind Energy Generation Based on Optimized Fuzzy System

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Keywords

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Abstract

Due to the increasingly significant energy crisis nowadays, the exploitation and utilization of new clean energy gain more and more attention. As an important category of renewable energy, wind power generation has become the most rapidly growing renewable energy in the world. However, the intermittency and volatility of wind power have restricted the large-scale integration of wind turbines into power systems. High-precision wind power forecasting is an effective measure to alleviate the negative influence of wind power generation on the power systems. In this paper, an intelligent forecasting method based on fuzzy systems is proposed to wind energy generation prediction. The proposed method includes two main modules: The forecasting module and the optimization module. In the forecasting module, an adaptive neuro-fuzzy inference system is used for prediction. In the adaptive neuro-fuzzy inference system, the value of the radii vector has a great effect on system performance and there is no systematic way to select the optimal value of the radii vector. For this purpose, in the second module, we used the chaotic bat swarm optimization algorithm to select the optimal radii vector. The proposed method is tested on real data and obtained results show that the proposed method has excellent performance.

1. Introduction

A rapid development of the world economy and a greater demand on energy lead to increasing aggravation of the energy crisis. In order to solve the energy crisis, environment friendly green energy, such as wind power, are ideal new energies, and wind power generation is the power technology with quick development and the most mature business model in the generation of new energy. However, randomness and fluctuation of wind power can cause fluctuation and instability of wind power output and impede large-scale wind power connected power systems, leading to electric power sector's difficulty in formulating generation scheduling and dispatching electric power. The short-term wind power prediction is expected to solve such complicated problems [1, 2].

Numerous methodologies have been proposed for wind speed and power forecasting, including the physical model, the combined model and the statistical model. The first takes advantage of the meteorological and geographical information for modeling. Researchers in [3–5] have presented a physical prediction models based on numerical weather prediction. These method have used some meteorological observation data in a certain time as initial values and solved equations of atmospheric dynamics and thermo dynamics to get wind speed forecast value. On one hand, these physical prediction models are traditional and less effective in short-term prediction [3]. On the other hand, the physical systems are complex to implement, take more time for execution, and are site dependent [5].

The combined model can be established by different schemes [6]. Wang et al. [7] used the wavelet decomposition technique to tackle the nonstationarity of load series for the evolutionary extreme learning machine. The proposed method obtained better forecasting results compared with other well-established models on two publicly available datasets. An et al. [8] proposed the empirical mode decomposition algorithm to decompose the raw wind power data into a set of subseries, and a hybrid prediction model based on chaos theory and grey theory was built. The results showed superior prediction accuracy. Wang et al. [9] presented a novel wind speed forecasting model based on ensemble empirical mode decomposition (EEMD) and genetic algorithm–back propagation (GA–BP) neural network. The simulation results showed that the proposed model was more accurate than the traditional GA–BP approach. Su et al. [10] established a hybrid method based

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on the autoregressive integrated moving average (ARIMA) and Kalman filter to forecast the daily mean wind speed. And the particle swarm optimization (PSO) algorithm was employed to optimize the parameters of the ARIMA model to improve the prediction performance. Osório et al. [11] presented a new hybrid evolutionary– adaptive methodology for short-term wind power forecasting and the results showed a significant improvement over previously reported methodologies.

The statistical approaches develop the mathematical model representing the mapping relationship of the input variables into the output through history data, which includes the traditional statistical methods, artificial neural networks and machine learning models. Bhaskar et al. [12] proposed a statistical based wind power forecasting model without using numerical weather prediction inputs. The proposed approach consisted of two stages. In the first stage, wavelet decomposition of wind series was carried out and adaptive wavelet neural network (AWNN) was used to regress upon each decomposed signal, to predict wind speed up to 30 h ahead. In the second stage, a feed-forward neural network (FFNN) is used for nonlinear mapping between wind speed and wind power output, which transforms the forecasted wind speed into wind power prediction. This model predict the wind power output with acceptable accuracy but the error of the output power can reach more than 80%.

Dutta et al [13] proposed the space correlation method for predicting the wind speed among adjacent locations. This paper pointed out that the proposed model was better than persistent ones. However, this model was not suitable for long-term prediction and the measurement equations were difficult to derive. Researchers in [14, 15] a strategy of wind speed prediction was based on fuzzy logic and artificial neural network (ANN). The proposed ANN had less neuron numbers and less learning time process. The proposed fuzzy logic provided significantly less rule base but with less rule and less learning time the accuracy was affected negatively.

Generally, statistical models have the advantage that they require no mathematical modeling and use available historical measurements for stochastic approximation between wind predictions and wind power output measurements. As mentioned, neural networks, support vector machine (SVM) and fuzzy systems are the widely statistical models used for wind power prediction. The advantage with neural network is that it is capable of handling noisy measurements requiring no assumption about the statistical distribution of the monitored data. In respect with neural network, there is no systematic way to select the topology and architecture of a neural network. In general, this has to be found empirically, which can be time consuming [16]. The accuracy of an SVM is dependent on the choice of kernel function and the parameters (e.g. cost parameter, slack variables, margin of the hyper plane, etc.). Failure to find the optimal parameters for an SVM model affects its prediction accuracy [17].

The developed method uses fuzzy rules for wind power prediction. In the proposed method, an expert system has been developed which has fuzzy rules obtained by adaptive neuro-fuzzy inference system (ANFIS). ANFIS represent the promising new generation of information processing systems. Adaptive network based fuzzy inference systems are good at tasks such as time series prediction, modeling and pattern matching and classification [18- 20] while traditional computers, because of their architecture, are inefficient at these tasks, especially time series prediction tasks. In ANFIS training process, the radius of clusters has high efficiency on the performance of system. For this respect, in this study, chaotic bat swarm optimization algorithm (CBSO) is chosen as an optimization technique to optimize the ANFIS parameter. This technique will improve the ANFIS performance.

This paper is organized as follows. Section 2 describes the concepts needed, including the basic ANFIS and CBSO concepts. Section 3 describe the used data. The data used in this paper are based on the ones collected at one hour intervals form Alaska Center for Energy and Power for a period of 1 year. Section 4 describes the CBSO-ANFIS hybrid system. Section 5 shows some simulation results and finally Section 6 concludes the paper.

2. Needed Concepts

2.1. ANFIS

ANFIS is a neuro-fuzzy system developed by Jang [21]. It has a feed-forward neural network structure where each layer is a neuro-fuzzy system component (Figure 1). It simulates TSK (Takagi–Sugeno– Kang) fuzzy rule of type-3 where the consequent part of the rule is a linear combination of input variables and a constant. The final output of the system is the weighted average of each rule's output. The form of the type-3 rule simulated in the system is as Eq. (1)

$$IF\ x_1\ is\ A_1\ AND\ x_2\ is\ A_2\ AND\ ...\ AND\ x_p\ is\ A_p$$

$$THEN\ y{=}c_0 + c_1x_1 + c_2x_2 + ... + c_px_p \tag{1}$$

where x_1 and x_2 are the input variables, A_1 and A_2 are the membership functions, y is the output variable, and c_0, c_1 and c_2 are the consequent parameters.

Layer 0) is the input layer. It has n nodes where n is the number of inputs to the system.

Layer 1) the fuzzy part of ANFIS is mathematically incorporated in the form of membership functions (MFs). A membership function $\mu_{Ai}(x)$ can be any continuous and piecewise differentiable function that transforms the input value x into a membership degree, that is to say a value between 0 and 1. The most widely applied membership function is the generalized bell (gbell MF), which is described by the three parameters, a, b, and c (Eq. (2)). Therefore, Layer 1 is the fuzzification layer in which each node represents a membership value to a linguistic term as a Gaussian function with the mean;

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{bi}} \tag{2}$$

where $a_i, b_i\ and\ c_i$ are parameters of the function. These are adaptive parameters. Their values are adapted by means of the back-propagation algorithm during the learning stage. As the values of the parameters change, the membership function of the linguistic term, A_i changes. These parameters are called premise parameters. In that layer there exist $n \times p$

nodes where n is the number of input variables and p is the number of membership functions. For example, if size is an input variable and there exist two linguistic values for size which are SMALL and LARGE then two nodes are kept in the first layer and they denote the membership values of input variable size to the linguistic values SMALL and LARGE.

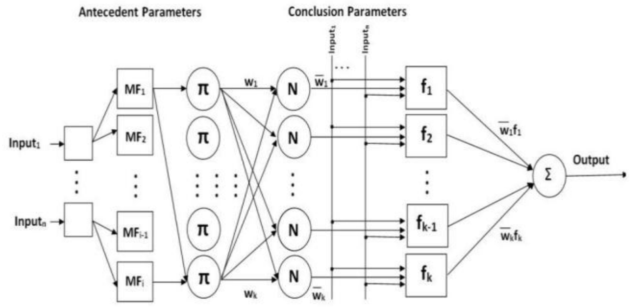

Figure 1. Basic ANFIS structure [21]

Layer 2) each node in Layer 2 provides the strength of the rule by means of multiplication operator. It performs AND operation (Eq. (3)).

$$w_i = \mu_{Ai}(x_0) \times \mu_{Ai}(x_1) \tag{3}$$

Every node in this layer computes the multiplication of the input values and gives the product as the output as in the above equation. The membership values represented by $\mu_{Ai}(x_0)$ and $\mu_{Bi}(x_1)$ are multiplied in order to find the firing strength of a rule where the variable x_0 has linguistic value A_i and x_1 has linguistic value B_i in the antecedent part of Rule I.

There are p^n nodes denoting the number of rules in Layer 2. Each node represents the antecedent part of the rule. If there are two variables in the system namely $x_1$and x_2 that can take two fuzzy linguistic values, SMALL and LARGE, there exist four rules in the system whose antecedent parts are as Eq. (4)

$$\begin{array}{l} IF\ x_1\ is\ SMALL\ AND\ x_2\ is\ SMALL \\ IF\ x_1\ is\ SMALL\ AND\ x_2\ is\ LARGE \\ IF\ x_1\ is\ LARGE\ AND\ x_2\ is\ SMAL \\ IF\ x_1\ is\ LARGE\ AND\ x_2\ is\ LARGE \end{array} \tag{4}$$

Layer 3) Layer 3 is the normalization layer which normalizes the strength of all rules according to the Eq. (5).

$$\overline{w_i} = \frac{w_i}{\sum_{j=1}^{R} w_j} \tag{5}$$

where w_i is the firing strength of the ith rule which is computed in Layer 2. Node i computes the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. There are p^n nodes in this layer [22].

Layer 4) Layer 4 is a layer of adaptive nodes. Every node in this layer computes a linear function where the function coefficients are adapted by using the error function of the multi-layer feed-forward neural network (Eq. (6)).

$$\overline{w_i} f_i = \overline{w_i}(p_0 x_0 + p_1 x_1 + p_2) \tag{6}$$

where p_i is the parameters, $i = n + 1$ and n is the number of inputs to the system (i.e., number of nodes in Layer 0). In this example, since there exist two variables (x_1 *and* x_2), there are three parameters(p_0, p_1 *and* p_2) in Layer 4 and w_i is the output of Layer 3. The parameters are updated by a learning step. Kalman filtering based on least-squares approximation and back-propagation algorithm is used as the learning step.

Layer 5) Layer 5 is the output layer whose function is the summation of the net outputs of the nodes in Layer 4. The output is computed as Eq. (7)

$$\sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

where $w_i f_i$ is the output of node i in Layer 4. It denotes the consequent part of rule i. The overall output of the neuro-fuzzy system is the summation of the rule consequences. ANFIS uses a hybrid learning algorithm in order to train the network. For the parameters in the layer 1, back-propagation algorithm is used. For training the parameters in the Layer 4, a variation of least-squares approximation or back-propagation algorithm is used [23].

2.2. Chaotic Bat Swarm Optimization

In recent years, nature based optimization algorithms have been used in many engineerning tasks [24- 32]. Bat swarm optimization is a novel heuristic optimization algorithm that is being used for solving different global optimization problems [33, 34]. The paramount problem in BSO is that it severely suffers from premature convergence problem, that is, BSO is easily trapped in local optima. In [35], chaotic-based strategies are incorporated into BSO to mitigate this problem. Ergodicity and non-repetitious nature of chaotic functions can diversify the bats and mitigate premature convergence problem. More details regarding CBSO can found in [35].

3. Data Description

The Alaska Center for Energy and Power is an applied energy research program based at the University of Alaska Fairbanks. ACEP provides leadership in developing energy systems for islanded, non-integrated electric grids and their associated oil-based heating systems. Integration is a central feature of ACEP program. Because many of the issues related to implementing innovative energy solutions are complex, ACEP not only address the technical integration of renewables with these small isolated diesel-based energy systems, but also look at integration from a broader perspective: integration of solutions into the social realities of a community, integration of the cultural fabric into sustainable energy solutions, integration of university researchers across disciplines and with community partners; and integration of our facilities and resources with those of our national partners. ACEP tries to develop and disseminate practical, cost-effective, and innovative energy solutions for Alaska and beyond.

Forecasting of wind turbine power generation has two main aspects. The first aspect is the historical and real time data. The historical data are used to analyze and model the forecasting system where the current real time data are used with historical data to calculate the future value of the generated power depending on the model parameters and analysis. The historical data can be obtained from any data storage media in a monitoring center where the real time data need a measuring system that fits for the conditions of the wind turbine. The second aspect is the modeling techniques that combine real time and historical data to predict the future value of wind turbine power depending on the analysis with acceptable error. The data used in this paper are based on the ones collected at one hour intervals form Alaska Center for Energy and Power (ACEP) for a period of 1 year [35].

The major factors affecting wind farm output power are air temperature, wind speed, air density and air pressure. Considering all these factors will increase the prediction accuracy of the proposed model. The data used in this paper includes the parameters of output power, temperature, density, pressure, and wind speed for 1 year for training prediction model and validating the model. The proposed model uses the latest 5 real values for all of the measured parameters as inputs to the prediction model to predict the power in next period i.e. the model use historical data for 4 h and current real time data for predicting the power in next 1 h. The input parameters of the model are listed in Table 1.

The parameters air temperature T(t), wind speed V(t), air density ρ(t), pressure P(t), and output power S(t) are the real time measured values coming from wireless sensor network.

4. Proposed System

Figure 2 shows the main structure of proposed forecasting system. The proposed system includes two main modules: The forecasting module and optimization module. In the forecasting module, ANFIS is used for prediction. In this module, we used 5 ANFIS for an hour ahead air temperature T (t), wind speed V (t), air density ρ (t) and pressure P (t) prediction. The first ANFIS (ANFIS 1) is applied to forecast the value of air temperature. As mentioned, we used 4 hours before value of air temperature (T (t -4), T (t- 3), T (t-2), T (t-1)) as input of ANFIS 1 and an hour ahead of air temperature value as output of ANFIS 1. The same procedure is applied for other parameters including wind speed V (t), air density ρ (t) and pressure P (t). Based on the predicted values by ANFIS 1 through ANFIS 4, the fifth ANFIS (ANFIS 5) compute an hour ahead power generated by wind turbine.

Table 1. Input parameters of the model.

Input no.	Parameter name	Abbreviation	Symbol	Unit
1-5	Air temperature	T	T(t -4), T(t- 3), T(t-2), T(t-1), T(t)	C°
6-10	Wind speed	V	V(t -4), V(t- 3), V(t-2), V(t-1), V(t)	mph
11-15	Air density	P	ρ (t -4), ρ (t- 3), ρ (t-2), ρ (t-1), ρ (t)	lb/ft^3
16-20	Pressure	P	P(t -4), P(t- 3), P(t-2), P(t-1), P(t)	Pa

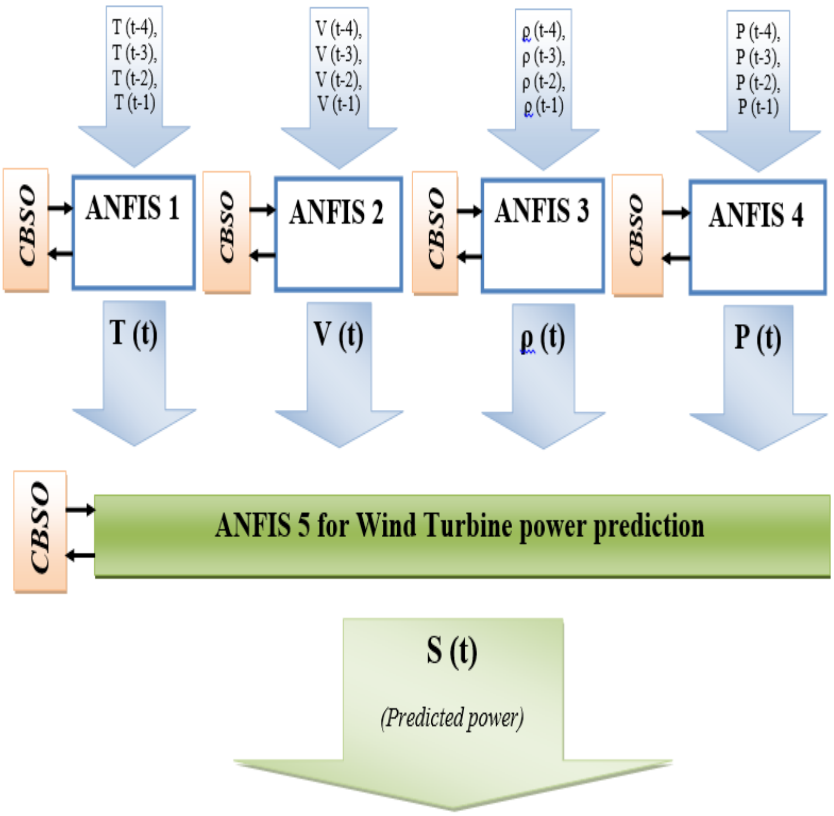

Figure 2. The main structure of proposed forecasting system

A radius value was given in the MATLAB program to specify the cluster center's range of influence to all data dimensions of both input and output. If the cluster radius was specified a small number, then there will be many small clusters in the data that results in many rules. In contrast, specifying a large cluster radius will yield a few large clusters in the data resulting in fewer rules [37]. In fact, there is no systematic approach to select the radii vector. Therefore in this study CBSO-ANFIS is proposed to find the optimum vector of radius. Figure 3 shows a sample bat in the optimization algorithm. In this figure p denotes the number of input-output variables.

$$Sample\ bat = \left[Radius_1 \quad Radius_2 \quad \dots \quad Radius_p\right]$$

Figure 3. A sample bat in the proposed method

In each optimization algorithm, the right definition of objective function has high importance. In the proposed method, we used average root mean square error (ARMSE) and average relative Error (AReErr) as objective function. The mathematical formulation of objective functions are presented by Eq. (8) and (9). The CBSO should find the best radii vector and reduce the objective functions. Minimum objective functions means good prediction.

$$ARMSE = \frac{\sum_{i=1}^{n} \frac{\sqrt{\sum_{j=1}^{k}(P_{meas}-P_{pred})^2}}{k}}{n} \tag{8}$$

$$AReErr(\%) = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{k}\left|\frac{P_{j\,max} - P_{j\,pred}}{P_{j\,max}}\right|\right) \times 100 \tag{9}$$

5. Simulation Results

In this section we evaluate the performance of proposed forecasting system. For this purpose, we have used the practical and real world data [36, 38]. For the selected wind turbine data, to cover all seasons of the year, four subsets are selected from data collected to train the prediction model in different periods of year. Table 2 shows selected subsets periods from collected data. Also Figure 4 shows the sample of turbine output in each subset data.

Table 2. Selected subsets periods from data

Subset no.	Period		No. of data row
	From	To	
1	15/3/2006	25/4/2006	1000
2	15/6/2006	25/7/2006	984
3	15/9/2006	25/10/2006	984
4	15/12/2006	25/1/2007	1000

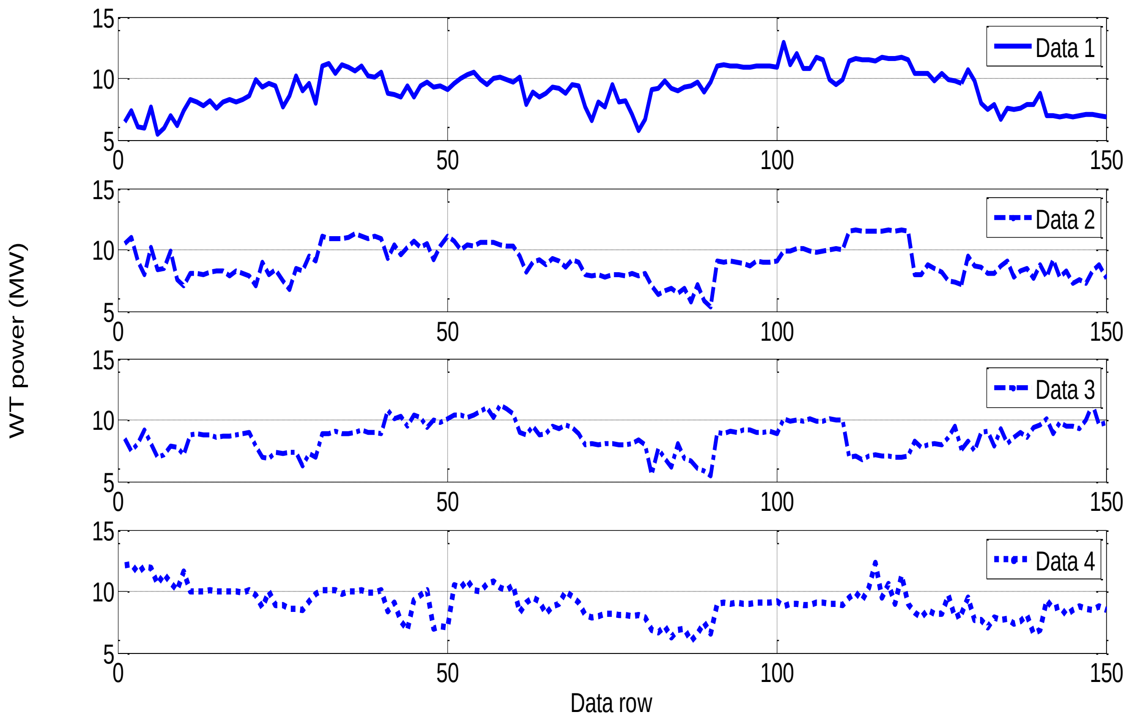

Figure 4. Sample of turbine output in each subset data

For this study, we have used 50% of the data for training and the rest for testing. All the obtained results are the average of 50 independent runs. The computational experiments for this section were done on Intel core i7 with 16 GB RAM using ASUS computer.

5.1. ANFIS Performance

In this section, the performance of traditional ANFIS is investigated. In this experiment, the radii vector selected without optimization and set to a scalar value equal 0.5 for all clusters. The other parameter of ANFIS are listed in Table 3. Also the performance of ANFIS is shown in Figure 5. It can be seen that ANFIS had pretty good performance on prediction of wind turbine output power for different subsets. In Figure 6, the error rate of ANFIS is shown. In this figure, the horixontal axis shows the time and the vertical axis shows the generated power.

Table 3. ANFIS parameters

Parameter	Value
Input membership function	Gaussian
Membership function constants	$\sigma = 2, C = 5$
No. inputs	4
Output membership function	Triangular-shaped
Membership function constants	$a = 3, b = 6, c = 8$
No. output	1
Defuzzification Methods	Centroid
Fuzzy inference method	Mamdani
Aggregation	Prob
Fuzzy Implication	Min
Degree of Fulfillment	Min
Radii vector	0.5

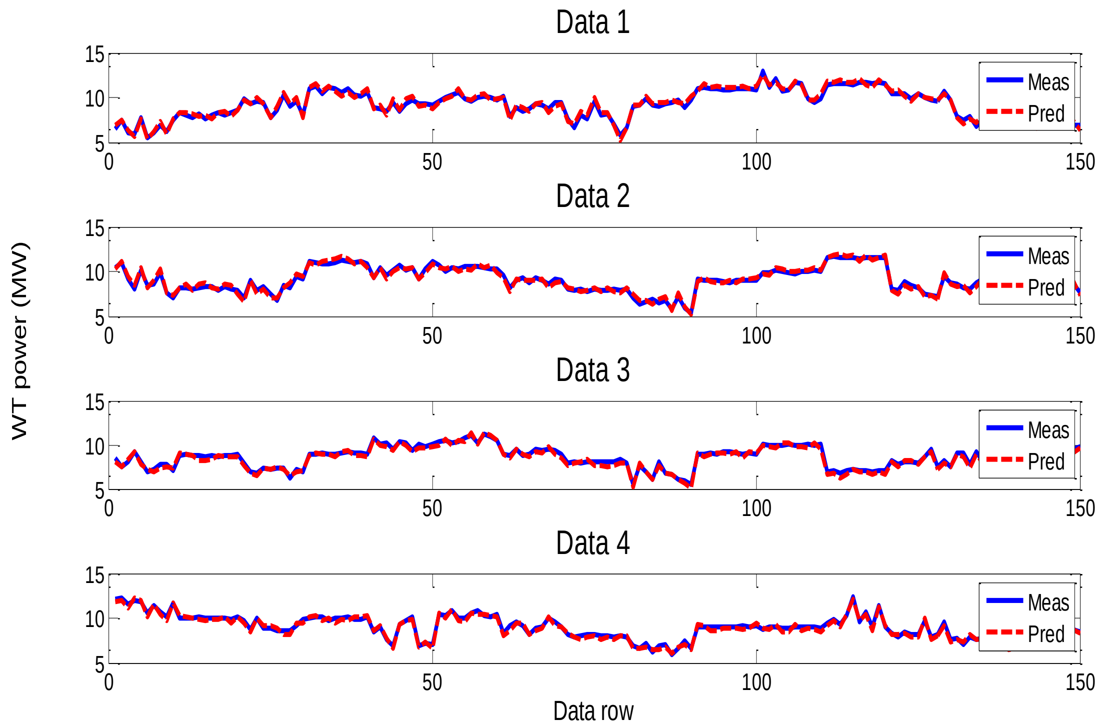

Figure 5. Performance of ANFIS without optimization

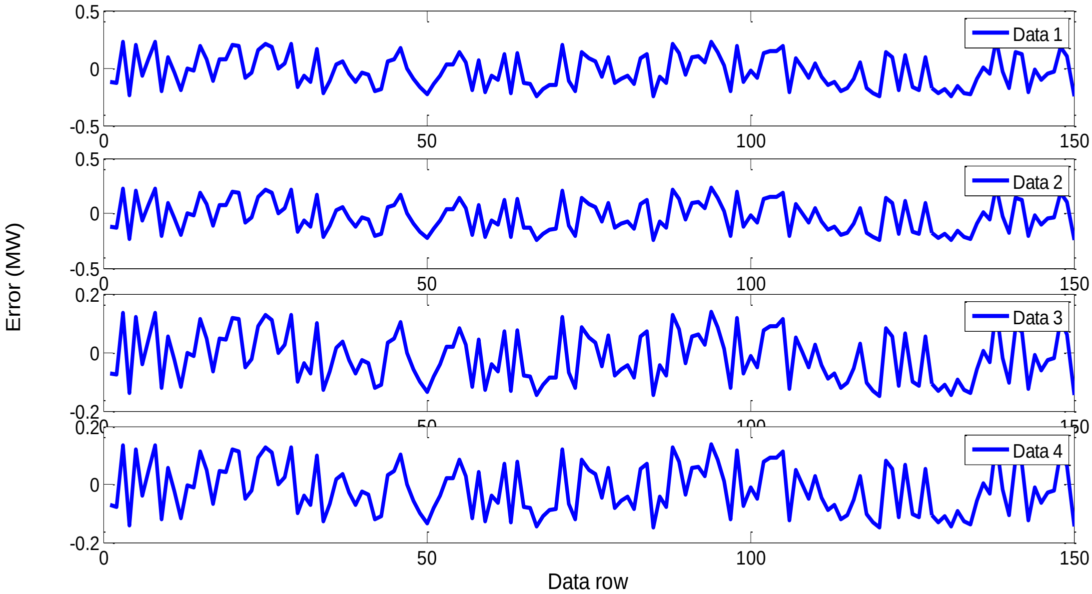

Figure 6. Error rate of ANFIS without optimization

Table 4. Radii effect on ANFIS performance

Radii	Data 1		Data 2		Data 3		Data 4	
	ARMSE	AReErr (%)	ARMSE	AReErr (%)	ARMSE	AReErr (%)	ARMSE	AReErr (%)
0.1	0.0076	10.34	0.0076	10.34	0.0052	7.10	0.0047	6.37
0.2	0.0076	10.32	0.0079	10.66	0.0055	7.39	0.0047	6.35
0.3	0.0074	10.03	0.0076	10.29	0.0054	7.29	0.0047	6.39
0.4	0.0080	10.77	0.0085	11.45	0.0053	٧.٢١	0.0046	6.22
0.5	0.0083	11.21	0.0083	11.28	0.0054	7.36	0.0051	6.87
0.6	0.0079	10.67	0.0083	11.19	0.0059	7.98	0.0045	6.06
0.7	0.0073	9.89	0.0078	10.56	0.0055	7.48	0.0045	6.10
0.8	0.0077	10.36	0.0080	10.87	0.0057	7.77	0.0046	6.27
0.9	0.0076	10.32	0.0081	10.98	0.0054	7.28	0.0047	6.33
1	0.0074	10.03	0.0083	11.27	0.0055	7.39	0.0046	6.25

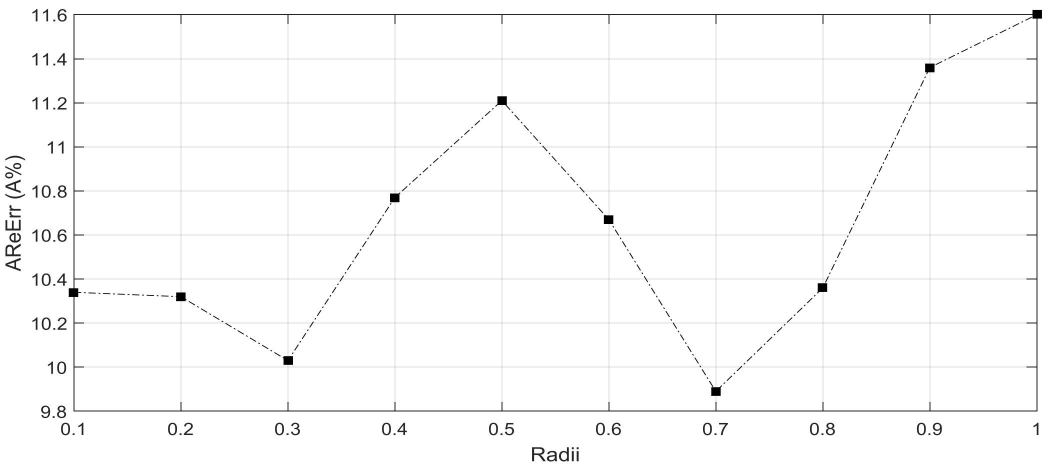

Figure 7. Effect of radii on ANFIS performance

In Table 4, the performance of ANFIS with different radii's are listed. In this experiment, scalar value is selected for radii. In Figure 7 the variation of ANFIS accuracy by variation of radii for Data 1 is illustrated. It can be seen that there is no linear relationship between radii and ANFIS accuracy. Therefore it is very hard to find the most appropriate value of radii vector.

5.2. Performance of Proposed Method

Next, we apply CBSO to find the optimum vector of radius. In each optimization algorithm, control parameters have vital role on its accuracy and convergence speed. The obtained results using proposed method are shown in Figure 8. It can be seen that proposed method has excellent performance on prediction of wind turbine output power for different subsets. In Figure 9, the error rate of proposed method and other methods are shown. ANFIS accuracy Improvement after optimization, show the radii importance and optimization effect. The best vector radii are listed in Table 5.

Table 5. Optimized radii vector

ANFIS 1	$[0.54\ \ 0.12\ 0.49\ \ 0.84]^T$
ANFIS 2	$[0.83\ \ 0.66\ 0.43\ \ 0.19]^T$
ANFIS 3	$[0.32\ \ 0.28\ 0.31\ \ 0.38]^T$
ANFIS 4	$[0.93\ \ 0.56\ 0.16\ \ 0.27]^T$

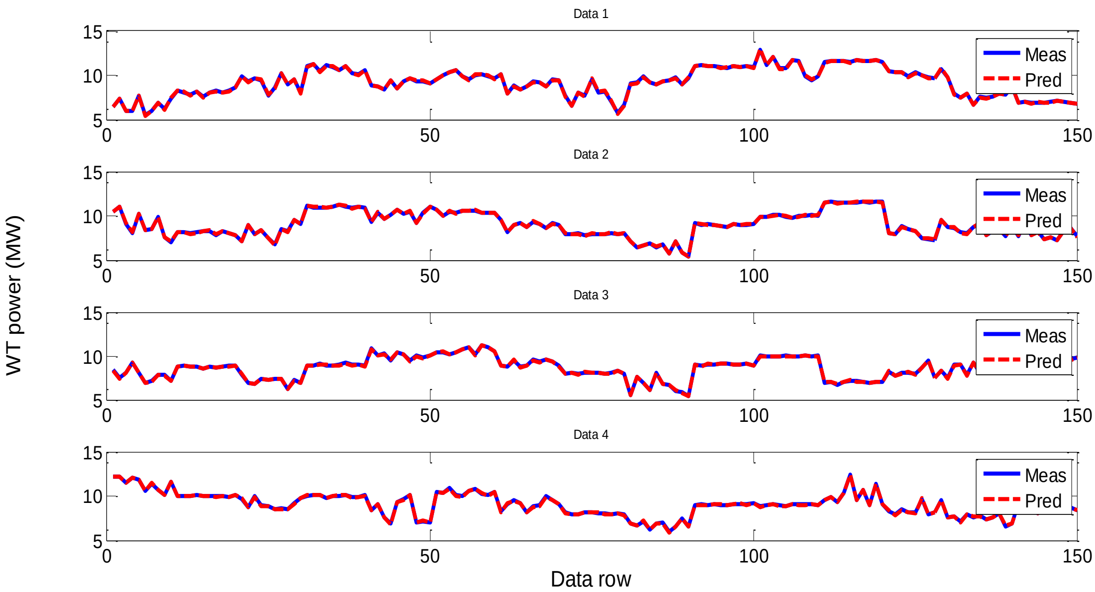

Figure 8. Performance of proposed method

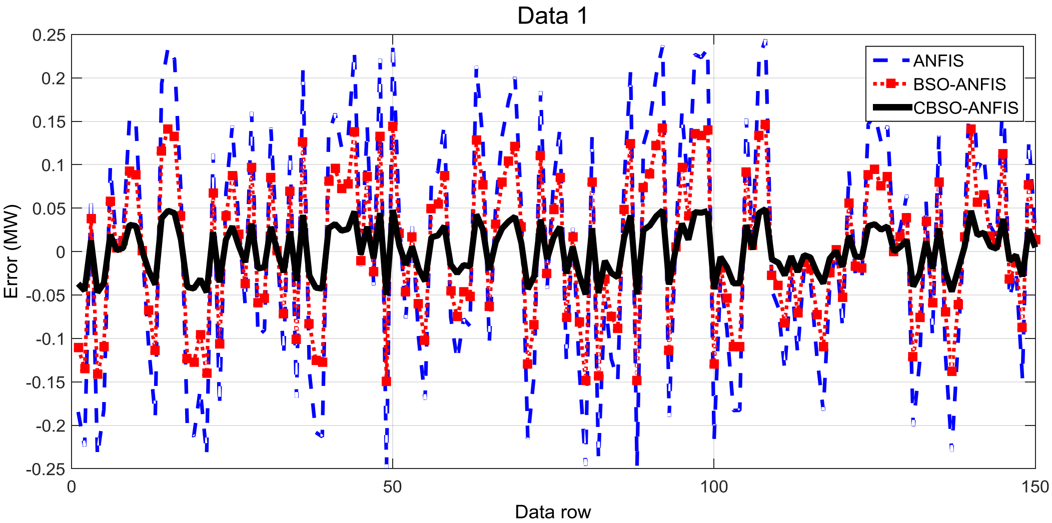

Figure 9. Error rate of proposed method

Table 6. Radii effect on ANFIS performance

Method	Data 1		Data 2		Data 3		Data 4	
	ARMSE	AReErr (%)	ARMSE	AReErr (%)	ARMSE	AReErr (%)	ARMSE	AReErr (%)
CBSO-ANFIS	**0.00438**	**5.87**	**0.00318**	**5.62**	**0.00259**	**4.32**	**0.0020**	**3.12**
BSO-ANFIS	0.00483	6.54	0.00351	6.38	0.00273	4.54	0.0022	3.49
Ref [29]	0.00544	7.37	0.00418	7.45	0.00287	4.79	0.0024	3.84

Table 6 shows the obtained results by proposed method and other method [35]. It can be seen that the proposed method (CBSO-ANFIS) has better performance compared with other methods.

6. Conclusion

Wind power forecasting can improve the economic and technical integration of wind energy into the existing electricity grid. Due to its intermittency and randomness, it is hard to forecast wind power accurately. For the purpose of utilizing wind power to the utmost extent, it is very important to make an accurate prediction of the output power of a wind farm under the premise of guaranteeing the security and the stability of the operation of the power system. In this paper an intelligent method proposed to forecast the wind turbine output power. The obtained results show that optimized ANFIS has excellent performance on wind turbine output power prediction.

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