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Predicting the wind power density based upon extreme learning machine

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ABSTRACT

Precise predictions of wind power density play a substantial role in determining the viability of wind energy harnessing. In fact, reliable prediction is particularly useful for operators and investors to offer a secure situation with minimal economic risks. In this paper, a new model based upon ELM (extreme learning machine) is presented to estimate the wind power density. Generally, the two-parameter Weibull function has been normally used and recognized as a reliable method in wind energy estimations for most windy regions. Thus, the required data for training and testing were extracted from two accurate Weibull methods of standard deviation and power density. The validity of the ELM model is verified by comparing its predictions with SVM (Support Vector Machine), ANN (Artificial Neural Network) and GP (Genetic Programming) techniques. The wind powers predicted by all approaches are compared with those calculated using measured data. Based upon simulation results, it is demonstrated that ELM can be utilized effectively in applications of wind power predictions. In a nutshell, the survey results show that the proposed ELM model is suitable and precise to predict wind power density and has much higher performance than the other approaches examined in this study.

1. Introduction

Nowadays, the current trend of fossil fuels consumption as well as environmental problems have further motivated incentives towards developing renewable and clean energy sources. As an appropriate renewable energy source, wind energy is being largely harnessed in various regions around the world to enhance the sustainability and reduce some negative environmental issues raised by excessive exploitation of fossil fuels. Owing to the outstanding nature of wind energy which is free, environmental friendly and inexhaustible, countries are performing tremendous efforts to assign a high priority to wind energy harnessing [1]. In fact, adaptation and utilization of the wind energy has received considerable attention all over the world as an alternative source to meet the energy demand. Wind energy is now viewed as the fastest growing source because its development has been characterized by a remarkable rate and this trend is expected to continue. Although investment on wind energy to generate electricity is the cheapest one among all renewables, inappropriate locations for wind turbines installation eventuates in losing huge amounts of money. Therefore, for providing secure wind energy utilization as well as enhancing the efficiency of wind energy markets, wind resources evaluation particularly in terms of realizing wind speed and power predictions is an imperative task [2]. Nevertheless, since the frequency distribution of wind speed may provide different wind power densities for the same wind speed, the knowledge of wind power density would be further reliable. Wind power density resembles the level of accessible energy at the site for converting to electricity by using wind turbines.

Despite the fact that a vast number of mathematical models have been suggested to simulate the wind energy related parameters, there are still disadvantages of the models such as being very

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demanding in terms of computation time. As a consequence, during the last decade, a large number of scientists worldwide have applied artificial intelligence and computational intelligence techniques to estimate, simulate and optimize various important elements in the realm of wind energy.

Shamshirband et al. [3] performed an investigation on the probability density functions of wind speed and directions based upon the ANFIS (adaptive neuro-fuzzy inference system). They compared the results of ANFIS technique with four wind distribution approaches of Weibull, Frechet, Gumbel and Joint probability density functions. They concluded that ANFIS can represent the wind speed and direction distribution favorably. Karki et al. [4] developed a probabilistic methodology to determine the wind variability and measure the wind power commitment risk throughout the operation of wind energy conversion systems. Chang [5] employed the PSO (particle swarm optimization) technique to assess the wind energy in Taiwan based upon the Weibull distribution function. He calculated the Weibull parameters, the wind speed distribution as well as many important parameters for wind energy evaluation. The obtained results indicated that the PSO method is viable in applications of wind energy. Ma et al. [6] utilized wind power data for all locations distributed across Ireland to suggest some scenarios for attaining the knowledge of error and fluctuation distribution of predicted short-term wind power. Bigdeli et al. [7] predicted the wind power time series for a wind farm located in Alberta, Canada. They developed some hybrid models by combining the NN (neural network) with ICA (imperialist competitive algorithm), GA (genetic algorithm) and PSO techniques. The achieved results showed that the hybrid NN-ICA outperforms other hybrid models. Mohandes and Rehman [8] applied three approaches: the PSO, the AIM (Abductory Induction Mechanism) and the PER (Persistence) for forecasting the 12-h ahead wind speed in Saudi Arabia. They found close agreement between the predicted wind speed data and the measured ones. Petković et al. [9] applied the ANFIS to control and design the wind generator system with CVT (continuously variable transmission). The ANFIS scheme regulated the CVT ratio to achieve the highest power generation efficiency of the wind turbine with extracting maximum wind energy. Bhaskar and Singh [10] proposed an approach, consisted of two steps, to predict wind power based upon the AWNN (adaptive wavelet neural network) as well as the FFNN (feed-forward neural network).

NN, as a major AI (Artificial Intelligence) approach, has been recently introduced and applied in different engineering fields. This method is capable of solving complex nonlinear problems which are difficult to solve by classic parametric methods. NNs can be trained by several algorithms including the GD (Gradient Descent), GDA (Adaptive Learning Rate Gradient Descent Momentum), GDX (Gradient Descent with Adaptive Learning Rate Back Propagation), OSS (One-Step Secant), SCG (Scaled Conjugate Gradient), CGB (Fletcher–Reeves Conjugate Gradient), CGP (Powell–Beale Conjugate Gradient) and CGF (Polak–Ribiere Conjugate Gradient Methods Gradient Descent) [11].

Nevertheless, the major disadvantage of NNs is its learning time requirement. Huang et al. [12,13] introduced an algorithm for single layer feed forward NN which is known as ELM (Extreme Learning Machine). The ELM algorithm is able to decrease the required time for training a NN. In fact, it has been proved that by utilizing the ELM, learning becomes very fast and it produces good generalization performance [14]. Accordingly, several researchers have been attracted towards applying ELM to solve the problems in considerable scientific areas [15–20].

A few studies have also been conducted by applying ELM to the wind energy field. Wu et al. [21] performed an investigation to develop an ELM-based model for estimating wind speed and sensorless control of wind turbine systems. Salcedo-Sanz et al. [22] combined the CRO (coral reefs optimization) with ELM to predict short-term wind speed in a wind farm situated in USA. Wan et al. [23] using ELM proposed a model for short-term probabilistic wind power forecasting in a wind farm of Australia.

Reviewing the literature indicates that there is no specific utilization of ELM in estimating wind power density. Therefore, the aim of this research work is to develop an ELM-based model in order to predict the monthly wind power density. The merit of ELM is verified by comparing its predictions accuracy with SVM (Support Vector Machine), ANN (Artificial Neural Network) and GP (Genetic Programming) successfully employed in wind energy area estimations. The wind power density values are calculated based upon the standard deviation and power density methods of the Weibull function to extract the required data for training and testing the models. Afterwards the performance evaluation is accomplished statistically by providing comparisons between the predicted results and the calculated wind powers using real data.

The ELM is a powerful algorithm with faster learning speed compared with traditional algorithms such as the BP (back-propagation). It also has a better performance too. ELM tries to get the smallest training error and norm of weights.

The organization of the remaining part of this paper is as follows: Section 2 explains the wind data and wind power estimation. Section 3 presents the description of ELM. The comparative results and discussion are brought forward in Section 4. Finally, the conclusions are presented in Section 5.

2. Wind data and power

2.1. Wind data

Basically, wind speed is measured at a desired site by utilizing anemometers established in a wind mast. In this study, we utilize 3-h wind speed data for the period of five years. In fact, the used wind speed data for this study have been measured at the elevation of 10 m above the ground level in 3-h interval periods. In the first step of analysis, the 3-h wind speed data were averaged to obtain daily data. As mentioned, the main objective of this study was evaluating the suitability of ELM algorithm to predict monthly wind power density based on existing methods of standard deviation and power density. Therefore, using the achieved daily data of each month, the monthly calculations were conducted over each specific month to evaluate the adequacy of ELM approach to predict wind power density. The extracted wind power densities from both Weibull methods were used to train and test the developed models. To achieve reliable evaluation and comparison, the developed models were tested with a data set that has not been used during the training process. For this purpose, the monthly data were divided into two subsets for training and testing.

2.2. Wind power density

To determine the potential of wind energy in a location, the knowledge of the wind speed and the mean wind power is essential. Nevertheless, because of high variation in wind speed in some sites, the amount of standard deviation is very high; thus, with lower average wind speeds and higher standard deviation, higher wind power is probable. Consequently, the wind power density should be estimated to assess the wind resource potential with further reliability. The wind power can be computed from measured wind speed values and the probability distribution function. The following equation can be used to calculate wind power density from measured wind speeds [24,25]:

$$\overline{P} = \frac{1}{2n}\rho\sum_{i=1}^{n} v^3 = \frac{1}{2}\rho\overline{v^3}\left(W/m^2\right) \tag{1}$$

where ρ is the air density (kg/m^3), v is the wind speed (m s^{-1}), $\overline{v^3}$ is mean of cube of wind speed and n is the number of data points over a specified time period.

2.3. Weibull distribution function

The 2-parameters Weibull distribution is broadly employed in wind energy statistical analysis to represent the wind speed distribution and calculate the wind power density. The Weibull distribution function is given by Refs. [26–29]:

$$f_w(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\exp\left(-\left(\frac{v}{c}\right)^{k}\right) \tag{2}$$

where v, k and c are the wind speed (m s^{-1}), shape factor (dimensionless) and scale factor (m s^{-1}), respectively.

The wind power density on the basis of the Weibull probability density function is estimated by Refs. [30,31]:

$$P = \frac{1}{2}\rho\int_0^\infty v^3 f_w(v)dv = \frac{1}{2}\rho c^3 \Gamma\left(1+\frac{3}{k}\right) \tag{3}$$

There are several methods to calculate the Weibull parameters. In this study, however, the standard deviation and the power density methods are utilized to calculate the parameters of the Weibull distribution function as further accuracy can be achieved in estimating the wind speed distribution and wind power.

2.3.1. The standard deviation method

Based upon the standard deviation method, the shape factor k and scale factor c are estimated using the following equations [32,33]:

$$k = \left(\frac{\sigma}{\overline{v}}\right)^{-1.086} \tag{4}$$

$$c = \frac{\overline{v}}{\Gamma\left(1+{}^{1}/_{k}\right)} \tag{5}$$

where $\overline{v}$ and σ are the mean wind speed and standard deviation of the wind speed. $\Gamma(x)$ is the gamma function.

2.3.2. The power density method

To estimate the shape and scale factors via the power density method, the energy pattern factor, E_{pf}, should be calculated. The E_{pf} is a parameter used for the turbine aerodynamic design, defined by Refs. [34,35]:

$$E_{pf} = \frac{\frac{1}{n}\sum_{i=1}^{n} v_i^3}{\left(\frac{1}{n}\sum_{i=1}^{n} v_i\right)^3} = \frac{\overline{v^3}}{\overline{v}^3} = \frac{\Gamma\left(1+{}^{3}/_{k}\right)}{\Gamma^3\left(1+{}^{1}/_{k}\right)} \tag{6}$$

In Eq. (6), v is wind speed, $\overline{v^3}$ is mean of cube of wind speed, $\overline{v}^3$ is cube of mean speed and n is number of wind speed data.

The shape factor can then be computed using the equation [34,35]:

$$k = 1 + \frac{3.69}{E_{pf}^2} \tag{7}$$

The scale factor is estimated by Eq. (5).

3. ELM (extreme learning machine)

The ELM as a tool of learning algorithm has been introduced for SLFN (single layer feed-forward neural network) architecture [12,36,37]. The ELM chooses the input weights randomly and determines the output weights of SLFN analytically. The ELM algorithm has a more favorable capability in the learning speed. This algorithm does not require too much human intervention, and can run much faster than the conventional algorithms. It is capable to determine all the network parameters analytically, which prevents trivial human intervention. The ELM is an efficient algorithm with numerous advantages including ease of use, quick learning speed, higher performance as well as suitability for many nonlinear activation and kernel functions.

3.1. Single hidden layer feed-forward neural network

A SLFN function with L hidden nodes can be represented as mathematical description of SLFN incorporating both additive and RBF (radial basis function) hidden nodes in a unified way [38,39]:

$$f_L(x) = \sum_{i=1}^{L}\beta_i G(a_i, b_i, x), \quad x\in R^n, \quad a_i\in R^n \tag{8}$$

here a_i and b_i represent the learning parameters of the hidden nodes. β_i is the weight connecting the ith hidden node to the output node. The output value of the ith hidden node with respect to the input x is shown by $G(a_i, b_i, x)$. The additive hidden node with the activation function of $g(x): R\rightarrow R$ (e.g., sigmoid and threshold) is [36]:

$$G(a_i, b_i, x) = g(a_i\cdot x + b_i), \quad b_i\in R \tag{9}$$

here a_i denotes the weight vector which connects the input layer to the ith hidden node. Also, b_i is the bias of the ith hidden node a_i. x is the inner product of vector a_i and x in R^n. $G(a_i, b_i, x)$ can be found for RBF hidden node with the activation function $g(x): R\rightarrow R$ (e.g., Gaussian), as [36]:

$$G(a_i, b_i, x) = g(b_i\|x - a_i\|), \quad b_i\in R^+ \tag{10}$$

a_i and b_i represent the center and impact factor of the ith RBF node. The set of all positive real values is indicated by R^+. The RBF network is a particular case of SLFN with RBF nodes in its hidden layer. For N arbitrary distinct samples $(x_i, t_i)\in R^n\times R^m$, x_i is $n\times 1$ input vector and t_i is $m\times 1$ target vector. Provided that a SLFN with L hidden nodes is able to approximate these N samples with zero error, it implies that there are β_i, a_i and b_i as:

$$f_L(x) = \sum_{i=1}^{L}\beta_i G(a_i, b_i, x), \quad j = 1, \ldots, N. \tag{11}$$

Eq. (11) may be expressed compactly as

$$H\beta = T \tag{12}$$

where

$$H\left(\tilde{a}, \tilde{b}, \tilde{x}\right) = \begin{bmatrix} G(a_1, b_1, x_1) & \cdots & G(a_L, b_L, x_1) \\ & \cdots & \\ (a_1, b_1, x_N) & \cdots & G(a_L, b_L, x_N) \end{bmatrix}_{N\times L} \tag{13}$$

with $\tilde{a} = a_1, \ldots, a_L$; $\quad \tilde{b} = b_1, \ldots, b_L$; $\quad \tilde{x} = x_1, \ldots, x_L$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \quad \text{and} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_L^T \end{bmatrix}_{N\times m} \tag{14}$$

H is the hidden layer output matrix of SLFN with ith column of H being the ith hidden node's output according to the inputs $x_1, \ldots, x_N$. In this study, 13 hidden nodes are used.

3.2. Principle of ELM

The ELM designed as a SLFN with L hidden neurons is able to learn L distinct samples with zero error [12,36]. Even if the number of hidden neurons (L) is smaller than the number of distinct samples (N), the ELM can still assign random parameters to the hidden nodes and compute the output weights by a pseudo-inversion of H giving only a small error $\varepsilon > 0$. The hidden node parameters of ELM a_i and b_i should not be tuned throughout training and can easily be assigned to random values. The following theorems state the same.

Theorem 1. (Liang et al. [39]) Let an SLFN with L additive or RBF hidden nodes and an activation function g(x) which is infinitely differentiable in any interval of R be given. Then for arbitrary L distinct input vectors $\{x_i|x_i \in R^n, \quad i = 1, \ldots, L\}$ and $\{(a_i, b_i)\}_{i=1}^{L}$ randomly generated with any continuous probability distribution, respectively, the hidden layer output matrix is invertible with probability one; then the hidden layer output matrix H of the SLFN is invertible and $\|H\beta - T\| = 0$.

Theorem 2. (Liang et al. [39]) Given any small positive value $\varepsilon > 0$ and activation function $g(x) : R \to R$ which is infinitely differentiable in any interval, there exists $L \le N$ such that for N arbitrary distinct input vectors $\{x_i|x_i \in R^n, \quad i = 1, \ldots, L\}$ for any $\{(a_i, b_i)\}_{i=1}^{L}$ randomly generated by any continuous probability distribution $\|H_{N\times L}\beta_{L\times m} - T_{N\times m}\| < \varepsilon$ with probability one.

Since the hidden node parameters of ELM should not be tuned throughout training and because they are easily assigned with random values, Eq. (12) becomes a linear system and the output weights can be estimated as [36]:

$$\beta = H^{+}T \tag{15}$$

where H^{+} is the Moore–Penrose generalized inverse [40] of the hidden layer output matrix H which can be computed via several approaches, e.g. orthogonal projection, orthogonalization, iterative and SVD (singular value decomposition) [40]. The orthogonal projection method can be utilized only when $H^T T$ is nonsingular and $H^{+} = (H^T T)^{-1} H^T$. Owing to the use of searching and iterations, the orthogonalization and iterative methods have limitations. The implementation of the ELM uses SVD to compute the Moore–Penrose generalized inverse of H, because it can be utilized in all situations. ELM is thus a batch learning method.

4. Results and discussion

In the current study, an ELM is employed to establish a model for predicting the wind power density. To demonstrate the merit of the ELM approach in estimating the wind power density, its prediction performance is assessed by making comparisons with SVM, ANN and GP. SVM, ANN and GP have been widely used by many researchers in solving various problems [41–48].

In the first step of analysis, the extracted wind power data from the standard deviation and power density methods were used. In fact, these obtained wind power density values from both methods were collected and defined as training and checking data. It is worthwhile to mention that the calculated values of both methods were combined together to attain the data required for the training and testing phases. Fig. 1 illustrates the sample of wind power density values based upon each Weibull method utilized as training data. After the training process the ELM scheme and the other approaches were tested using the remaining data set. As it is clear from Fig. 1, the predictions of both methods are consistent with each other and the values are in agreement.

The descriptive statistics of mean values, standard deviation, minimum and maximum values and the range of wind power density are listed in Tables 1 and 2, respectively for the training and testing phases. Even though this information is not an indicator to determine the models' accuracy, they can be useful in terms of identifying the distribution of the predicted wind power by the ELM approach and the other techniques applied for this study as compared to the distribution of the calculated wind power using measured data.

The predicted monthly wind power density values by ELM, SVM, ANN and GP are plotted against the calculated wind power based on measured data, in the form of scatter plot, respectively in Fig. 2(a–d) for the training data set. Also, Fig. 3(a–d) shows the scatter plots between monthly wind power densities computed via ELM, SVM, ANN, GP and those calculated based upon measured data, respectively for the testing data set. These results which show the linear relationship of models with obtained wind power using measured data may be profitable to illustrate the ability of models for a wind power density prediction. Since the slope of the straight line for ELM is closer to one, the number of either overestimated or underestimated values produced are really limited. This demonstrates the higher rate of correlation between computed wind power values by ELM and those obtained from measurements. Therefore, it is obvious that the predicted values by ELM enjoy greater accuracy compared to SVM, ANN and GP.

Table 3 provides the results of statistical performance of the developed models for wind power density predictions in terms of MAPE (mean absolute percentage error) (%), MABE (mean absolute bias error) (W m^{-2}) and R^2. The definitions of these statistical indicators are presented in Appendix. For all models it is seen that the MAPE and MABE values increased relatively in the testing phase. Nevertheless, the results presented in Table 3 demonstrate that the proposed ELM model is capable of predicting wind power density with relatively minimal error and the highest preciseness. In fact, the results clearly reveal that ELM outperforms SVM, ANN and GP.

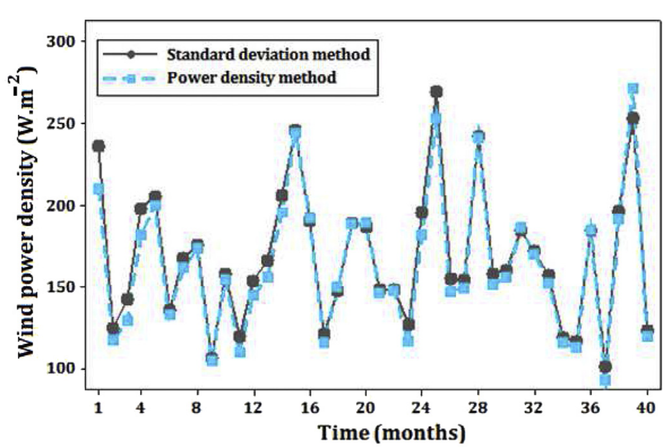

Fig. 1. Sample of wind power density values obtained using the standard deviation and power density methods utilized as learning inputs for all approaches.

Table 1
Descriptive statistics for predictions of wind power density (W m^{-2}) based upon different approaches for training data.

Statistics	ELM	SVM	GP	ANN	Measured data
Mean	161.70	163.50	161.49	160.92	163.71
St. dev.	35.97	31.99	32.29	36.34	42.53
Min	93.47	96.56	82.99	80.92	93.16
Max	251.64	231.13	232.73	244.53	273.38
Range	158.18	134.57	149.75	163.61	180.21

Table 2
Descriptive statistics for predictions of wind power density (W m^{-2}) based upon different approaches for testing data.

Statistics	ELM	SVM	GP	ANN	Measured data
Mean	155.29	158.13	157.76	155.88	147.10
St. dev.	37.08	36.95	35.16	35.92	40.07
Min	94.36	94.20	97.55	90.20	80.74
Max	228.51	241.22	219.63	218.28	224.60
Range	134.15	147.03	122.08	128.07	143.86

The predictions of the wind power density based upon the ELM approach, as the superior model, in comparison to calculated wind power density using measurements are depicted in Figs. 4 and 5 for the training and testing data sets, respectively. It is obviously observed that ELM is able to predict the wind power with very high level of preciseness in most of observations.

5. Conclusions

The accurate wind power and speed estimations are of great significance in enhancing the financial efficiency and acceptability of the wind energy harnessing. In this paper, an efficient learning model based upon the ELM (extreme learning machine) was developed to estimate the monthly wind power density. The predictions of the ELM model were compared with those of SVM, ANN and GP approaches to determine the suitability of the established ELM model for wind power density predictions. As input elements for the training and testing phases, the estimated wind power density based upon the two Weibull function methods (standard deviation and power density) were considered. The accuracy level of the predicted values was assessed in comparison to the calculated wind power values on the basis of real measurements. The simulation results revealed that the ELM model is able to predict the wind power favorably so that it provides the most accurate predictions and, therefore, it outperforms other models. Thus, the ELM algorithm can generally be effectively utilized in wind energy applications and particularly in wind power density estimations. The developed ELM model has many appealing and remarkable features which make it distinguishable from traditional popular gradient-based learning algorithms for feedforward neural networks. ELM is much faster in learning speed compared to the traditional feedforward network learning algorithms such as the back-propagation algorithm. Second, unlike the traditional learning algorithms, the ELM model is able to achieve the smallest training error and also norm of weights.

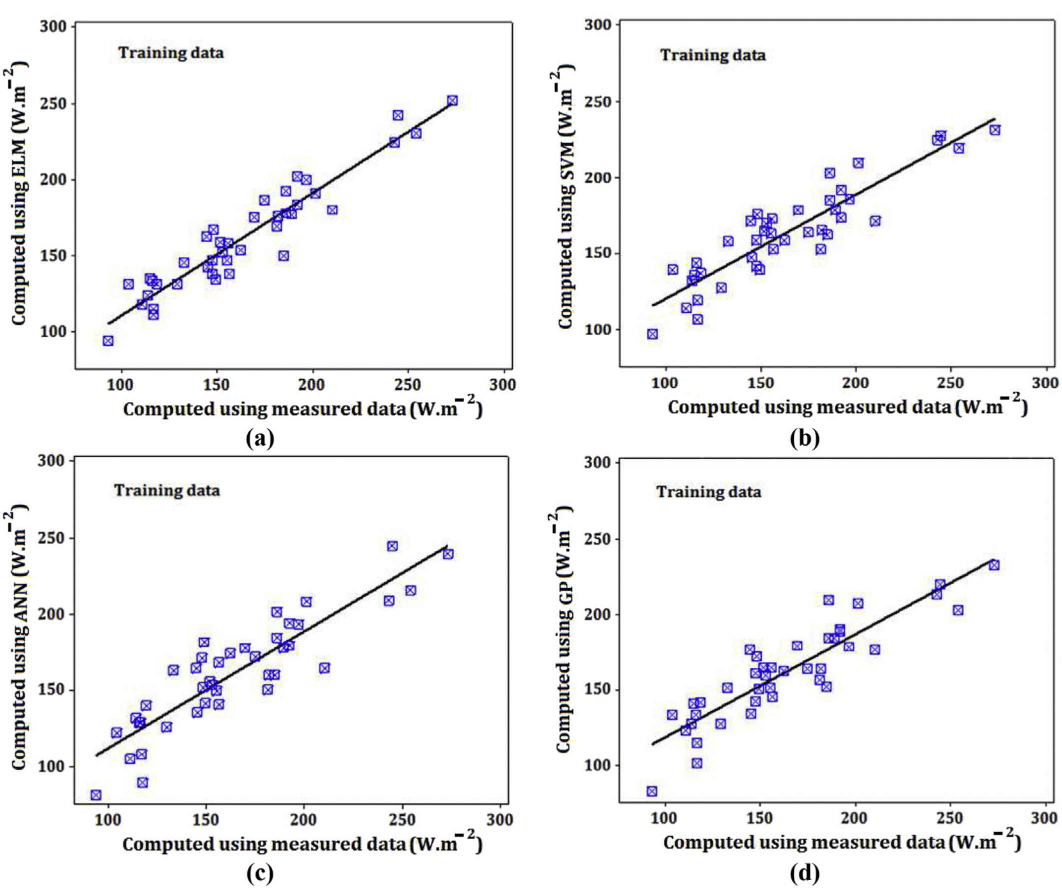

Fig. 2. Scatter plot of the wind power values based on measured data versus predicted ones via: (a) ELM, (b) SVM, (c) GP and (d) ANN for the training data set.

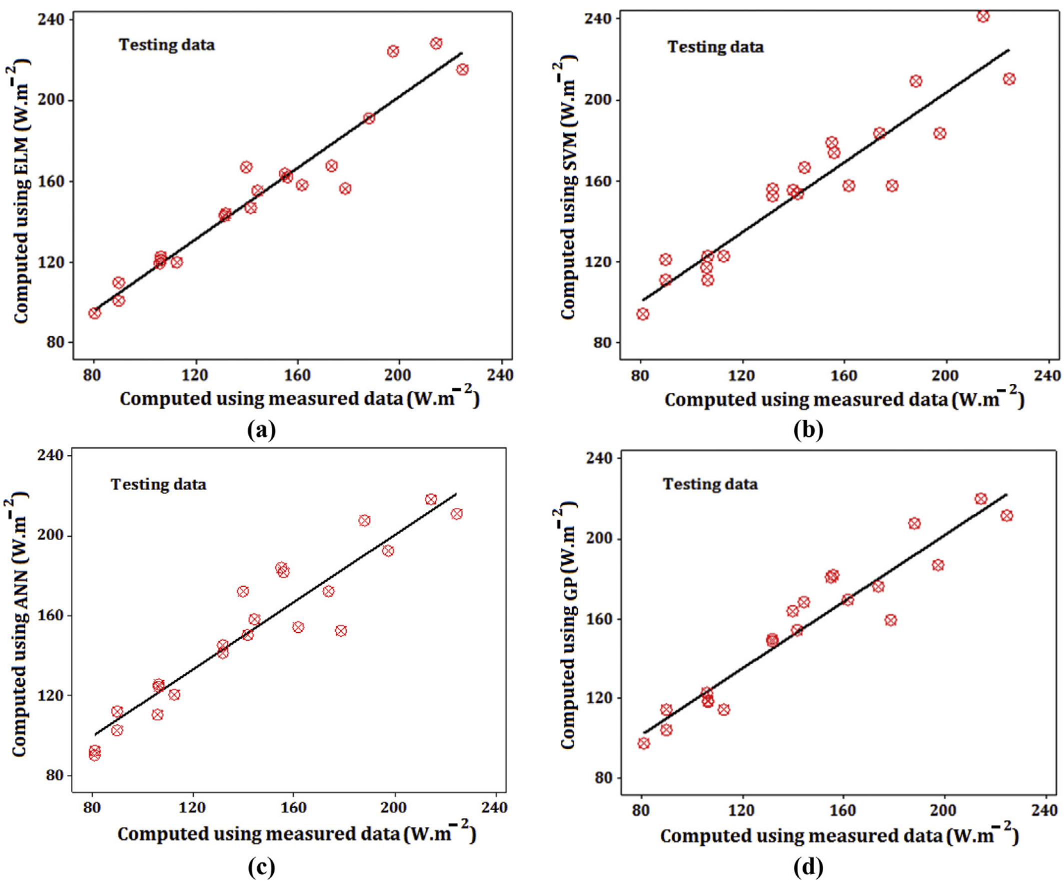

Fig. 3. Scatter plot of the wind power values based on measured data versus predicted ones via: (a) ELM, (b) SVM, (c) ANN and (d) GP for the testing data set.

Table 3
Statistical indicators obtained for ELM, SVM, GP and ANN approaches for both training and testing data sets.

Model	Training data set			Testing data set		
	MAPE (%)	MABE (W m^{-2})	R^2	MAPE (%)	MABE (W m^{-2})	R^2
ELM	7.1280	11.3543	0.9057	9.1944	12.3419	0.9056
SVM	9.6350	15.4098	0.8294	11.8674	16.4264	0.8513
ANN	9.8267	15.8598	0.8113	11.1717	15.0393	0.8691
GP	9.7155	15.4045	0.8228	10.4563	14.2664	0.8673

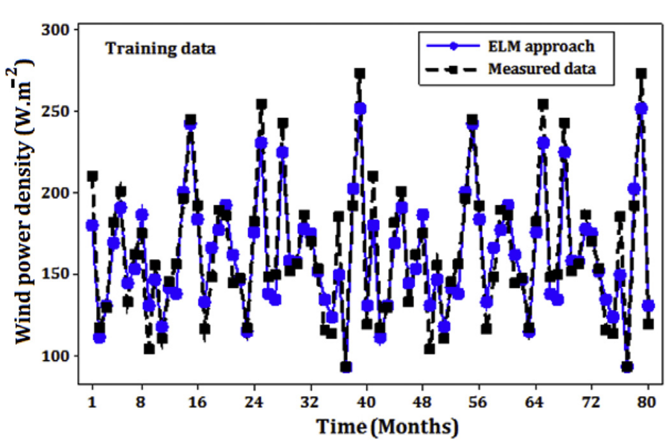

Fig. 4. ELM wind power predictions in comparison to the values obtained from measurements for the training data set.

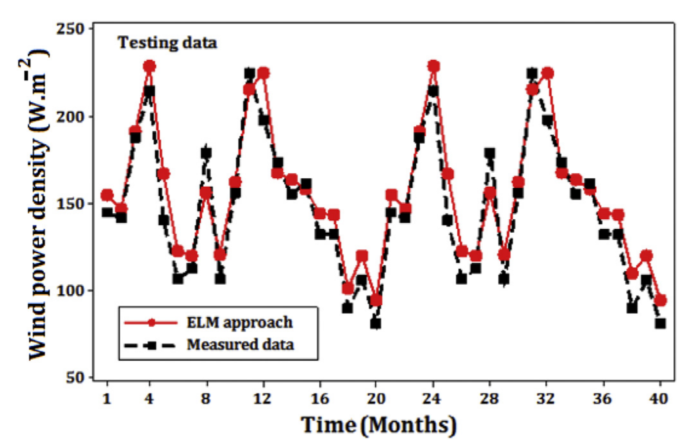

Fig. 5. ELM wind power predictions in comparison to the values obtained from measurements for the testing data set.

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Appendix

1. MAPE (mean absolute percentage error):

The MAPE is an indicator of the accuracy of a model and is defined as the mean absolute percentage difference between estimated and real data:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_{i,pred} - P_{i,meas}}{P_{i,meas}}\right| \times 100$$

2. MABE (mean absolute bias error):

The MABE represents the average quantity of total absolute bias errors between estimated and measured values:

$$MABE = \frac{1}{n}\sum_{i=1}^{n}\left|P_{i,pred} - P_{i,meas}\right|$$

3. Coefficient of determination (R^2):

The R^2 provides a measure of the linear relationship between the estimated and the measured values:

$$R^2 = \frac{\sum_{i=1}^{x}\left(P_{i,meas} - P_{meas,avg}\right)^2 - \sum_{i=1}^{n}\left(P_{i,pred} - P_{i,meas}\right)^2}{\sum_{i=1}^{x}\left(P_{i,meas} - P_{meas,avg}\right)^2}$$

where $P_{i,pred}$ and $P_{i,meas}$ are the ith predicted wind power value based on applied approaches and ith calculated wind power value using measured data, respectively. Also $P_{meas,avg}$ is the average of the wind power values computed from measurements and n is the total number of observations.

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