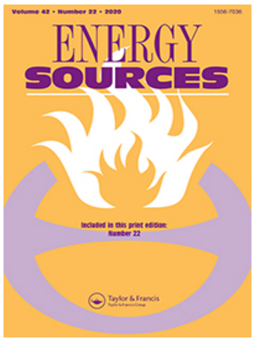

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An extreme learning machine based very short-term wind power forecasting method for complex terrain

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ABSTRACT

In this study, wind power forecasting is performed for a Wind Power Plant (WPP) with an installed capacity of 135 MW in Turkey. The ruggedness index (RIX) of the terrain where WPP was installed is analyzed with Wind Atlas Analysis and Application Program (WAsP). According to the obtained RIX value, the terrain of WPP is found to be complex. Due to the complexity of the terrain, wind power forecasting becomes difficult. To deal with this problem, a forecasting method with fast, accurate, and high performance is needed. Therefore, Extreme Learning Machine (ELM) based method is proposed for wind power forecasting in this study. Electrical and meteorological measurements are obtained from WPP for the application of the proposed method. These measurements are provided with high quality measuring devices. Also, Global Positioning System (GPS) time synchronization is used to prevent lags between measurements. The wind speed, wind direction, and wind power data of 1-year period are obtained from WPP. These data are used to compare the proposed method with a classical Artificial Neural Network (ANN) based method in terms of two, three and four hours-ahead wind power forecast performances. In the forecast studies performed for all data related to 2, 3, and 4-hours ahead, Normalized Root Mean Square Error (NRMSE) values of ELM are obtained as 7.01, 10.12, and 12.06, respectively, while these values are found as 8.19, 12.18, and 13.09 for ANN. In addition, the values of Correlation Coefficients (R) of the proposed forecast method results regarding 2, 3, and 4-hours ahead are 0.96588, 0.93528, and 0.88984, respectively. The R values related to ANN are observed as 0.95421, 0.91373, and 0.87576, respectively. According to the obtained results, it is observed that ELM has better performance features than classic method under all forecast conditions and it is clearly seen that ELM has by far short training time than other one.

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Short Term; wind Power; forecast; extreme Learning Machine; complex Terrain

Introduction

During the last century, energy resources have been the hot discussion topic from different point of views in energy industry (Smil 1994). Energy supply security, energy economy, environmental impact, and sustainability are among the prominent ones. The current literature on these topics concluded that renewable energy resources are good alternatives to fossil fuels (Turner 1999). Energy market regulators took this conclusion into account and established renewable energy supporting mechanisms (Abolhosseini and Heshmati, 2014; Yuan et al. 2015). Thanks to these supportive policies, there has been a rapid increase in renewable energy power plant installed capacity

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(Tascikaraoglu and Uzunoglu 2014). Wind Power Plants (WPPs) have had a large share of this installed capacity. Fluctuating and uncertain nature of WPP power have been a problem for Transmission System Operators (TSO) and power plant owners. Greater part of the literature on solving this problem has concluded that it is possible to integrate huge amount of WPP to electrical grid with the help of energy storage systems and wind power forecasts (Assareh et al. 2012; Weitemeyer et al. 2015; Zhao et al. 2015). Therefore, there has been a growing interest in energy storage and wind power forecast topics. Researchers have been achieved new improvements. Today, it is possible to store a huge amount of electrical energy in a very short time interval (Chen et al. 2009). However, studies on wind power forecast systems have not got exactly accurate forecasts yet (Lei et al. 2009). So, most researchers have been accepted wind power generation and forecasting as stochastic processes and proposed the stochastic programming approach to solve problems arising from the uncertainty of wind power (Yildiz et al. 2017). It is well known that stochastic programming is time-consuming and difficult approach. To replace the stochastic approach with deterministic one, it is needed to decrease the uncertainty of wind power forecast. Therefore, developing new wind power forecasting methods continues to be a hot topic now.

In literature, three different approaches have been used to forecast wind power (Giebel et al. 2004). First one is physical approach. Numerical Weather Prediction (NWP) models were used in this approach to forecast wind speeds. Then, wind farm power curves were used to convert forecasted wind speeds into electrical power. Second one is statistical approach. In this approach, artificial intelligence and classical regression methods were used to forecast wind speed and power. The third approach can be considered as a combination of the first and second ones. Different NWP outputs and statistical methods were used together to forecast wind power. Also, in literature the time-scale of the forecast horizon has been used to separate wind power forecasts into three classes:

- Very-short term forecast: Few minutes to several hours
- Short-term forecast: From several hours to day or days ahead
- Medium term: From several days to one week

The aim of this study is to develop a very-short term wind power forecast model. Literature revealed that statistical models can achieve better results than NWP-based models when the forecast horizon is very short (Foley et al. 2012). In this study, some important studies on very-short term wind power forecasting are selected from literature and summarized as follows. The hybrid kernel function support vector machine was employed for Wind power forecast (Tian et al. 2018a). Also, the Particle Swarm Optimization (PSO) algorithm was used to improve the performance of the proposed forecast method (Tian et al. 2019a). An improved small world ANN-based model was proposed to forecast short-term wind power (Wang et al. 2019). Xueli et al. developed a wavelet decomposition and chaotic time series-based model to forecast wind power (An et al. 2011). The variational mode decomposition and Extreme Learning Machine (ELM) methods were used to develop short-term wind power forecasting model (Abdoos 2016). The forecasting models given above have reached high accuracy levels. However, the application of all these studies and great part of the studies in literature were carried out in different wind farms (conditions). Therefore, comparing the results of these studies will not be possible by classical performance indexes. The ruggedness index (RIX) will be useful to express wind farm conditions. So, giving RIX value will help researchers to evaluate their model's performance. Wang et al. proposed ELM-based model to forecast wind speeds (Wang, Li, and Bai 2018). Lui et al. proposed ARIMA-Artificial Neural Network (ANN) and ARIMA-Kalman filter hybrid method to forecast wind speeds (Liu, Tian, and Li 2012). A method based on local mean decomposition and combined kernel function least squares support vector machine is proposed for short-term wind speed forecast (Tian 2020). A method based on state-space support vector regression with Kalman filter was proposed to forecast short-term wind speeds (Chen and Yu 2014). The ensemble empirical mode decomposition-permutation entropy and the regularized ELM are proposed for wind speed forecast (Tian et al.

2019b). Artificial Bee Colony Algorithm-based adaptive online sequential ELM with an effective sample updating mechanism is used to forecast short-term wind speed (Tian et al. 2018b). These forecast models need wind farm power curve to convert wind speeds into power. But, it is not possible to obtain accurate power curve of a wind farm that has lots of turbines spread over a wide area. As a result of this literature review, it has been observed that the studies in the literature did not take into account the RIX values and many studies were focused on wind speed forecasts. Since RIX values affect the instability of WPPs significantly, WPPs with different RIX values have different characteristics. In this study, the RIX value of the investigated terrain was specifically emphasized in order to demonstrate the operating conditions of the WPP.

In this study, ANN-based model is proposed to forecast very-short term wind power. ANNs have been widely used in the problem of pattern recognition, regression, and prediction. Training of the ANNs is commonly carried out by backpropagation algorithms (Li and Shi 2010; More and Deo 2003). The learning speed of backpropagation algorithms is slower. This feature of backpropagation algorithms is the most important drawback. Such learning algorithms are based on gradient descent and parameters are iteratively tuned. Mentioned two cases slow down learning speed of backpropagation algorithms. Further, there are several uncertainties in adaptive neuro-fuzzy inference systems. To eliminate the drawbacks of ANNs, a novel algorithm for training was suggested by Huang (Huang, Zhu, and Siew 2006). This algorithm is called ELM and it is a quite dissimilar learning algorithm for training of Single Layer Feedforward Neural Networks (SLFN). This method is completely different from conventional methods used in the training of ANNs. In addition, ELM is carried out by using simpler mathematical operations when compared to traditional methods. In theory, weights in output of the SLFN are analytically computed whereas random values for weights and biases in the input layer are assigned. There is no rule in the determination of the number of hidden neurons and the type of activation function. However, the learning performance of ELM algorithm affects the number of hidden neurons of the ELM and type of hidden layer activation function. These parameters are quite important for improving both generalization performance and stability of the SLFNs (Bin, Li, and Rong 2013; Gurgenc et al. 2019; Huang et al. 2015; Ucar et al. 2019).

The main aim of this study is to develop an effective short-term wind power forecast system for WPP which is installed on a terrain with high RIX. For this purpose, an ELM-based forecast system has been developed. An application of this ELM-based model is carried on a grid-tied WPP that operates in a complex terrain. The mean RIX value of the terrain is calculated by WAsP as 19.5%. The application process of this study consists of three main stages. In the first stage, electrical and meteorological data are collected from WPP by high-quality measurement systems. These advanced electrical and meteorological measurement systems can meet the recommendations of IEC standards numbered 61000-4-30 and 61400-12-1, respectively. In addition, Global Positioning System (GPS) time synchronization is used to prevent lags between electrical and meteorological data. In the second stage, ELM and classical ANN-based methods are used to develop wind power forecast models. Site measurements are utilized to train and test these models. In the last stage of the study, test results of the developed models are compared to evaluate the performances. One of the most important features that distinguish this study from other studies in the literature is the development of an ELM-based short-term power forecast system for a WPP in the determined and high complexity terrain. The contributions of the study are two-fold.

- The advanced electrical and meteorological measurements systems that meet the IEC standards are used to obtain site data. Also, GPS time synchronization is used to improve accuracy.
- ELM and classical ANN are used to forecast power output of a huge WPP that located in a complex terrain with the 19.5% mean RIX value.

This paper is divided into six sections. Section-1 gives a brief overview of the study and related literature. The detailed explanation of the study site and measurement systems are given in Section-2. Theoretical background of the methodology is given in Section-3. Section-4 describes the application of proposed wind power forecast model. Results of the study are summarized in the fifth section. Finally, some conclusions and recommendations are given in the last section.

Wind power plant

A method proposed in this study is tested on a WPP. This WPP was started operation in 2009 in the south-east region of Turkey. Due to commercial restrictions, exact location of the power plant is not given in this article. However, some technical details of the plant are summarized in Table 1. Also, general view of the WPP is given in Figure 1. The WPP was located in a very complex terrain. The mean RIX value of the terrain was calculated as 19.5% by WAsP software. It is difficult to forecast wind power in complex terrains because orographic effects increase the uncertainty of WPP power output.

The WPP has 54 wind turbines. The layout of these turbines is given in Figure 1. Furthermore, some technical details of turbines are presented in Table 2.

The real data sets measured from WPP are used to develop and test the proposed forecast model. The detailed explanation of these data sets and measurement processes are given in the next section.

Table 1. Wind farm technical details.

Technical detail	Value
Mean Wind Speed (m/s)	5.912
Number of Turbines	54
Electrical Frequency (Hz)	50
Rated Power (MWe)	135
Annual Energy (GWh)	326.055

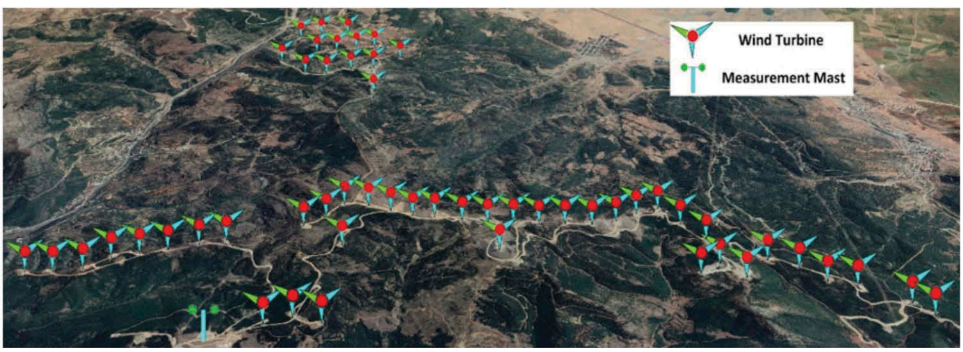

Figure 1. Wind power plant layout.

Table 2. Wind turbine technical details.

Technical detail	Value or Identity
Manufacturer	General Electric
Turbine Model	GE2.5-100
Rated Power (kW)	2500
Cut-in Wind Speed (m/s)	3
Rated Wind Speed (m/s)	13
Cutout Wind Speed (m/s)	25
Hub Height (m)	85
Rotor Diameter (m)	100
Swept Area (m^2)	7854
Number of Blades	3

Description of site measurements and data

In this study, it is aimed to develop a very short-term wind power forecast model. This model uses historical power plant generation, wind speed, and direction values to forecast short-term WPP electrical power outputs. So, it is needed to have two kinds of measurements to carry out the experimental study. These are electrical and meteorological measurements. Time synchronization between these measurements is essential to get accurate results. For this purpose, Global Positioning System (GPS) time synchronization is used to prevent undesired time delays between electrical and meteorological measurements.

Meteorological measurements

Meteorological measurements have always played a crucial role in wind energy industry. Especially, in WPP feasibility studies, the accurate wind speed and direction measurements minimize uncertainty of power generation calculations. After installation of WPP, plant owners usually perform wind turbine performance tests to check the manufacturer's guaranteed power generation. Meteorological measurement masts are indispensable parts of these tests. In order to specify the requirements of wind turbine performance tests, IEC developed a standard numbered 61400-12-1. This standard also specifies measurement mast and sensor installation procedures. And it has been the most preferred standard of wind measurements. Meteorological measurement equipment used in this study was installed in accordance with the standard 61400-12-1. The details of the meteorological measurement system configuration are given in Table 3.

In this study, two meteorological parameters (wind speed and direction) are used as forecast model inputs. Distribution of measured wind speeds is given in Figure 2. IEC standard recommends Rayleigh function to model wind speed distribution and also in feasibility studies Weibull function has mostly been preferred to model wind speed distribution.

These commonly preferred parametric probability distribution functions are used to model wind speed distribution. Maximum Likelihood Estimation (MLE) method is used to calculate function

Table 3. Details of measurement mast configuration.

Technical detail	Value or Identity
Anemometer Model	Thies first class
Wind Vane Model	Thies first class
Data Logger Model	Campbell CR 100
Tower Height (m)	80
Anemometer Installation Heights (m)	80,65,50
Wind Vane Installation Heights (m)	78,48

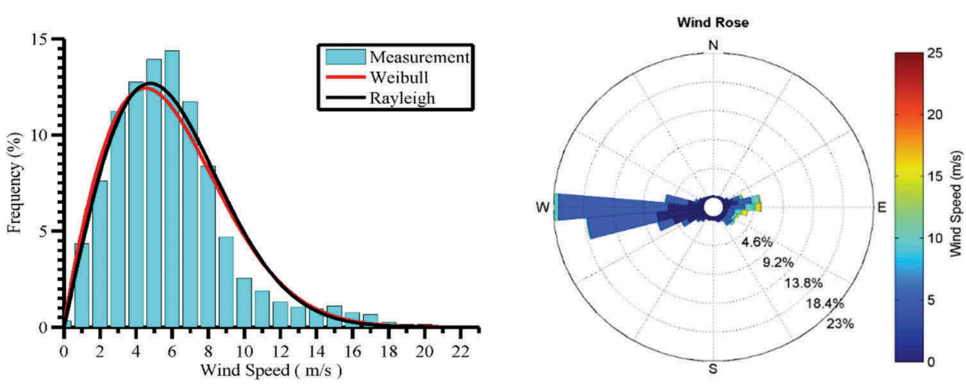

Figure 2. Wind speed distribution and wind rose.

Table 4. Statistical properties of meteorological data.

Statistical property	Wind speed (m/s)	Wind direction(°)
μ	5.912	208.578
M	5.497	255.680
σ	3.283	80.569
σ^2	10.780	6491.338

μ: Mean; M: Median; σ: Standard Deviation; σ^2: Variance.

parameters. The obtained results are given in Figure 2. These results show that Weibull and Rayleigh functions are not so suitable to model measured wind speed distribution. But this problem is not in the scope this paper. The graphic in Figure 2 is only created to illustrate measured values. Finally, the wind rose graphic is created to summarize measured wind direction values. The obtained graphic is given in Figure 2. Also, some basic statistical properties of measured wind speed and direction values are given in Table 4.

Electrical power measurements

In this study, accurate electrical power measurement data is essential since the proposed forecast model output is hour-ahead forecast of WPP electric power generation. Furthermore, this model uses historical electrical power data as input. In this study, an advanced power quality analyzer is used to achieve accurate electrical data. This Analyzer is manufactured by The Scientific and Technological Research Council of Turkey in accordance with IEC standard numbered 61000-4-30. A schematic expression of this equipment is given in Figure 3.

Analyzer takes voltage and current values through sensors, signal conditioner, and data acquisition card to mini pc. Mini PC uses these values to calculate active, reactive power, and quality parameters. The analyzer uses GPS time synchronizer to synchronize measured electrical power data with meteorological data. To illustrate the general characteristics of power data, histogram graphic, and some basic statistical properties are given in Figure 4 and Table 5, respectively.

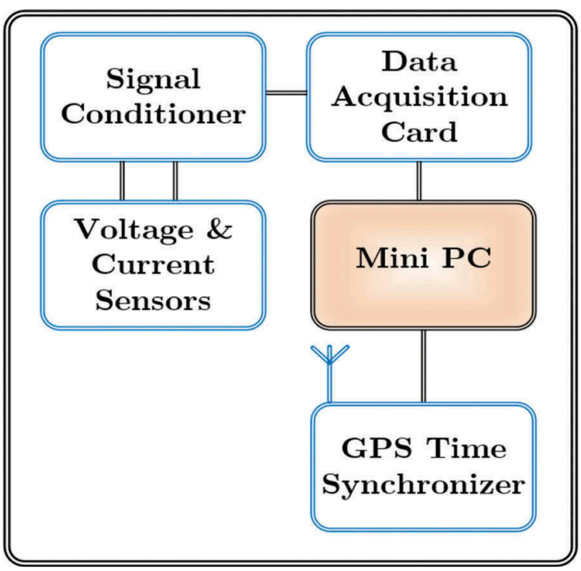

Figure 3. Power quality analyzer schematic expression.

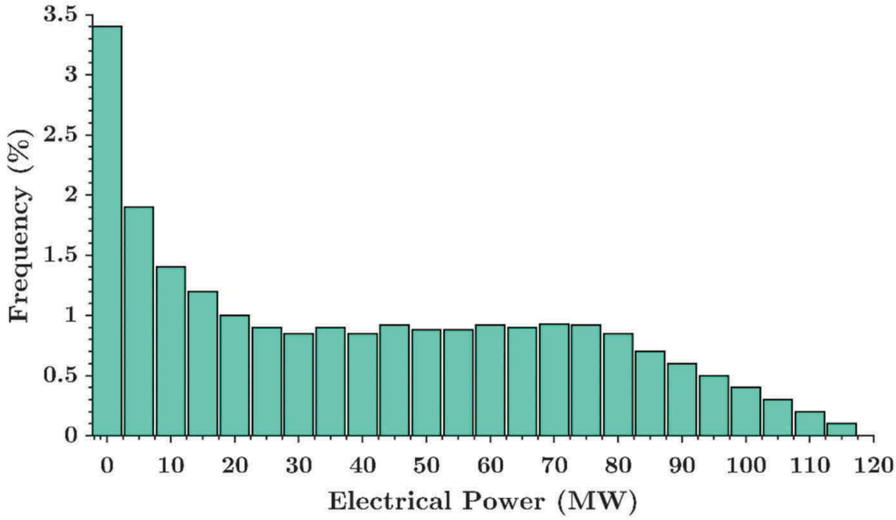

Figure 4. Electrical power distribution.

Table 5. Statistical properties of electrical power data.

Statistical property	Electrical power (MW)
μ	37.221
M	30.683
σ	32.313
σ^2	1044.106

μ: Mean; M: Median; σ: Standard Deviation; σ^2: Variance.

Extreme learning machine

The classic learning algorithms used in training of the neural networks are based on gradient and network parameters are iteratively tuned in these algorithms (Huang et al. 2015; Li and Shi 2010). Therefore, these learning algorithms have slow learning speed and this feature of traditional algorithms is the most important drawback. For eliminating the drawbacks of traditional learning algorithm, Huang proposed a learning algorithm for single-layer feedforward neural network. This algorithm is called ELM that is completely different from the traditional ones. In this method, input weights and bias are randomly assigned and output weights are obtained mathematically (Huang et al. 2015; Huang, Zhu, and Siew 2006).

While training in a feed-forward ANN requires repetition, this condition is transformed into a mathematical equation in ELM. Therefore, ELM has the extremely fast learning ability. In addition, ELM has better generalization ability than a feedforward neural network trained by the conventional backpropagation algorithm.

In addition, since the output weights of ELM calculates with the generalized inverse Moore-Penrose matrix, there are no problems directly affecting performance such as the determination of optimal learning parameters (Huang et al. 2015; Huang, Zhu, and Siew 2006). The basic structure of SLFN with hidden layer number of L is given in Figure 5. As can be seen from this figure, the inputs and outputs of the network are determined as x and y, respectively.

$$x = [x_1, x_2, x_3, \ldots, x_N]^T \in R^N \tag{1}$$

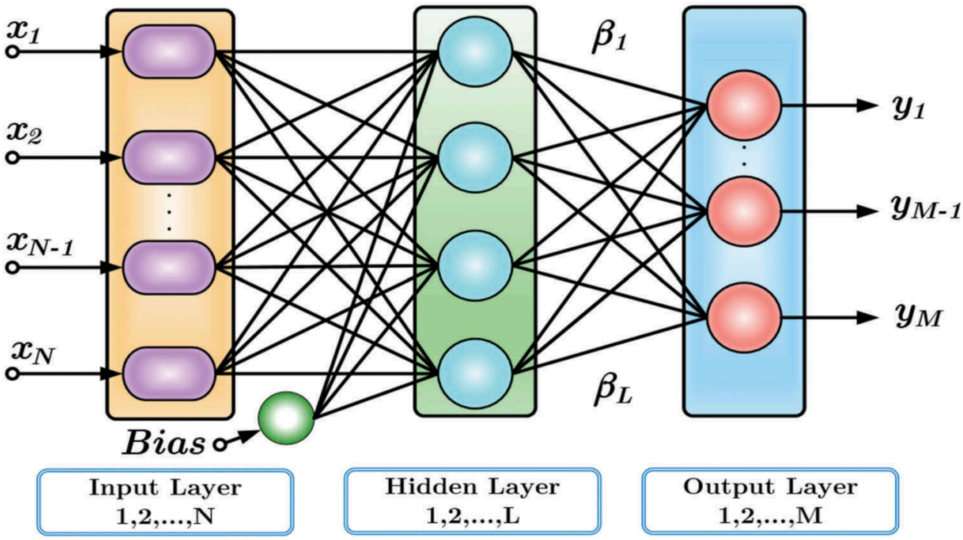

Figure 5. Basic structure of SLFN.

$$y = [y_1, y_2, y_3, \ldots, y_M]^T \in R^M \tag{2}$$

$$\sum\nolimits_{i=1}^{M} \beta_i g\left(w_i x_j + b_i\right) = o_j, \mathrm{j} = 1, 2, 3, \ldots, \mathrm{N} \tag{3}$$

Where; w denotes the input weight vector, which is connected to the input nerve cell, and can be expressed by $w_i = [w_1, w_2, \ldots, w_N]^T$. $\beta_i = \left[\beta_1, \beta_2, \ldots, \beta_M\right]^T$is the output weight vector. b_i is biases of hidden nodes and g is activation function. In the standard structure of SLFN with activation functiong(x), the error is zero if the target value and the output value of the network are equal (Huang, Zhu, and Siew 2006). That is, there are output weights to provide $\sum\nolimits_{j=1}^{L} o_j - y_j = 0$. Considering that single-layer neural network has linear activation function in the output layer, then the output of SLFN can be written for N arbitrary distinct samples as follows:

$$o_j = \sum_{i=1}^{L} \beta_j g\left(w_i x_j + b_i\right) = y_j \mathrm{j} = 1, \ldots, \mathrm{N}. \tag{4}$$

In addition, Equation (3) can also be expressed as follows:

$$y = H \cdot \beta \tag{5}$$

The matrix H in this equation can be expressed as follows:

$$H = \begin{bmatrix} g(w_1.x_1 + b_1) & \cdots & g(w_L.x_1 + b_L) \\ \vdots & \cdots & \vdots \\ g(w_1.x_N + b_1) & \cdots & g(w_L.x_N + b_L) \end{bmatrix}_{NxL} \tag{6}$$

In this case, the input layer weights and hidden layer bias values are randomly selected to calculate H analytically. In conventional SLFN, while the network needs to be trained, the training in ELM is completed by solving a linear equation given in Equation (5). The output weights β are obtained by the solution given in Equation (7).

$$\beta = H^{+}.Y \tag{7}$$

Table 6. Algorithm of ELM and ANN.

Inputs $x = [windspeed, directionandpower]^T$	
Output $y = [forecastedwind\ power]^T$	
1: Load dataset	► 3 × 8760 sized matrix format
If Season = = **'Winter'**; 'Spring'; **'Summer';** 'Autumn'	
starting = **1**; 2190; **4380**; 6570;	► Selection of seasons
finishing = **2190**; 4380; **6570**; 8760;	
end	
2: Generate randomly dataset	
3: Define train data	► Randomly chosen 3 × 1690 samples
4: Define test data	► Randomly chosen 3 × 500 samples
5: Normalization train and test inputs	
6: For k = 1,2, …, 5.	► 15-fold loop
7: Build training and validating folds	
8: Define input weights and biases randomly	►ELM setup
9: Calculate H matrix	►Using Equation (6)
10: Calculate the output weights	►Using Equation (7)
11: Define ANN parameters	►ANN setup
12: Calculate ANN biases and output weights	
13: Predict an unknown test fold	►ELM and ANN
14: End for	
15: Find training performance	
16: Find best ELM and ANN models	►Performance criteria (NRMSE)
17: Predict unknown test data	

Where; $H^{+}$is the Moore–Penrose generalized inverse of H. It is known that ELM has superior properties in many ways compared to conventional methods. Therefore, ELM-based wind power forecast method is preferred in this study. The processing of ELM structure is presented with the algorithm given in Table 6. As can be seen from the algorithm, the inputs and outputs are first determined. The dataset obtained from the actual values is loaded. The samples in this dataset are divided into separate seasons. Then, these samples are randomly identified for training and testing. As can be seen from the algorithm, 1690 samples are selected for testing and 500 samples are selected for training. K-fold cross-validation is used to obtain the best performance from the proposed ELM model. With the help of this validation, the best selected model is used for a separate test with unknown test data. K-fold includes a set of training data randomly divided by K-groups. These folds are repeated K-times and these are divided into groups.

Therefore, the different groups are obtained in each loop. The accuracy of these groups is repeated in every loop. Figure 6 presents the cross-validation used in this study. As seen in Table 6, the inputs and outputs are first selected for this validation. The samples mentioned above have been determined for 15-folds trained cross-validation. Finally, the optimal number of hidden layers for ELM is found to be 41.

Activation functions also played an important role in the performance of ELM. In this study, the performances of activation functions such as *"radbas"*, *"tribas"*, *"sig"*, *"tansig"*, *"sin"* and *"logsig"* are also evaluated separately. With the help of this algorithm, it is aimed to obtain the most optimum Normalized Root Mean Square Error (NRMSE), Correlation Coefficients (R), and training time.

From the obtained results, the best activation function is determined as *"tansig"* and therefore, this activation function is preferred in the studies. These operations are also performed in ANN model. The number of hidden layers for ANN is found to be 16. In order to assess the performance of ELM, a single layer feed-forward ANN model is used. Additionally, the backpropagation based Levenberg–Marquardt algorithm is preferred in the training of ANN model.

Experimental studies

In this paper, a total of 8760 samples was taken from the investigated WPP (Start Time: 01/01/2018; End Time: 01/01/2019). One sample information was obtained as a mean for per hour. Wind speed,

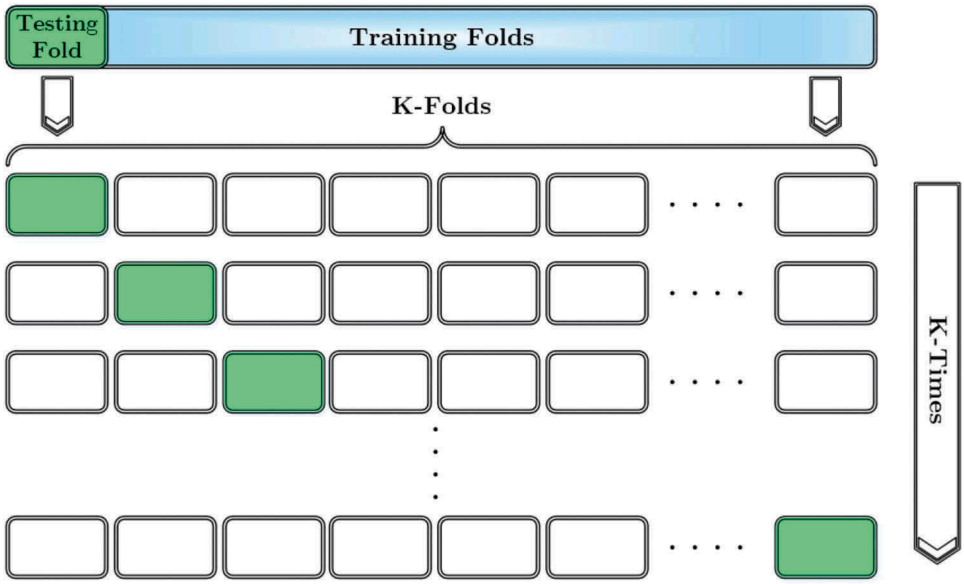

Figure 6. The K-fold cross-validation scheme.

wind direction, and wind power information obtained from WPP are given in Figure 7. These data are used to forecast two, three and 4 hours ahead of the obtained wind power. In addition, the obtained dataset is divided into seasons. Thus, the seasonal wind power forecasting is also realized. In this study, it is aimed to forecast the wind power quickly and accurately. ELM method has been proposed for this purpose. The performance of ELM method is confirmed by comparing with ANN.

The parameters of ELM and ANN used in this study are given in Table 7. In order to analyze the reliability and performance of the proposed method, a number of experimental studies has been conducted. The experimental studies are divided into two parts as hour-ahead and seasons forecasts.

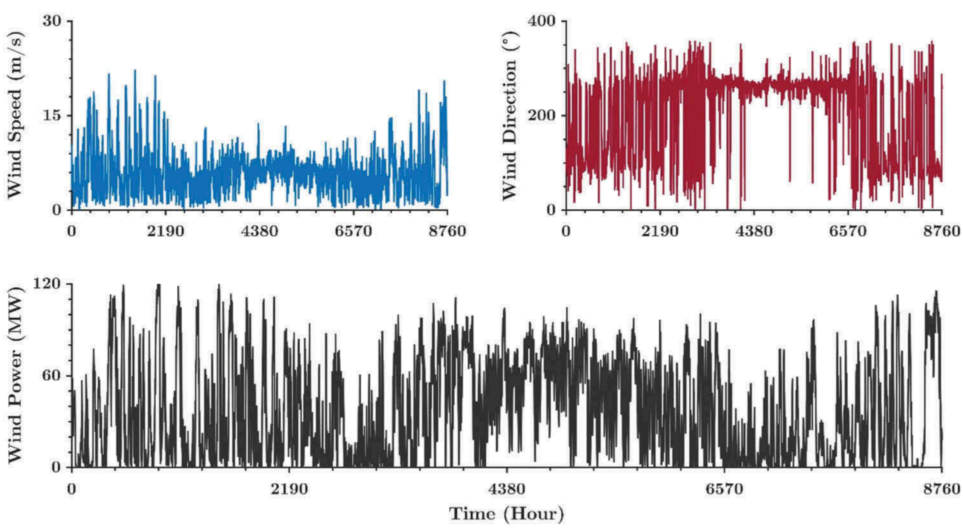

Figure 7. Whole data obtained from WPP.

Table 7. Parameters of ELM and ANN.

Method	Learning algorithm	The number of hidden layers	Activation function
ELM	-	41	Tangent Sigmoid
ANN	Back Propagation	16	Tangent Sigmoid

In the first part, various hour-ahead conditions are created and wind power forecasts are carried out. The results obtained from this part are shown in Figure 8. For a better understanding of the figures, the axis intervals are kept close. To evaluate the performances of both models, R, NRMSE and training time are analyzed.

When the 2 hours-ahead figure is examined, the NRMSE and R values of ELM are 7.01 and 0.96588 while these values of ANN are 8.19 and 0.95421, respectively. Furthermore, ELM has 210 times faster training time than ANN. From these results, it is seen that more reliable and faster wind power forecasting can be done with ELM. As can be seen from the figure, given for the 3 hours-ahead forecast, the wind power response obtained from ELM appears to be closer to the actual value. ELM has a faster training time than ANN (nearly 189 times) and ELM has better performance criteria in terms of NRMSE and R values. When forecast figure of the 4 hours-ahead is analyzed, the R, NRMSE, and training time for ANN method are 0.87576, 13.09, and 0.9729, respectively. The results obtained from this section are given in Table 8.

In the second part, the data from WPP are grouped into seasons. Thus, the performance of the proposed method is evaluated seasonally. The experimental study results for this part are shown in Figure 9. The axes are zoomed in order to demonstrate the performance of ELM. Two hours-ahead wind power forecast is made for all seasonal data. According to the results obtained from Spring, ELM has better forecasting response than ANN. The ELM has much faster training time than ANN (nearly 202 times). When the performance parameters obtained from Summer are investigated, it is seen that ELM has superior features than ANN. The R values for ELM and ANN are 0.97011 and 0.96374, respectively. As expected, ELM provides faster training time for Summer. With the help of Autumn results, the R, NRMSE, and training time of ELM are calculated as 0.96597, 5.99, and 0.0046, respectively. For ANN, these values are found to be 0.94793, 7.44, and 0.9456. As can be seen from the obtained values, ELM has superior response in all performance criteria. Finally, considering that WPP is installed on a complex terrain, it should be taken into consideration that wind power forecast for Winter will be more difficult. ELM, which has a very fast training time, provides a close response to the actual wind power values. The results obtained from the experimental studies performed for this part are summarized in Table 9.

Conclusion

In this study, the aim is to develop a powerful very short-term wind power forecast system for WPP that operates in a very complex terrain. For this purpose, an advanced ELM-based forecasting system is proposed to achieve good performance. This system uses meteorological and electrical data as inputs and outputs. Therefore, these two kinds of data are needed to carry out the application of the proposed forecast system. Advanced measurement devices that met the related IEC standards are used to measure the data. GPS time synchronization is used to prevent time lags between separately measured meteorological and electrical data. The experimental site study is carried out on a huge WPP that operates in a very complex terrain. The installed capacity of WPP is 135 MW and it has 54 wind turbines that spread over a large area. The mean RIX value of terrain was calculated as 19.5% by WAsP software. These site conditions increase the uncertainty of WPP power output. So, it is difficult to forecast wind power in the investigated WPP. In order to evaluate the stability and the accuracy of the proposed system performance, several performance studies are carried out for different test conditions. The obtained results are compared with classical ANN-based system to demonstrate the improvements. Firstly, hours-ahead forecast performances are obtained for 1-year

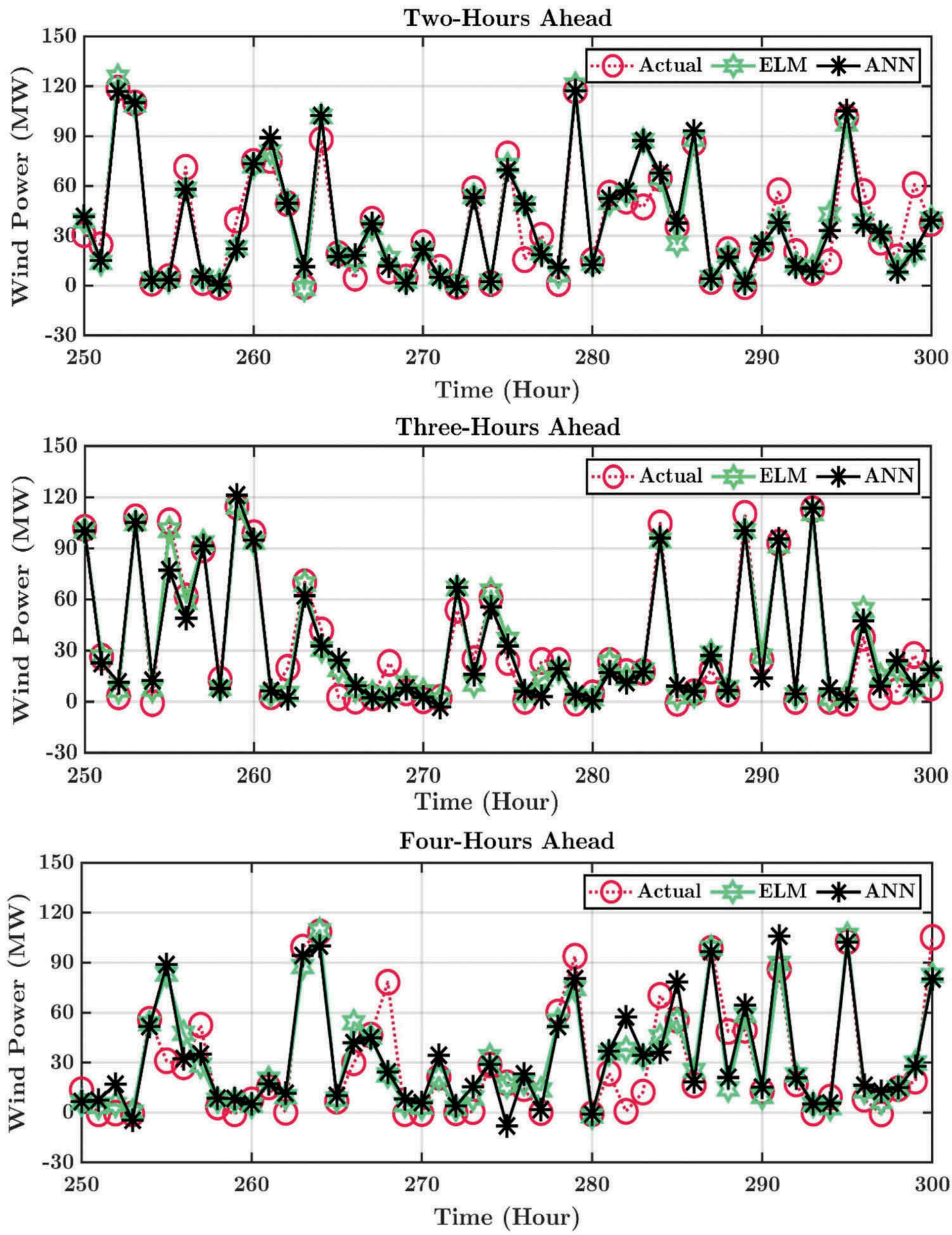

Figure 8. Comparison of different hour-ahead results.

Table 8. Comparison of ELM and ANN models for hours ahead forecasts.

Time	Method	NRMSE (%)	*R*	Training time (s)
2-Hours Ahead	ELM	7.01	0.96588	0.0045
	ANN	8.19	0.95421	0.9454
3-Hours Ahead	ELM	10.12	0.93528	0.0051
	ANN	12.18	0.91373	0.9607
4-Hours Ahead	ELM	12.06	0.88984	0.0068
	ANN	13.09	0.87576	0.9729

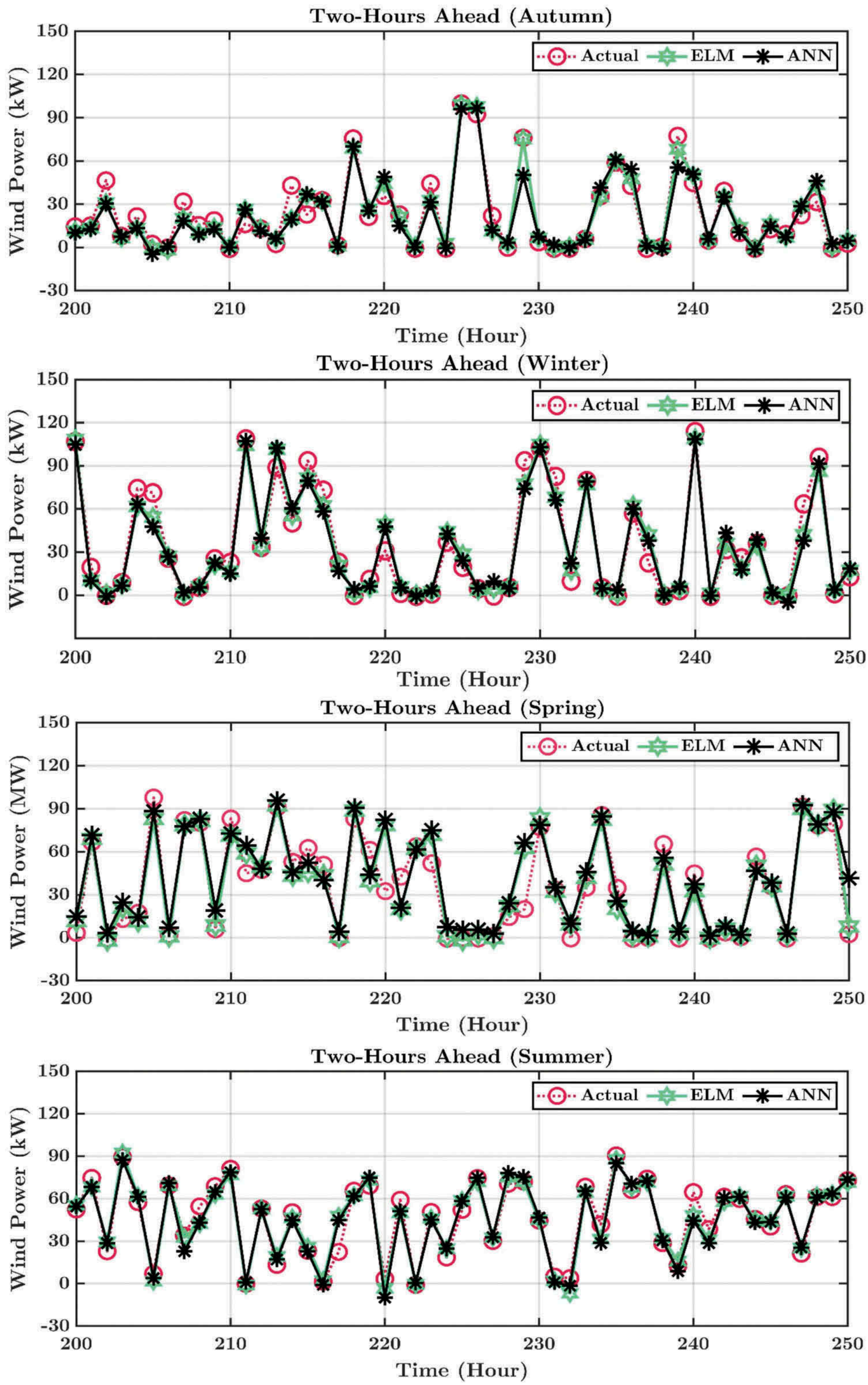

Figure 9. Comparison of different season results.

Table 9. Comparison of ELM and ANN models for four seasons.

Season	Method	NRMSE (%)	*R*	Training time (s)
Spring	ELM	6.74	0.96734	0.0045
	ANN	7.68	0.95718	0.9098
Summer	ELM	5.01	0.97011	0.0059
	ANN	5.87	0.96374	0.9551
Autumn	ELM	5.99	0.96597	0.0046
	ANN	7.44	0.94793	0.9456
Winter	ELM	6.91	0.96554	0.0049
	ANN	7.65	0.93980	0.9925

period. Then, seasonal forecasting performances of the proposed and classical system are obtained to compare seasonal performances. The main three conclusions regarding the results of these tests are summarized as follows:

- The proposed ELM-based wind power forecast system can successfully forecast the power output of the investigated huge WPP that located in a very complex terrain.
- The proposed forecast system achieved seasonal and annual performance improvements when compared with the classical ANN-based forecast system.
- The evaluated two forecast systems are provided best performances in Summer and worst performances in Winter.

In this study, the proposed forecast system achieved some improvements and successful results for the investigated complex terrain. Besides, other power plants that have various RIX values and turbine clusters that spread over large area will constitute different test conditions for wind power forecast systems. Therefore, it is suggested for future studies to use RIX values, number of turbines, installed capacity values, etc., to illustrate test conditions clearly.

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