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Forecasting of short-term wind speed at different heights using a comparative forecasting approach

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Abstract: The forecasting of wind speed with high accuracy has been a very significant obstacle to the enhancement of wind power quality, for the volatile behavior of wind speed makes forecasting difficult. In order to generate more reliable wind power and to determine the best model for different heights, wind speed needs to be predicted accurately. Recent studies show that soft computing approaches are preferred over physical methods because they can provide fast and reliable techniques to forecast short-term wind speed. In this study, a multilayer perceptron neural network and an adaptive neural fuzzy inference system are utilized to both forecast wind speed and propose the best model at heights of 30, 50, and 60 m. It is obvious that various internal and external parameters for soft computing methods have paramount importance for forecasting. In order to analyze the impact of these parameters, new wind speed data were collected from a wind farm location. Miscellaneous models were created for every wind turbine elevation by adjusting the parameters of soft computing methods in order to improve wind speed forecasting errors. The experimental results demonstrate that elevation of collected wind speed data significantly affects the wind speed forecasting. Our experimental results reveal that although behavior of wind speed for every height appears identical there is no single model to predict wind speed with the best accuracy. Therefore, every model for the soft computing methods shall be modified for every particular wind turbine height so that wind speed forecasting accuracy is improved. In this way, the approaches perform with fewer errors and models can be used to predict wind speed and power at different heights.

Key words: Forecasting, wind energy, soft computing methods, time series analysis

1. Introduction

Nowadays, most countries rely heavily on fossil fuels to generate their own electricity. Power plants based on fossil fuels, however, cause many environmental problems. These power plants have emitted large amounts of greenhouse gases. As a result, many people face a sharply high risk of breathing problems, cancer, and heart attacks [1]. Thus, worldwide many people are seeking out new energy sources that will produce cleaner energy.

Even though nonrenewable energy sources (e.g., coal, petroleum, and natural gas) are available in most of the world, these sources will get more expensive because of restricted reserves [2,3]. On the other hand, renewable energy is clean, environmentally friendly, and inexhaustible. Over the last decade renewable electricity generation capacity has increased significantly, but this capacity has still not been enough to replace the energy capacity that comes from fossil fuels. If we want to replace fossil fuels with renewable energy sources, then more

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research is needed concerning their negative sides, and better renewable energy technologies must be developed. This could well lead to people having cheaper and cleaner energy.

Wind energy is one of the fastest growing forms of renewable energy. For instance, over the last 10 years in Turkey, installed wind power capacity has increased approximately 10% each year [4]. Despite this rapid growth of wind power, it still does not look like a reliable energy source that can meet future demands of the electricity grid. One of the most important reasons for this is the unreliability issue: wind speed profiles are irregular [5]. In this regard, it is essential to make accurate wind speed estimates in order to develop a more reliable structure for wind power plants.

In the present paper, a comparative forecasting approach based on soft computing methods is proposed to improve the prediction of short-term wind speed at different heights. It is well known that soft computing methods outperform other methods and can achieve better results in short-term wind speed forecasting [6]. Therefore, we utilized algorithms of ANFIS and MLP neural network to predict wind speed with minimum errors. In order to achieve this goal, we created different models for each forecasting method and compared these models based on forecasting errors so that wind speed estimation error can be diminished.

This paper presents current and future research aimed at the development of comprehensive wind speed forecasting for different wind turbine heights. The study is performed as experimental work in order to guide wind speed forecasting researchers who might utilize soft computing methods. With these methods, a large number of model parameters shall be optimized and the best models can be determined for realistic wind speed forecasting. However, the authors are not familiar with publications featuring experimental studies for wind speed prediction at different heights using soft computing methods. As a result, we present a comparative forecasting approach in order to forecast short-term wind speed at different heights for the same location. Since wind speed has nonlinear behavior, the features of models of soft computing methods should be particularly distinguished for different wind turbine height.

Furthermore, many studies on soft computing based wind speed forecasting were conducted at height of 10 m. It is obvious that wind speed data at 10 m is not sufficient for selection of wind turbine location and not feasible for wind energy estimation and so we collected new data directly from a data logger located at a wind farm. Therefore, the present study aims to enhance soft computing based wind speed prediction results regarding their use in industrial applications for choosing different wind turbine heights of 30, 50, and 60 m.

The rest of this paper is organized as follows. Section 2 describes related work. In Section 3 we present the materials and methodologies used in our problem formulations. In Section 4 we introduce our results to show the proposed models predict wind speed at different heights with outperformance. Finally, we provide a conclusion with the best models to forecast wind speed in Section 5.

2. Related work

Different forecasting methods are used in most research studies. Generally speaking, all forecasting techniques can be described under three main approaches: physical, statistical, and hybrid methods. The most used physical method is the numerical weather prediction method (NWP) developed by experts in meteorology. The main purpose of NWP is to define atmospheric phenomena using mathematical models. This can be done using large amounts of weather data that represent every small region. It is quite hard to develop a perfect weather prediction because it needs many calculations, and these calculations need supercomputers. Even when supercomputers are used to predict weather, however, the calculation time is very long. Although NWP needs long calculation times, it is more effective for long-term prediction. Therefore, many industries and government agencies are extensively using the NWP technique. Furthermore, it has been very important in allowing military operations to forecast weather. However, the NWP technique is quite ineffective for short-term wind forecasting because wind speed has a very high variation in a short period of time [7].

Recent publications have preferred using statistical methods over physical methods. Statistical methods can be developed in which historical values of wind speed are utilized. Statistical prediction methods can be classified into two main approaches: (1) time-series models (such as autoregressive and moving average models) and (2) soft computing models (such as artificial neural networks (ANNs), fuzzy logic). Recent publications demonstrate that genetic algorithms (GAs), support vector machines (SVMs), and Kalman filtering (KF) models are integrated into gray-box methodologies in order to reduce prediction errors. A brief review of recent studies on wind speed prediction is introduced in the following paragraphs.

Based on the time series models, short-term wind speed prediction is performed by linear and nonlinear autoregressive models [8]. Wind speed prediction models differ regarding their prediction intervals ranging from 10 min to 1 h. According to [9], KF can be successfully implemented for short-term predictions and the authors propose a new KF method instead of using the standard KF in order to yield better prediction results. In [10], the researchers develop a new technique using heteroscedastic support vector regression diminishing the uncertainty of short-term wind speed. The wind speed prediction results are obtained for wind power plants in China and predicted for 30, 60, and 120 min in the future with errors above 10% MAPE.

Today, more and more researchers are using soft computing algorithms based on ANNs to make short-term forecasts [11–14]. This is because ANNs use linear assumptions and they are more effective in modeling the nonlinearity relationship of wind speed data [15].

The literature on this issue includes many publications. These can be summarized in the following studies. Cadenas and Rivera [16] used the ANN model to predict short-term wind speed. The results of their study show that the two-layer and three-neuron models for the training and testing stages give satisfactory accuracy for short-term forecasting. The implementation of ANN to forecast wind speed in [17] demonstrates that ANN models predict wind speed with acceptable accuracy (8.9% MAPE and correlation of 0.9380 m/s). In the study conducted by De Giorgi et al. (the wind farm model in southern Italy), wind energy prediction is made by autoregressive moving average (ARMA), five different ANN models, and the neuro-fuzzy inference system (ANFIS) [18]. For predictions of 1, 3, 6, and 12 h, multilayer perceptron (MLP) performance appears better than other methods and gives a short calculation time.

Another study is conducted by [19], where the authors predict daily wind speed using an MLP neural network and propose to utilize meteorological parameters (e.g., temperature, air pressure, solar addition, and altitude) as input variables. However, the collected data are obtained for only two different altitudes that are very close to each other (14.5 m and 18.5 m). The recently published article by [20] presents a short-term wind speed prediction technique that demonstrates that wind speed can be forecasted easily using ANNs, but the maximum lead time for the measured data must be 14 h.

In [7], several different ANFIS models were used to predict very short-term wind speed. The data set is prepared by a 21-month time series using 2.5-min intervals. In that study, the ANFIS model estimates results in less than 4% MAPE. Approaches using BPNN, RBFNN, and ANFIS short-term wind speed forecasts, which are 1-h-ahead and 3-h-ahead, are assessed in [21]. These forecasting techniques are combined with a similar day (SD) approach. ANFIS models based on the SD approach are more successful in transforming historical data into wind speed forecasts.

Furthermore, in the literature, hybrid approaches are able to predict wind speed with high accuracy. Hybrid models can consist of not only physical and statistical techniques but also can only be developed by different statistical methods. In [22], two new hybrid approaches, known as the ARIMA-ANN and ARIMA-Kalman filter models, are found suitable for wind speed prediction. Guo et al. [23] presented a case study using a hybrid forecasting method with a back propagation neural network (BPNN) and seasonal adjustment. The results show that rather than using only BPNN a hybrid technique must be used to improve prediction performance.

In spite of that, in the literature, the performance of ANFIS and MLP approaches is not evaluated in terms of different heights in a particular wind farm location. In order to propose or establish a reliable soft computing method for short-term wind forecasting in the wind power industry, multivariate soft computing models must be evaluated considering their use at different heights. The main contribution of the present paper is to provide researchers with a comprehensive analysis of the effects of various heights on short-term wind speed forecasting by using ANFIS and MLP approaches.

3. Materials and methods

3.1. Adaptive neural fuzzy inference systems approach

ANFIS methodology was first introduced by Roger Jang in 1993 [24]. It aims to combine fuzzy logic and ANN methods. Figure 1 provides a simple description of the ANFIS architecture, which has two inputs and one output. In the first layer (called the "input layer"), input values are transferred to the second layer. The second layer, known as the "fuzzification layer", enables nodes to change output depending on the membership function. The parameters are defined for membership functions (μ (e.g., bell-shaped) as given by the equations below:

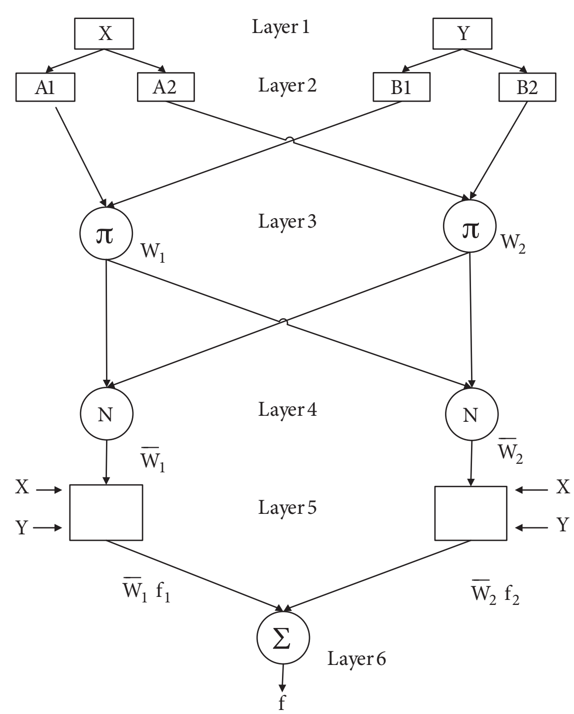


Figure 1. Architecture of a two input ANFIS model.

$$O_{2,i} = \mu_{A_i}(x) \tag{1}$$

$$O_{2,j} = \mu_{B_{j-2}}(y) \tag{2}$$

$$\mu(x) = exp\left\{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2\right\}, \tag{3}$$

where c and σ are parameters that correspond to the mean and standard deviation of the membership function, respectively. In general, these parameters are referred to as premise or antecedent parameters.

In the third layer, each neuron represents a single fuzzy rule. The output of each node can be calculated by the firing power of each fuzzy rule as Eq. (4).

$$O_{3,k} = \mu_{A_k}(x)\,\mu_{B_k}(y) = \omega_k,\ k = 1,\, 2 \tag{4}$$

The fourth layer can be described as a normalization layer. The normalized firing level can be expressed as the ratio of the k_{th} firing power of the sum of all firing powers.

$$O_{4,k} = \frac{\omega_k}{\sum \omega_k} = \bar{\omega_k},\ k = 1,\, 2 \tag{5}$$

In the fifth layer, in order to calculate the results of the fuzzy logic rules, weighted result values for each node are calculated by the following formula, where $\alpha, \beta\gamma$ are constant values:

$$O_{5,k} = \bar{\omega_k}\left(\alpha_k + \beta_k x + \gamma_k y\right),\ k = 1,\, 2 \tag{6}$$

Finally, in the last layer, the sum of each output value received from previous layers is calculated and found as f.

3.2. MLP artificial neural network approach

ANNs are a commonly used technique in different tasks from process monitoring, fault diagnosis, and adaptive human interference to artificial intelligence based on atmospheric processes and computers [25]. The MLP is a widely used type of neural network and usually called a feed-forward neural network. It consists of an input layer, one or more hidden layers, and an output layer. Basically, the MLP solves the complex relationship between input vector and output vector using connections of weighted layers. To solve a relationship of this complexity the MLP needs training sets that consist of both input and output data. The MLP uses delta learning, which is based on the least square method. This learning methodology consists of two training steps: feed-forward and backpropagation.

The feed-forward learning is usually called feed forward because feedbacks among the nodes do not appear. With a feed-forward neural network, the connection between the i_{th} and j_{th} neuron can be described by the weight coefficient ω_{ij} [26]. The output of each node for n input neuron and m hidden neuron can be represented by the following equation:

$$y_i = f_H\left(v_i + \sum_{j=1}^{n} \omega_{ij} x_j\right), \tag{7}$$

where f_H is called the activation function of a node and V_i is the threshold coefficient that corresponds to the weight coefficient of each j_{th} neuron. This coefficient is called the bias value when x_j equals 1. All connection weights and bias values must be initially assigned random values. In the training process, these values will be adjusted by the network to find the best output results.

The sigmoid function, which varies between 0 and 1, is used as the activation function of a node, as given in the following equation:

$$f_H(s) = \frac{1}{1+e^{-s}} \tag{8}$$

The supervised adaption process changes weight coefficients and bias values between predicted and target outputs [26]. By minimizing the objective function with a training algorithm, these values can be obtained. The objective function can be calculated as

$$e = \sum_{i=1}^{n} (t_i - y_i)^2 \tag{9}$$

In the case of backpropagation training, a Bayesian approach was utilized to accomplish better fit, minimum error, and minimum number of patterns and weights of the network. This process can be demonstrated by the following equations:

$$\omega_{ij}^{(k+1)} = \omega_{ij}^{(k)} - \lambda \left(\frac{\partial e}{\partial \omega_{ij}}\right)^{(k)} \tag{10}$$

$$v_i^{(k+1)} = v_i^{(k)} - \lambda \left(\frac{\partial e}{\partial v_i}\right)^{(k)}, \tag{11}$$

where is λ a constant learning rate. The learning process is repeated by many iterations so that the MLP network may memorize the training data. Therefore, generalization between input and output patterns can be eliminated.

3.3. Forecasting of wind speed at different heights

The steps used to predict accurate wind speeds as seen in Figure 2 can be summarized as follows:

(1) Use the ANFIS method and select the most accurate models separately for all heights.

(2) Use the MLP-based method and select the most accurate models separately for all heights.

(3) Do a comparison between the MLP and ANFIS models for every height and determine the best models and wind speed prediction values.

The Silivri region in İstanbul was selected in order to implement wind speed forecasting methods. The latitude and longitude of the recorded area is N 041°08.377' and E 028°19.110', respectively and the site elevation is 210 m. Silivri is in the Marmara region, which has very high energy potential. It has been thus a very investable area for the wind energy sector [27]. Wind speeds were measured at heights of 30 m, 50 m, and 60 m via NRG #40C cup anemometers. The wind speed data was recorded as 10 min samples between February 2009 and March 2010, and the total data has 56,548 points.

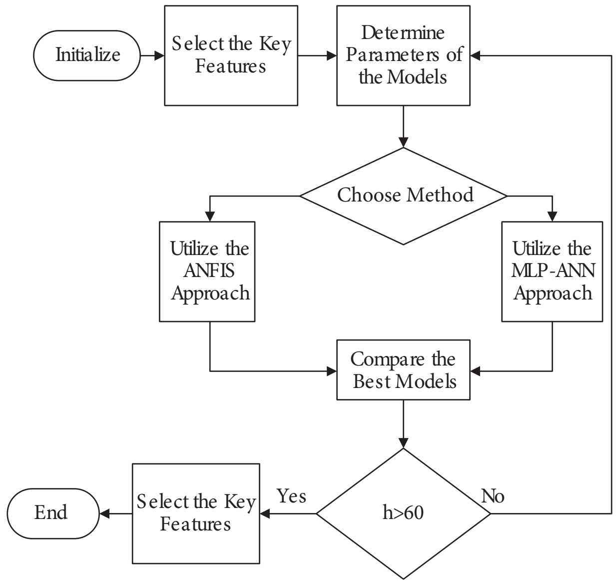


Figure 2. The flow chart of the framework for forecasting wind speed.

The recorded dataset is used as inputs for all ANFIS and ANN models. Firstly, the dataset was split into training (50%), evaluation (25%), and testing (25%) sets. The training set is used to train parameters of the ANFIS and ANN models. The evaluation dataset is used to evaluate measures of forecasting accuracy by tuning its parameters. The testing set is utilized to show error between real and forecasted wind speed values.

In order to solve wind forecasting problems using ANFIS and ANN methods, the input of each model must be chosen correctly. The most common way to choose wind vectors is time-series methodology. Hence, this methodology was used to determine model inputs in the present study. For instance, if one wants to predict wind speed at $v\,(t+1)$ time lag, the inputs of time series must be chosen using m previous measurements (such as $v\,(t-m)$, $v\,(t-m+1)$, $v\,(t-m+2)\ldots v\,(t))$. In this particular wind forecasting study, the number of previous observations was changed for both methodologies, and then for the selected wind speed input number, each model was named Model 1, Model 2, Model 3, and Model 4.

3.3.1. Models of adaptive neural fuzzy inference systems

In the present study, many different ANFIS architectures are compared to find the best wind forecasting accuracy. In order to use ANFIS methods, the type of membership function must be decided on. The membership function is considered as linear and constant. After many experiments, we settled on 2 and 3 membership functions as the appropriate number. Furthermore, since membership function type changes are linear and constant, the number of epochs for each model must be selected. A lot of research has shown that a large number of epochs usually does not improve the accuracy of models or significantly increase the forecasting time [28]. Therefore, it is adjusted to 10 and 100 in the structure of ANFIS. All of the parameter changes above were implemented in all combinations individually.

3.3.2. Models of MLP artificial neural networks

In order to test MLP based neural networks, the characteristic parameters of each model must be chosen so that the number of input neurons is changed to 1, 2, 3, and 4. For all MLP models, hidden layers are used and the output neuron number is assigned to 1. The error between computed and desired wind speed values is selected as 1×10^{-5} instead of 0 to stop training in a specific time. The number of epochs is selected as 50. The reason for the selection of a fixed number of iterations and errors is that after a certain number these values do not affect the results of estimated wind speed values.

3.4. Performance metrics for forecasting results

It is also essential to compare the performance of models in terms of forecasting accuracy. Unfortunately, there is no unique metric to evaluate models as a universal standard [29]. Thus, the performance of models must be evaluated by using different metrics such as determination of coefficient (R^2), root-mean-square error (RMSE), and mean absolute percentage error (MAPE).

$$R^2 = 1 - \frac{\sigma_E}{\sigma_Y} \tag{12}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(T_i - Y_i)^2} \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{T_i - Y_i}{Y_i}\right| \times 100 \tag{14}$$

The values of σ_Y and σ_E indicate the standard deviation of observation values and error values, which is calculated by each actual and forecasted wind speed difference, and T_i and Y_i values show observation and forecast values, respectively. The number of the dataset is also symbolized as n in the equations.

The coefficient of determination shows the accuracy of predicted values. This value is expected to be between 0 and 1. To have the best forecast model, the coefficient of determination value should approach 1. The RMSE is known as the standard deviation of the estimation errors in regression analyses. It can be found by calculating the square root of the average of quadratic errors. The last metric is chosen as MAPE to calculate forecast error. Since it is indicated by percentage expression, it gives the idea to everyone to understand the calculated error simply. In the present study, the RMSE and the MAPE are minimized. In many papers, it goes nearly to zero, but in this particular research some large numbers might be seen due to the large number of test datasets used.

4. Results for wind speed prediction at different heights

Forecasting methods ensure decision makers develop stronger knowledge for better decision making [30,31]. The purpose of the present research is to analyze the applicability of soft computing methods such as ANFIS and ANN. In order to address this issue, we formed different soft computing models based on ANFIS and ANN and then compared the best models in each category. The same validation data through forecasting measures (R^2, RMSE, and MAPE) are used to evaluate and compare the proposed models. In order to obtain experimental wind speed forecasting results MATLAB is utilized in developing various soft computing models.

4.1. Evaluation of the models and results

In order to compare the performance of models in terms of forecasting accuracy, both algorithms for every height were performed and the forecasting results are tabulated in Tables 1 through 6. In the ANFIS results, when 3 input membership functions are chosen for all models, the prediction values are less accurate. The best predicted wind speed values are found when the MF number equals 2. For predicted wind speed values at 30 m, the 4 input model gives the fewest errors and higher R^2 values except MAPE. The lowest RMSE obtained is 0.5942 m/s and the highest R^2 values obtained is 0.9753 m/s. At 50 m, Model 3 gives better wind speed prediction results, both in the test period and the validation period. Table 3 shows that estimated values are more accurate for Model 1 and Model 4. At 60 m, wind speed values are more irregular because the wind speed changes sharply at this height. Thus, when the number of input models increase, poor forecasted results are observed, and so Model 1 gives a better MAPE. However, during the testing period Model 3 would produce better results in terms of R^2 and RMSE values. In order to demonstrate performance of the best models, Figure 3 is shown to analyze best-fitting lines for predicted and actual wind speed at 30 m, 50 m, and 60 m, respectively. In addition, Figure 4 demonstrates that the best models predict wind speed with perfect accuracy at all heights.

Table 1. Wind speed forecasting errors for 30 m.

No.	Inputs		Output	Test			Validation		
	MF no.	Epoch no.	MF type	R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	2	10	Linear	0.9749	0.5992	8.9115	0.9791	0.6715	9.3041
2	2	100	Linear	0.9739	0.6103	8.9902	0.9789	0.6745	10.145
3	2	100	Constant	0.9752	0.595	8.972	0.9791	0.6715	10.238
4	2	100	Constant	0.9753	0.5942	8.945	0.9792	0.6702	10.648

Table 2. Wind speed forecasting errors for 50 m.

No.	Inputs		Output	Test			Validation		
	MF no.	Epoch no.	MF type	R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	2	10	Linear	0.9762	0.61	8.0197	0.9808	0.6838	8.9543
2	2	10	Linear	0.9739	0.6387	8.1602	0.9808	0.6836	10.3151
3	2	100	Constant	0.9766	0.6052	8.1222	0.9848	0.6846	10.309
4	2	100	Constant	0.9765	0.6094	8.1273	0.9809	0.6833	10.3887

Table 3. Wind speed forecasting errors for 60 m.

No.	Inputs		Output	Test			Validation		
	MF no.	Epoch no.	MF type	R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	2	10	Linear	0.9779	0.6125	8.0716	0.9821	0.69	9.22
2	2	100	Constant	0.9778	0.6139	8.4279	0.9816	0.7044	11.649
3	2	100	Constant	0.9781	0.6096	8.1991	0.9816	0.7011	10.436
4	2	100	Constant	0.9199	1.1721	17.015	0.928	1.3866	19.424

The wind speed was forecasted by different MLP models. As can be seen from Tables 4 and 5, Model 4 performs better than the other models. The amount of input wind data significantly affects wind speed estimation. According to the 30 m and 50 m values, input model 4 performs much better than other models

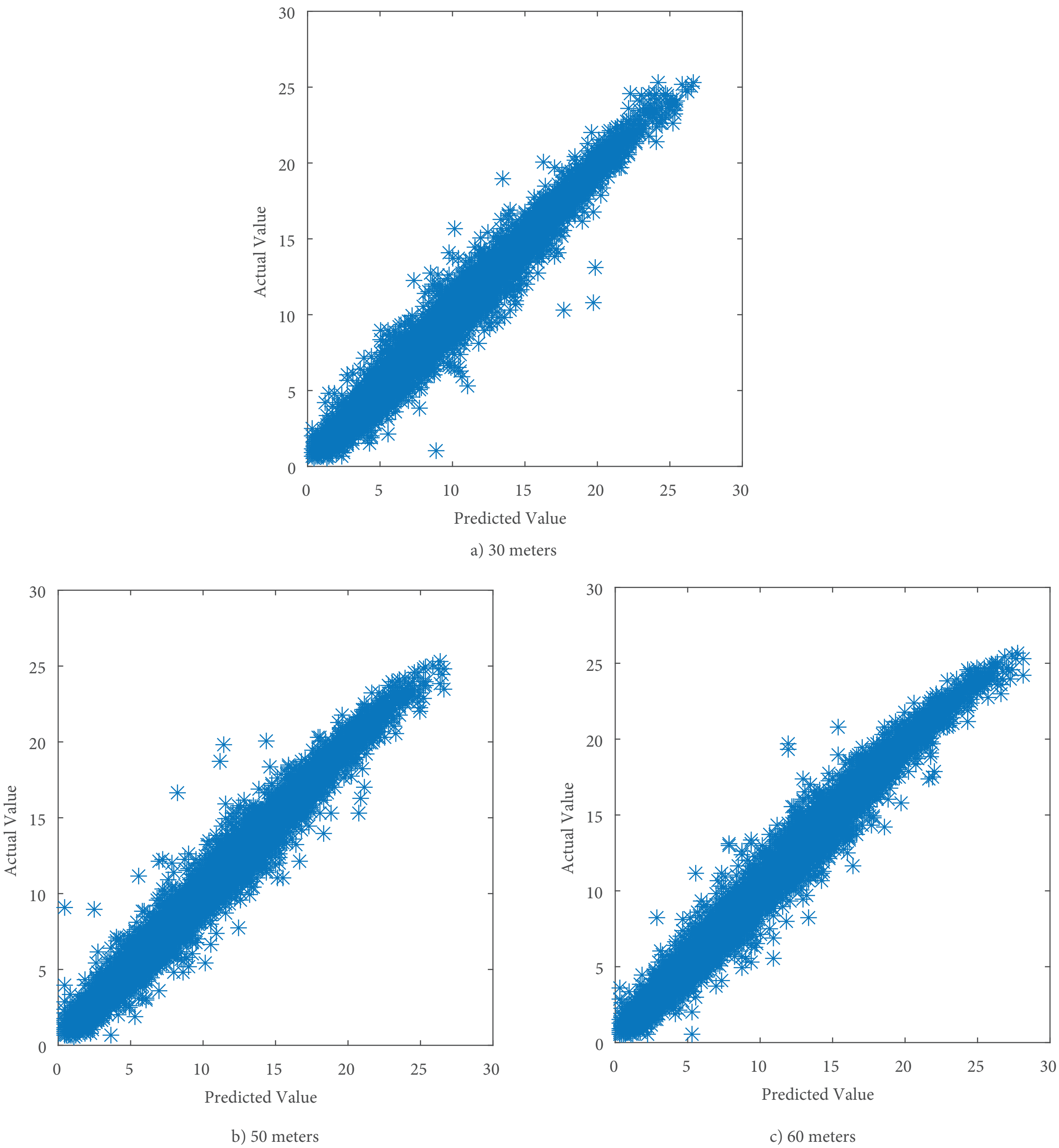
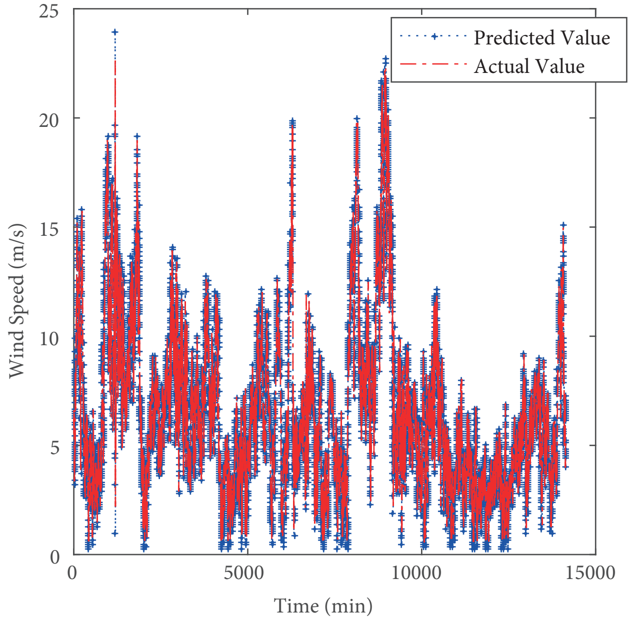
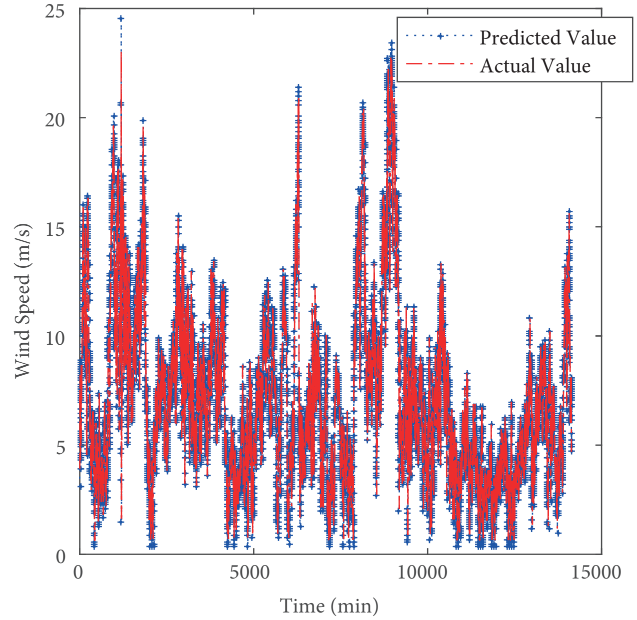


Figure 3. Correlation between actual and predicted values for the ANFIS testing stage.

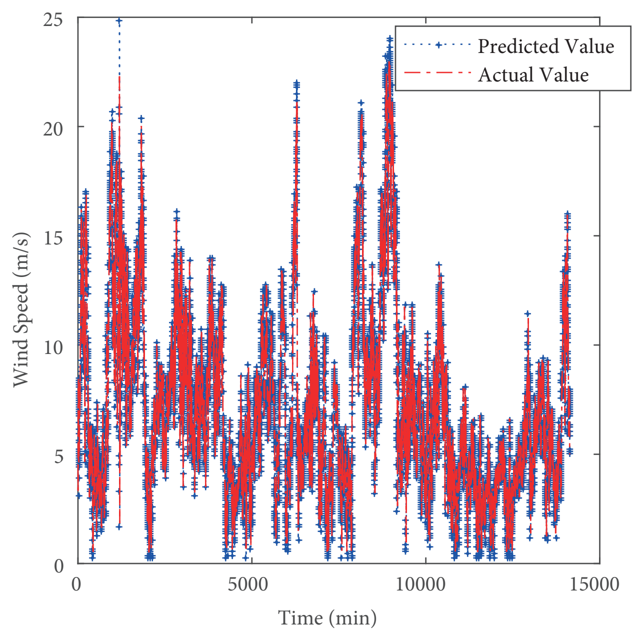
with 8.8431% and 8.042% MAPE. The results in Table 6 demonstrate that the accuracy improves when the input number of models is increased. Figure 5 shows best-fitting lines for predicted and actual wind speed at 30 m, 50 m, and 60 m, respectively. The predicted and actual values are almost the same as shown in Figure 6. Figure 6 demonstrates that the best models predict wind speed with perfect accuracy at all heights.



a) 30 meters



b) 50 meters



c) 60 meters

Figure 4. Comparison between prediction and actual results for ANFIS models.

4.2. Discussion

In the present study, it is noted that although the behavior of wind speed for all heights seems to be very similar, the prediction of wind speed is substantially influenced by changing collected data containing wind speed at various heights. As seen in the forecasting wind speed results, it is not possible to say that a single model might present good prediction results for all heights. Furthermore, a detailed experimental analysis was carried out due to effects of the various internal and external parameters on the wind speed forecasting. Tables 1–3 show

Table 4. Wind speed forecasting errors for 30 m.

No.	Test			Validation		
	R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	0.9773	0.6398	10.3683	0.9803	0.7709	18.0652
2	0.9543	0.8883	13.0279	0.9601	1.0407	18.9147
3	0.9357	1.0456	15.003	0.9435	1.2262	18.8005
4	0.975	0.597	8.8431	0.9792	0.6698	9.5798

Table 5. Wind speed forecasting errors for 50 m.

No.	Test			Validation		
	R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	0.9123	1.1713	18.0428	0.9222	1.3786	24.5106
2	0.9293	1.051	15.4362	0.9349	1.2211	20.4918
3	0.9507	0.8777	12.3616	0.9582	1.0107	15.6393
4	0.9763	0.6083	8.042	0.981	0.6809	9.3231

Table 6. Wind speed forecasting errors for 60 m.

No.	Test			Validation		
	R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	0.9773	0.6398	10.3683	0.9803	0.7709	18.0652
2	0.9543	0.8833	13.0279	0.9335	1.0407	18.9147
3	0.9357	1.0456	15.003	0.9435	1.2262	18.8004
4	0.9187	1.1805	16.9167	0.9271	1.3957	18.0814

that increasing the input number of ANFIS models does not always demonstrate better estimation errors for all heights. In spite of that, for the best estimation results, the input number of wind speed data is usually between 4 and 6 [15].

The constant type output MF usually shows better performance for all models. There is a certain rule in the literature that increasing the epoch number of ANFIS models decreases the estimation errors. In the current study, this is not obtained for every model because it depends on the output MF type. When output MF decides linear function, better results can be seen with a lower number of epochs. However, it is also observed that linear output MF function with big epoch numbers significantly affects the calculation time of short-term wind speed prediction. Thus, in order to obtain realistic wind speed predictions and propose reliable ANFIS models, epoch number must be limited to the satisfied values especially for the linear MF output functions.

From the MLP-ANN prediction results, we observed that with respect to the amount of input wind speed data MLP-ANN models illustrate the same patterns except at the height of 60 m. The 60 m wind speed forecasting results show that various numbers of input wind speed data are required for all heights to accomplish better prediction results. Furthermore, the height of the measured wind speed may significantly affect the results. For instance, while MLP-ANN gives sufficient results for heights of 30 m and 50 m, it produces very undesirable results when 60 m wind data are used for the MLP-ANN approach.

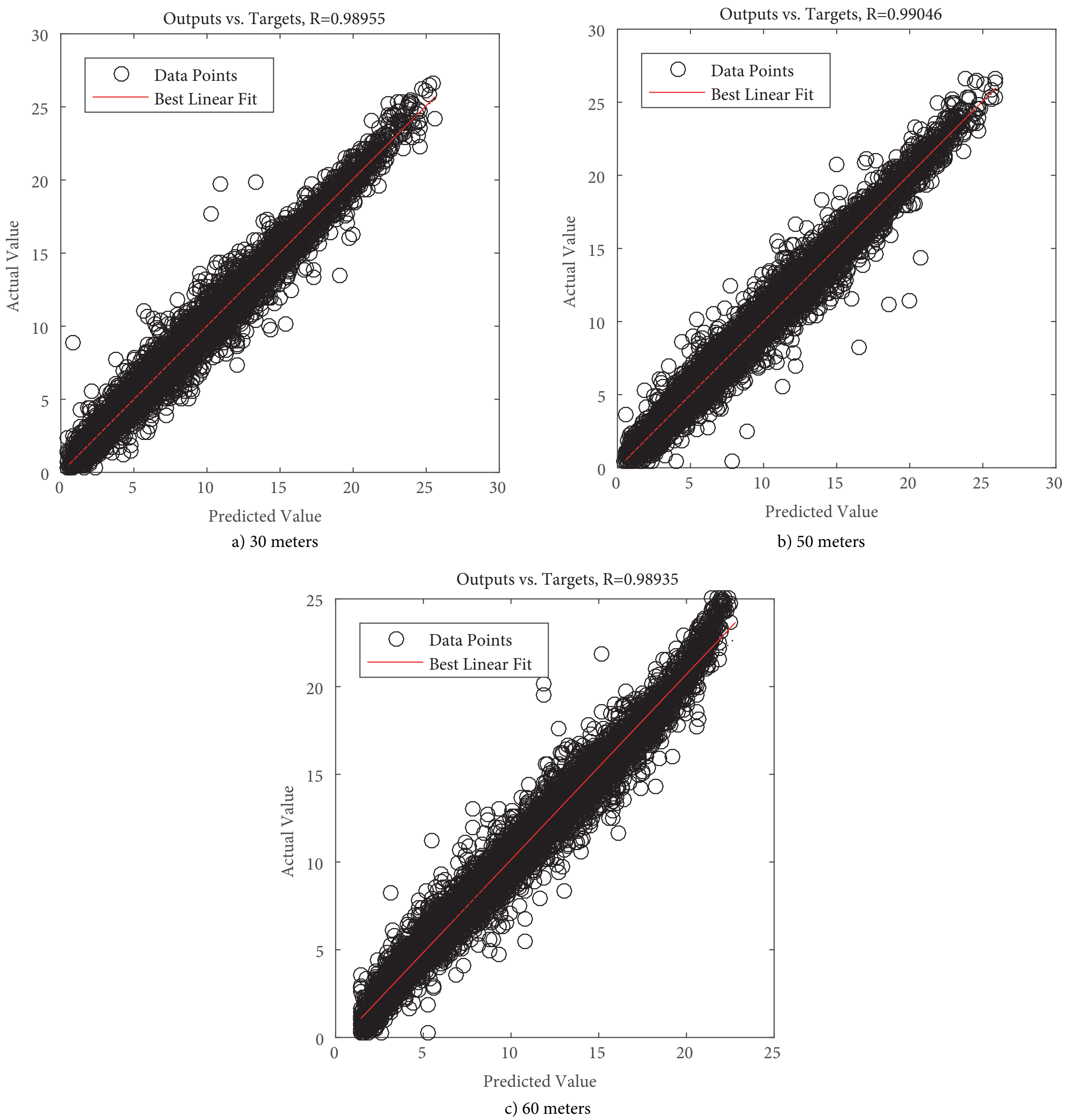
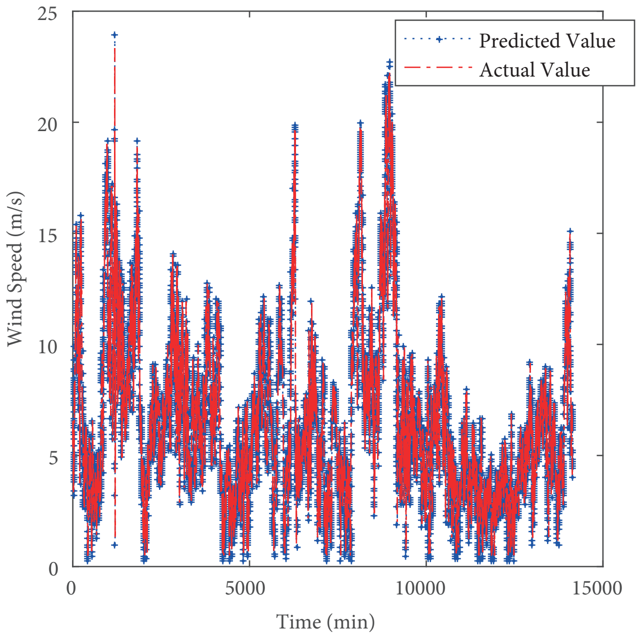
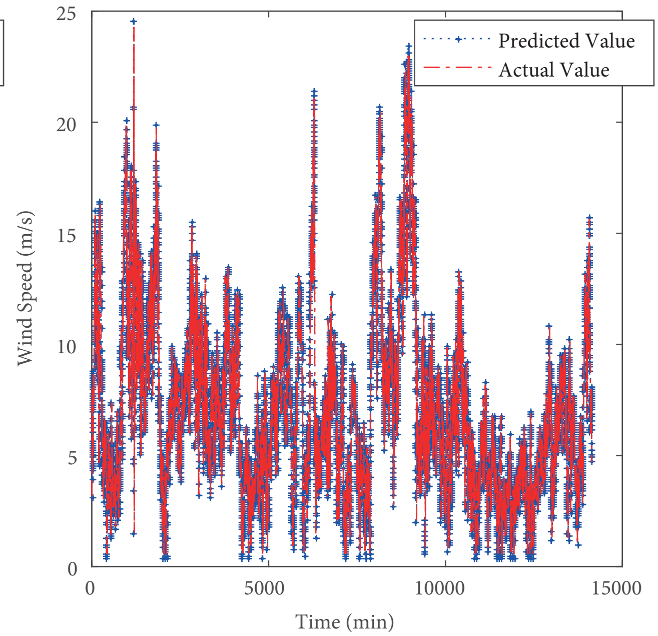


Figure 5. Correlation between actual and predicted values for MLP neural network testing stage at a) 30 m, b) 50 m, c) 60 m.

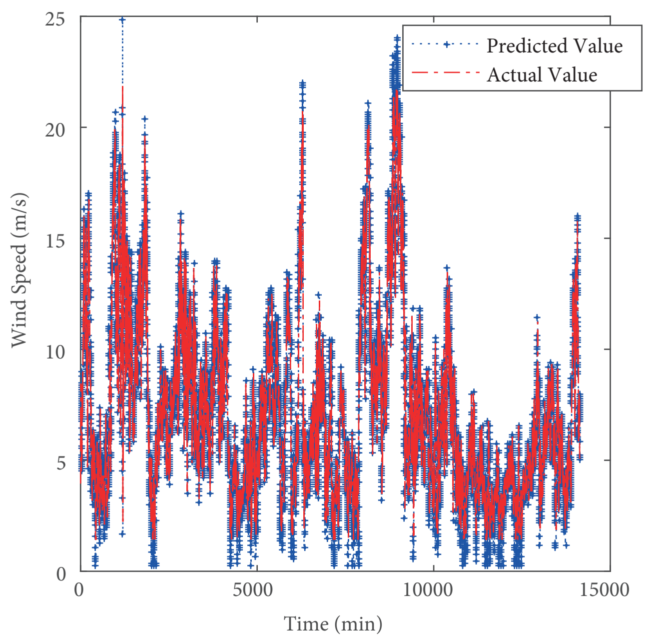
In the evaluation and testing stages, both methods are compared according to the above tables. Two methods are compared and then the best models are determined for each selected height according to three different evaluation metrics. The error values are compared in Table 7. In this table, only testing errors are shown because the differences between actual and last estimated wind speed values are shown at this stage. The evaluation stage optimizes parameters of artificial intelligence algorithms. As seen in Table 7, according to



a) 30meters



b) 50 meters



c) 60 meters

Figure 6. Comparison between prediction and actual results for MLP neural network models.

the results at heights of 30 and 50 m, MLP-ANN provides better forecasting results for only the MAPE metric. Additionally, while MLP-ANN performs as the poorest model with above 10% error, the ANFIS approach gives satisfactory results for all heights in terms of R^2 and RMSE values. Therefore, we can say that ANFIS models perform with reliable accuracy for all heights.

Table 7. Comparison of performances of methods.

Height	Method	Model no.	Test stage		
			R^2	RMSE	MAPE
30 m	ANFIS	4	0.9753	0.5942	8.945
	MLP	4	0.975	0.597	8.8431
50 m	ANFIS	3	0.9766	0.6052	8.1222
	MLP	4	0.9763	0.6083	8.042
60 m	ANFIS	3	0.9781	0.6096	8.1991
	MLP	1	0.9773	0.6398	10.3683

5. Conclusions

Wind power generation has grown considerably in recent years; however, it is still unreliable as a main grid supplier because variability in wind speed dramatically affects the predicted wind energy. Since wind speed at various heights exhibits very different behavior, forecasted wind speed may not be calculated accurately. The primary significance of this study is that we fill a research gap for short-term wind speed prediction at different heights. Recent research has shown that the MLP-ANN and ANFIS methods can successfully predict short-term wind speed variation. However, wind speed predictions can be done at different heights and thus model performances may be different at various heights.

In light of the results and discussion presented so far in this paper, it is clear that MLP-ANN and ANFIS based algorithms can be used to predict wind speed 10 min in advance. The forecasting models vary by the number of wind data inputs. MLP-ANN and ANFIS give satisfactory results for short-term wind speed prediction with approximately under 10% MAPE and 0.6398 m/s RMSE. In light of the results of the best models, we see that no single model works best for all heights. Thus, it is difficult to say with certainty that one model works better for every height. Moreover, at all heights, the ANFIS approach gives better prediction results. The best ANFIS models for wind prediction show that 3 and 4 inputs give the most accurate prediction results. The MLP-ANN algorithm with 3 and 4 input wind speed models shows better performance for 30 and 50 m; however, a 1 input wind speed model enables better forecasting results for 60 m.

In conclusion, for the first time, different ANFIS and MLP-ANN models are proposed to understand the behavior of wind speed and to obtain the most accurate speed forecast at different heights. For different heights, the proposed model can be used to define the best location of wind turbines and to forecast irregular wind energy. Short-term wind energy forecasting can be improved by using these models to enhance wind power quality.

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References

[1] Markandya A, Wilkinson P. Electricity generation and health. Lancet 2007; 370: 979-990.

[2] Rahman MM, Mostafiz SB, Paatero JV, Lahdelma R. Extension of energy crops on surplus agricultural lands: a potentially viable option in developing countries while fossil fuel reserves are diminishing. RenewSust Energ Rev 2014; 29: 108-119.

[3] Tutun S, Chou CA, Canıyılmaz E. A new forecasting framework for volatile behavior in net electricity consumption: a case study in Turkey. Energy 2015; 93: 2406-2422.

[4] Turkish Wind Energy Association (TWEA). Turkish Wind Energy Statistics Report 2015.

[5] Şahin AD. Progress and recent trends in wind energy. Progr Energ Combust 2004; 30: 501-543.

[6] Lei M, Shiyan L, Chuanwen J, Hongling L, Yan Z. A review on the forecasting of wind speed and generated power. Renew Sust Energ Rev 2009; 13: 915-920.

[7] Potter CW, Negnevitsky M. Very short-term wind forecasting for Tasmanian power generation. IEEE T Power Syst 2006; 21: 965-972.

[8] Lydia M, Kumar SS, Selvakumar AI, Kumar GEP. Linear and non-linear autoregressive models for short-term wind speed forecasting. Energ Convers Manage 2016; 112: 115-124.

[9] Zuluaga CD, Álvarez MA, Giraldo E. Short-term wind speed prediction based on robust Kalman filtering: an experimental comparison. Appl Energ 2015; 156: 321-330.

[10] Hu Q, Zhang S, Yu M, Xie Z. Short-term wind speed or power forecasting with heteroscedastic support vector regression. IEEE T Sustain Energ, 2016; 7: 241-249.

[11] Noorollahi Y, Jokar MA, Kalhor A. Using artificial neural networks for temporal and spatial wind speed forecasting in Iran. Energ Convers Manage 2016; 115: 17-25.

[12] Yousefi M, Hooshyar D, Yousefi M, Khaksar W, Sahari KSM, Alnaimi FBI. An artificial neural network hybrid with wavelet transform for short-term wind speed forecasting: a preliminary case study. International Conference on Science in Information Technology (ICSITech); 27–28 October 2015; Yogyakarta, Indonesia: pp. 95-99.

[13] Singh R, Sahay KB, Srivastava SA. Short-term wind speed forecasting of Oak Park Weather Station by using different ANN algorithms. In Smart Grid Technologies-Asia (ISGT ASIA); 3–6 November 2015; Bangkok, Thailand: pp. 1-6.

[14] Huang SH, Mu KM, Lu PY, Tsao CY, Leu YG, Chou LF. The application of neural network in wind speed forecasting. In Networking, Sensing and Control (ICNSC), IEEE 12th International Conference; 9–11 April 2015; Taipei, Taiwan: pp. 366-370.

[15] Tascikaraoglu A, Uzunoglu M. A review of combined approaches for prediction of short-term wind speed and power. Renew Sust Energ Rev 2014; 34: 243-254.

[16] Cadenas E, Rivera W. Short-term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks. Renew Energ 2009; 34: 274-278.

[17] Fadare DA. The application of artificial neural networks to mapping of wind speed profile for energy application in Nigeria. Appl Energ 2010; 87: 934-942.

[18] De Giorgi MG, Ficarella A, Tarantino M. Error analysis of short-term wind power prediction models. Appl Energ 2011; 88: 1298-1311.

[19] Ramasamy P, Chandel SS, Yadav AK. Wind speed prediction in the mountainous region of India using an artificial neural network model. Renew Energ 2015; 80: 338-347.

[20] Ghorbani MA, Khatibi R, Fazelifard MH, Naghipour L, Makarynskyy O. Short-term wind speed predictions with machine learning techniques. Meteorol Atmos Phys 2016; 128: 57-72.

[21] Haque AU, Mandal P, Kaye ME, Meng J, Chang L, Senjyu T. A new strategy for predicting short-term wind speed using soft computing models. Renew Sust Energ Rev 2012; 16: 4563-4573.

[22] Liu H, Tian HQ, Li YF. Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction. Appl Energ 2012; 98: 415-424.

[23] Guo ZH, Wu J, Lu HY, Wang JZ. A case study on a hybrid wind speed forecasting method using BP neural network. Knowl-Based Syst 2011; 24: 1048-1056.

[24] Jang JSR. ANFIS: adaptive-network-based fuzzy inference system. Systems, IEEE T Syst Man Cyb 1993; 23: 665-685.

[25] Izgi E, Öztopal A, Yerli B, Kaymak MK, Şahin AD. Short–mid-term solar power prediction by using artificial neural networks. Sol Energy 2012; 86: 725-733.

[26] Svozil D, Kvasnicka V, Pospichal J. Introduction to multi-layer feed-forward neural networks. Chemometr Intell Lab 1997; 39: 43-62.

[27] Ozcira S, Bekiroglu N, Agcal A. A study on feasibility of wind energy production in Silivri region by using laboratory setup. Renewable Energy Research and Applications (ICRERA); 20–23 October 2013; Madrid, Spain: pp. 1175-1179.

[28] Taşcıkaraoğlu A, Uzunoğlu M. Dalgacık dönüşümü ve yapay sinir ağları ile rüzgar hızı tahmini. Elektrik Elektronik Bilgisayar Sempozyumu (FEEB 2011); 5–7 October 2011; Elazığ, Turkey: pp. 106-111.

[29] Li G, Jing S. On comparing three artificial neural networks for wind speed forecasting. Appl Energ 2010; 87: 2313-2320.

[30] McNelis PD. Neural Networks in Finance: Gaining Predictive Edge in the Market. Burlington, MA, USA: Elsevier Academic Press, 2005.

[31] Cankurt S, Subaşı A. Tourism demand modelling and forecasting using data mining techniques in multivariate time series: a case study in Turkey. Turk J Elec Eng & Comp Sci 2016; 24: 3388-3404.