Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 6[7] June : 73-84

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com
CODEN: BEPLAD
Global Impact Factor 0.876
Universal Impact Factor 0.9804
NAAS Rating 4.95

ORIGINAL ARTICLE **OPEN ACCESS**

Wind forecasting using artificial neural network in Jask

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ABSTRACT
Wind is one of the meteorological component that has a huge impact on the ecosystem, the environment and air cleanness, evapotranspiration, agricultural production and so on. Today, many forecasting methods using artificial neural network and fuzzy logic have been to model the wind speed, as a fully nonlinear physical phenomenon, have been used to predict the wind speed in several next steps. Thus, in this study, using artificial neural networks, wind speed and direction in time steps of 3, 6, 9, 12, 15, 18, 21 and 24 hours at Jask Weather Station during the period 1992 to 2005 were predicted. In the beginning, climatic parameters, wind speed and direction, relative humidity, temperature, and air pressure, were selected from Jask Weather Station as model inputs. In the first step, to reduce the volume of data, principal component analysis (PCA) was used. In the next step, training samples, testing and verification were prepared. To prepare these samples, lag time equal to two as inputs and eight units (here three hours) of lead time were used. Simulation results in Trainlm networks compared to other models used in this study are of better efficiency, Trainlm with 5 hidden layers in the training stage provide a better simulation than other Trainlm, but the results of these simulations (both in the training and verification stages) show that the results of the models have relatively low efficiency coefficient for high input combinations and do not seem appropriate for simulation. This type of network usually does not have high performance in cases where the input and output fluctuations are high, and due to geographical location and climatic conditions, Hormozgan is such that fluctuations in wind speed and direction are high from an hour to another, which can be one of the reasons for the failure of these networks in this regard.
Keywords: *Wind, Model, Neural Network, Jask*

Received 11.03.2017 Revised 25.04.2017 Accepted 19.05.2017

INTRODUCTION

Wind is one of the manifestations of solar energy and is the moving air and a small fraction of solar radiation that reaches out into the atmosphere always turns into wind energy. Unequal warming of earth and its atmosphere generates convective flows (displacement) and the relative motion of the atmosphere compared to earth produces wind. Given that fossil combustibles on earth are declining, recently much progress has been made in the use of wind energy. Wind energy is often available and has no pollution and can economically be comparable with other energy sources in the long run. In recent years intensive efforts are done to use wind energy and producing energy from wind in large-scale using advanced technology seems necessary [5].

On the other hand, various forms of artificial neural networks, especially in recent decades, have been used in the field of watershed management and hydrology. Of the uses of artificial neural network in the field of watershed investigating the relationship between rainfall and runoff within a watershed, hydrograph and flood routing, estimating sediment load in rivers, streams and reservoirs management and predicting erosion and sediment in a field can be cited. Among other applications of artificial neural network method in this area is to use this model in predicting wind direction and speed. Therefore, monitoring and forecasting wind parameter, especially in terms of speed and direction, using artificial neural network, has a lot of importance in regional studies and planning and can play a useful role in experts and planners' making decisions in the areas of energy, the environment , agriculture, meteorology and so on. Thus, in a study in Japan, Aymen Chaouchi and Ken Nagasaka [3] used different ANN algorithms to predict wind power in a short period of time and all these algorithms have great ability to predict. However, NNE algorithm had the best results, because in this algorithm, fitting increases noise tolerance, and forecasting extended performance compared to a conventional network, and Monfared and colleagues [4] offered a new statistical model to forecast the changes in wind speed and direction. In this paper, it was suggested that data on wind speed and direction in a period could effectively represent wind speed and direction data over a larger period and a comparison was made between the results of the proposed model and other models showing that the prediction accuracy in the latter method is much higher.

Akinci [2] in a study predicted the short-term wind speed using artificial neural networks in Batman, Turkey and as a result, these prediction models that were developed in Batman in southeastern Turkey, Anatolia, can be used as a start to investigating and testing for wind stations that may be built in Batman.

Pegahfar and colleagues [6] examined the wind speed gradient and nondimensional turbulence intensity using Monin–Obukhov (M–O) similarity theory in a substrate roughness in an urban area with complex topography (Tehran), so in this study, the theory was examined in urban area with complex topography (Tehran) and substrate roughness was investigated. As the results showed, according to non-constant flux of temperatures at lower altitudes, M-O theory with local scaling approach can be used in this area. In the second phase, by comparing the results obtained for Tehran and other investigations at different levels, it can be seen that the intensity of nondimensional turbulence (for three components of wind) and wind nondimensional gradient in this region is more than the results of other research.

MATERIALS AND METHODS

The meteorological station studied

To predict wind speed and direction, meteorological information was used from synoptic station in Jask. The general features of this station are given in Table (1). The station is located in Hormozgan. Hormozgan Province is located at geographical coordinates from 25 degrees 24 minutes to 28 degrees and 57 minutes north latitude and from 53 degrees 41 minutes to 59 degrees 15 minutes east longitude from Greenwich meridian. The province is about 68 thousand square kilometers, in this regard is the eighth in the country. In the north and northeast of, Hormozgan is neighbor of Kerman, West and North West; Fars and Bushehr, East; Sistan and Baluchestan; and in the south; warm waters of Persian Gulf and Oman Sea south to the approximate length of 900 km stipe.

Table 1: General Characteristics of Jask Station

Meteorology Station	Longitude	Latitude	Height above sea level
Jask	57.77	25.63	5.2

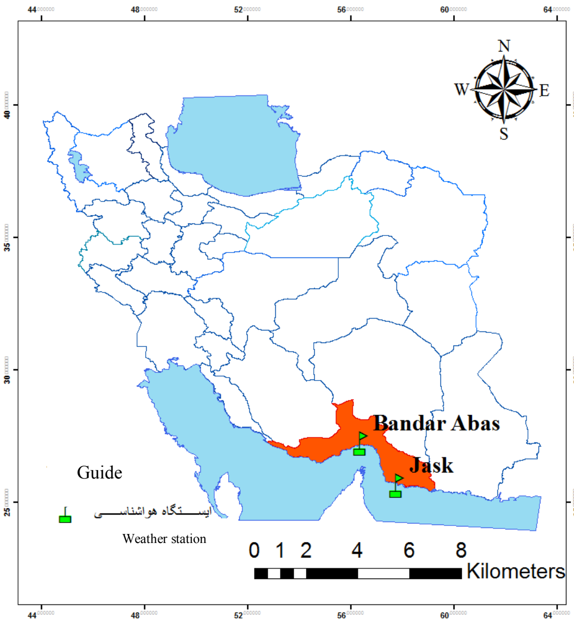

Figure 1. Map of Hormozgan (area under study)

In this research, wind speed and direction are predicted at time steps of 3, 6, 9, 12, 15, 18, 21 and 24 hours in Jask Station using the artificial neural networks. Flow chart of the study is shown in Figure 2. As is shown in the figure, In the beginning, climatic parameters, wind speed and direction, relative humidity, temperature, and air pressure, were selected from Jask Weather Station as model inputs. Model outputs are wind and wind direction. Period is considered from 1992 to 2005. The time series used in hours is 3, 6, 9, 12, 15, 18, 21 and 24. Tus, in the first phase, there is a very large volume of data for initial analysis. However, this can cause further problems including hardware failure in analysis of this information, memorizing, or too much learning trouble by model. Therefore, before providing training samples, test and verification were used to reduce the volume of data by principal component analysis (PCA) method. PCA is a conversion in vector space, which is often used to reduce the size of the data set. PCA was presented in 1901 by Karl Pearson. In the next stage, training, testing, and verification samples were prepared. To prepare the samples lag time of two as inputs and 8 lead time units of time were used. Obviously, the model's inputs are composed of five main components constitute with two units of lag. This is while output of the model consists of eight units of lead time of wind speed or direction. About 70% of the generated samples were used to train model. In addition, about 30 percent of the samples were also used to test the model. Fifty last samples were used in order to verify the generated models.

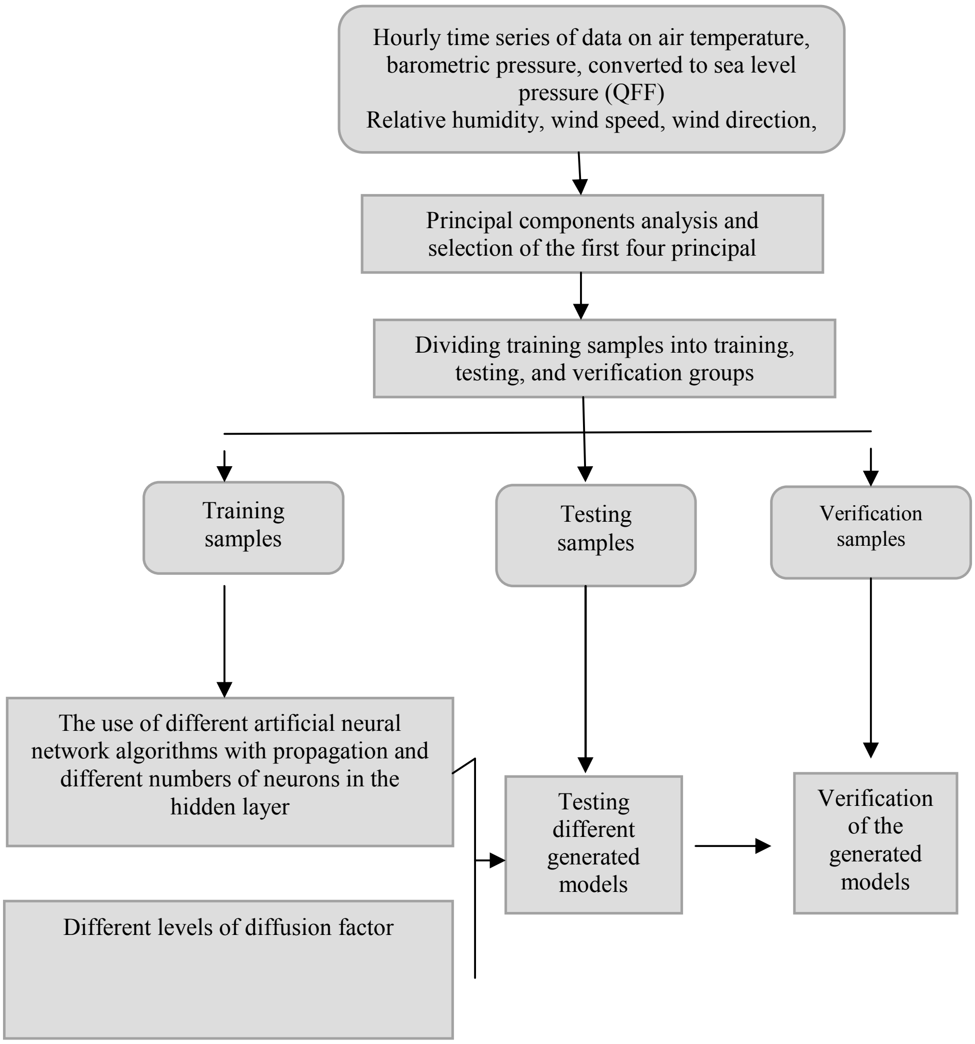

Figure 2: Flow Chart of the case studied

Two types of neural networks, one multilayer perceptron (MLP) and generalized regression neural networks (GRNN) were used for modeling and prediction of wind speed and direction.

MLP Neural Networks:

This network consists of input, middle, and output layer. In the input layer, given the number of inputs layer that is five, we will also have five neurons. In conjunction with the middle layer, depending on the type of training of the network and based on trial and error, different number of neurons were considered. Transfer function of these neurons is tangent sigmoid and finally, the output of the network is wind speed and direction in some hours, which corresponding to it, we will have eight output neurons, whose transfer function is a linear transfer function, and training method of the network is back propagation. Of the best and most effective methods, which exists in MATLAB software as well, is

Marquardt - Levenberg method shortly known as LM in MATLAB environment that strongly increases the speed of convergence and speeds the conclusion. As for training the neural network based on Lm algorithm parallel computation is performed, it is considered as the fastest methods for propagation neural network training with less than a hundred weight connection. Lm algorithm is based primarily on the Hessian matrix used for nonlinear optimization based on least squares (Hagan & Menhaj, 1994). In this study, the number of neurons in the middle layer of networks produced and trained based on Lm is between 1 and 5 neurons.

GDX algorithm acts based on the principle of reducing slope, and it includes specific parameters such as momentum coefficient and rate of learning (a response network gives to local errors). Although this algorithm is trained with less training speed than other algorithms, in many networks, it is considered a good option. In this study, the number of neurons in the middle layer of the networks produced and trained based on GDX is between 7 and 10 neurons [8].

SCG (Scaled Conjugate Gradient) Algorithm is developed by Muller to avoid time-consuming searches. This algorithm is very complicated, but the idea of working is combining Model-trust region approach with the gradient approach. Trainscg rule may need more iterations to converge compared to other integrated gradient algorithms. However, the number of computations in each iteration substantially reduces as no string search is done. In this study, the number of neurons in the middle layer of the produced and trained networks based on SCG is between one and five [8].

The number APECs or iterations were determined by trial and error. In fact, APECs is the number of rotations the network performs for training and reducing its error in each rotation. The optimal number of these rotations is obtained by trial and error. The number of APEC in different networks and depending on the type of middle and output functions is different. Sometimes, network stop before reaching the intended APEC. In this study, based on trial and error, the number of iterations for Trainlm model is equal to 50, 300 for Trainscg, and 700 for Traingdx [8].

Generalized regression neural networks (GRNN):

Generalized regression neural network is composed of four layers including an input layer, pattern layer, summation layer and output layer (Figure 13). The total number of parameters is equal to input units in the first layer. The first layer fully connects to this pattern layer, which is the second layer. In pattern layer, each unit symbolizes a training pattern, and their output measures the input gap from the stored patterns. Each pattern-layer unit links to two neurons in the summation layer that contains summation neurons S and D. Thus, total output weighted neuron from the pattern layer is calculated by S set, and weightless outputs are calculated by D set neuron. Weight link between S set neuron and i-th in pattern layer is yi. Output has target value as i-th neurons in the pattern layer. Weight link for Neuron is D units. The output layer is divided only to each output neuron of S with D neurons needed to predict the value in entry X in the following formula.

$$\hat{y}_i(x) = \frac{\sum_{n=1}^{n} y_i \exp[-D(x,x_i)]}{\sum_{n=1}^{n} \exp[-D(x,x_i)]} \quad (1)$$

Where training number of the pattern is shown with n and Gaussian with D in the above equation

$$D(x,x_i) = \sum_{j=1}^{p} \left(\frac{x_i - x_{ij}}{\xi}\right)^2 \quad (2)$$

Where P is the number of input elements, x_i and x_{ij} are the representative j-th element of the X and Xi respectively. ξ is diffusion factor, which often acquires the optimum value through experiment .

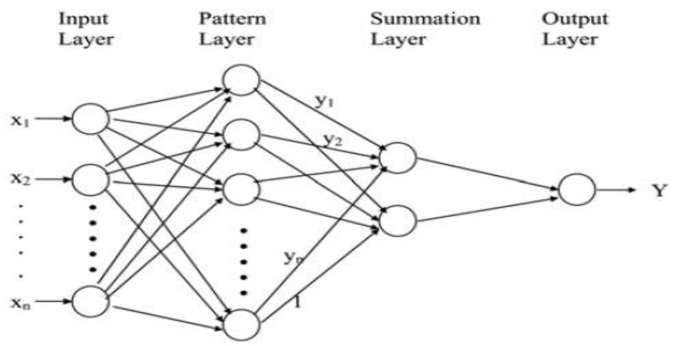

Figure 3: Schematic of structure of generalized regression neural networks (GRNN)

Most research in conjunction with neural network is done in MATLAB environment. In this study, this software was used to model and predict wind speed [8].

Evaluating Network Performance

To evaluate the networks performance in this study, two statistical parameters are used that are root mean square error (RMSE) and the square root of the correlation coefficient (R), respectively, given in the following relations.

$$RMSE = \sqrt{\left(\frac{1}{p}\sum_{i=1}^{p}[(X_m)-(X_s)]^2\right)} \qquad (3)$$

Where X_m and X_S are, respectively, the amounts of observational and simulation data and P is as the total number of events.

$$R = \sqrt{1-\frac{\sum_{i=1}^{n}(o_i-p_i)}{\sum_{i=1}^{n}(o_i-\bar{o})}} \qquad (4)$$

Where Oi and Pi are, respectively, the values of the observed and predicted data and $\bar{O}$ is the observed data and n is the number of data. Each network or method that has less RMSE or more R is selected as the best method [1].

RESULTS AND DISCUSSION

Results of Tables 2 and 3 as well as Figures 4 to 7 represent not so acceptable performance in relations to MLP networks. In fact, in all cases, the efficiency ratio was relatively low at this stage, though it acts very well in many studies [7]. Simulations of data on wind speed and direction in Jask stations did not show good results. MLP networks usually do not have high performance in cases where the input and output fluctuations are high, and due to geographical location and climatic conditions, Hormozgan is such that fluctuations in wind speed and direction are high from an hour to another, which can be one of the reasons for the failure of these networks in this regard that is consistent with the results of Afkhami [1].
The results showed that this type of artificial neural networks have better capabilities to better predict wind speed and direction. Following is the results of each type of artificial neural networks and training of these networks.

The results of the MLP networks

As indicated in Tables 2 and 3, simulation results in Trainlm networks are of better efficiency compared to other models used in this study, Trainlm with 5 hidden layers in the training stage has better simulations than othe Trainlms, but the overall result of these simulations (both in the training and verification) shows that the results of the models for high input combinations has relatively low efficiency coefficient and do not seem appropriate for simulation. Frequency scatter diagrams (both in training and verification) related to each type of artificial neural networks of MLP type were produced that because of the frequency of the models and consequently the generated forms, only the forms related to the best performance are shown in Figures 4 to 7.

Table 2: R and RMSE values of predicting wind speed in Jask Station in testing and verification stages based on the use of various propagation algorithms of neural network

Row	Type of algorithm training (BP)	Number of neurons in the hidden layer	Model efficiency in testing phase		Model efficiency in verification phase	
			R	RMSE	R	RMSE
1	Trainlm	1	0.48	2.18	0.05	2.60
2	Trainlm	2	0.51	2.14	0.20	2.54
3	Trainlm	3	0.54	2.09	0.32	2.50
4	Trainlm	4	0.55	2.09	0.34	2.40
5	Trainlm	5	0.58	2.03	0.45	2.19
6	Trainscg	1	0.42	2.26	0.07	2.65
7	Trainscg	2	0.43	2.25	0.10	2.74
8	Trainscg	3	0.45	2.22	0.16	2.57
9	Trainscg	4	0.42	2.26	0.08	2.63
10	Trainscg	5	0.44	2.23	0.12	2.60
11	Traingdx	7	0.23	2.42	0.09	2.70
12	Traingdx	8	0.13	2.47	0.15	2.92
13	Traingdx	9	0.33	2.35	-0.03	2.83
14	Traingdx	10	0.40	2.29	0.11	2.87

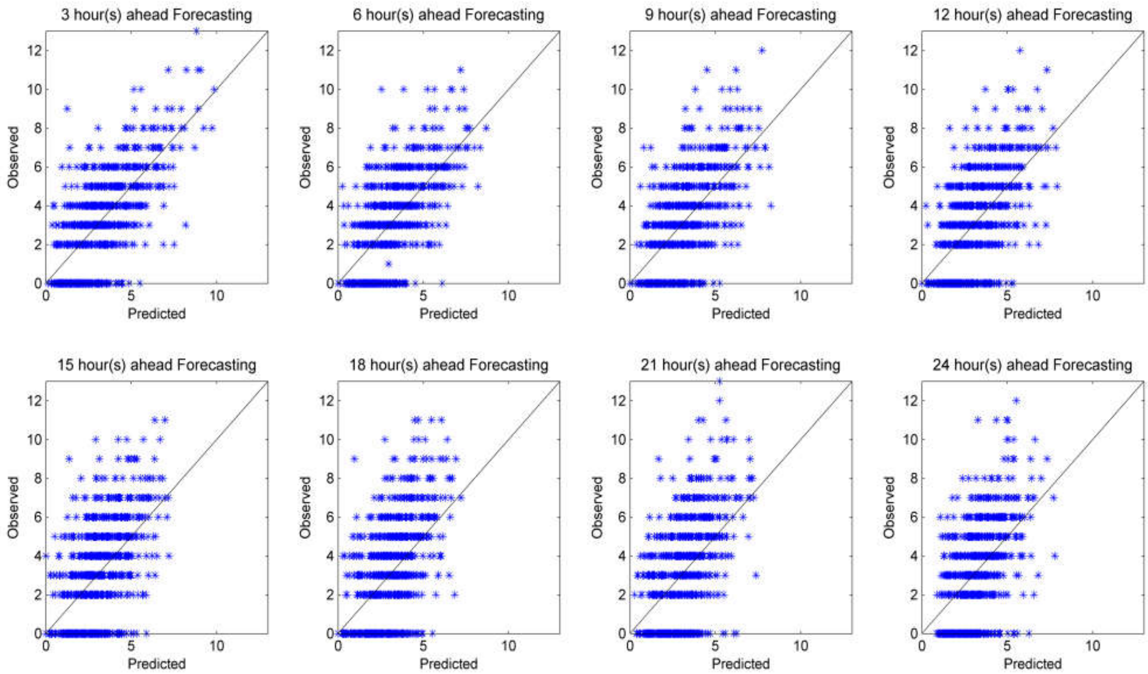

Figure 4: The observed and predicted values for wind speed in steps 3, 6, 9, 12, 15, 18, 21 and 24 hours in Jask Station (test phase)

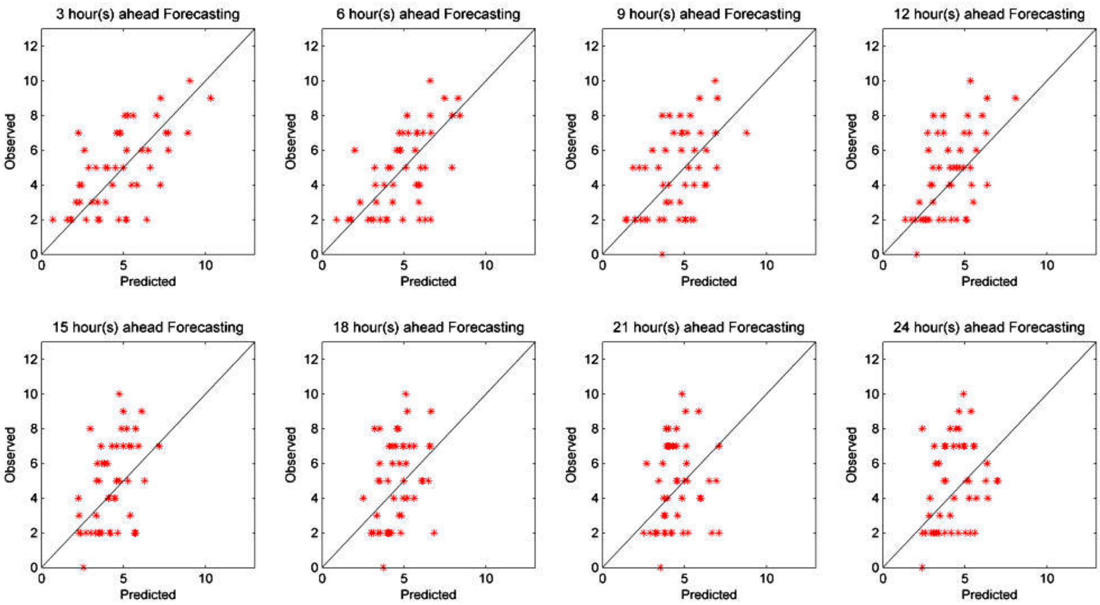

Figure 5: The observed and predicted values for wind speed in steps 3, 6, 9, 12, 15, 18, 21 and 24 hours in Jask Station (Verification phase)

Table 3: R and RMSE values of predicting wind speed in Jask Station in testing and verification stages based on the use of various propagation algorithms of neural network

Row	Type of algorithm training (BP)	Number of neurons in the hidden layer	Model efficiency in testing phase		Model efficiency in verification phase	
			R	RMSE	R	RMSE
1	Trainlm	1	0.47	97.66	0.64	87.51
2	Trainlm	2	0.50	95.97	0.66	86.68
3	Trainlm	3	0.55	92.77	0.65	86.74
4	Trainlm	4	0.54	93.40	0.60	89.89
5	Trainlm	5	0.55	92.65	0.64	85.87
6	Trainscg	1	0.47	97.70	0.57	94.23
7	Trainscg	2	0.47	98.09	0.63	87.04
8	Trainscg	3	0.53	93.68	0.67	84.38
9	Trainscg	4	0.50	95.84	0.57	93.76
10	Trainscg	5	0.49	96.88	0.59	91.87
11	Traingdx	7	0.46	98.34	0.58	95.70
12	Traingdx	8	0.46	98.16	0.57	96.13
13	Traingdx	9	0.45	98.55	0.56	98.66
14	Traingdx	10	0.45	99.00	0.58	92.10

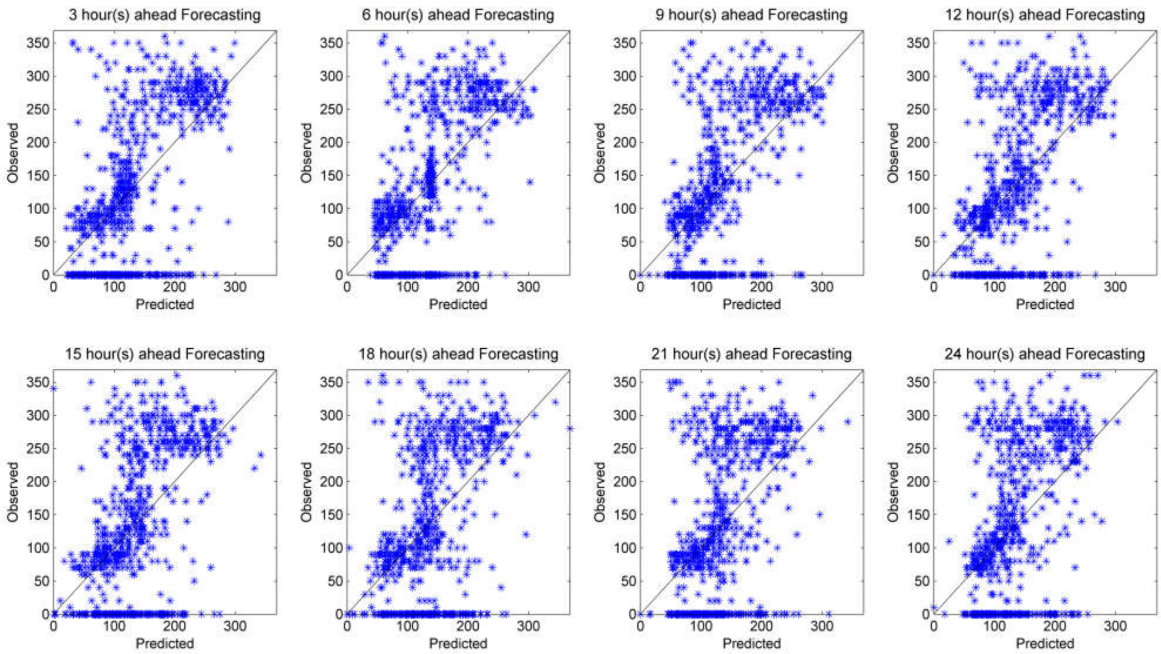

Figure 6: The observed and predicted values for wind direction in steps 3, 6, 9, 12, 15, 18, 21 and 24 hours in Jask Station (Testing phase)

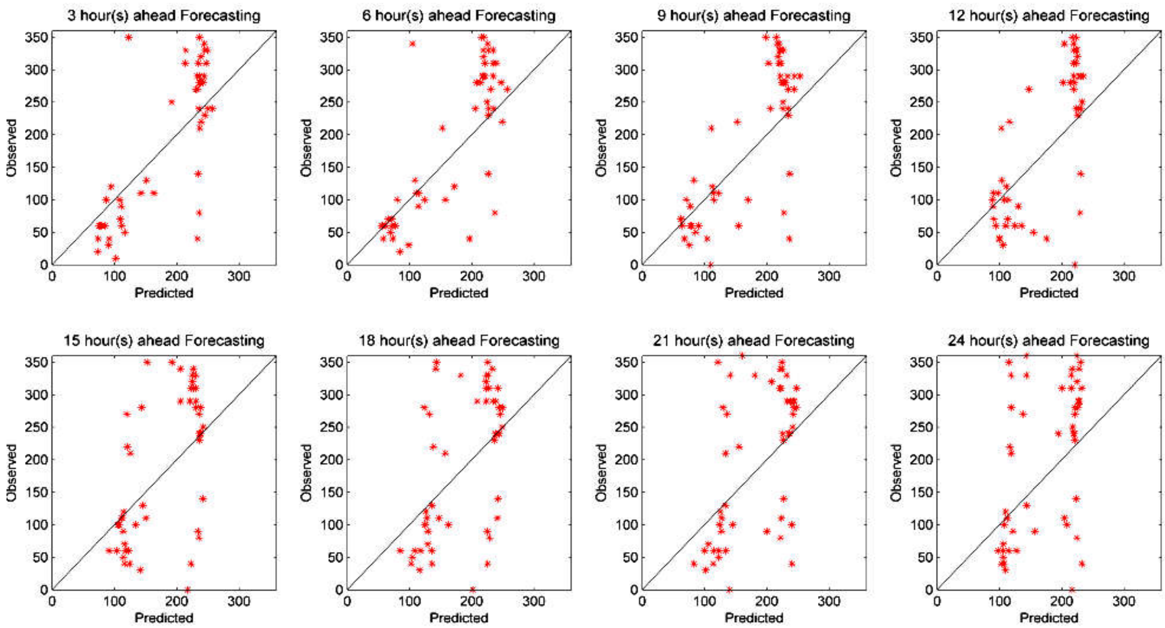

Figure 7: The observed and predicted values for wind direction in steps 3, 6, 9, 12, 15, 18, 21 and 24 hours in Jask Station (Verification phase)

The results of generalized regression neural network:

In GRNN, diffusion factor (ξ) from 0.025/0 to 0.5 range was used, as the results in Tables 4 and 5 show, the best performance efficiency is for generalized regression neural network with 0.1.

By applying this method, much better efficiency ratio compared to previous models can be offered that can be used in data that has high volatility during statistical period, such as wind speed and direction. Scatter diagrams (both in training and verification) of each combination were obtained with their real data, because of the frequency of the generated forms, only the forms related to the best performance are shown in Figures 8 to 11.

Table 4: R and RMSE values for predicting wind speed in Jask Station for testing verification stages based on generalized regression artificial neural network (GRNN)

Row	Diffusion factor	Performance of model in the test phase		Performance of the model at verification phase	
		R	RMSE	R	RMSE
1	0.025	0.798	1.575	0.790	1.559
2	0.050	0.805	1.535	0.793	1.531
3	0.075	0.813	1.484	0.793	1.507
4	0.100	0.816	1.453	0.787	1.513
5	0.125	0.807	1.480	0.767	1.585
6	0.150	0.786	1.557	0.734	1.708
7	0.175	0.758	1.653	0.695	1.859
8	0.200	0.727	1.747	0.655	2.016
9	0.225	0.697	1.833	0.618	2.166
10	0.250	0.666	1.910	0.583	2.304
11	0.275	0.636	1.978	0.549	2.425
12	0.300	0.608	2.037	0.517	2.528
13	0.325	0.581	2.088	0.488	2.616
14	0.350	0.557	2.131	0.463	2.689
15	0.375	0.535	2.169	0.441	2.750
16	0.400	0.516	2.202	0.421	2.801
17	0.425	0.499	2.231	0.403	2.842
18	0.450	0.484	2.256	0.387	2.874
19	0.475	0.471	2.279	0.372	2.899
20	0.500	0.458	2.299	0.357	2.916

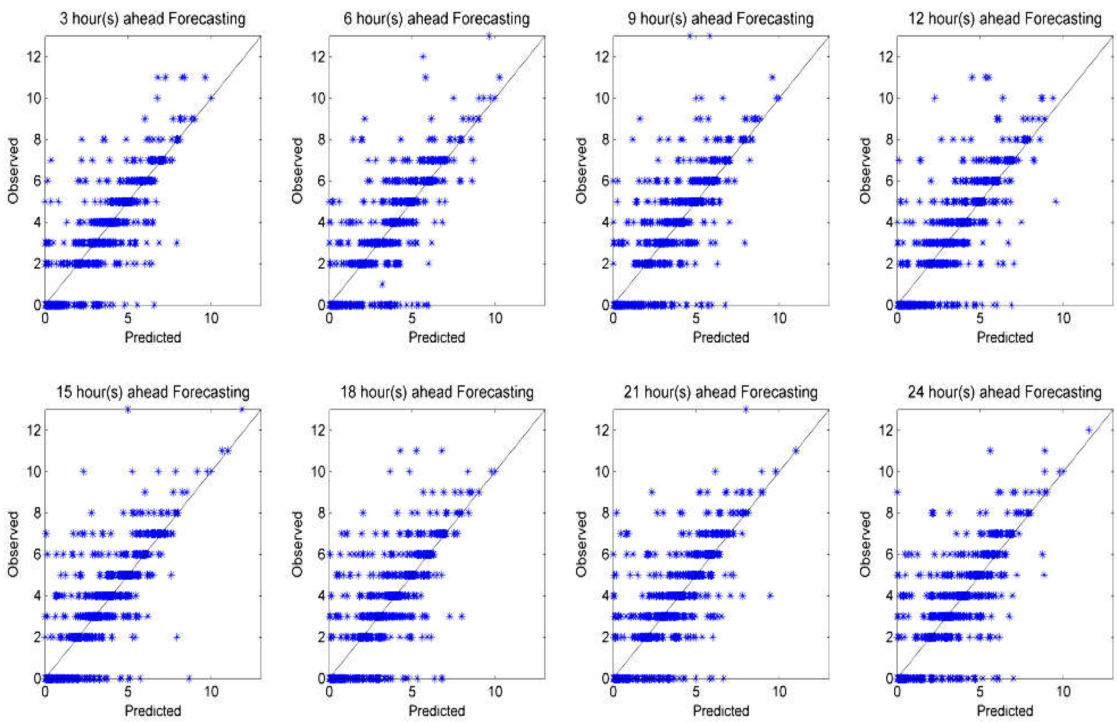

Figure 8: The observed and predicted values for wind speed in steps 3, 6, 9, 12, 15, 18, 21 and 24 in Jask Station (test phase)

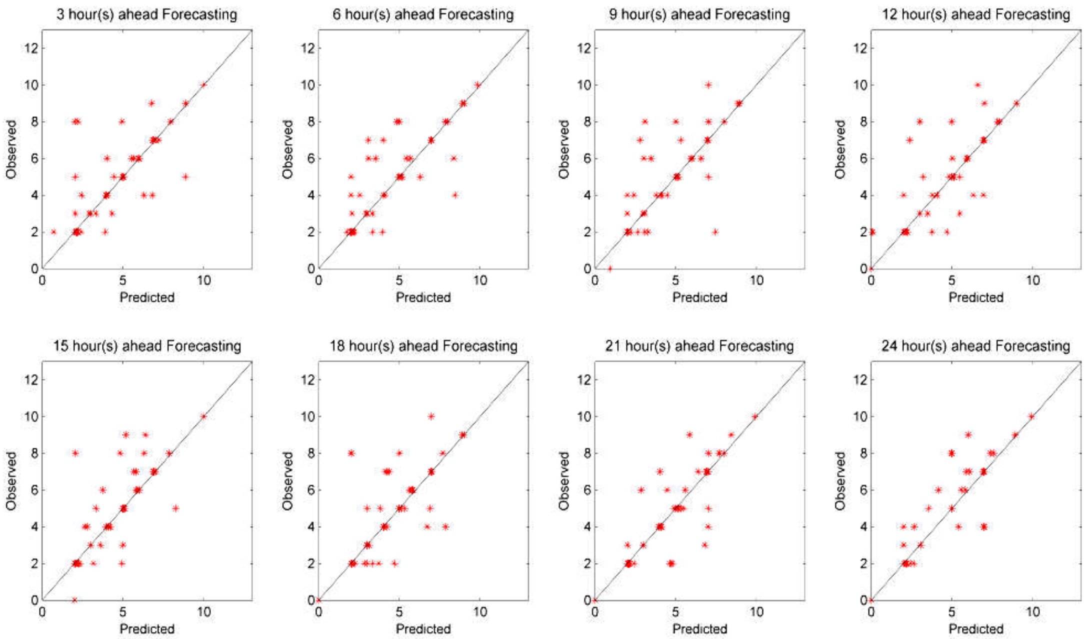

Figure 9: The observed and predicted values for wind speed in steps 3, 6, 9, 12, 15, 18, 21 and 24 in Jask Station (verification phase)

Table 5: R and RMSE values for predicting wind direction in Jask Station for testing verification stages based on generalized regression artificial neural network (GRNN)

Row	Diffusion factor	Performance of model in the test phase		Performance of the model at verification phase	
		R	RMSE	R	RMSE
1	0.025	0.811	66.851	0.763	77.090
2	0.050	0.816	65.607	0.771	75.006
3	0.075	0.822	63.745	0.770	73.677
4	0.100	0.824	62.300	0.769	72.186
5	0.125	0.817	62.797	0.767	71.553
6	0.150	0.798	65.663	0.755	73.093
7	0.175	0.770	69.941	0.733	75.899
8	0.200	0.736	74.444	0.710	78.884
9	0.225	0.701	78.560	0.689	81.597
10	0.250	0.667	82.090	0.671	83.977
11	0.275	0.636	85.020	0.657	86.123
12	0.300	0.608	87.421	0.645	88.137
13	0.325	0.584	89.395	0.635	90.083
14	0.350	0.563	91.042	0.626	91.992
15	0.375	0.545	92.452	0.618	93.878
16	0.400	0.530	93.699	0.611	95.748
17	0.425	0.516	94.825	0.604	97.601
18	0.450	0.504	95.855	0.599	99.427
19	0.475	0.493	96.798	0.594	101.211
20	0.500	0.483	97.663	0.589	102.934

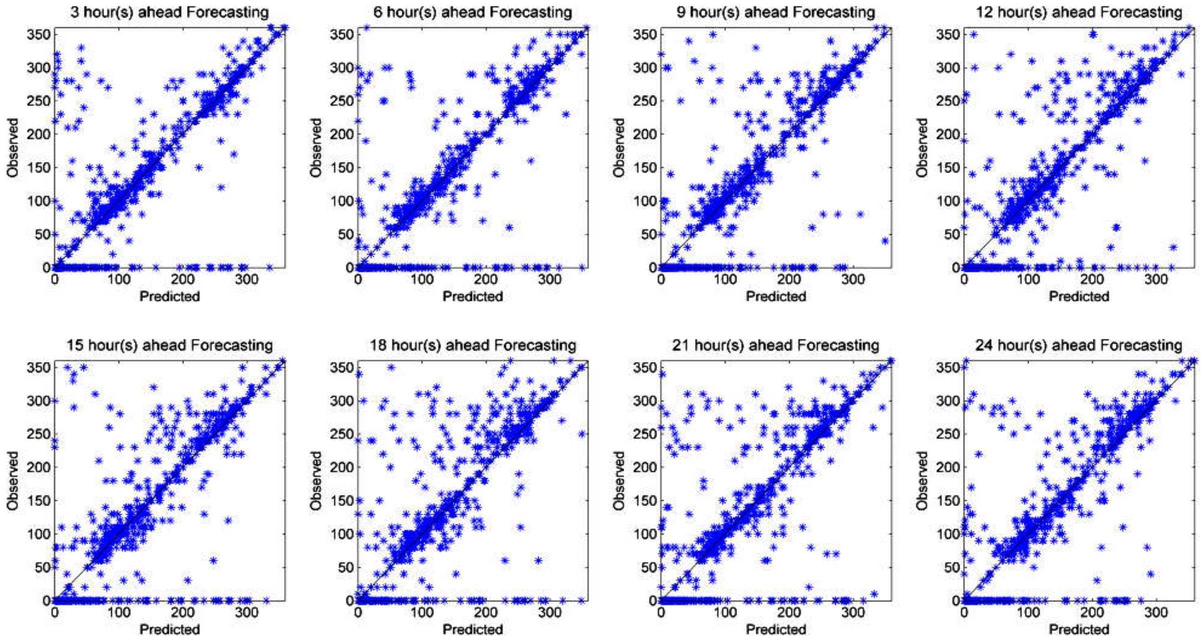

Figure 10: The observed and predicted values for wind direction in steps 3, 6, 9, 12, 15, 18, 21 and 24 in Jask Station (testing phase)

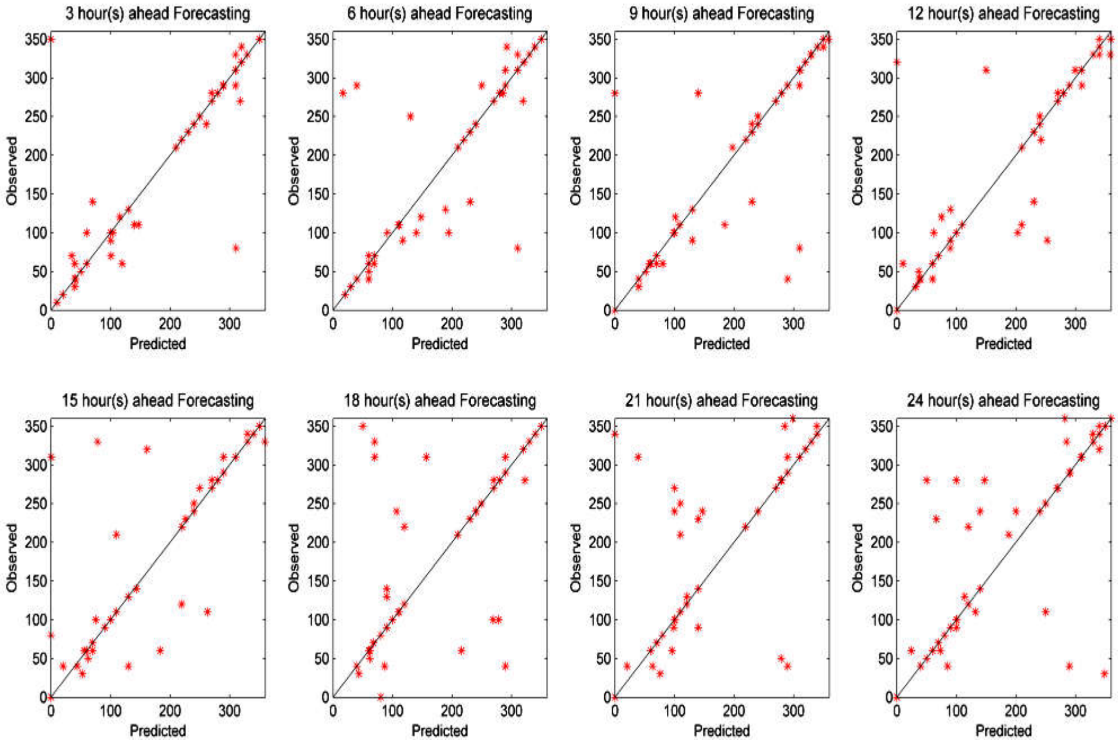

Figure 11: The observed and predicted values for wind direction in steps 3, 6, 9, 12, 15, 18, 21 and 24 in Jask Station (verification phase)

CONCLUSION

Wind is one of the most important climatic parameters that while being important, has wide fluctuations and significant changes that make its modeling challenging from various aspects whether predicting or estimation. For example, compared to other climatic parameters, even precipitation, estimation of statistical errors associated to wind has more problems. This is while in expecting more accurate prediction of a time series for 24 hours in eight three-hour forms more caution must be accompanied. Today, with the development of software and hardware of computers as well as the development of artificial intelligence models that have considerable potential for solving nonlinear issues, one can expect higher precision level in predicting highly variable parameters such as wind and its direction. What was examined in this study was the evaluation of performance of artificial neural networks in predicting wind

speed and direction at Jask Weather Station. Despite the fact that in many studies, MLP networks have had appropriate and acceptable results, in this study, simulation of wind speed and direction at the stations and based on this type of network does not have good performance and do not show good results (Tables 2 and 3).
These types of networks usually do not have high performance in cases where the input and output fluctuations are high, and due to geographical location and climatic conditions, Hormozgan is such that fluctuations in wind speed and direction are high from an hour to another, which can be one of the reasons for the failure of these networks in this regard that is consistent with the results of Afkhami [1].
The results show higher precision in this type of network in predicting wind speed and direction (Tables 4 and 5). The results of this study showed that predicting wind both in terms of parameters and in terms of location varies. In other words, the results of modeling wind speed and direction are quite different. Moreover, the spatial variations or changes in meteorological stations lead to different results in prediction. Searching in different kinds of artificial neural networks, the number of neural network layers, network training method, the number of neurons in the hidden layer as well as the number of iterations (APEC) are all of the issues that could affect the accuracy of the network and its predictions. In relation to the types of MLP networks, on the whole, LM networks were more efficient. This was despite the fact that these types of networks had very little efficiency compared to generalized regression neural networks and the success of generalized regression neural networks was far greater in predicting the speed and direction of wind.
Finally, it should be said that the results of this research studied some of the most important capabilities of neural networks to predict wind speed and direction. Although the results show the good performance of generalized regression network model, to implement the results of this study, the use of other forms of artificial intelligence models, especially neuro-fuzzy hybrid model, along with the use of preparing input data methods using wavelet can also be proposed to achieve greater levels of accuracy and efficiency of the models in predicting the wind speed and direction.

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CITATION OF THIS ARTICLE

G Javadizadeh, H Ghahramani. Wind forecasting using artificial neural network in Jask.. Bull. Env. Pharmacol. Life Sci., Vol 6[7] June 2017: 73-84