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Article

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Research paper

Wind speed prediction using a hybrid model of the multi-layer perceptron and whale optimization algorithm



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ABSTRACT

Wind power as a renewable source of energy has numerous economic, environmental, and social benefits. To enhance and control renewable wind power, it is vital to utilize models that predict wind speed with high accuracy. In the current study, for predicting wind speed at target stations in the north of Iran, the combination of a multi-layer perceptron model (MLP) with the Whale Optimization Algorithm (WOA) was used to build new method (MLP-WOA) with a limited set of data (2004–2014). Then, the MLP-WOA model was utilized at each of the ten target stations, with the nine stations for training and tenth station for testing (namely: Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh, and Deylaman) to increase the accuracy of the subsequent hybrid model. The capability of the hybrid model in wind speed forecasting at each target station was compared with the MLP optimized by the Genetic Algorithm (MLP-GA) and standalone MLP without the WOA optimizer. To determine definite results, numerous statistical performances were utilized. For all ten target stations, the MLP-WOA model had precise outcomes than the MLP-GA and standalone MLP model. In other words, the hybrid MLP-WOA models, with acceptable performances, reduced the RMSE values from 0.570~2.995 to 0.523~2.751. Also, the obtained results indicated that the examined MLP-GA did not have a significant effect in increasing the estimation accuracy of standalone MLP models. It was concluded that the WOA optimization algorithm could improve the prediction accuracy of the MLP model and may be recommended for accurate wind speed prediction.

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1. Introduction

By increasing the need for energy in today's societies and declining fossil resources, the importance of renewable energies appears more than ever. Wind energy, as a substitute of fossil

resources, has received rising attention from all over the world owing to its abundant supply, extensive dispersal, and finances as a clean and renewable form of energy. Also, increasing alertness of the ecological effects of greenhouse gas releases has encouraged an impressive rise in renewable energy. Therefore, to encounter the energy request and the problems of greenhouse gas releases, it is essential to concentrate on substitute renewable energies (Deo et al., 2018; Hoolohan et al., 2018; Marchal et al., 2011). Although the wind supply in most parts of the world is plentiful, its unpredictable and irregular nature leads to some problems such as acquiring a safe and persistent amount of electricity. By predicting the wind power, the request for electricity

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can be cautiously controlled, and their precision has a direct effect on consistency and productivity (Hoolohan et al., 2018).

Local and regional climates, topography, and impediments including buildings, affect wind energy. Due to the cyclical, daily pattern and high stochastic variability, accurate prediction of wind power is too complicated. Therefore, it is clear that efficient transformation and application of the wind energy resources require exact and complete information on the wind features of the region. Wind power prediction relies on wind speed estimation. In the last decades, different models were established to predict the wind speed to reach accurate information about wind energy. In general, these models are divided into three types: physical, statistical, and intelligence learning models. Physical approaches, which are based on a detailed physical description of the atmosphere, used meteorological data such as air temperature, topography, and pressure to predict wind speed. These types of methods have not been applied in short-term wind speed prediction owing to intricate calculation methods, high costs, and poor performance. Still, they can have more accurate predictions in the long-term compared with other types of prediction models. For example, Cheng et al. (2017) used physical algorithms to integrate observation data of wind turbines into numerical weather prediction (NWP) systems to enhance the precision of wind speed forecasting. Moreover, Charabi et al. (2011) and Al-Yahyai and Charabi (2015) evaluated wind sources in Oman by NWP models, and Jiang et al. (2013) investigated wind energy capacities in coastal regions of China by utilization of remotely sensed wind field information. For short-term periods statistical methods and intelligence learning models, which have been applied in most of the recent studies, can forecast wind speed better and more accurately than physical approaches. The autoregressive (AR), autoregressive moving average (ARMA), and the autoregressive integrated moving average (ARIMA) models are used as statistical methods. As an example of statistical methods, Torres et al. (2005) predicted wind speeds up to 10 h earlier by applying the ARMA model in Navarre (Spain). Enhancements over a persistence model were presented in the study, but it was noted that the model could only be used in short-term predictions. Kavasseri and Seetharaman (2009) utilized the fractional autoregressive integrated moving average (f-ARIMA) model to predicted wind speed for the upcoming two-day periods. The results expressed that the precision off-ARIMA model was higher than the persistence model. In the case of intelligence learning models, fuzzy systems, artificial neural networks (ANN), support vector regression (SVR), neuro-fuzzy systems, extreme learning machines, and the Gaussian process are the most current methods for wind prediction. Also, hybrid models are used for wind speed forecasting, which is usually made with a combination of statistical and intelligent methods (Chitsazan et al., 2019). Shukur and Lee (2015) used the data from Malaysia and Iraq to predict daily wind speed by the utilization of a hybrid model with a combination of an artificial neural network (ANN) and Kalman filter (KF). The outcomes showed that the KF-ANN as a hybrid model had high performance in comparison with single algorithms. Bilgili and Sahin (2013) predicted wind speed in daily, weekly, and monthly periods by exploiting the ANN method with data from four different stations of Turkey. The results showed that the applied method performed well. Moreno and Coelho (2018) utilized the Adaptive Neuro-Fuzzy Inference System (ANFIS) with a combination of Singular Spectrum Analysis (SSA) for wind speed predicting. The results expressed that forecasting errors were considerably reduced by the utilization of the proposed method. Cadenas and Rivera (2010) developed hybrid models, including ANN and ARIMA models, to forecast wind speed in three different locations. First, they used the ARIMA model to forecast wind speed of time sequences, and the ANN

model was used to considering the nonlinear features that the ARIMA model could not recognize. It was concluded that in this process, the hybrid models are more precise than the ANN and ARIMA models. Hui Liu et al. (2015) integrated four decomposing algorithms including Empirical Mode Decomposition (EMD), Fast Ensemble Empirical Mode Decomposition (FEEMD), Wavelet Decomposition (WD), and Wavelet Packet Decomposition (WPD) with two nominated networks including ANFIS and MLP Neural Network to estimate wind speed. Based on the results, the hybrid ANN algorithms have high accuracy in comparison with their corresponding single ANN algorithms in wind speed prediction. Furthermore, the ANFIS had poor performance than the MLP in the forecasting neural networks.

In this study, a hybrid technique was developed based on an MLP model for predicting the wind speed without any requirement for the atmospheric datasets. Therefore, to predict the wind speed value of the target station, data of reference stations were used. Moreover, to improve the precision of the model, the whale optimization algorithm (WOA) is utilized, and the novel MLP-WOA model is developed. Furthermore, the capabilities of MLP-WOA were compared to the hybrid MLP-GA in wind speed estimation. The WOA model has been used as an optimizer in earlier investigations (e.g. Du et al., 2018) in electrical power forecasting and so on. Still, to the best of our knowledge, hybrid MLP-WOA has not been used for wind speed prediction, especially using the wind speed values of neighboring stations. So, the aim of this research is to investigate the capabilities of MLP-WOA model for wind speed forecasting for a set of ten spatially-scattered stations in the north of Iran by applying data of the reference stations.

This paper is structured as follows: In the next section, the methods and materials are described in detail. The results and discussions of the models are presented in Section 3, and lastly, Section 4 presents the conclusions.

2. Materials and methods

2.1. Multilayer perceptron neural networks

Multilayer perceptron models, which are constructed based on the nervous system of the human brain, have high capabilities in modeling nonlinear behavior of complex systems. Furthermore, the nature of these models allows them to address prediction problems with nonlinear structure. This model operates based on the learning the problem-solving process for reaching the output by finding the implicit relationship in the process. For this purpose, a bunch of data is used in the training stage, by the usage of the relationship found in that stage, then, the proper output is calculated. There are several samples of the neural networks, but among all of them, the back-propagation network is used more than others. This network consists of layers, and they have parallel-acting elements called neurons. Each layer is entirely connected to the layer before and after itself.

In this study, the composition of (i) input layer, (ii) hidden layer, and (iii) output layer is used as a three-layered structure (Fig. 1). The independent parameters in the input layer consist of nine neighboring stations. The dependent variable that utilized as an output is the target station. The optimum network design includes 9, 8, and neurons for input, hidden, and output layers, respectively. Moreover, the sigmoid tangent and linear functions using the Levenberg–Marquardt Algorithm (LMA) with 200 repeating were utilized for input and output layers. These functions were selected based on the trial and error procedure for obtaining the accurate estimations of wind speed. Moreover, the complexity of each machine learning network increases by adding additional configuration in internal nodes. So, for controlling the mentioned complexity, eight neurons in the hidden layer were selected.

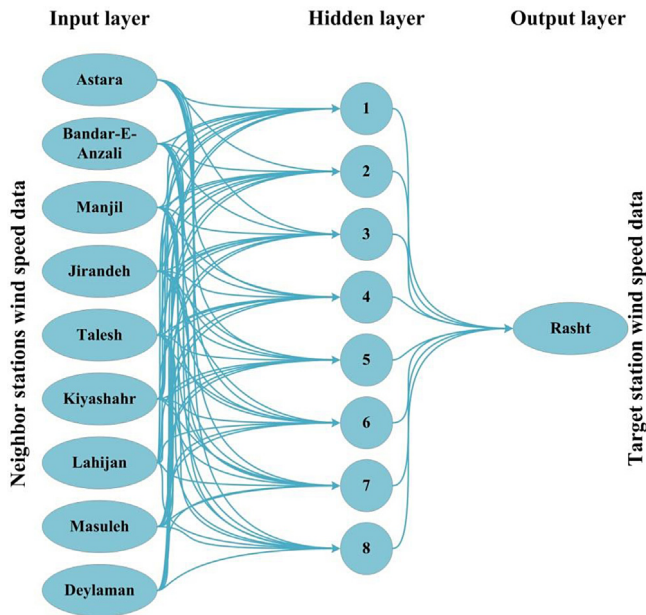


Fig. 1. An artificial neural network arrangement in this study.

2.2. Multi-layer Perceptron-Whale Optimization Algorithm (MLP-WOA)

Mirjalili and Lewis (2016) suggested a whale optimization algorithm, which is a new heuristic algorithm. WOA impersonates the foraging of humpback whales. The humpback whales have a particular hunting method identified as a bubble-net feeding technique in which they catch a group of small fishes near the surface. They create distinctive bubbles along a spiral-shaped route by swimming around prey within a diminishing circle (Fig. 2). The WOA is done in two stages. The first one is exploitation in which the prey is encircled, and the bubble spiral attack technique is used. In the second step, prey selected randomly, which is named exploration.

The WOA can discover the situation of the hunt to encircle them. In the whale method, it is supposed that the present best location is target prey, or it is near the optimum since the optimum search location is not defined earlier. The following equations characterize this performance:

$$\vec{D} = |\vec{C} \cdot \vec{X}^* - \vec{X}(t)| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{2}$$

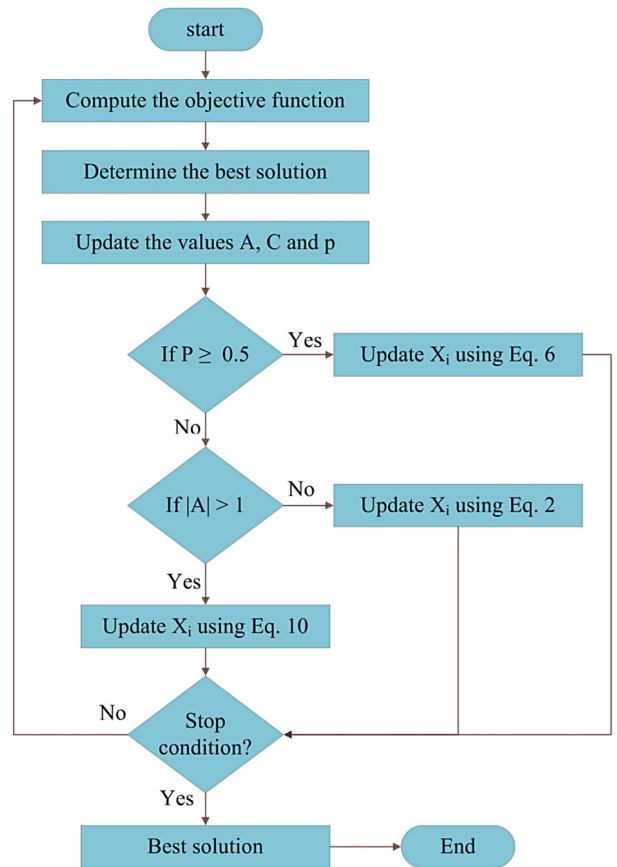
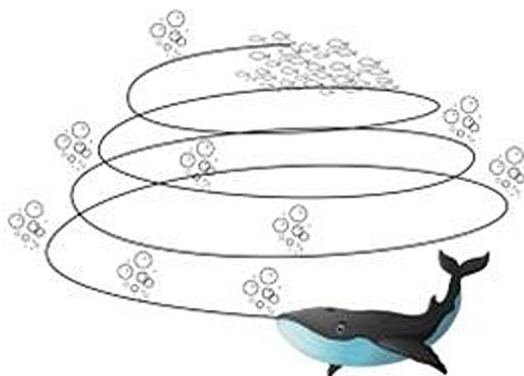


Fig. 3. Overall block diagram elaborating the MLP-WOA algorithm.

where \vec{C} and \vec{A} are considered as coefficient vectors, t represents the current iteration, \vec{X} is the location vector, and \vec{X}^* is the location vector of the best solution. The following equations represent A and C:

$$\vec{A} = 2 \vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{4}$$

where r is a random vector produced with steady diffusion in the interval of [0, 1] and a declines from two to zero by order of iterations. In Eq. (2) solutions verify their locations according to the site of the best solutions (prey). In WOA for achieving the shrinking encircling behavior in a trap, a is reduced with the

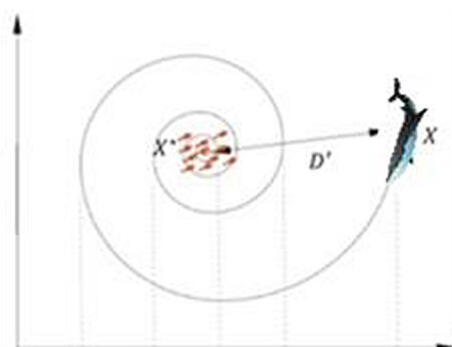


Fig. 2. Artificial neural network-whale optimization algorithm (MLP-WOA).

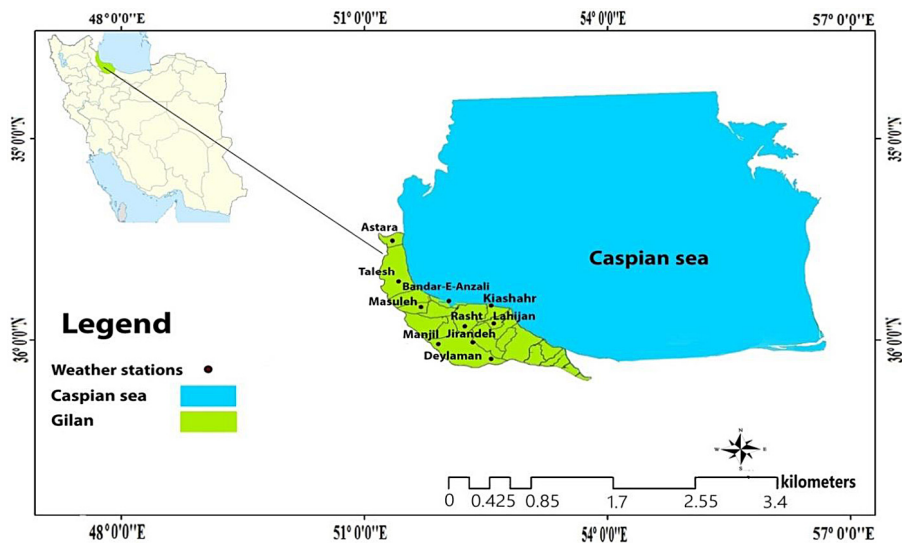


Fig. 4. The location of studied stations in the region.

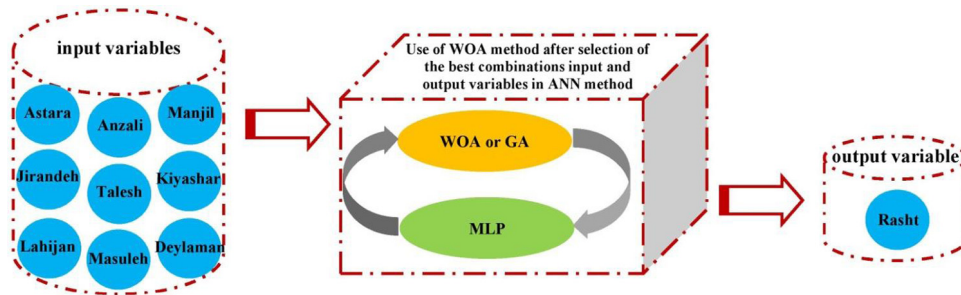


Fig. 5. Methodology development of proposed hybrid models.

Table 1
Coordinates of studied stations in the area and the statistical characteristics of wind data.

Station	Latitude	Longitude	Altitude (m)	Mean wind speed (m/s)	Maximum wind speed (m/s)
Astara	38°21'53.9"N	48°51'17.6"E	−21.1	1.48	12.8
Bandar-E-Anzali	37°28'46.6"N	49°27'27.2"E	−23.6	3.31	14.6
Rasht	37°19'21.9"N	49°37'25.8"E	−8.6	1.51	9.0
Manjil	36°43'42.4"N	49°24'36.0"E	338.3	5.02	15.3
Jirandeh	36°42'27.5"N	49°48'05.6"E	1581.4	5.25	25.6
Talesh	37°50'22.5"N	48°53'51.2"E	7	1.75	17.8
Kiyashahr	37°23'21.0"N	49°53'37.5"E	−22	1.66	10.0
Lahijan	37°11'32.5"N	50°00'58.2"E	34.2	1.46	10.6
Masuleh	37°09'02.3"N	48°59'09.9"E	1080.9	1.78	12.8
Deylaman	36°53'08.2"N	49°54'35.7"E	1447.6	2.38	14.6

Table 2
Reference and target stations in the studied region.

Target station	Reference station	Models
Astara	Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh, Deylaman	MLP1, MLP-WOA1, MLP-GA1
Bandar-E-Anzali	Astara, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh, Deylaman	MLP2, MLP-WOA2, MLP-GA2
Rasht	Astara, Bandar-E-Anzali, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh, Deylaman	MLP3, MLP-WOA3, MLP-GA3
Manjil	Astara, Bandar-E-Anzali, Rasht, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh, Deylaman	MLP4, MLP-WOA4, MLP-GA4
Jirandeh	Astara, Bandar-E-Anzali, Rasht, Manjil, Talesh, Kiyashahr, Lahijan, Masuleh, Deylaman	MLP5, MLP-WOA5, MLP-GA5
Talesh	Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Kiyashahr, Lahijan, Masuleh, Deylaman	MLP6, MLP-WOA6, MLP-GA6
Kiyashahr	Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Lahijan, Masuleh, Deylaman	MLP7, MLP-WOA7, MLP-GA7
Lahijan	Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Masuleh, Deylaman	MLP8, MLP-WOA8, MLP-GA8
Masuleh	Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Deylaman	MLP9, MLP-WOA9, MLP-GA9
Deylaman	Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh	MLP10, MLP-WOA10, MLP-GA10

following formula:

$$a = 2 - t \frac{2}{MaxIter} \tag{5}$$

where t is repeating number, and $MaxIter$ is the maximum allowable iterations. The distance between the best-known search (X^*) and a search factor (X) is calculated to simulate the spiral-shaped

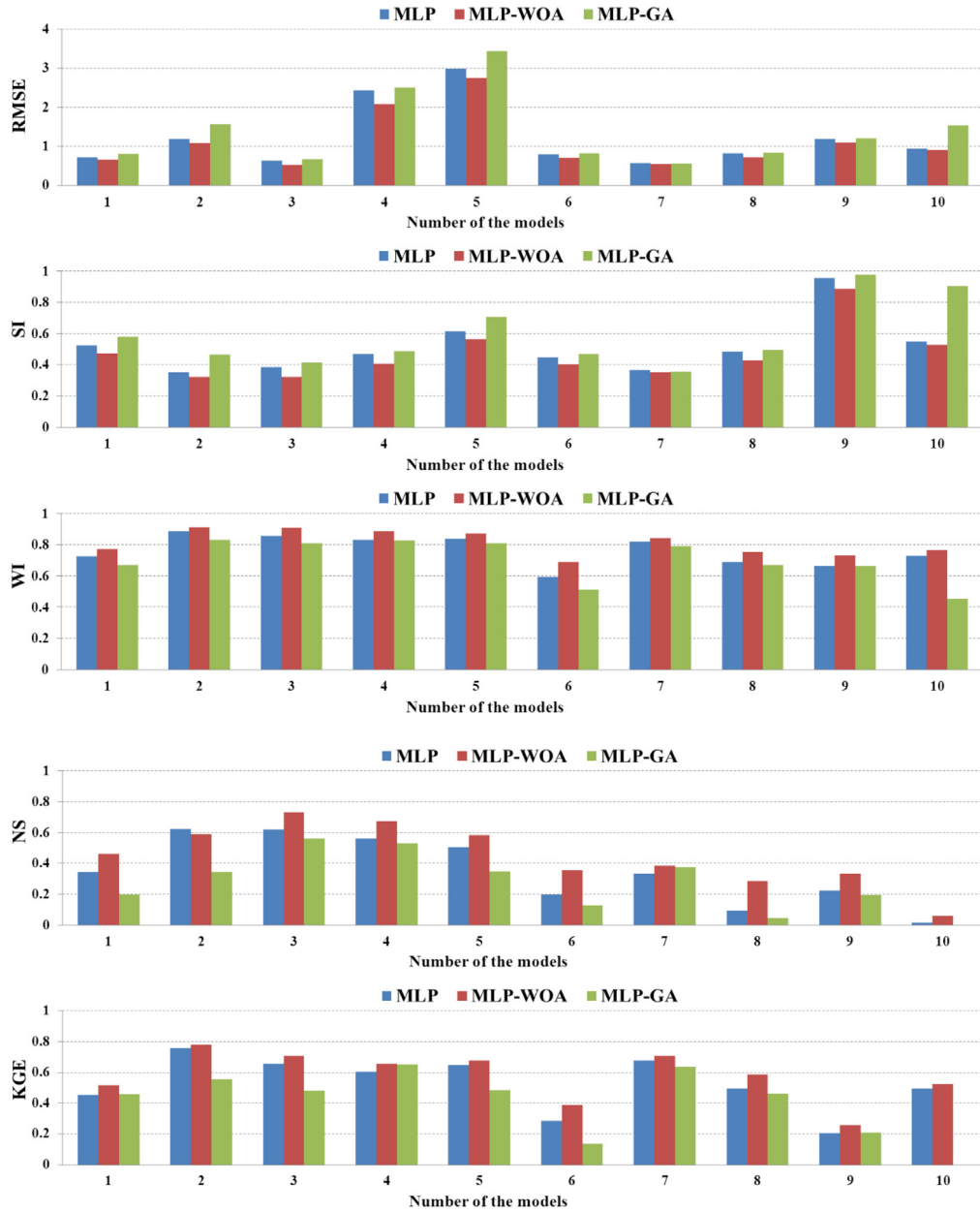


Fig. 6. Bar graphs of the statistical parameters for different considered models.

Table 3

Correlation coefficient values of wind speed among all studied stations two by two.

Station	Astara	Bandar-E-Anzali	Rasht	Manjil	Jirandeh	Talesh	Kiyashahr	Lahijan	Masuleh	Deylaman
Astara	1.00									
Bandar-E-Anzali	0.44	1.00								
Rasht	0.48	0.71	1.00							
Manjil	0.20	0.31	0.27	1.00						
Jirandeh	0.19	0.29	0.26	0.70	1.00					
Talesh	0.29	0.05	0.18	0.16	0.16	1.00				
Kiyashahr	0.40	0.50	0.54	0.15	0.19	0.17	1.00			
Lahijan	0.38	0.37	0.46	0.15	0.12	0.28	0.40	1.00		
Masuleh	0.07	-0.18	0.00	-0.28	-0.09	0.16	0.15	0.06	1.00	
Deylaman	0.24	0.08	0.20	0.10	0.27	0.13	0.28	0.11	0.43	1.00

route. Then to create the adjacent search agent location, a spiral equation is formed as follows:

$$\vec{X}(t + 1) = D' \cdot e^{bl} \cdot \cos(2\pi L) + \vec{X}^*(t) \tag{6}$$

where L is a random number in $[-1,1]$, b is a constant and the space of the i th whale, and the prey is considered as D' which is calculated by:

$$D' = \left| \vec{X}^*(t) - \vec{X}(t) \right| \tag{7}$$

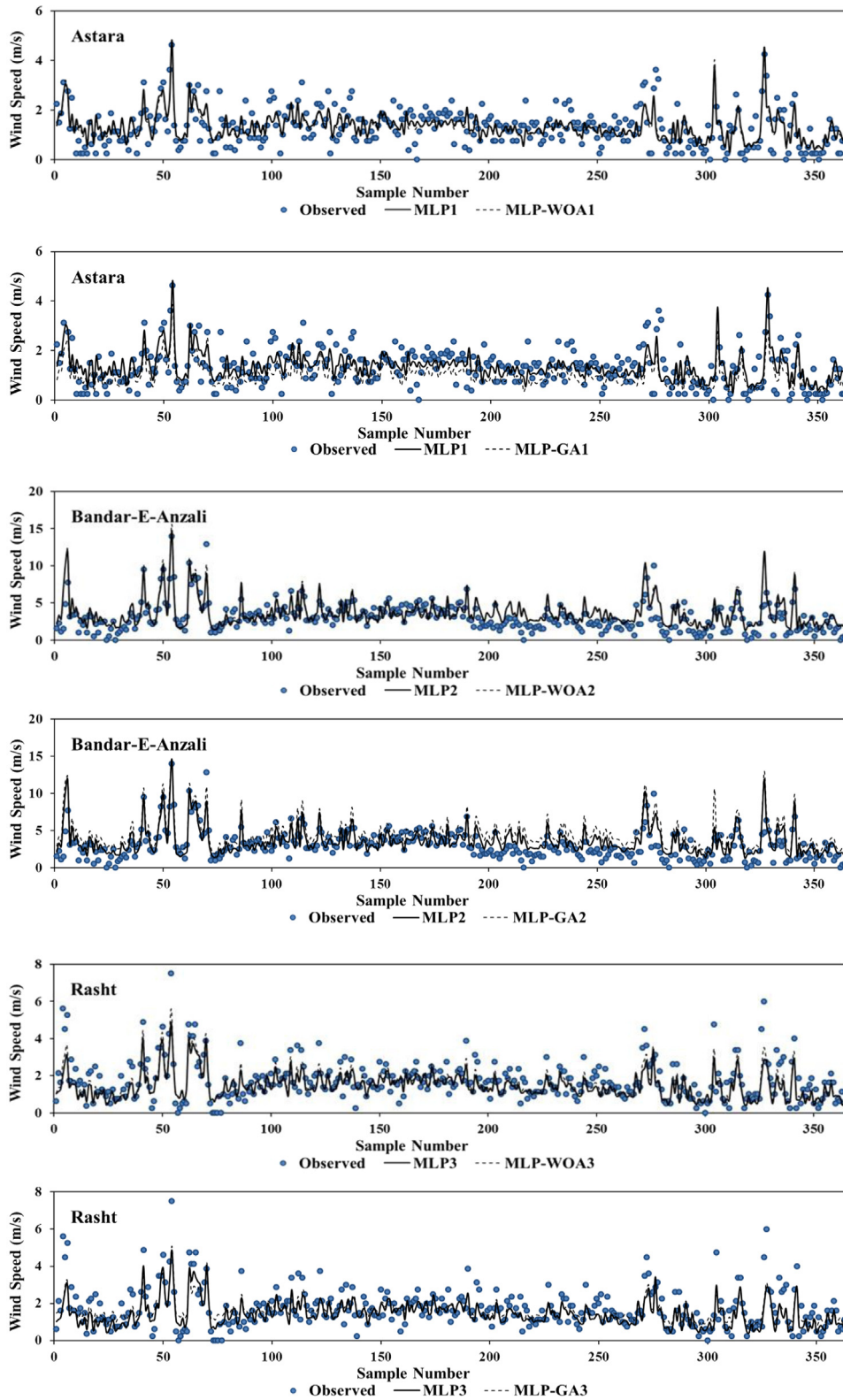


Fig. 7. Comparison of the predicted and observed daily wind speed values using the hybrid MLP-WOA, MLP-GA, and classical MLP models.

As mentioned above, the humpback whales swimming around preys in a diminishing circular as well as a spiral-shaped route simultaneously. To simulate the two mechanisms, during the optimization process, there is a likelihood of 50% to select between

them:

$$\vec{X}(t+1) = \begin{cases} \text{Shrinking Encircling (Eq. (5))} & (P < 0.5) \\ \text{Spiral-shaped path (Eq. (6))} & (P \geq 0.5) \end{cases} \quad (8)$$

where P is a random number in $[0, 1]$.

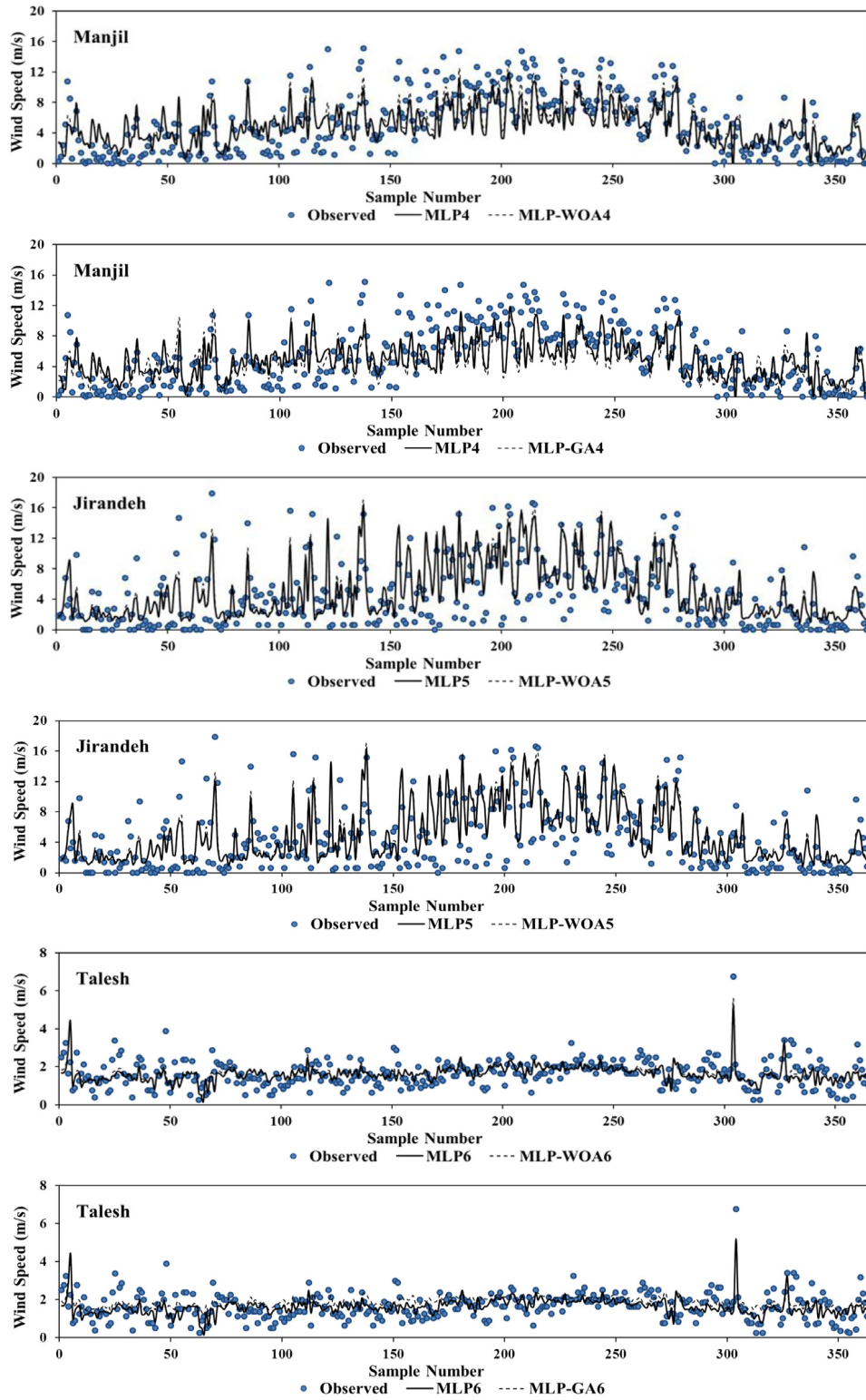


Fig. 7. (continued).

Nevertheless, humpback whales may be searching for prey in an unselective way. So, their location may be updated on the basis of randomly selected whale $x_{rand}(t)$ as follows:

$$\vec{D} = \left| \vec{C} \cdot \overrightarrow{x_{rand}(t)} - \vec{X}(t) \right| \quad (9)$$

$$\vec{X}(t+1) = \overrightarrow{x_{rand}(t)} - \vec{A} \cdot \vec{D} \quad (10)$$

Fig. 3 presents the overall block diagram elaborating the MLP-WOA algorithm. In the current research, the value of L and P were 0.65 and 0.37, respectively. Also, the size of the population was 30, and the maximum iteration was 50. Furthermore, the optimum number of neurons was considered 8 in the hidden layer.

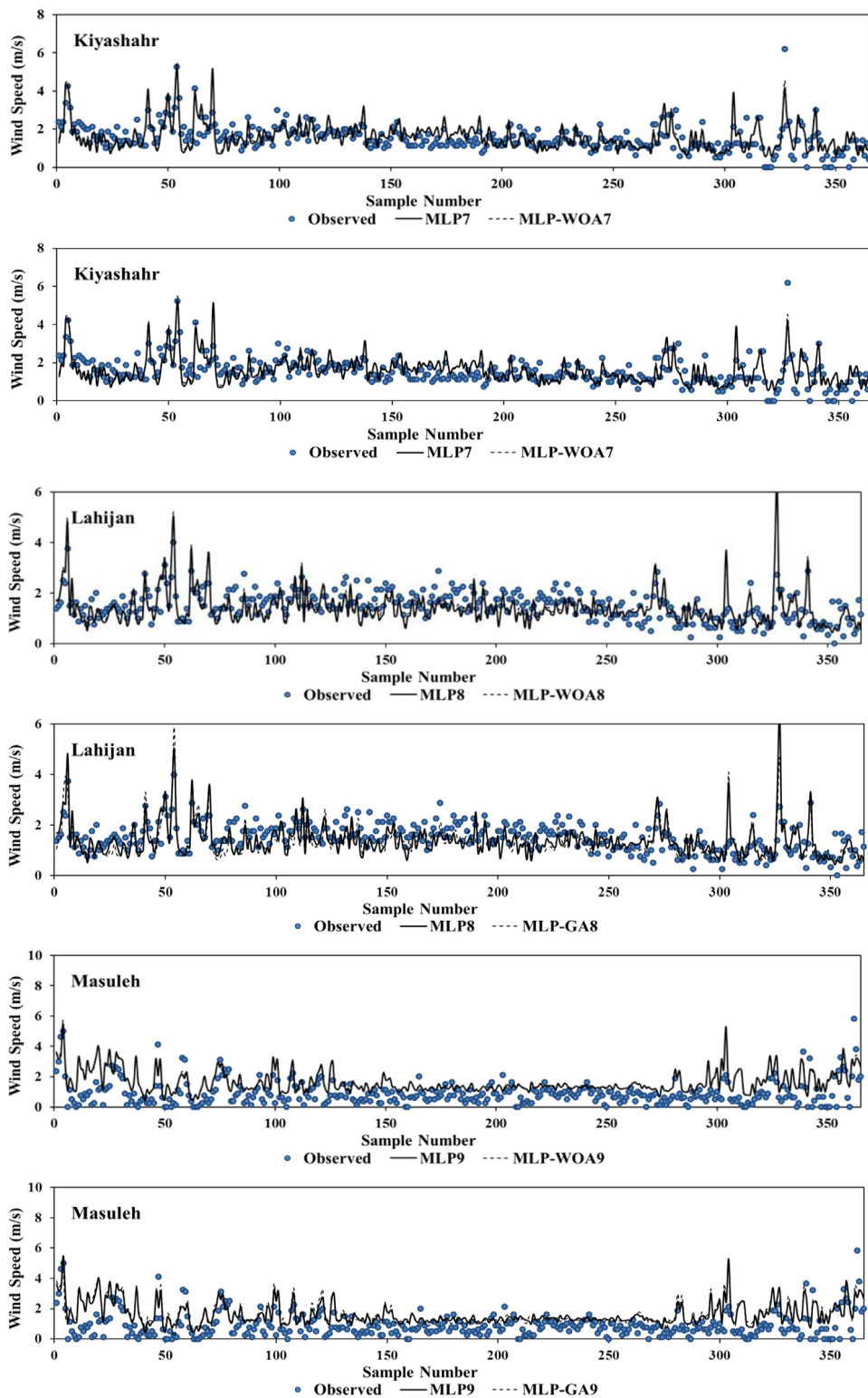


Fig. 7. (continued).

2.3. Multi-layer Perceptron-Genetic Algorithm (MLP-GA)

Holland (1992) and Goldberg (1989) developed a genetic algorithm, which is an evolutionary method and taken from Darwin's principle of natural selection. A set of genes make up each chromosome. The composition of genes is discovered by the genetic algorithm, which is vital in maximizing or minimizing the fitness function. Moreover, the quality of the solution is uttered

by the fitness function. The GA has three steps; in the first step, this method produces a group of strings (generation) with chromosomes that entail variables. The second step consists of an assessment of every string's fitness function. In the last step, GA creates the next generation by the usage of selection, crossover, and mutation. In the selection part, chromosomes are selected from the present generation to increase based on their fitness amount.

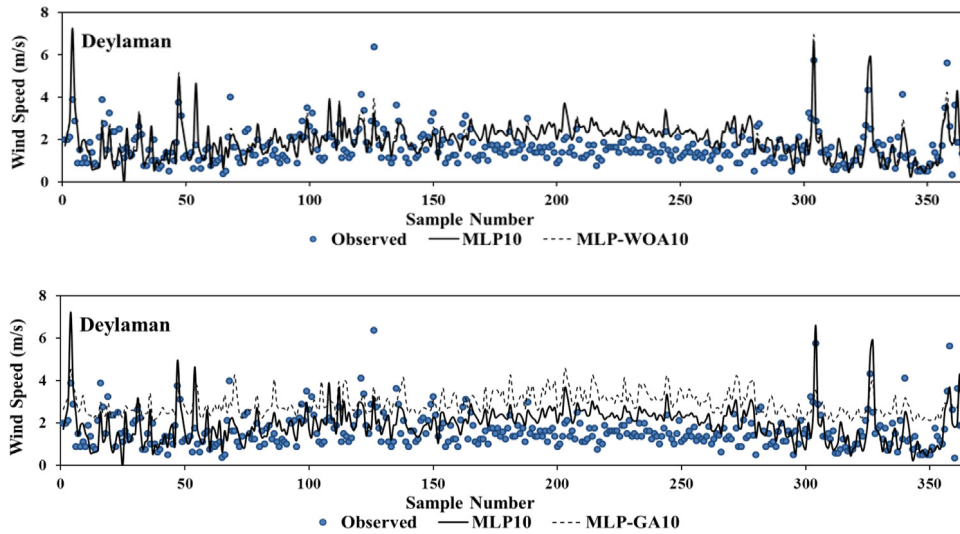


Fig. 7. (continued).

The genetic algorithm technique is used in the training stage of the MLP model to improve its performance. In the first step of this process, a random initial population is employed. In this population, any individual has a diverse number of neurons in the hidden layer. The best population selected as an elite population that entails the best individuals. By running individuals many times, an appropriate function is found, and the best one is saved. In the MLP model, the Levenberg–Marquardt algorithm, which has a random nature, is utilized frequently. The GA method used to choose a proper function for layers and affect the model's performance.

2.4. Error measures

Several statistical parameters have been utilized to measure the accuracy of the model. In the present study, various statistical parameters, including root mean square error (RMSE), scattered index (SI), Willmott's index (WI), Nash–Sutcliffe efficiency (NS), and Kling–Gupta efficiency (KGE) are utilized. These accuracy criteria are defined as follows.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (11)$$

$$SI = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2}}{\bar{O}} \quad (12)$$

$$WI = 1 - \left[\frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (|P_i - \bar{O}_i| + |O_i - \bar{O}_i|)^2} \right] \quad (13)$$

$$NS = 1 - \frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (14)$$

$$KGE = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (15)$$

$$r = \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (P_i - \bar{P})^2}} \quad \beta = \frac{\bar{P}}{\bar{O}} \quad \gamma = \frac{CV_P}{CV_O}$$

where n is the number of data set, O_i and P_i are the observed and estimated values, \bar{O} and \bar{P} are the observed mean and estimated mean, respectively. Also, CV_O and CV_P is the standard deviation of observed and estimated values from MLP or MLP-WOA, individually.

RMSE is a commonly implemented error parameter for investigating the differences between observed and estimated values. RMSE is considered as a non-negative parameter, which 0 specifies the perfect estimation by the model. Also, lower RMSE values are superior for indicating the best fit. Nevertheless, SI is computed by dividing RMSE with the mean of the observations. So, it presents the expected error of the parameter. Similar to RMSE values, the lower SI values are suitable. Additionally, WI is a standard measure indicating the degree of model prediction error. WI values fluctuate between 0 and 1. The WI of 1 designates a perfect match, and 0 specifies no agreement between observed and estimated values. Moreover, NS compares the residual variance to the measured data variance. If the NS value is equal to 1, it shows the perfect match between observed and estimated values. The zero value of NS specifies that the model estimations are precise as the observed mean. Furthermore, the negative NS values indicate that the observed mean may be more accurate than the model estimates. Finally, the KGE parameter was defined based on decomposing NS to its components, including correlation, variability bias, and mean bias. So, similar to the NS criteria, if KGE value is equal to 1, it presents the perfect agreement between observed and estimated values. Thus, lower KGE values indicate the unsuitable fit of observed data.

2.5. Study area and predictive model development

In the present study, the monthly mean wind speed data of ten locations in Gilan province, from 2004 to 2014, were acquired from Iran Meteorological Organization (IRIMO). The studied stations included: Astara, Bandar-E-Anzali, Rasht, Manjil, Jirandeh, Talesh, Kiyashahr, Lahijan, Masuleh, and Deylaman (Fig. 4). Latitude and longitude of studied stations vary between $36^{\circ}42'$ to $38^{\circ}21'$ North and $48^{\circ}51'$ to $50^{\circ}00'$ East respectively, while their height above sea level differs between -23.6 m to 1581.4 m. Table 1 shows coordinates of studied stations in the region and the statistical characteristics of wind data. Relative to the other stations, the lowest mean wind speed belongs to the Lahijan station (≈ 1.46 ms^{-1}), whereas the station with the windiest climate is Jirandeh with the mean wind speed of 5.25 ms^{-1} . Furthermore, Jirandeh station with a value of 25.6 ms^{-1} had the maximum wind speed in the studied period.

Table 2 presented the list of reference and target stations in the studied region. Also, the correlation values of wind speed between target and reference stations are shown in Table 3.

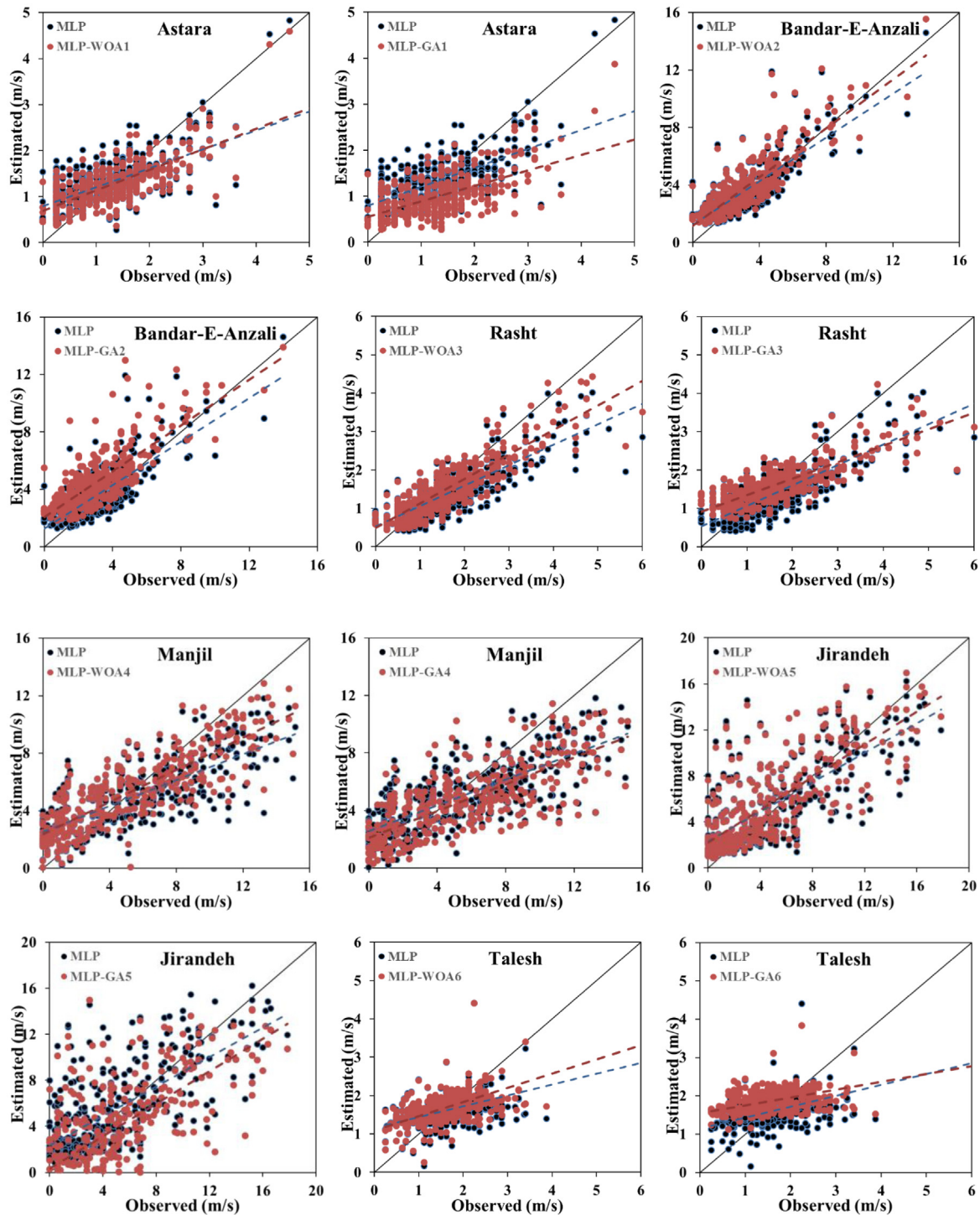


Fig. 8. Scatter plots of estimated and observed values of wind speed at various stations.

3. Result and discussion

In this research, the abilities of both the MLP model and MLP optimized model with WOA and GA in predicting wind speed by using datasets of nine neighboring sites in the North of Iran were investigated and compared with each other. In this research, by the usage of nine adjoining stations, the wind speed of the target station is estimated by three models of MLP, MLP-WOA, and MLP-GA. Moreover, there is no straightforward way of splitting training and testing data. For instance, the study of Kurup and Dudani (2014) utilized a total of 63% of their data for model

development, whereas Qasem et al. (2019) utilized 67% of data and Deo et al. (2018), Samadianfard et al. (2018, 2019a,b) and Shamshirband et al. (2020) used 70% and Zounemat-Kermani et al. (2019) implemented 80% of entire data to develop their models. Consequently, to create models for wind speed prediction, 70% of the data (2534 data) is applied for training, and 30% of them (1077 data) are utilized for the testing phase. It should be noted that code was written in the Wolfram Mathematica software so that the dataset is randomly selected for each two training and testing period for several times. Then the desired model was selected based on the best values for the root mean

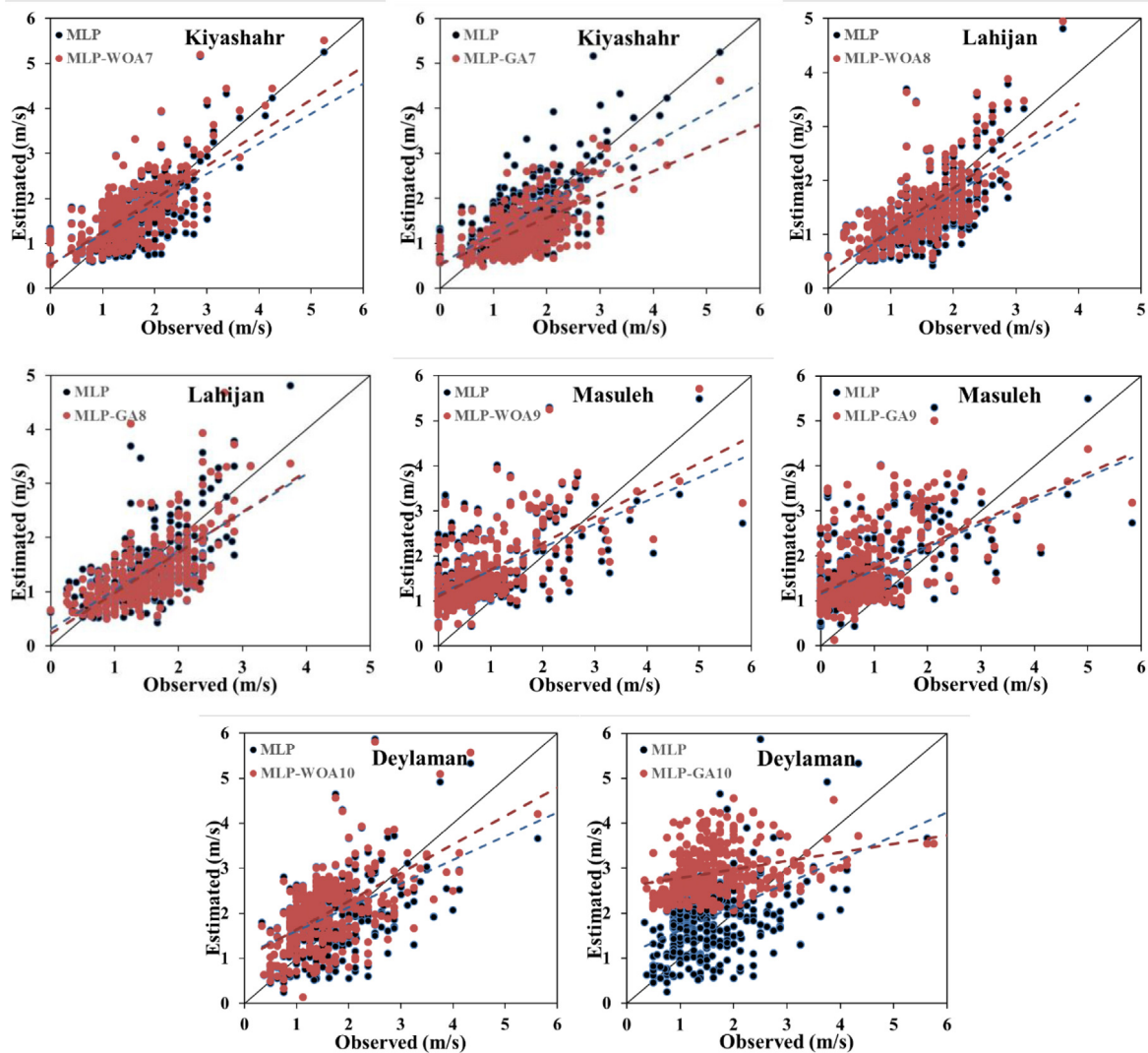


Fig. 8. (continued).

square error (RMSE). After 50 repetitions of the above-mentioned random selection criteria in the Wolfram Mathematica software, the best conditions for R^2 and RMSE were selected and the data was entered into the process of the WOA and GA methods (Fig. 5).

So, Table 4 shows the statistical results of different MLP, MLP-WOA, and MLP-GA models. Moreover, Fig. 6 shows bar graphs of the statistical parameters in the testing phase.

The RMSE, and SI of models that optimized with WOA were lower and their WI, NS, and KGE values were higher than standalone MLP models at all stations in the testing phase. So, the hybrid MLP-WOA models reduced the RMSE and SI values from 0.570~2.995 to 0.523~2.751, 0.353~0.957 to 0.321~0.887, and increased the WI, NS and KGE values from 0.592~0.885 to 0.689~0.913, 0.016~0.624 to 0.058~0.732 and 0.206~0.758 to 0.255~0.779, respectively. But, unexpectedly, MLP-GA models did not have better performance than classical MLP models, and the accuracy of optimized models was lower than standalone MLP models. However, two stations of Manjil and Jirandeh in MLP, MLP-WOA, and MLP-GA models had higher RMSE, SI, and Lower WI, NS, KGE values. Between the studied stations, in classical MLP models, Kiyashahr and Rasht had the best performance according to their error meters. Similarly, in WOA-MLP models, the mentioned stations were the most accurate models with the RMSE of 0.54 and 0.52 and SI of 0.523 and 0.548, respectively. Moreover, according to other statistical parameters used in this

study, WI, NS, and KGE of the models that optimized with the WOA algorithm demonstrated better performance in comparison with classical MLP models. A similar result was reported by Deo et al. (2018), who implemented a firefly optimization algorithm for wind speed estimation using the correspondent values of neighboring stations in different stations of East Azerbaijan province, North West of Iran. Deo et al. (2018) stated that utilizing the firefly optimization algorithm had significant improvements in reducing estimation errors. Fig. 7 demonstrated the performance of the hybrid MLP-WOA and MLP-GA models in comparison with the standalone MLP model for ten study stations. As mentioned, it can be concluded from Fig. 7 that the WOA algorithm improved the accuracy of wind speed forecasting of the MLP model. Conversely, the MLP-GA models could not improve the efficiency of MLP models. Moreover, to further evaluation of the precision of the developed models, a scatter plot of observed and predicted wind speed between the two datasets is presented in Fig. 8.

It should be noted that in the current study, the null hypothesis was that the WOA and GA methods do not have significant effects in increasing the accuracy of MLP estimations of wind speed using the correspondent wind speed values of neighboring stations. So, evaluating the impact of implementing both mentioned models revealed that the mentioned hypothesis was not

Table 4
Statistical results of comparing different MLP, MLP-WOA, and MLP-GA models in the testing phase.

Models	Statistical parameters				
	RMSE	SI	WI	NS	KGE
MLP1	0.723	0.522	0.725	0.346	0.454
MLP2	1.185	0.353	0.885	0.624	0.758
MLP3	0.623	0.385	0.856	0.620	0.656
MLP4	2.424	0.470	0.832	0.561	0.603
MLP5	2.995	0.615	0.837	0.507	0.649
MLP6	0.784	0.447	0.592	0.197	0.286
MLP7	0.570	0.367	0.819	0.335	0.676
MLP8	0.814	0.483	0.689	0.092	0.493
MLP9	1.184	0.957	0.661	0.224	0.206
MLP10	0.938	0.549	0.727	0.016	0.493
MLP-WOA1	0.657	0.474	0.771	0.461	0.518
MLP-WOA2	1.078	0.321	0.913	0.589	0.779
MLP-WOA3	0.523	0.323	0.908	0.732	0.705
MLP-WOA4	2.086	0.405	0.887	0.675	0.654
MLP-WOA5	2.751	0.565	0.870	0.584	0.679
MLP-WOA6	0.703	0.401	0.689	0.354	0.387
MLP-WOA7	0.548	0.353	0.841	0.386	0.707
MLP-WOA8	0.722	0.429	0.753	0.285	0.585
MLP-WOA9	1.097	0.887	0.732	0.334	0.255
MLP-WOA10	0.903	0.529	0.766	0.058	0.524
MLP-GA1	0.800	0.579	0.669	0.199	0.458
MLP-GA2	1.562	0.465	0.832	0.346	0.558
MLP-GA3	0.668	0.413	0.808	0.562	0.478
MLP-GA4	2.506	0.486	0.829	0.531	0.651
MLP-GA5	3.449	0.708	0.808	0.347	0.484
MLP-GA6	0.817	0.467	0.511	0.128	0.134
MLP-GA7	0.554	0.357	0.790	0.373	0.636
MLP-GA8	0.835	0.496	0.669	0.045	0.463
MLP-GA9	1.206	0.976	0.662	0.194	0.210
MLP-GA10	1.545	0.905	0.454	-1.754	-0.175

correct for the WOA method. Therefore, the significant improvements of wind speed estimations using WOA were proved by statistical analysis. Moreover, there were some limitations to the current study. The utilized dataset was gathered from ten sites in Gilan province, Iran. So, the studied places have approximately similar climates. So, it would have been better if different locations with different climates were implemented, and the accuracy of the proposed methods was evaluated. Furthermore, it would be more interesting to estimate wind speed in the studied locations using the meteorological parameters of that station and comparing the obtained accuracy with the case of using wind speed in neighboring stations.

4. Conclusion

One of the problems of artificial intelligence algorithms is selecting the finest weights in the layers of neural networks that must permit the extraction of the relevant features within the input information for creating an accurate model. Constructing the best predictive model demands input data, which is considered as a crucial and useful tool for calculation of wind energy potential. In the present study, the utility of a reliable and robust method for predicting the wind speed for ten locations is revealed, where the wind speed amount of the target location was forecasted using input data of neighboring reference locations. In the current study by using the MLP, MLP-WOA, and MLP-GA models where the Whale Optimization and genetic algorithms combined with standalone MLP for each of the ten target stations, daily wind speed values are predicted. Furthermore, another climate or atmospheric information is not used for wind speed prediction with this method. To evaluate the performance of MLP-WOA, Several statistical indices were used. The results demonstrated that the hybrid MLP-WOA model had superior capabilities in increasing the accuracy of standalone MLP models. So, the potentials of

MLP-WOA models were approved for accurate estimation of wind speed almost in all of the stations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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