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Forecasting of Wind-Wave Height by Using Adaptive Neuro-Fuzzy Inference System and Decision Tree

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ABSTRACT

Wind-induced waves are considered to be the most important waves in the sea due to their high energy and frequency. Among the characteristics of the waves, height is one of the most important parameters that are used in most equations related to marine engineering designs. Since the application of soft computing methods in marine engineering has been developed in recent years, in present research, an adaptive neuro-fuzzy inference system and a decision tree have been used to predict the wind-induced wave height in Bushehr port. In order to identify the effective parameters, implementing different models from different inputs. By considering the accuracy of the models, the effective parameters in wave height were identified using statistical measures correlation coefficient (r), Mean Square Error (MSE). The final results of this study showed that in the prediction of wind-induced wave height, compared to the decision tree, the accuracy of the model of the neural-fuzzy system for 3, 6 and 9 hours was higher. Also, the results showed that the use of wind shear velocity instead of wind speed at 10 meters above the water level had a higher accuracy in forecasting of the significant wave height. The results also indicated that among the presented models, the combined model of the significant wave height, shear velocity, and the difference between the direction and wind speed as well as the length of the fetch has the highest accuracy.

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1. Introduction

Waves are generated by wind passing over the surface of the sea. As long as the waves propagate slower than the wind speed just above the waves, there is an energy transfer from the wind to the waves. Both air pressure differences between the upwind and the lee side of a wave crest, as well as friction on the water surface by the wind, making the water to go into the shear stress causes the growth of the waves [1]. Exact forecasting and the conditions that will occur over the lifetime of the structure are effective in achieving an accurate understanding of the design elements for each structure. Therefore, over the years, human beings have sought to use some tools that can help predict the probable conditions for structures in the post-design stages. It is clear that these tools are more comprehensive and include forecasting of the different states of conditions, such as atmospheric, geology, exploitation conditions, etc., the relevant results and a design based on this understanding will be more comprehensive, more secure, and more comfortable. Coastal and off-shore structures are not exception, and it is important to have an accurate understanding of the wave characteristics and its future forecasting in different periods for the design of a harbor, groin, breakwater, coastal wall or near-coastal zone, and its proper forecasting ensures the efficiency of the structures. The prediction of wave characteristics has always been of interest to various researchers. Researches on the forecasting of wave characteristics can be divided into two groups: employing empirical and soft computing methods. Today, soft computing methods has been widely used in many sciences due to its high benefits in predicting and estimating various parameters and some of these methods include Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System, Fuzzy Inference Systems (FISs), Decision Tree and Genetic Programming (GP). In this section, some previous researches are investigated.

Taleghani and Amiri Timori (2008), used the field data of the waves of the Caspian Sea, measured by a waveguide buoy, in an artificial neural network. Finally, the comparison of actual data measured by the measurement systems with the results of the neural network has shown a good agreement that indicates the accuracy and speed of the method used in the short time [2].

Kamranzad et al. (2011a), studied the prediction of wind-induced waves in Assaluyeh using the SWAN numerical model. For this purpose, information on the Asaluyeh bay located in the area used by the Ports and Maritime Organization in the region, which recorded their data in 1-hour time series, was used. The calculated error indices in the verification periods also show the acceptable accuracy of the SWAN modeling, so the constructed model used to forecast wave height and periodicity in Assaluyeh [3].

Mavedatnia et al. (2014), studied the characteristics of the waves in Musa (Imam Khomeini Port) using artificial neural network software. The data used in this research, include the time series of wind and wave characteristics of Shahid Dehghan and Shahid Rashidi and Boyeh Khorshas stations Which are located near Imam Khomeini port and the average depth of water in the Boya area is 17 meters and during the collection period from 2006 to 2009. In the present study, it was found that the experimental formulas for this region are not suitable tools for predicting waves, and ALYUDA software and then the neural network are better in ability to predict [4].

Nitsure et al. (2014), study sea levels in directly by predicting sea level anomalies (SLAs) using hourly local wind shear velocity components of the present time and up to the previous 12 h as inputs at four stations near the USA coastline with the techniques of Genetic Programming and Artificial Neural Network [5].

Kurniawan et al. (2014), studied the feasibility of applying mutual information theory by evaluating the amount of information contained in observed and prediction errors of non-tidal bar tropic numerical modeling. this research explores the possibility of employing 'genetic programming' (GP) as an offline data driven modeling tool to capture the sea level anomaly(SLA) dynamics and then using them for updating the numerical model prediction in real time applications. These results suggest that combination of data relationship analysis and GP models helps to improve the forecasting ability by providing information of significant predicative parameters [6].

Akpinar et al. (2014 a,b), studies on significant wave height estimation by parametric models including Wilson, SPM, JONSWAP, and CEM for the south of Black Sea indicate that although CEM method provides better results than the others, parametric methods are unable to provide sufficient result. However, ANFIS models provide more accurate results than the parametric methods [7].

Londhe et al. (2016), in a study to predict the characteristics of waves on the coast of India using numerical model. In his study, he used the combination of Mike 21 and the artificial neural network method. The prediction took place for a period of 24 hours. He concluded that the outputs of the Artificial neural network model are more accurate than the Mike 21's mathematical model [8].

Krishnakumar et al. (2016), in a study using artificial neural network, predicted wave height in 13 different coastal areas. This research was carried out using low resource allocation network (MRAN) and radial growth function methods. The results of their research show that the second method requires more neurons than the first method to predict wave properties, so the accuracy of the first method is higher than the accuracy of the second method [9].

Hashim et al. (2016), study dealt with finding the sequence of the most influential parameters among the factors that affect the offshore wave height. The result of this research showed that, the following sequence of parameter have the most to least influence on the predictions of Hs, U, Ta, Tw, and θ. In addition, it was found that combination of three variables, namely U, Ta, and θ, forms the most influential set of input parameters with RMSEs of 0.82,0.44 and0.62, respectively for the predicted Hs at three stations [10].

Tur et al (2017), studied, significant wave heights (Hs) for Konyaaltı coast, located in Antalya at Mediterranean Sea coastline of Turkey. Significant wave height estimation is performed according to the wind data set which is obtained from The European Centre for Medium-Range Weather Forecasts (ECMWF) and Turkish State Meteorological Service (TSMS) by numerical and parametric methods in literature including WAM, CEM, Wilson and SMB method. While 13 years of wind data obtained from ECMWF is used for WAM and CEM method, 30 years of wind data provided from TSMS is used for SMB and Wilson method. The accuracy of these methods is investigated by comparing the Gumbel distribution results with Wind and Deep Water Wave Atlas for Turkish Coast for Konyaaltı Coast. Consequently, CEM method provides more consistent results for the study area compare to other significant wave height prediction methods [11].

Mohammad Beigi Kasvaei et al. (2019), developed A three-dimensional numerical simulation (Open Foam) of regular waves passing over a mono pile with square and circular cross-sectional shape. The result show that by increasing Keulegan-Carpenter (KC) numbers, this coefficient and its frequency increased. When KC=20, the lift coefficient is larger for square pile compared to the circular pile. For both square and circular cross-sectional shape, the number of pile oscillation increased by increasing KC number. Also, the Strouhal number and vortex shedding frequency were larger for the circular pile compared to that of the square pile in vortex shedding regime [12].

Akbarinasab et al. (2019), Used Multi-Layer Perceptron (MLP), Radial Basis Function Neural Network (RBFNN) and Adaptive Neuro Fuzzy Inference System (ANFIS)] were assessed for predicting significant wave height. The result showed that the ANFIS techniques with requirements of past and current values of atmospheric pressures and heightwaves has more accuracy than the other techniques in the specified time andlocation. Meanwhile, in high lead times, the friction velocity decreases the accuracy of wave height forecasting [13].

Sayehbani and Ghaderi (2019), Used Mike 21 model to predict Wave and Current Patterns of Beris Port in East of Chabahar-Iran. The result showed that the significant effect of the breakwater on the stillness of the basin and the change in flow direction [14].

The evaluation of previous studies regarding the use of soft computing methods in forecasting wave characteristics showed that the majority of researches had focused on finding a proper optimal model for networking and a little is done about the impact of different parameters on wave characteristics and high accuracy of the model. Therefore, in the present reserach, it has been try to identify the effective parameters by considering different models and then the modeling was conducted and finally, determined the effective parameters and the optimal model for the significant wave height for 3 and 6 hours.

In the present research, employ two common soft computing methods such as adaptive neuro-fuzzy inference system and decision tree for forecasting. The present research, was aimed to predict the significant wave during the period from December 2008 to 2010 in the Bushehr port region.

Considering the importance of the Bushehr port in implementing different coastal projects and sea exploitation, this research has been carried out in Bushehr port area. In this research, we employed the wind and wave data recorded by Bushehr buoy. buoy of Bushehr was located in this region by the Ports and Maritime Organization and its information was available as a 1 hour time series. These data include wave measurement and meteorology data such as wind speed, wind direction, air temperature and air pressure, and wave measurement data such as wave height and wave period. The wave measurement buoy of Bushehr region is located at a depth of 30 meters and 50° 55' E and 28° 58' N by the Ports and Shipping Organization. The data including 14,000 series over the period from December 2008 to 2010 recorded the characteristics of the waves. Figure 1 illustrates the study area.

2. Study area

In the present research, we employed wind and wave data recorded by Bushehr buoy. The buoy of Bushehr was located in this region by the Ports and Maritime Organization and its information was available as a 1-hour time series. These data include wave measurement and meteorology data such as wind speed, wind direction, air temperature and air pressure, and wave measurement data such as wave height and wave period. Figure 1 illustrates the study area.

Fig. 1. Position of study area.

3. Description of research

The applied data include the time series of wind and wave characteristics in buoy of Bushehr port, located in the deep water area of the Persian Gulf and near the Bushehr port. Two common model including adaptive neuro-fuzzy inference system are used to predict wave height. Table (1) shows the maximum, minimum and average values of various parameters.

Table 1
Statistical characteristics of measured parameters in Bushehr port.

average	minimum	maximum	measured parameters	raw
2.32	0	14.53	wind velocity (m/s)	1
227.13	0	358.59	wind direction (degree)	2
19.64	9	38.86	air temperature (°c)	3
26.56	5	39.93	water temperature(°c)	4
1009.72	0	1031.51	air pressure (pa)	5
0.47	0	2.8	wave height (m)	6

3.1. Adaptive neuro-fuzzy inference system

Modify network-based fuzzy inference (ANFIS) is a combination of two soft-computing methods of ANN and fuzzy logic. Fuzzy logic has the ability to change the qualitative aspects of human knowledge and insights into the process of precise quantitative analysis. However, it does not have a defined method that can be used as a guide in the process of transformation and human thought into rule base fuzzy inference system (FIS), and it also takes quite a long time to adjust the membership functions (MFs) .Unlike ANN, it has a higher capability in the learning process to adapt to its environment.

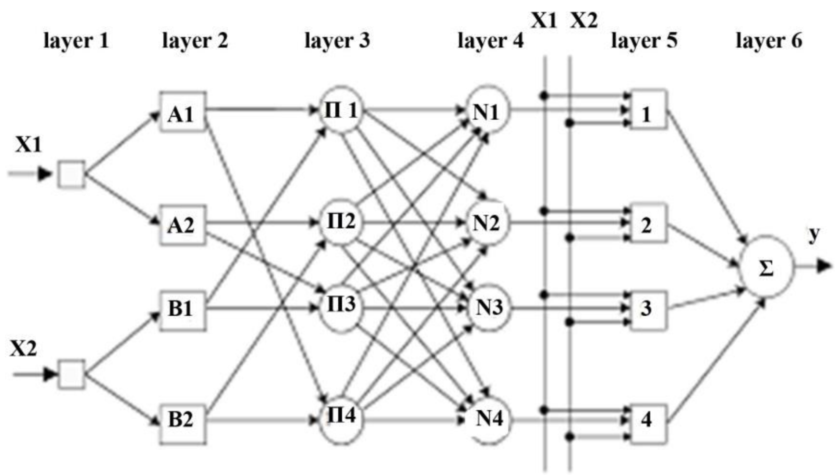

Fig. 2. Structure of Adaptive Neuro-Fuzzy Inference System.

3.2. Decision tree

Decision tree is one of the data mining methods that have been developed mostly in the last two decades. Despite the neural network, the decision tree produces law. This means that the prediction decision tree in the form of a series of rules explains, while the neural network expresses only the prediction and its method is hidden in the network. Decision tree algorithm is started with the selection of type of test for the best separation of the sets. Therefore, these methods are for discovering and extracting knowledge from databases and for creating prediction models.

3.3. Data

In this research, to prepare the data, the data were first divided into three parts of training and calibration and verification. 70% of the data are considering for training, 15% for validation and 15% for the network verification were considered. The data are assigned in an Excel file with three sheets titled Train, Total, and Test. In the total sheet, the whole existing data, in the Train sheet, the data related to the model training and in the Test sheet, the data of the model test are placed. In the mentioned sheets, input data of the model are placed in the first to fifth columns and in the last column, the target data are inserted. In order to compare and evaluate the results obtained from different methods, statistical criteria can be used to indicate the degree of adaptation of the two data series.

3.4. Choice of parameters

According to the study of the prevailing theory of research, experimental relations and other previous studies we have the followings: the parameters of gravity (g), wind continuance time (t), wind velocity (U), wind direction (deg), wave height (H_s), wave period (T), fetch length (X), air temperature (T_a), air pressure (P).

In order to use wind velocity in forecasting wave characteristics, Zamani et al. (2008) [15] used wind shear velocity (U_*) instead of wind speed at 10 m height(U_{10}). Wind shear velocity can be obtained from equation (5) (Zamani et al.,2008) [15].

$$U_* = U_{10}\sqrt{C_D} \tag{1}$$

Where C_D is wind drag coefficient and is calculated by Equation (12) (Zamani et al., 2008) [15]

$$C_D = \begin{cases} 1.2875 \times 10^{-3} \quad if\ U_{10} < 7.5\frac{m}{s} \\ \quad (0.8 + 0.065 \times U_{10}) \\ \quad \times 10^{-3} \quad if\ U_{10} \geq 7.5\frac{m}{s} \end{cases} \tag{2}$$

Besides velocity parameter, wind direction and wave direction are effective parameters on formation and growth of waves. Thus, these parameters should be considered accurately in the models. To consider the effect of wind direction and wave, Therefore $(\cos(\emptyset - \theta))$ function was used, in which $\emptyset$ is the wind direction and θ is the wave direction. This function has been also used in the empirical formula (Donelan, 1980) [16].

In the present study, at first by dimensional analysis and the review of literature, the effective parameters were identified. Then, by combination of these parameters, we built new parameters and in this study, the parameters of wind shear velocity, significant wave height, period and combined parameter of shear velocity, wind and wave direction were extracted as the effective final parameters. After the identification of the effective parameters, these parameters were considered as the model input.

After the identification of the effective parameters, different combinations of these parameters are considered as the model input and finally the most optimal states are selected. In implementation of the mentioned models using the presented statistical indices in Equations (2), (3) and (4), it was shown that the parameter of period as the input parameter had not considerable impact on wave height forecast. Therefore, the models with period input are excluded from the models. In the next stage, the models with the input of significant wave height, wave share velocity and combination of shear velocity, wind direction and wave direction had high accuracy. This, this time, new models were defined by the combination of these parameters. The researches have shown that the applied algorithm at the most optimal state is hybrid algorithm. This algorithm consists of the combination of two algorithms of back propagation algorithm with gradient descent. Error back propagation algorithm is the most common type of neural network. A multi-layer network with two signals is used. One signal moves in going and another one in coming path from the right to left.

The relevant formula is presented in Equations (3) to (6):

$$model\ A: Hs_{\ t+i} = f(Hs_{\ t}\ ; Hs_{\ t-1}) \tag{3}$$

$$model\ B: Hs_{\ t+i} = f(U_{*t}; U_{*t-1}) \quad (4)$$

$$model\ C: Hs_{\ t+i} = f(Hs_t; Hs_{t-1}; U_{*t}; U_{*t-1}; X_i) \quad (5)$$

$$model\ D: Hs_{t+i} = f(Hs_t; Hs_{t-1}; X_i; U_{*t}cos(\emptyset_t - \theta_t); U_{*t-1}\cos(\emptyset_{t-1} - \theta_{t-1})) \quad (6)$$

Table 2
Combine different parameters to enter the model.

Fetch length (X)	Index parameter of wave and wind $U_*Cos(\emptyset - \theta)$	Shear velocity of wave U_*	Weak peak period (T_P)	Significant wave heigth (H_s)	Model number
				✓	**1**
			✓		**2**
	✓	✓			**3**
			✓	✓	**4**
		✓		✓	**5**
	✓			✓	**6**
		✓	✓		**7**
	✓		✓		**8**
	✓	✓			**9**
		✓	✓	✓	**10**
	✓	✓	✓		**11**
	✓	✓	✓	✓	**12**
✓				✓	**13**
✓	✓	✓	✓	✓	**14**
✓	✓	✓	✓		**15**
✓	✓	✓			**16**
✓	✓	✓		✓	**17**
✓				✓	**18**

Table 3
Experiment and error to obtain proper grid arrangement in models for both methods of combining inference system and decision tree in training part.

Model	**Forecasting time (hr)**	**Error index**	**1**	**2**	**12**	**14**
C(Decision tree)	3	R^2	0.71	0.72	0.75	0.79
		mse	0.017	0.019	0.015	0.014
	6	R^2	0.69	0.7	0.71	0.74
		mse	0.019	0.021	0.017	0.016
	9	R^2	0.58	0.6	0.62	0.65
		mse	0.021	0.023	0.019	0.018
D(Decision tree)	3	R^2	0.7	0.71	0.74	0.78
		mse	0.019	0.017	0.016	0.015
	6	R^2	0.68	0.66	0.7	0.73
		mse	0.021	0.015	0.018	0.018
	9	R^2	0.63	0.65	0.68	0.7
		mse	0.023	0.021	0.02	0.019
C(Anfis)	3	R^2	0.85	0.84	0.86	0.87
		mse	0.014	0.016	0.013	0.012
	6	R^2	0.81	0.8	0.82	0.85
		mse	0.015	0.017	0.012	0.011
	9	R^2	0.8	0.78	0.78	0.81
		mse	0.018	0.02	0.015	0.012
D(Anfis)	3	R^2	0.89	0.88	0.90	0.91
		mse	0.013	0.014	0.012	0.011
	6	R^2	0.88	0.85	0.89	0.9
		mse	0.012	0.014	0.011	0.010
	9	R^2	0.80	0.79	0.86	0.85
		mse	0.014	0.015	0.014	0.012

3.5. Validation of applied models

As previously stated, in the present study, the adaptive neuro-fuzzy inference system and decision tree and also MATLAB software are used to forecast the wave's height software Validation and calibration of the applied models are as follows: Figures 3&4 show the results of validation and Table 2 illustrates the statistical investigation of the results.

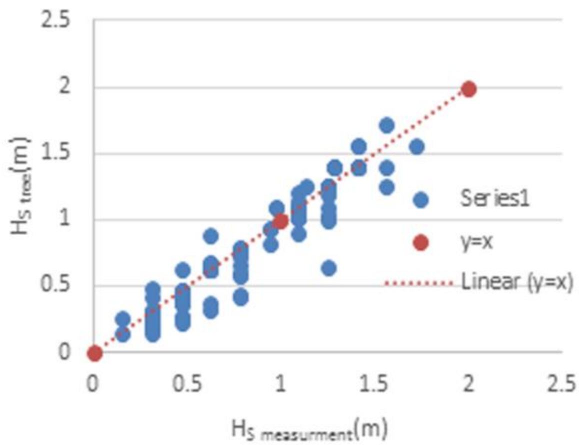

Fig. 3. Verification of wave height prediction using decision tree model.

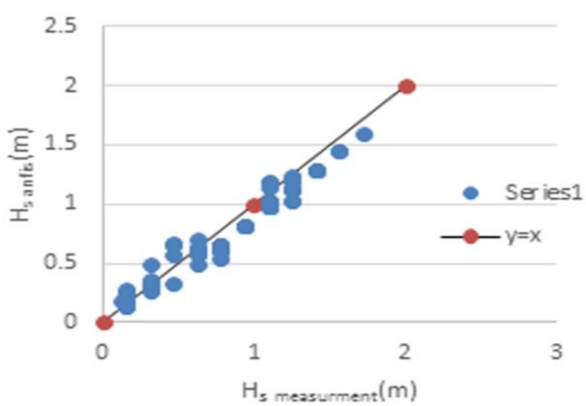

Fig. 4. Verification of wave height prediction using adaptive neuro-fuzzy inference system

In this study, for quantitative evaluation of models used correlation coefficient (r) and mean square error (MSE):

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2} \sqrt{\sum_i (y_i - \bar{y})^2}} \tag{7}$$

$$\mathrm{MSE} = \frac{\sum_i (x_i - y_i)^2}{n} \tag{8}$$

Table 4
Comparison error parameters obtained from verification of models.

R2	MSE	model
0.94	0.025	adaptive neuro-fuzzy network
0.92	0.0196	decision tree

4. Results and discussion

Evaluation of the results of the implementation of adaptive neuro-fuzzy network and decision tree in comparison with the observed wave to identify the accuracy of the models, the error of each model was calculated. These results are presented in Table 3.

Figures 5 and 6 indicate the time chart of the wave height changes calculated by the model of the neuro-fuzzy inference system and the observed values. Figures 7 and 8, show the time chart of the variations in the wave height calculated by the decision tree model and the observed values for 3 and 6 hours.

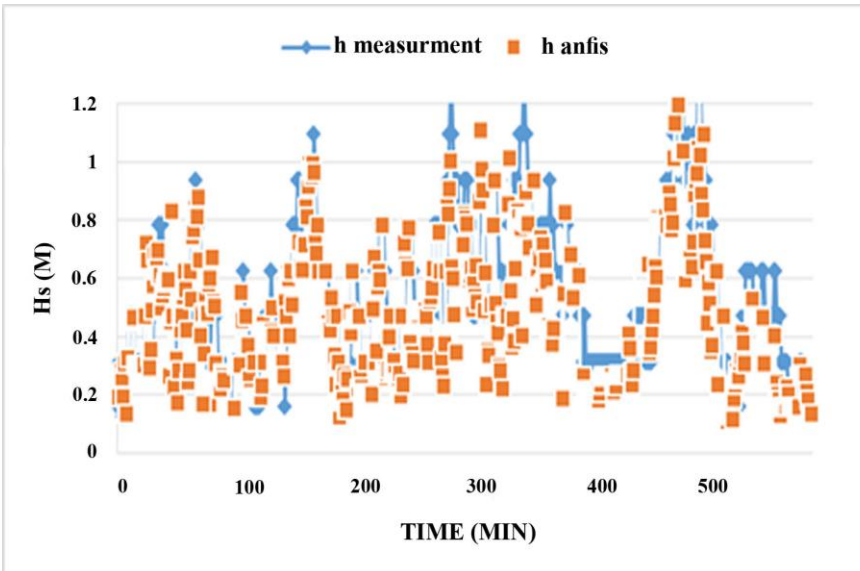

Fig. 5. Comparison of the extracted wave height from the adaptive neuro-fuzzy network to the observed wave using a three-hour time series.

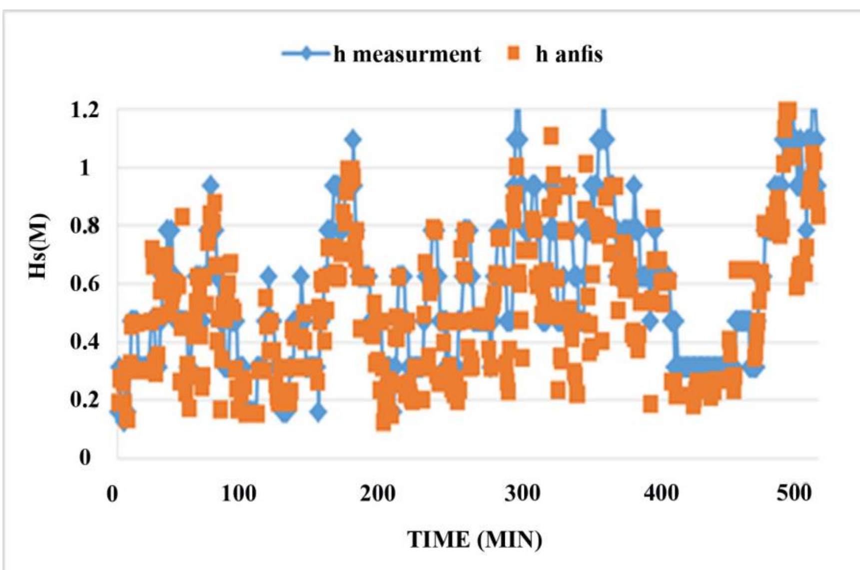

Fig. 6. Comparison of the extracted wave height from the adaptive neuro-fuzzy network to the observed wave is using a six-hour time series.

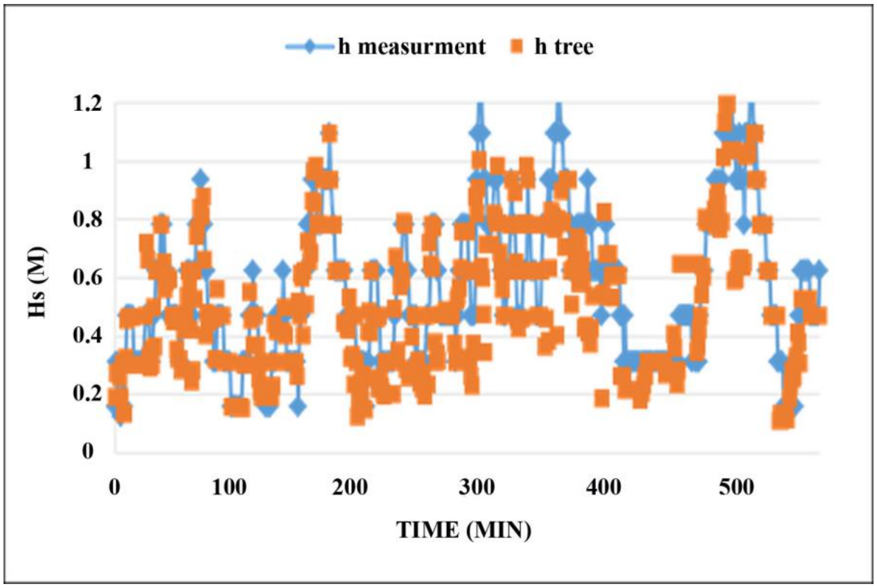

Fig. 7. Comparison of the extracted wave height from decision tree method to the observed wave using a three-hour time series.

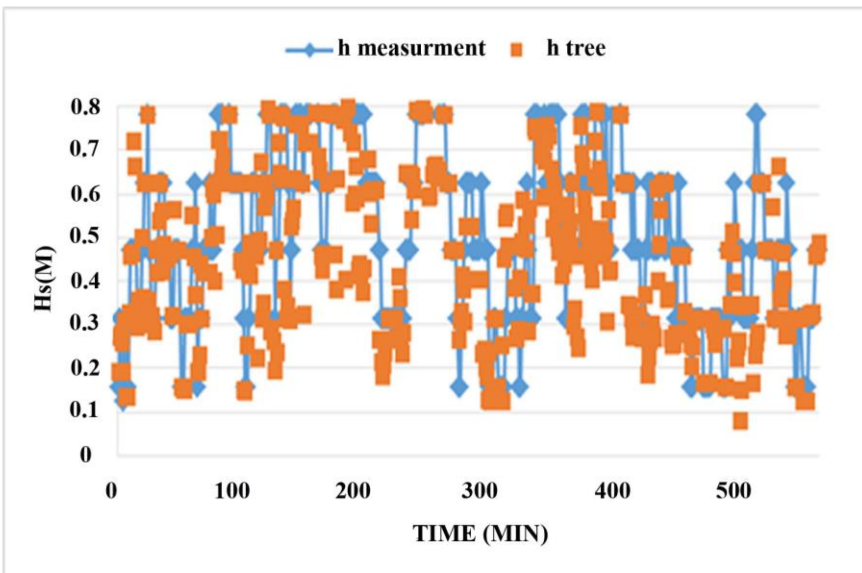

Fig. 8. Comparison of the extracted wave height from decision tree method to the observed wave is using a six-hour time series.

The researches have shown that among the models implemented for both adaptive neuro- fuzzy networks and the decision tree of model D, in which the combination of parameters of the significant wave height, wind shear velocity, the difference between the wind and the wave direction and fetch length used for model training was the highly accurate one. After model D, the model C, in which the combination of significant wave height, wind shear velocity, and wave length was used, had the best accuracy among other models. The investigations show that in all of the studied models, both in the combined inference system and the decision tree, with increasing prediction time, the difference between predicted values and calculated values of model, accuracy has decreased. This is due to the fact that the correlation between the wave height with the wind characteristics and the previous wave was reduced at larger times. This is clearly shown in Table 3.

In this section, a more detailed comparison is made between the results for different models.

As previously stated, in Model A, only wave characteristics (wave height) were used as input parameters for model training. The results for this model show that in forecasting of three hours, like other models C and D, this model also has a high accuracy in wave height forecasting, but at higher times, the accuracy of the model is reduced. This can be because the dependence of the model on the wind parameters over longer periods is higher. The results of this model also indicate that the accuracy of this model is generally lower than the models C and D, which is due to the importance of considering wind characteristics such as wind speed and direction. It should be noted that the obtained result is similar to the results obtained from Deo (2001) [17], Zamani et al (2008) and Kamranzad et al (2011b) [18]. They considered the parameters of wind characteristics effective on the proper prediction of wave height.

In model B, only the wind speed parameter was used as input parameter for model training. The results obtained for this model were similar in both methods of the combined inference system and the decision tree, so that the accuracy of the model was much lower than the other models. The results obtained in this model in each method showed that the accuracy of the model for predicting a 3-hour wave height was higher than the forecasting of 6 and 9 hours.

In model C, wave height and wind shear velocity parameters are used to model training. The results obtained for both methods of the combined inference system and the decision tree are similar to each other, so that in the predictions, the accuracy of the model in the forecasting of 3 and 6 hours is greater than the 9-hour forecasting. Also, the accuracy of model C was much higher than models A and B. It should be noted that the results are consistent with the results of Deo (2001) [17] and Kamranzad et al (2011) [18] , as these parameters were effective on the wave height forecasting.

In order to show the accuracy of the models used in this study, the correlation coefficient and mean squared error for all models are shown in Figures 10 and 11.

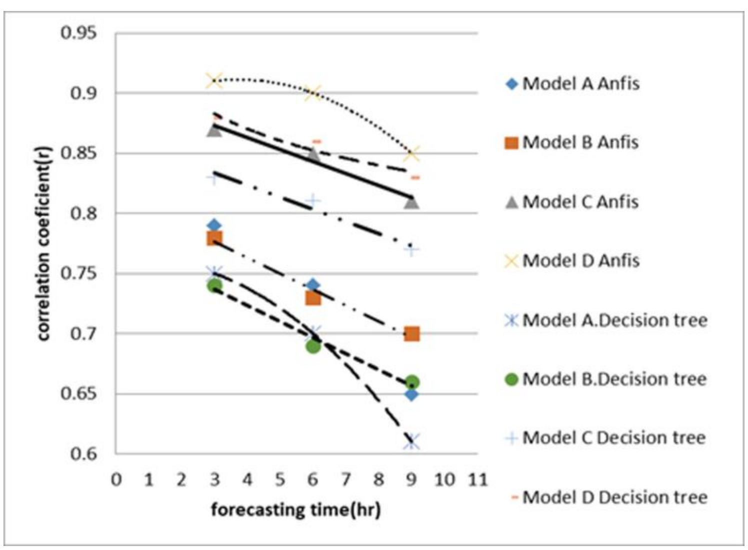

Fig. 9. Changes in correlation coefficient at prediction times for all models.

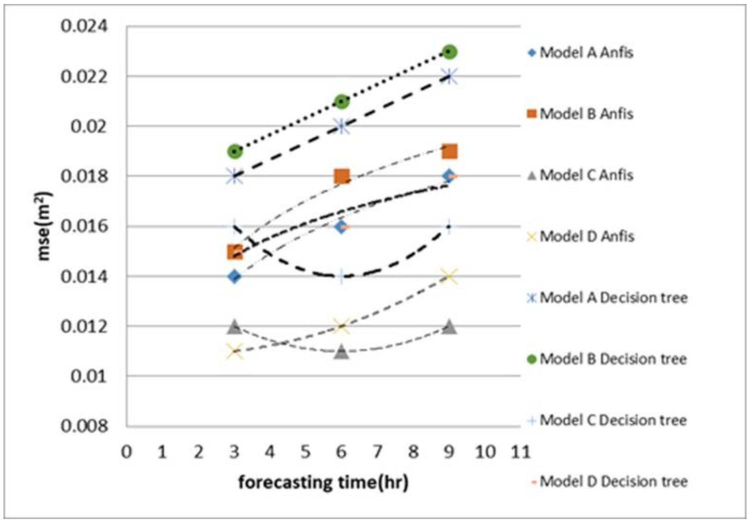

Fig. 10. Mean squared error variation in prediction times for all models.

The results showed that in both methods of adaptive neuro-fuzzy network and decision tree, model D had the highest correlation coefficient and the lowest error level. Also, the results indicated that in both methods, after model D, model C, A and B, respectively had the highest accuracy. Also, the accuracy of adaptive neuro-fuzzy network was higher than that of decision tree. Table 5 shows the calculation of the error indices for model D with the highest accuracy in both methods of adaptive neuro-fuzzy network and decision tree. The obtained results show the high accuracy of adaptive neuro-fuzzy network than the decision tree.

Table 5
Error Indicators for Different Models in Different Conditions of Implementing Models.

Model	Error index	Forecasting time (hr)		
		3	6	9
ANFIS	R^2	0.91	0.9	0.85
	mse(m^2)	0.011	0.012	0.014
Decision Tree	R^2	0.88	0.86	0.83
	mse(m^2)	0.015	0.016	0.018

5. Conclusion

In the present study, by using neuro-fuzzy inference network and decision tree, we predicted the significant wave height for 3, 6 and 9 hours in Bushehr port. For this purpose, firstly, using the dimensional analysis method, effective parameters were identified. Then, modeling was carried out based on various models that were obtained from a combination of different input parameters; also the final determination of effective parameters and optimal models was made. In the research, considering the nature of the problem, we tried to select the effective parameters by different methods.

In general, the results of this study can be summarized as follows:

1- Among the parameters affecting the wave height, the parameters of wind shear velocity, the difference between wind direction and wave direction, and fetch length, are more significant parameters in predicting the significant wave height.

2- Using the shear velocity (U_*) instead of the speed at 10 meters, provided better results in forecasting the significant wave height, which is consistent with the results of Zamani et al., (2008) and Karmarzad et al. (2011).

3- The results of the surveys show that forecasting for shorter periods in the neuro-fuzzy inference network and the decision tree are more in line with the recorded field data. This result is consistent with the results of other researchers Including Kamranzad et al (2011) [18] and Derakhshan et al (2004) [19].

4- Results of the research showed that the accuracy of the results obtained in the neuro-fuzzy inference system method is higher than the results obtained to predict wave height in decision tree method.

5- Among the provided models, a model that combined the parameters of wave height, shear velocity, wind and the difference between the wind and wave direction and fetch length was used in the model input and had the highest accuracy compared to other models.

6- Considering the form of the governing equation on the optimal training algorithm, it can be argued that the correlation between the wave height and the previous characteristics of the wave and the wind was lower during higher periods of time.

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