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Abstract

Forecasting of wave parameters is necessary for many marine and coastal operations. Different forecasting methodologies have been developed using the wind and wave characteristics. In this paper, Artificial Neural Network (ANN) as a robust data learning method is used to forecast the wave height for the next 3, 6, 12 and 24 hours in the Persian Gulf. To determine the effective parameters, different models with various combinations of input parameters were considered. Parameters such as wind speed, direction and wave height of the previous three hours, were found to be the best inputs. Furthermore, using the difference between wave and wind directions showed better performance. The results also indicated that if only the wind parameters are used as model inputs the accuracy of the forecasting increases as the time horizon increases up to 6 hours. This can be due to the lower influence of previous wave heights on larger lead time forecasting and the existing lag between the wind and wave growth. It was also found that in short lead times, the forecasted wave heights primarily depend on the previous wave heights, while in larger lead times there is a greater dependence on previous wind speeds.

Keywords: wave forecasting, data learning methods, artificial neural networks, Persian Gulf

1. Introduction

Accurate forecasting of wave characteristics is vital for many coastal and marine activities. Different methods such as empirical, numerical and soft computing or data learning methods have been developed for this purpose. Empirical methods such as Coastal Engineering Manual, or CEM (US Army, 2006), Shore Protection Manual, or SPM (US Army, 1984), SMB (Sverdrup and Munk, 1947) and Donelan (Donelan, 1980) are examples of simple and fast methods. However, they are mostly accurate in simple and limited cases. Numerical models such as Wave Analysis Model, or WAM (Komen et al., 1994), primarily for deep-water conditions and Simulating WAves Nearshore, or SWAN (Booij et al., 1999) mainly for shallow water regions, are also used for wave forecasting. These numerical models show higher accuracy both in time and in space. However, they are costly and require high speed computers (Goda, 2003).

Recently, developments in soft computing methods such as Artificial Neural Network (ANN), Fuzzy Inference Systems (FISs), Classification and Regression Trees (CART) and Genetic Programming (GP) have rendered them more applicable. Ease of the application, as well as less required computational time, has made these soft computing methods more suitable for wave modeling. Deo and Naidu (1999), Agrawal and Deo (2002), Makarynskyy (2004), Makarynskyy et al. (2005), Kazeminezhad et al. (2005), Mahjoobi et al. (2008), Gaur and Deo (2008) and Etemad-Shahidi and Mahjoobi (2009), among others, employed soft computing methods for wave simulation. Several investigations have used soft computing methods specifically to forecast the wave parameters. Ozger and Sen (2007) used fuzzy inference system while Deo et al. (2001) used recurrent neural network and Gaur and Deo (2008) used genetic programming for wave forecasting.

One of the most common soft computing methods is ANN. ANN is based on analysis of input parameters and finds the best nonlinear regression between input and output parameters. ANN has been employed extensively in ocean engineering and many investigators have used ANN to forecast the wave parameters. Jain and Deo (2006) presented many applications of ANN in different aspects of ocean engineering. The traditional stochastic time-series auto regressive methods have been also used for forecasting purposes, although the auto regressive models are less flexible in fitting to data than ANN models that are self-learning (More and Deo, 2003). Deo and Naidu (1999) compared the results of forecasting using ANN and auto regressive models. They used 3-hourly significant wave height as inputs of model and obtained a correlation coefficient of 0.81 for 3 hours horizon time. They found that the ANN models were more accurate than the auto regressive models. Moreover, their results showed that the accuracy decreases by increasing lead time. Agrawal and Deo (2002) also used ANN and auto regressive models, i.e. ARMA (Auto Regressive Moving Average) and ARIMA (Auto Regressive Integrated Moving Average) for wave prediction. They used 3-hourly significant wave height information as input and compared three training algorithms to find the best one. They found that ANN has higher accuracy than the auto regressive methods for 3 and 6 hours lead times. However, in larger lead times, results of all methods were similar. Deo et al. (2001) employed ANN to forecast the wave height and average period. They used only wind speeds as the inputs and used different training algorithms to find the proper training algorithm. They found that satisfactory results can be obtained using a trained network in open deep water areas when the intervals for sampling and forecasting are large. They also found that it is not necessary to use fetch length and wind duration as input parameters in ANN models. Mandal and Prabaharan (2006) used a recurrent neural network to forecast the significant wave height at the west coast of India. They showed that the recurrent neural networks are more accurate than those used in the previous studies. Tsai et al. (2002) used neural network to forecast the significant wave height and period from the observed wave records. They used the multi-station wave data to forecast and supplement the wave data to optimize the topology of the network by means of changing the range of the training data. They showed that the performance of the ANN model are satisfactory for both wave forecasting and data supplement. Jain and Deo (2007) also used the ANN for wave forecasting. They found that filling the gaps in the wave height time series using both temporal and spatial approaches improves the learning capability of the model. They also indicated that if the amount of gaps is restricted to about 2% per year or so, it is possible to obtain 12 hours ahead forecasts with 0.08 m accuracy and 24 hours ahead forecast with a mean accuracy of 0.13 m. Zamani et al. (2008) forecasted wave height in the Caspian Sea using ANN and Instance Based Learning (IBL) methods. They used Average Mutual Information analysis to determine the most relevant inputs of the model. They considered wind direction in their models and showed that the accuracy of ANN is more than that of IBL. They also found that utilization of ANN in prediction of extreme values yields higher accuracy compared to utilization of IBL. While most of the previous studies have focused on the optimization of the networks topology, the effects of various parameters such as the difference between the wind and wave directions have not been investigated. In this study, the significant wave heights (H_s) for 3, 6, 12 and 24 hours lead times have been forecasted in the northern part of the Persian Gulf using ANN and linear regression models. In addition, the governing parameters have been determined by training and testing different ANN models with various input parameters. Following that, the effects of considering the different input parameters on various forecasting lead times have been investigated.

2. Study Area

The study area is located in Dayyer region at the southern coast of Iran in the Persian Gulf (Figure 1). Dayyer is an important economical region in the Persian Gulf because it is close to the Pars gas field and marine transportation activities. Wind and wave data were gathered by the Islamic Republic of Iran Meteorological Organization (IRIMO) and Iranian National Center for Oceanography (INCO), respectively. The recorded wave data was collected by a buoy at 52° 30' 17'' E and 27° 35' 39'' N and the recorded wind data was obtained from a coastal station that was located at 51° 56' E and 27° 50' N. Dayyer synoptic station was the closest source of wind data. The wind forecasting at this station can be available while the wind is not measured/forecasted in the buoy location. Moeini et al. (2010) also used Dayyer data for wave modeling and showed that this data can be used successfully for wave hindcasting. Therefore, the Dayyer synoptic station wind data was used in this study for wave forecasting. The water depth at the wave station was about 7.5 m and the buoy was nearly located on the near shore. The period of data collection was from Nov., 1, 2002 to Oct., 31, 2003. Wave and wind data were collected for 1 and 3-hour intervals, respectively. Therefore, wind information was interpolated to 1-hour intervals and the wind and wave data were considered simultaneously. Statistics of wave and wind characteristics are indicated in Table 1. Table 1 shows that the average wind and wave directions are from the southeast and south directions, respectively. Another important subject is the possible existence of swells. Since the Persian Gulf is a semi-enclosed sea, swells cannot easily propagate into it from the Indian Ocean due to the existence of Strait of Hormuz. It is also indicated in ISWM (2003) that the wind waves are the dominant waves in the Persian Gulf. Therefore, the waves were considered to be seas in this study.

3. ANN and the structure of the employed network

Artificial neural network models the biological neurons of the human brain. It is one of the soft computing methods employed widely in the last decade for wave modeling. In this method, every input vector is related with the corresponding output vector (Jain and Deo, 2006). Figure 2 shows a three-layer feed forward type artificial neural network with input, output and hidden layers and the relation between the neurons. The neural network contains computational elements called nodes or neurons, which undertake the task of combination of inputs and estimation of their weights. Then values of all nodes are applied on the transfer function. For example, for a sigmoid transfer function the relation between inputs and output is shown as follows:

$$O = 1/[1 + e^{-S}] \tag{1}$$

$$S = (a_1 w_1 + a_2 w_2 + a_3 w_3 + ...) + B \tag{2}$$

in which O is the output of each neuron, a_i's are the input values, w_i's are the weights and B is the bias. In the training stage, the outputs are compared with the observed data, and weights and biases are changed to achieve the acceptable tolerance.

The most commonly used network and training algorithm combination is the feed forward network with standard back propagation algorithm (Jain and Deo, 2006). In this study, different algorithms were studied in order to select the optimum network and the most proper training algorithm and training function were found to be Conjugate gradient and Levenberg Marquardt, respectively. Therefore, a feed forward-conjugate gradient network was selected for further processing. The sigmoid transfer function was also employed for the modeling. In this network, the output layer had one neuron (i.e. the significant wave height) and the number of neurons in the input layer depends on the model inputs. The number of neurons in the hidden layer depends on the number of model inputs. These values are given after the description of the models in section 4. Learning rate and iteration were 0.01 and 1000, respectively while training automatically stopped when the mean square error increased. Deo et al. (2001), Agarwal and Deo (2002) and Mandal and Prabaharan (2006) have used 80% of data for training and the remaining 20% for testing. Therefore, 80% of data were selected for the training stage and the remaining 20% were used for testing. This division of the data satisfied the statistical similarity required for selecting the training and testing data. Other percentages were also tested and the performances of the models did not change significantly.

For quantitative evaluation of the models, different error indices i.e. correlation coefficient (*r*), mean square error (*mse*) and index of agreement (I_a) were calculated:

$$r = \frac{\sum_i ((x_i - \bar{x}) \times (y_i - \bar{y}))}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \tag{3}$$

$$mse = \frac{\sum_i (x_i - y_i)^2}{n} \tag{4}$$

$$I_a = 1 - \frac{\sum_i (y_i - x_i)^2}{\sum_i \left[|y_i - \bar{x}| + |x_i - \bar{x}| \right]^2} \tag{5}$$

where x_i is the measured parameter, $\bar{x}$ is the mean value of the measured parameters, y_i is the predicted parameters, $\bar{y}$ is the mean value of the predicted parameters and n is the number of measurements.

4. Parameters of the employed models

Accurate forecasting of wind-wave parameters needs identification of the wave generation governing factors. One of the most important factors is the wind speed. Recently, Zamani et al. (2008) used wind shear velocity (U_*) instead of wind speed at 10 m height (U_{10}) and showed that it improves the behavior of modeling in extreme events. Wind shear velocity can be obtained from equation (6):

$$U_* = U_{10}\sqrt{C_D} \tag{6}$$

where C_D is wind drag coefficient (Wu, 1982):

$$C_D = \begin{cases} 1.2875 \times 10^{-3} & if\ U_{10} < 7.5\dfrac{m}{s} \\ (0.8 + 0.065 \times U_{10}) \times 10^{-3} & if\ U_{10} \geq 7.5\dfrac{m}{s} \end{cases} \tag{7}$$

This parameter has been also used in recent engineering manuals such as CEM (US Army, 2006) and numerical models such as SWAN (Booij et al., 1999). Therefore, two models were tested separately using the wind speed and wind shear velocity as inputs. Table 2 shows the error indices for both models. According to this table, using wind shear velocity yields more accurate results and therefore it was employed for further modeling.

The wind and wave directions also play an important role in the wave growth rate and need to be considered in the modeling. It is clear that if there is no difference between wind and wave directions, the wind would have the most influence on the wave generation; and the wind becomes less effective if the wind and wave have different directions. Therefore a cosine-shaped function ($\cos(\Phi-\theta)$) was used to quantify this issue, in which Φ is the wind direction and θ is the wave direction. This function has been also used in the empirical formula developed by Donelan (1980). Since the previous wave height changes the roughness of the sea surface, it may be used as an important input parameter. The previous peak period (T_p) may also be an input parameter in wave height forecasting. The fetch length and wind duration can be used in the modeling because the studied waves were in the developing sea condition. Previous investigators (e.g.Deo et al. 2001, Mahjoobi et al. 2008) have shown that using fetch and duration as inputs parameters does not increase the accuracy of ANN model significantly. Hence, fetch length and wind duration were not used as inputs in this study.

All possible combinations of input parameters, i.e. U_*, $U_*\cos(\Phi-\theta)$, H_s, and T_p , used in different models, are shown in Table 3. In order to decrease the number of models and computation cost, utilization of peak period as an input parameter was the first tested. For this purpose, two models were developed. One of them was trained merely based on the significant wave height and the other one was trained using the peak period as well as the significant wave height. Results presented in Table 4 demonstrate that the inclusion of wave period as an input parameter did not improve the modeling accuracy significantly. Therefore, the peak period was not considered as an input parameter in modeling and models 1, 2, 3, 5, 6, 9, 10 and 13 were excluded. Models 4 and 11 redundantly contained both U_* and $U_*\cos(\Phi-\theta)$ as input parameters. In addition, in model 15 the wave direction was considered while the wave height was ignored. Therefore, models 4, 11 and 15 were not used for further investigations. The remaining four models were renamed to models A, B, C and D and were used to evaluate the most important parameters.

The required lag times for wind and wave parameters were investigated next. Using trial and error, the models with the most appropriate lag times were as follows:

Model A: $H_{t+i} = f(H_t, H_{t-1}, H_{t-2}, U_{*t}, U_{*t-1}, U_{*t-2})$ (8)

Model B: $H_{t+i} = f(H_t, H_{t-1}, H_{t-2}, U_{*t}\cos(\Phi_t-\theta_t), U_{*t-1}\cos(\Phi_{t-1}-\theta_t), U_{*t-2}\cos(\Phi_{t-2}-\theta_t))$ (9)

Model C: $H_{t+i} = f(H_t, H_{t-1}, H_{t-2})$ (10)

Model D: $H_{t+i} = f(U_{*t}, U_{*t-1}, U_{*t-2})$ (11)

where "$_i$" denotes the forecasting time horizons of 3, 6, 12 and 24. In model D, it is assumed that the wave information is not available and the wind speed is only measured in the coastal station.

The number of neurons in the hidden layer was selected based on the following criteria given by Hecht-Nielson (1987) and Rogers and Dowla (1994):

$$N^H < 2N^I + 1 \tag{12}$$

$$N^H < N^{TR} / (N^I + 1) \tag{13}$$

where N^H is the number of hidden layer neurons, N^I is the number of inputs and N^{TR} is the number of training samples (in this study, N^{TR}=5934).

According to equations 12 and 13, the number of hidden layer neurons must be less than 13 for models A and B and less than 7 for models C and D. Therefore, the number of hidden layer neurons was selected based on the trial and error. The results of trial and error processes for all of the forecasting horizons are shown in Tables 5 and 6. These tables indicate that five neurons are the best option for all models.

5. Results and discussion

Models A, B, C and D were used to forecast the significant wave height for 3-24 hours lead times. In order to compare the performances of the models quantitatively, their error statistics were calculated. For this purpose, correlation coefficient (r), mean square error (mse) and index of agreement (I_a) were calculated for each of them. Error statistics in the testing stages of all models are shown in Table 7. As shown, the parameter I_a decreases and mse increases in models A, B and C when forecasting time increases. Results presented in Table 7 show that Model B outperforms the other ones in terms of prediction capability. The architecture of the employed network for model B is given in Figure 3.

As an example, time series of 3 and 24 hours forecasting for models B and D are given in Figures 4-7. Figures 4 and 5 indicate that for short time horizons, time series of forecasted wave heights are in agreement with those of the observed wave heights. The difference between time series of the forecasted and observed wave heights increases for larger lead times (24 hours). Comparison of Figures 4 and 5 also indicates that, similar to other modeling schemes (e.g. third generation models), the ability of the ANN for modeling the extreme events decreases as the forecasting time increases. Powell et al. (2003) showed that the wind drag coefficient in the extreme condition is very different from that of weak winds condition. This may change the relationship between the wind and wave and hence decreases the accuracy of forecasting extreme events, especially in large lead times. Comparison of Figures 6 and 7 shows similar results. From comparison between Figures 4 and 6 it can be seen that for 3-hourly lead time, the results of model B are more accurate than those of model D ; while the results of both models are similar for 24-hourly forecast (Figures 5 and 7).

According to Table 7, the accuracy of results decreases as the forecasting time horizon increases. This is due to the fact that the correlation of the wave heights with the previous wave/wind characteristics becomes lower in large lead times. This is clearly observed in the results of models A, B and C; I_a decreases and *mse* increases by increasing the forecasting time horizon from 3 hours to 24 hours (Table 7). In order to compare the models' performance, the error indices are plotted in Figures 8, 9 and 10 for various forecasting lead times. These figures illustrate that model B, in which cos(Φ-θ) is utilized as an input parameter, yields more accurate results. In addition, results of model D for up to 6 hours forecasting are different from those of the other models and its error of 6 hours forecasting is less than that of 3 hours forecasting. According to equation (8), model D is trained only with wind parameters. The results of model D indicate that there is a high correlation between the forecasted wave height and the previous wave heights up to 6 hours. These figures also show that the correlation between the wave height and the previous wave characteristics decreases as the lead time increases; and the wind characteristics are more influential in large lead times. In lead times larger than 6 hours, model D shows the same behaviour as the other models. The correlation coefficient of this model is 0.629 for three hours forecasting. These results have higher accuracy than those obtained by Deo et al. (2001) using wind speed with 2 lags. They stated that using wind statistics from coastal regions several kilometers away from the buoy is the primary reason for the unsatisfactory results. Therefore, it could be argued that selecting the proper inputs for different forecasting horizons is very important and improves the accuracy of the results.

When model C (the model without wind inputs) is compared with models A and B, it is found that this model yields nearly similar results to those of other models for short time horizons. This means that the need for wind parameters as inputs in shorter-time forecasting is less than that in longer-time forecasting. The results of model C have lower accuracy than those of models A and B in large lead times. This is due to the fact that the accuracy of the model depends on the previous wind speed as well as wave parameters. This can also be due to the correlation between the future winds and the current wind. More and Deo (2003) also used the previous wind speeds to forecast wind speeds while Zamani et al. (2008) used 7 hours lag time of the wind speed for wave forecasting.

The complicated conditions in the studied region, which is located on the nearshore, can also contribute to the observed errors. It should be noted that in coastal regions, interaction of sea hydraulics and shore morphology causes a complex relation between wind and wave. Zamani et al. (2008) compared the results of modeling for two locations, one located in deep water and the other one in shallow water. They obtained better results in deep water stations. Tsai et al. (2002) also stated that the relationship between wind and wave is uncertain in coastal regions because of the complicated geometry and seabed conditions.

For assessing the performance of the ANN model, a linear regression model was also employed for comparison. For this purpose, the inputs of the best model (model B) were used to find the best linear regression between the inputs and output for each forecasting horizon. The constants of each linear regression model, i.e. the coefficients and the intercept values are shown in Table 8. According to this table, the coefficient (or the weight) of H_t decreases as the forecasting horizon increases. This shows that the importance of using this parameter decreases in larger lead times. In addition, the coefficient of $U_{*t}\cos(\Phi_t\text{-}\theta_t)$ for 6 hours forecasting is higher than that of 3 hours forecasting. This supports the results obtained from model D. Table 9 shows the error indices of model B and linear regression model. According to this table, ANN is more accurate than the linear regression model.

6. Summary and Conclusions

In this study, forecasting of wave height was conducted for 3, 6, 12 and 24 hours lead times in Dayyer, Persian Gulf for the first time and new input parameters i.e. $\cos(\Phi\text{-}\theta)$

and U_* which have physical justifications were used as the model inputs. Moreover, the effects of different parameters were evaluated using different models with various combinations of wind and wave parameters. Then, the error statistics of the models were compared with those of a linear regression model. The most important findings of this study are:

1. Using U_* instead of U_{10} increases the accuracy of the wave forecasting.
2. The best time lag of the input parameters such as the wind speed and the wave height/direction was found to be 3 hours in this area.
3. Model B, in which the new parameter cos(Φ-θ) was used as an input parameter outperforms other models.
4. In short lead times, the predicted wave height mainly correlates to the previous wave heights. In larger lead times, however, the correlation between the predicted wave height and previous wave heights decreases.
5. Comparison between ANN-based model (model B) and linear regression-based model with similar input parameters showed that the ANN technique outperforms the linear regression methods in terms of accuracy.

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Figures Caption

Fig.1. Map of Persian Gulf at Dayyer station.

Fig.2. A typical artificial neural network.

Fig.3. Architecture of the ANN for model B.

Fig.4. Comparison of the predicted and observed time series of wave height using model B for 3 hours forecasting.

Fig.5. Comparison of the predicted and observed time series of wave height using model B for 24 hours forecasting.

Fig.6. Comparison of the predicted and observed time series of wave height using model D for 3 hours forecasting.

Fig.7. Comparison of the predicted and observed time series of wave height using model D for 24 hours forecasting.

Fig.8. Variation of correlation coefficient (r) vs. forecasting time.

Fig.9. Variation of *mse* vs. forecasting time.

Fig.10. Variation of I_a vs. forecasting time.

Table 1: Maximum, minimum and average values of the used data.

Parameter	Minimum	Average	Maximum
Significant Wave Height (m)	0.01	0.29	1.86
Wave Direction (degree)	0.00	190.90	359.89
Wave Peak Period (s)	0.00	4.83	9.07
Wind Speed (m/s)	0.00	4.43	19.08
Wind Direction (degree)	0.00	133.61	360.00

Table 2: Error indices for using wind speed and wind shear velocity as input parameters.

Input parameter	Error index	3 hr	6 hr	12 hr	24 hr
U_{10}	*r*	0.538	0.589	0.526	0.270
	mse (m^2)	0.047	0.043	0.048	0.066
U_*	*r*	0.541	0.591	0.529	0.274
	mse (m^2)	0.046	0.043	0.047	0.066

Table 3: Various combinations of parameters as different model inputs.

Model number	Input parameter			
	H_s	T_p	U_*	$U_*\cos(\Phi\text{-}\theta)$
1	*	*	*	*
2	*	*	*	
3	*	*		*
4	*		*	*
5		*	*	*
6	*	*		
7	*		*	
8	*			*
9		*	*	
10		*		*
11			*	*
12	*			
13		*		
14			*	
15				*

Table 4: Error indices for using peak period as input parameter.

Input parameter	Error index	3 hr	6 hr	12 hr	24 hr
H_s	r	0.868	0.711	0.510	0.269
	mse (m^2)	0.016	0.033	0.050	0.069
H_s and T_p	r	0.868	0.707	0.506	0.267
	mse (m^2)	0.016	0.033	0.051	0.070

Table 5: Trial and error for the number of hidden layer neurons of models A and B for various forecasting time horizons.

Model name	Forecasting horizon	Error index	12	10	5	4	6
A	3 hours	R	0.879	0.883	0.892	0.884	0.879
		mse	0.018	0.016	0.014	0.016	0.018
	6 hours	R	0.789	0.789	0.803	0.789	0.792
		mse	0.025	0.024	0.023	0.025	0.024
	12 hours	R	0.587	0.626	0.650	0.635	0.635
		mse	0.054	0.042	0.038	0.040	0.040
	24 hours	R	0.359	0.384	0.417	0.408	0.410
		mse	0.065	0.065	0.058	0.059	0.063
B	3 hours	R	0.900	0.904	0.907	0.903	0.903
		mse	0.015	0.012	0.012	0.012	0.013
	6 hours	R	0.800	0.804	0.820	0.815	0.816
		mse	0.025	0.025	0.022	0.023	0.022
	12 hours	R	0.643	0.648	0.663	0.647	0.653
		mse	0.041	0.039	0.037	0.038	0.038
	24 hours	R	0.320	0.357	0.379	0.371	0.370
		mse	0.070	0.065	0.060	0.062	0.063

Table 6: Trial and error for the number of hidden layer neurons of models C and D for various forecasting time horizons.

Model name	Forecasting horizon	Error index	6	5	4
C	3 hours	R	0.867	0.875	0.870
		mse	0.019	0.016	0.019
	6 hours	R	0.735	0.745	0.743
		mse	0.032	0.029	0.033
	12 hours	R	0.519	0.542	0.527
		mse	0.049	0.046	0.047
	24 hours	R	0.364	0.378	0.368
		mse	0.066	0.060	0.061
D	3 hours	R	0.602	0.629	0.610
		mse	0.041	0.040	0.041
	6 hours	R	0.637	0.645	0.635
		mse	0.041	0.038	0.038
	12 hours	R	0.568	0.599	0.573
		mse	0.049	0.042	0.050
	24 hours	R	0.314	0.319	0.315
		mse	0.064	0.063	0.064

Table 7: Error indices for all models for 3-24 hourly forecasts.

Model name	Input Parameters	Error Index	3 hr	6 hr	12 hr	24 hr
A	H_s and U_*	r	0.892	0.803	0.650	0.417
		mse (m^2)	0.014	0.023	0.038	0.058
		I_a	0.935	0.884	0.757	0.526
B	H_s and $U_*\cos(\Phi\text{-}\theta)$	r	0.907	0.820	0.663	0.379
		mse (m^2)	0.012	0.022	0.037	0.060
		I_a	0.949	0.893	0.774	0.468
C	H_s	r	0.875	0.745	0.542	0.378
		mse (m^2)	0.016	0.029	0.046	0.060
		I_a	0.927	0.843	0.642	0.455
D	U_*	r	0.629	0.645	0.599	0.319
		mse (m^2)	0.040	0.038	0.042	0.063
		I_a	0.734	0.754	0.712	0.433

Table 8: Coefficients of input parameters for linear regression for 3-24 hourly forecasts.

Input parameter	3 hr	6 hr	12 hr	24 hr
H_{t-2}	-0.102	0.061	0.107	-0.069
H_{t-1}	-0.131	-0.160	-0.057	0.012
H_t	1.024	0.739	0.478	0.501
$U_{*t-2}\cos(\Phi_{t-2}-\theta_t)$	0.087	0.006	0.006	-0.020
$U_{*t-1}\cos(\Phi_{t-1}-\theta_t)$	0.015	-0.022	-0.079	-0.020
$U_{*t}\cos(\Phi_t-\theta_t)$	0.214	0.491	0.481	0.260
Intercept	0.046	0.083	0.122	0.158

Table 9: Error indices for model B using ANN and linear regression for 3-24 hourly forecasts.

Method	Error index	3 hr	6 hr	12 hr	24 hr
ANN	r	0.907	0.820	0.663	0.379
	mse (m^2)	0.012	0.022	0.037	0.06
	I_a	0.949	0.893	0.774	0.468
Linear regression	r	0.885	0.749	0.555	0.301
	mse (m^2)	0.014	0.029	0.046	0.067
	I_a	0.936	0.841	0.684	0.452