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The Application of Neural Networks to Predict Wind Waves

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Abstract

This paper reports the application of the back-propagation neural network to predict wind-wave height by considering the lag effect of energy transfer between wind and wave. Using the wind and wave data from one of the stations in Pacific Ocean of the the National Data Buoy Center, this study examined the validity and accuracy of the neural network model. It is found that the significant wave height can be predicted by training the previous twelve hours data of wind speeds. The results show that the neural network model provide a prediction for fifteen-days of waves using the records of the previous 20-days.

Keywords: back-propagation neural network, wind wave, significant wave height.

1 Introduction

The prediction of wave height is of great importance for the construction of ocean and coastal structures, the operation of voyages, as well as the human activities in maritime area. Many forecasting methods for ocean waves have been presented in the literature, such as the traditional SMB and PNJ manual methods [1], the numerical model based on differential equations [2] and SWAN model [3] etc.. These methods for waves forecasting were based on the wind and wave relationships. However, the error of the prediction of waves can become substantial as the wind scenario becomes complex or less well known.

Alternative to traditional statistical methods or numerical simulations, artificial neural network (ANN) has been effectively applied to predicting natural phenomena containing some seemingly ambiguous interrelationships among their physical parameters. In the field of ocean and coastal engineering, the neural networks have been successful applied, such as for the assessment of the stability of breakwaters [4], for forecasting the time series of tidal-level [5][6] and storm surge [7], and for forecasting the time series of waves [8][9][10]. For wind-wave prediction, Deo et al. [8] employed ANN to predict wave height with real-time wind speed data. The correlation coefficients of their results, however, between the observed and the predicted data were not very satisfactory, possibly due to the uncertainties of the wind-wave relationship.

By applying the technique of an artificial neural network (ANN), this paper considers the lag effect of energy transfer between wind and wave. The topology of the network including the selection of neurons of inputs and output is discussed in this study. The neural network model is then applied to predict waves using a previous' records.

2 Neural Network

ANN is an information-processing system which mimics the biological neural network of the brain by interconnecting many artificial neurons. There are many types of the ANN, including the supervised, unsupervised and associated learning network and the optimization application network. The back-propagation neural network (BPN) is one of the most used model for a forecasting problem, which is adopted in this study. A typical three-layered network with an input layer, a hidden layer and an output layer is considered in the study. Each layer may consist of several neurons and the layers are interconnected by sets of the correlation weights.

Each neuron receives inputs from the initial inputs or the interconnections and produces outputs by the transformation using an adequate nonlinear transfer function. The training process of the neural network is essentially executed through a series of observed data. The interconnection weights between the neurons are then obtained from the learning process of the ANN based on the input and output information.

The main procedure of the BPN is the error estimated at the output layer being propagated backward to the input layer through the hidden layer in the network to obtain the final desired outputs. The gradient descent method is often utilized to calculate the weight of the network and to adjust the weight of interconnections for minimizing the output error. The details of the BPN algorithm can be found in Rumelhart et al. [11].

The root-mean-squared error (*RMS*) between the observed and simulated values is used for the agreement index to estimate the accuracy in the paper, which is defined as

$$RMS = \sqrt{\frac{\sum_{k=1}^{n}(y_k - \hat{y}_k)^2}{n}} \tag{1}$$

in which n is the number of sample, $\hat{y}_k$ is the value of observation and y_k denotes the value of prediction. The other agreement index used in the work is the correlation coefficient (CC).

3 Illustrative Examples

3.1 Data source

Data sources applied were gathered from deep-sea station No. 46001 located in the Pacific Ocean, under the administration of National Data Buoy Center (NDBC), USA. The geographical location is at 56.30°N, 148.17°W, where the water depth is 4,206 m. This study applied the following principle to select the wind-wave records: only select wind speed data when its loss does not exceed four consecutive hours a day and under five days a month due to the potential data loss. Temporary data loss is supplemented through conventional interpolation methods to constitute a complete wind-wave data for a period of one month.

This study has adopted the wind-wave data of 1989 (relatively complete) as our subjects based on the aforementioned selection and supplementation principles. The wind-wave data was placed into an ANN for learning. It generated an ANN wind wave forecasting model that enabled the calculation of significant wave height value through the input of wind speed data.

The original format of wind-wave data collected from the station is at one record per hour. However, the wind speed varied per hour is unstable but changes drastically within the wind field data. This type of data has noise when placed in the ANN with ineffective results. Consequently, this study has processed original data from one record per hour to an average of one every three hours to minimize noise by allowing better learning of input and output variables. This conveniently considers wind speed and wave height trends without the cost of data authenticity. The processed data is used as input and output neurons for ANN.

3.2 Construction of NN

The present model is aimed to forecast the significant wave height by input wind speed data into the ANN. According to the theory of wind wave [1], the energy transfer between wind and wave exists the time lag effect. That is, the significant height of wave further relates to the wind speeds involving some previous hours. This model indicates adopting wind speeds of previous hours as the inputs to construct a suitable ANN topology.

The network frame is demonstrated by ANN (p, q, r), where p represents the input neurons, q represents the hidden neurons, and r represents the output neurons. For example, ANN (4, 2, 1) refers to four neurons in the input layer, indicating the average wind speed from the previous 10th to 12th hours (W_{t-9}), 7th to 9th hours (W_{t-6}), 4th to 6th hours (W_{t-3}), and 1st to 3rd hours (W_t), respectively; while the output layer refers to the average significant wave height value from 1st to 3rd hours (H_t) and two neurons in the hidden layer. We use one hidden layer. Figure 1 shows the average RMS error of significant wave height during 5-day forecasting based on different training days in five network frameworks. The results show that the network framework of ANN (4, 2, 1) is optimal and the RMS values of ANN (5, 3, 1) shows slight differences with ANN (4, 2, 1). In terms of the influence of training days on forecasting performance, the RMS values of each framework is higher when forecasting five-days based on five-day training, suggesting that five-day training is inadequate. When the training days are increased to 20, the forecasting result of ANN (4, 2, 1) framework obtained the lowest RMS value. It shows the network reached an optimal learning of wind wave characteristics simulation based on wind wave data during a 20-day period. The RMS values of forecasting in different frameworks demonstrate slight upward trend as training period extends to 30- and 45-days.

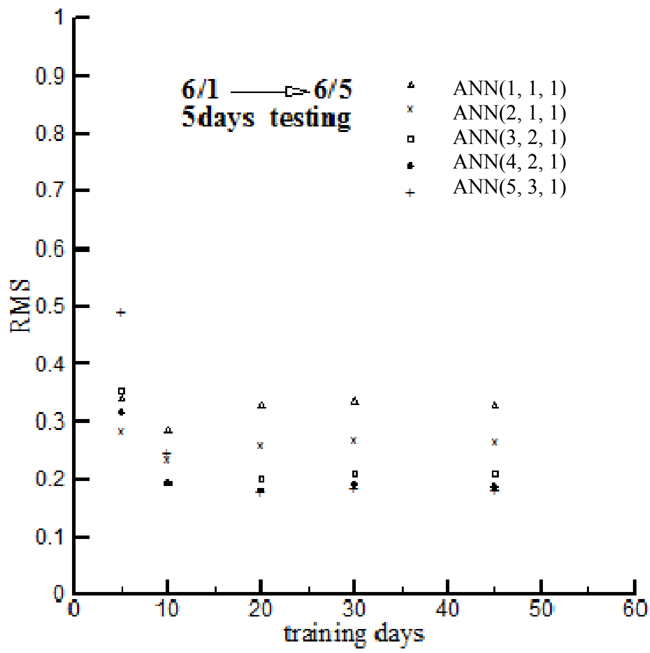

Figure 1: Comparisons of RMS error of significant wave height during 5-day forecasting based on different training days in five network frameworks.

After the learning and testing of NN through numerous models, the wind wave forecasting network framework are suggested using ANN (4, 2, 1) and described as below:

Number of input layer neurons is 4: (W_{t-9}, W_{t-6}. W_{t-3}, W_t);
Single hidden layer neuron is 2;
Output layer neuron is 1: (H_t);
Learning factor = 0.1, momentum factor = 0.5;

3.3 Applications of NN

Table 1 shows the applications of NN to the wind-wave height forecast, in which we generated five cases derived from the data gathered from May to September 1989. Further, the cases were formulated based on the training-quantity (20-days) and testing-quantity (5-days, 10-days, and 15-days). Every case has analyzed the significant wave heights for 5-days, 10-days, and 15-days through ANN (4, 2, 1) network framework. In Case 1, for instance, the training period is from April 26 to May 15 (20-days), while its forecasting period is from May 16 to May 20 (5-days), May 16 to May 25 (10-days), and May 16 to May 30 (15-days). The forecasting performance of each case is demonstrated through RMS value and CC values shown in Table 1.

Case	Learning period	Forecasting period	*RMS*	*CC*
1	Apr 26 – May 15	May 16 - 20	0.1429	0.9372
		May 16 - 25	0.1601	0.9192
		May 16 - 30	0.2290	0.8539
2	May 27 – Jun 15	Jun 16 - 20	0.1572	0.9417
		Jun 16 - 25	0.2698	0.6442
		Jun 16 - 30	0.3297	0.6595
3	Jun 26 – Jul 15	Jul 16 - 20	0.1894	0.8906
		Jul 16 - 25	0.1638	0.9027
		Jul 16 - 30	0.2035	0.8815
4	Jul 26 – Aug 15	Aug 16 - 20	0.1972	0.9389
		Aug 16 - 25	0.1842	0.8967
		Aug 16 - 30	0.2017	0.8462
5	Aug 27 – Sep 15	Sep 16 - 20	0.2146	0.9088
		Sep 16 - 25	0.2221	0.6803
		Sep 16 - 30	0.2448	0.6289

Table 1. Forecasting performance of each case.

The time-series of wave height of observation, training, and the forecasting values of each case are shown in Figure 2 to Figure 6. They demonstrate the learning and forecasting performance of ANN model in this study. The result shows that the model forecasts with higher accuracy for 5-15 days wave heights after the training based on 20-day wind wave data. In terms of 5-day wave height forecast, each case reaches satisfactory forecasting results; whereas 10-day and 15-day forecast demonstrate high correlation coefficient except Case 2 and Case 5. The forecasting inaccuracy of the two cases, nevertheless, is still within an acceptable range overall.

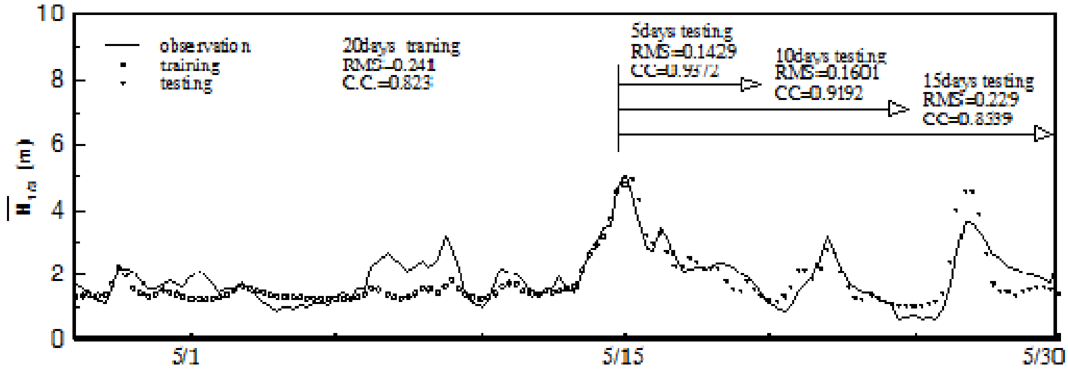

Figure 2: Comparisons of wave height of observed, training, and forecasting variations (Case 1).

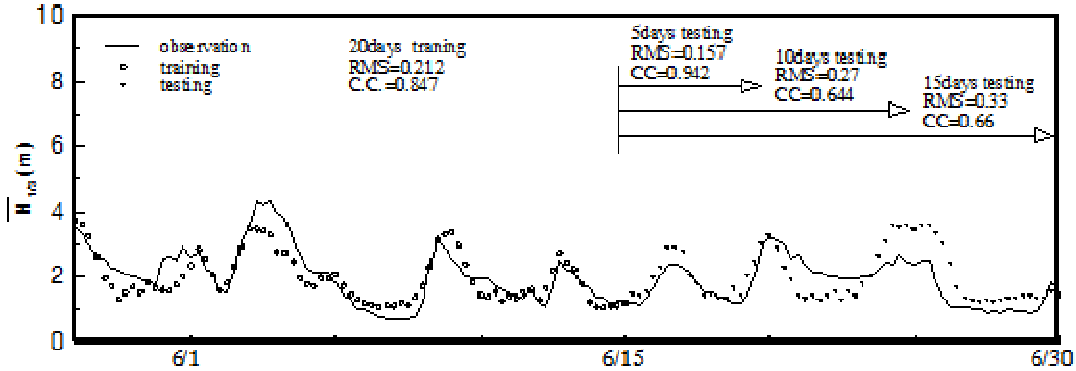

Figure 3: Comparisons of wave height of observed, training, and forecasting variations (Case 2).

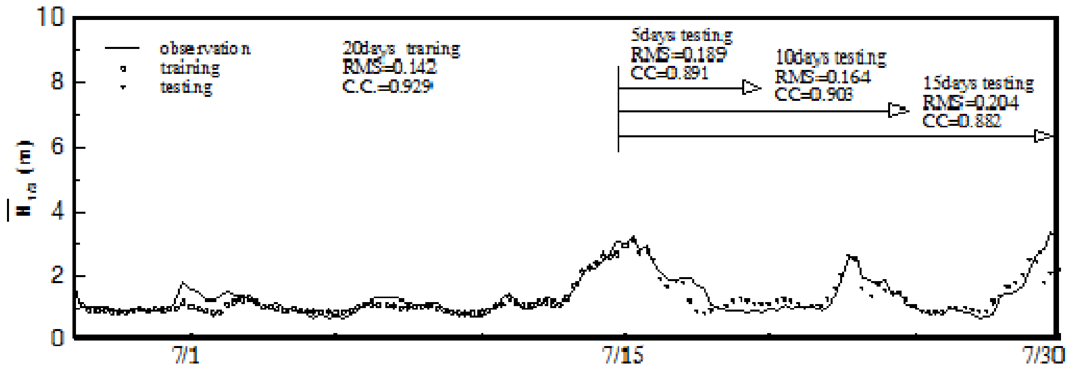

Figure 4: Comparisons of wave height of observed, training, and forecasting variations (Case 3).

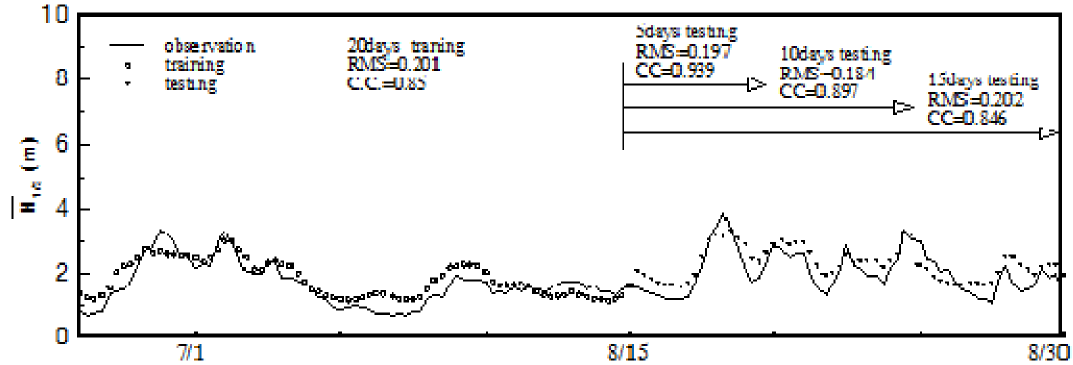

Figure 5: Comparisons of wave height of observed, training, and forecasting variations (Case 4).

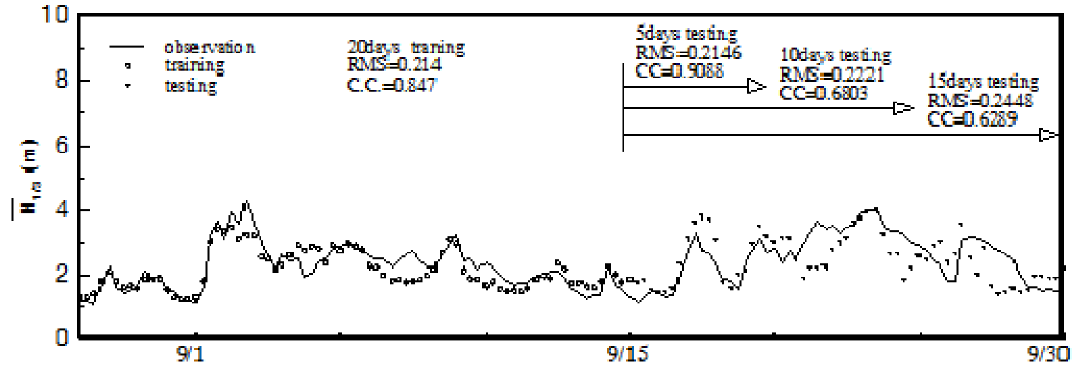

Figure 6: Comparisons of wave height of observed, training, and forecasting variations (Case 5).

4 Conclusion

As a result of the complexity and randomness of the wind waves, the prediction of waves based on the simplified relationship may contain substantial errors. This study predicts the wind waves by applying the technique of an artificial neural network (ANN), in which the supervised learning model with back-propagation scheme is adopted. The network evaluated the interconnection weights between the waves and the corresponding wind speeds by training the past records. The selection of the neurons of input, outputs and the hidden layers is discussed in detail in the study. Using long-term wind and wave data from one of the National Data Buoy Center (NDBC) stations in the Pacific Ocean, this study examined the validity and accuracy of the ANN model. It is found that the three-hourly average significant wave height can be predicted from training the previous nine hours data of wind speeds. The results show that the neural network model can provide a good prediction in the short-term (five days to fifteen days) of the waves using the records for the previous 20-days.

Acknowledgments

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