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Improving wave predictions with artificial neural networks

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Abstract

Accurate predictions of wind waves with different lead times are necessary for a large scope of coastal and open ocean activities. Attempts to improve wave short-term forecasts based on artificial neural networks are reported. Hourly observations of significant wave heights and zero-up-crossing wave periods from two sites offshore the Atlantic and the Irish Sea coasts of Ireland are used to train and validate these networks. Two different approaches are involved. One of them corrects the predictions solely using the initial simulations of the wave parameters with leading times from 1 to 24 h. Another one allows merging the measurements and initial forecasts. The proposed procedures provide satisfactory results at both locations.

Keywords: Oceanic; Semi-enclosed sea; Buoy observations; Neural networks; Simulation; Correction

1. Introduction

The veracious forecasts of wind waves are of great importance in ocean and coastal engineering applications as well as in managing oceanic resources. The wave parameters are simulated using global and local numerical models, or alternatively some methods of the time series extension. The former require abundant bathymetric, meteorological and oceanographic data. Meanwhile, the latter simulate new members of time series solely using the history of the wave parameters' behavior observed at a specified site. As such, stochastic models employing the

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auto-regressive moving average (ARMA) or the auto-regressive integrated moving average (ARIMA) (Agrawal and Deo, 2002), or involving the technique of artificial neural networks (ANNs) (Deo and Kiran Kumar, 2000; Deo et al., 2001; Deo and Jagdale, 2003; Makarynskyy et al., 2002a, b; Tsai et al., 2002) could be used.

The ARMA and ARIMA models were evolved from the time series analysis technique. The linearity is the fundamental property of systems described with these models. Linear operators transform the signal into a weighted sum of the previous observations and of the Gaussian white noise. Consequently, predictions can be expressed in terms of model coefficients and residuals.

Inspiration for the development of artificial neural networks was found in the biological neural system (Fausett, 1994). Artificial neural networks belong to that type of information-processing systems, which allow approximation of the non-linear behavior (Haykin, 1999). After training a neural net over a number of input–output patterns belonging to a system, feeding the network with an independent input should result in producing an appropriate output. Hornik et al. (1989) proved that a feed-forward artificial neural net with an arbitrary number of processing units in a single hidden layer is a universal function approximator.

By comparing predictions of significant wave heights obtained with the stochastic and neural techniques, Deo and Sridhar Naidu (1999) and Agrawal and Deo (2002) noticed a better performance of the latter. Such considerations gave a reason to regard the neural technique as reliable when wave simulations are concerned.

The accuracy of the mathematical predictions in geophysics is limited by many factors. For instance, an implementation of the numerical wave models introduces and propagates inaccuracies in the specification of the initial and boundary conditions and forcing functions into the inner parts of computational domains, while the time series extension methods are as a rule site-sensitive and their use is limited by the presence of temporal correlation patterns.

In order to improve the accuracy of the wave numerical forecasts, several data assimilation methodologies were proposed, such as the optimum interpolation (Voorrips, 1999) or the Kalman filtering (Voorrips et al., 1998). Neural networks were the basis of a hybrid forecast model, which, when compared to a deterministic modeling system, produced more accurate predictions of the sea currents assimilating observations of the currents, sea levels and wind (Babovic, 1999).

In this work, neural approaches to the problem of the wave predictions' improvement are discussed. The initial hourly forecasts of significant wave heights and zero-up-crossing wave periods are made over 1–24 h time intervals. The first correcting approach is solely based on these predictions. The second approach merges the last day measurements with the next day predictions aiming to improve the latter. The predicting, correcting and merging procedures exploit the internal ability of ANNs to recognize presented patterns as true ones, and to simulate a plausible output in series of independent experiments.

Section 2 gives a general outline of artificial neural networks. Data and neural networks used at each stage of the study are described in Sections 3 and 4, respectively. The results of the neural simulations are discussed in Section 5. Concluding remarks are presented in Section 6.

2. Outline of artificial neural networks

The basis of an artificial neural net is the concept of the neuron considered as a unit. The unit takes an argument formed as a sum of a weighted input and bias, and produces an output by means of some transfer (activation) function, which is typically the step or sigmoid function. There can be many input-weight products to form a unique argument of the transfer function in the jth neuron, where $j = 1, \ldots, R$ and R is the number of neurons in the hidden layer. Several such neurons can be combined into a layer, whereas a particular network can contain one or more interconnected layers of neurons. The pattern of these interconnections is called the architecture.

Non-linear activation functions (like the log sigmoid or the hyperbolic tangent sigmoid) for the hidden units are needed to make artificial neural nets capable of representing non-linear dependencies. For the output units, one should choose an activation function suited to the distribution of the target values.

The method of determining the weights and biases is called learning. The learning process requires a set of patterns "input–target output". During the learning process, the weights and biases of a network are iteratively adjusted to minimize the network performance function (the averaged squared error between the network outputs and the target outputs is the default one for the feed-forward networks) making the entire network to perform in some expected way. The amount by which the weights change is the learning rate parameter. Each representation of a training set to a net is called an epoch.

The gradient descent backpropagation learning algorithm is the basic one permitting stable training. This algorithm updates the weights and biases of artificial neural nets in the direction of the negative gradient of the performance function with a pre-set learning rate. This can cause a very slow training when the gradient has a small magnitude.

The resilient backpropagation algorithm, used in this study, eliminates harmful effects of the magnitudes of the partial derivatives as it accounts for the derivatives' signs. The sign is used to determine the direction of the weight update: it is increased whenever the derivative of the performance function has the same sign for two successive iterations, or decreased whenever the derivative changes the sign. When the derivative is close to 0, the update value remains the same. Usually, this procedure provides a training which is several times faster than the gradient descent backpropagation. However, more attention should be paid to the training process itself since the algorithm produces from time to time strong oscillations in the values of the weights and biases.

3. Data used

Time series of hourly wave observations were obtained from two Ocean Data Acquisition System (ODAS) buoys at the M1 and M2 stations (Fig. 1). The data from the M1 buoy moored in November 2000 about 60 mile west of the Aran

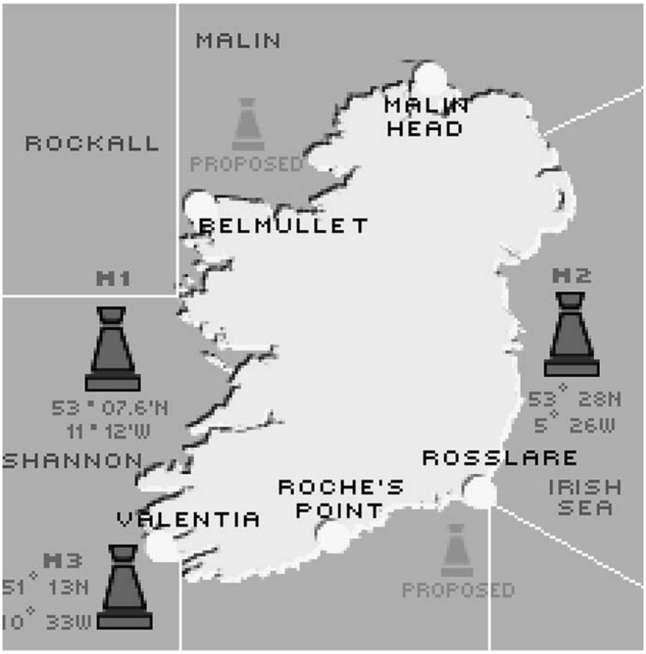

Fig. 1. Locations of moored and proposed ODAS buoys offshore the Irish coast.

Islands, west coast of Ireland, at latitude 53° 07.6′ north and longitude 11° 12.0′ west, for the period March 2001–December 2002 were used. The second buoy M2 deployed in late April 2001 about 20 nautical miles east of Lambay, 53° 28.8′ north and 05° 25.5′ west, provided the information for a shorter period, May 2001–December 2002. There is one more ODAS buoy at the M3 station but due to much shorter operational time starting in July 2002, its data were not included into consideration. These buoys are maintained by the Met Éireann (the Irish Meteorological Service) and by the Marine Institute of Ireland.

The quality control procedure was applied to the measurements to fill the gaps and to replace the unrealistically large values with the linearly interpolated ones. The time series plots of the rectified observations are shown in Figs. 2 and 3. It is clear that the data from the M1 buoy reflect energetic conditions of the North Atlantic. The registered wave heights range from about 0 value up to almost 12 m. The recorded wave periods stagger between 4 and 15 s. Two periods of the autumn–winter rough sea are clearly visible in the plots of these wave parameters. Meanwhile, the M2 buoy measurements exhibit conditions of the western part of the semi-enclosed Irish Sea with the wave heights reaching 5 m at maximum and the wave periods varying from 3 to 8 s. The periods of rough sea are distinguishable here as well, but the wave conditions are much smoother than those at the previous location.

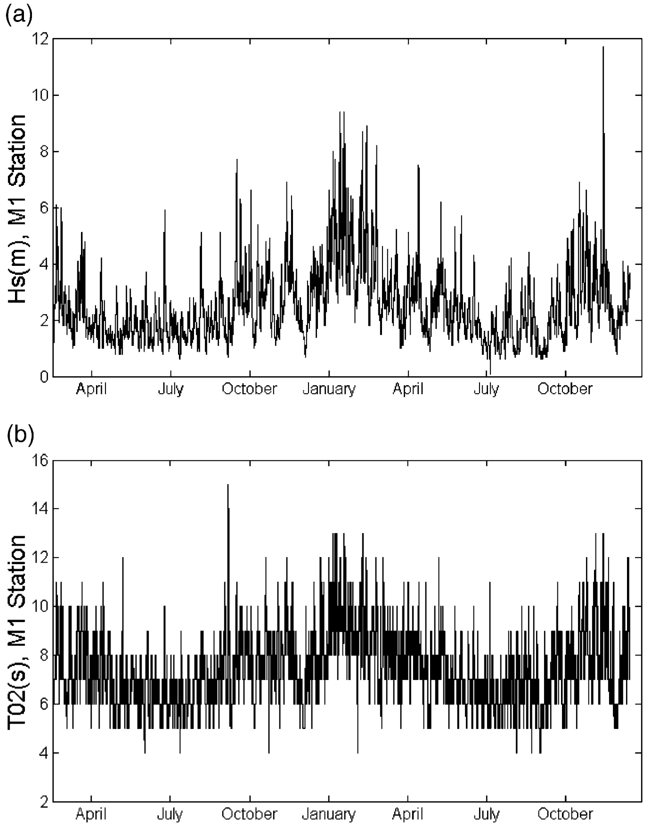

Fig. 2. Time series plots of the significant wave height and the zero-up-crossing wave period obtained from measurements at the M1 station for the period, March 2001–December 2002.

In order to train the forecasting and the sequential correcting and merging neural networks and to validate the improved forecasts, each time series of 15,684 data points from the M1 buoy and 14,388 data points from the M2 buoy was divided into three equal non-overlapping data sets. Data set 1 was used for training neural networks producing the initial forecasts. Data set 2 served for training the nets correcting the initial simulations as well as the networks merging the measurements with results of the simulations. Finally, data set 3 provided an independent validation of these predictions.

4. Neural networks involved

The commonly used three-layer feed-forward networks with a non-linear differentiable log–sigmoid transfer function in the hidden layer and a linear transfer function in the output layer were employed in this study.

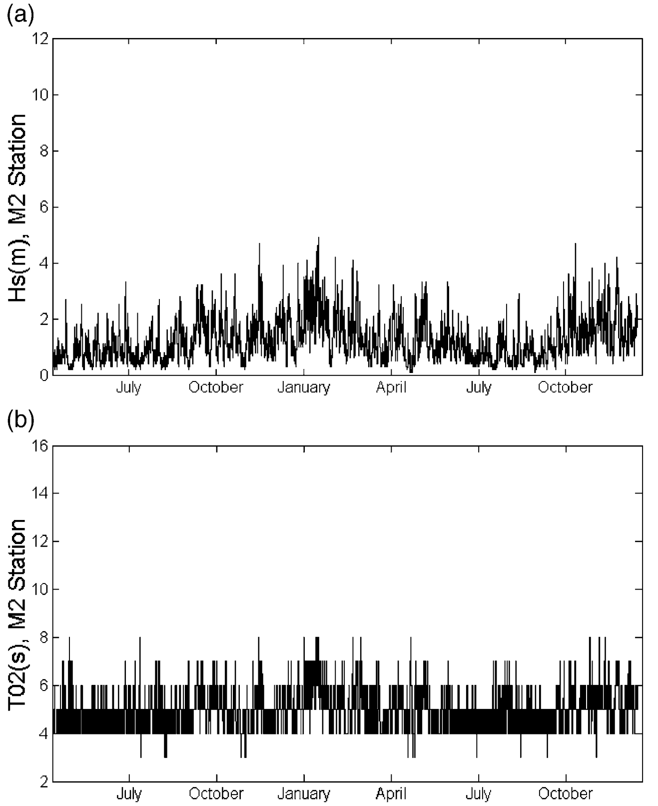

Fig. 3. Time series plots of the significant wave height and the zero-up-crossing wave period obtained from measurements at the M2 station for the period, May 2001–December 2002.

To begin with, a separate neural network was developed to forecast each wave parameter at every location. Assuming that a 48 h history contains all the necessary information to estimate hourly wave parameters for the next day, each input layer of these four neural networks consisted of 48 nodes, while each output layer had 24 nodes.

Further, an additional procedure was implemented to correct the results of these predictions. The procedure was based on the outcomes of the previous simulations solely. Four neural networks were developed, which, according to the number of the prediction intervals in the initial and final forecasts, had 24 nodes in the input as well as in the output layers.

Finally, another approach to the wave predictions' betterment was tested. This was based on the idea that the recent observations merged with the initial forecasts—each of them for 24 h time interval—will increase the accuracy of the final estimates. Therefore, the ANNs involved had 48 nodes in the input layer and 24 nodes in the output layer.

The number of nodes in the hidden layer h of all these networks was calculated using an empirical expression $h = (2z + 1)$ (Huang and Foo, 2002), where z is the number of input nodes. Each network was trained in 200 epochs.

5. Discussion of the results

To assess the accuracy of the initial and the amended predictions, the correlation coefficient R, the root mean square error $RMSE$ and the scatter index SI were computed using the following expressions:

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}}, \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}}, \tag{2}$$

$$SI = \frac{RMSE}{\bar{x}}, \tag{3}$$

where x_i is the observed at the ith time step value, y_i is the simulated at the same moment of time value, N is the total number of data points in validation, $\bar{x}$ is the mean value of observations, and $\bar{y}$ is the mean value of simulations.

Figs. 4–6 and 7–9 display graphs of these statistical characteristics estimated by the results of the wave heights initial forecasts, and the correction and the merging procedures applied at the M1 and M2 stations, respectively. The predicting neural

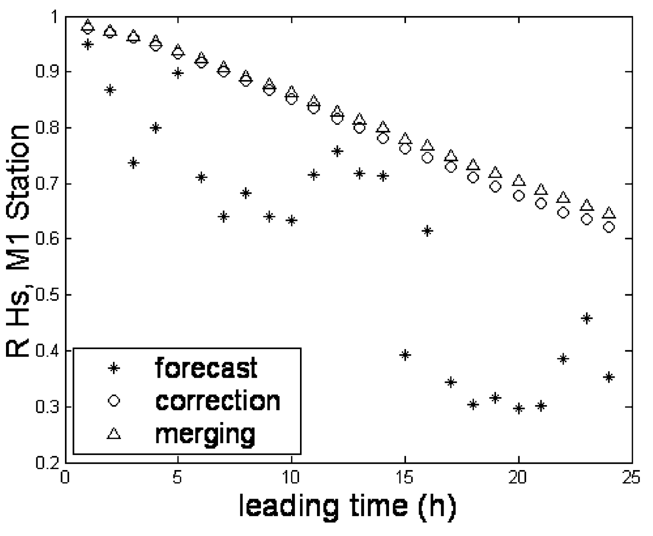

Fig. 4. Comparison of the correlation coefficient estimated from the results of wave height simulations over different time intervals, M1 station.

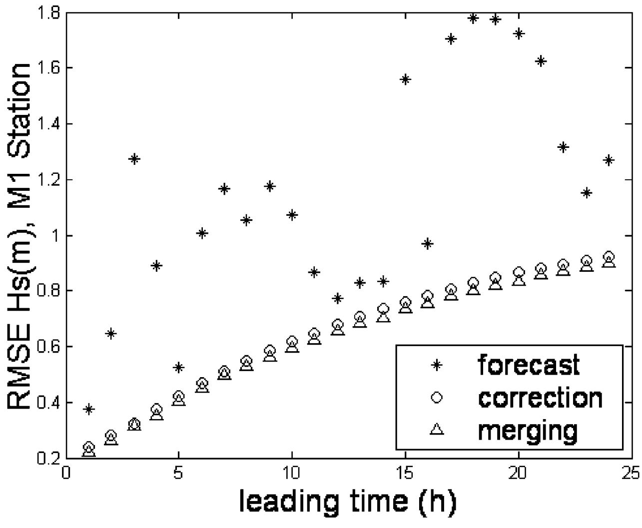

Fig. 5. Comparison of the root mean square error estimated from the results of wave height simulations over different time intervals, M1 station.

networks show different accuracy levels where different leading times concerned. Two patterns in the statistics' behavior could be distinguished. With an increase of the prediction interval, the accuracy of the simulations for the M1 station changes rather chaotically, whereas it reduces gradually in the forecasts for the buoy M2 location.

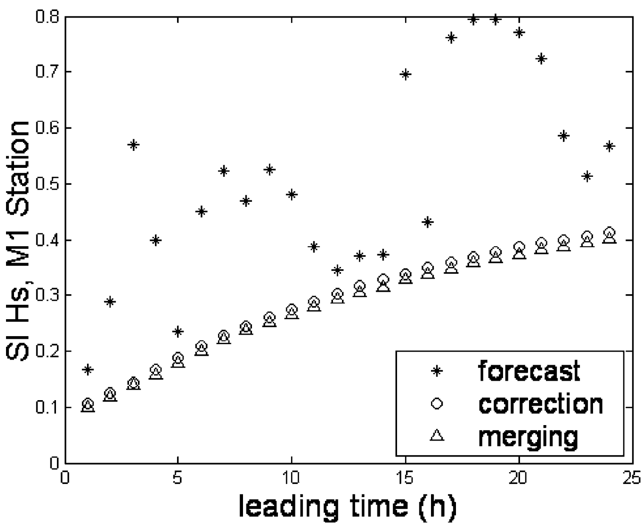

Fig. 6. Comparison of the scatter index estimated from the results of wave height simulations over different time intervals, M1 station.

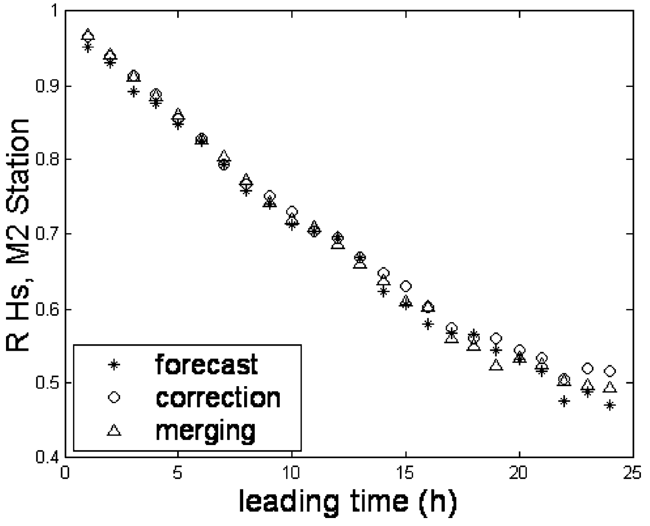

Fig. 7. Comparison of the correlation coefficient estimated from the results of wave height simulations over different time intervals, M2 station.

Similar considerations apply to the predictions of wave periods (Figs. 10–12 and 13–15), with a distinction that the statistics estimated from the simulations at the M1 station fluctuate much less.

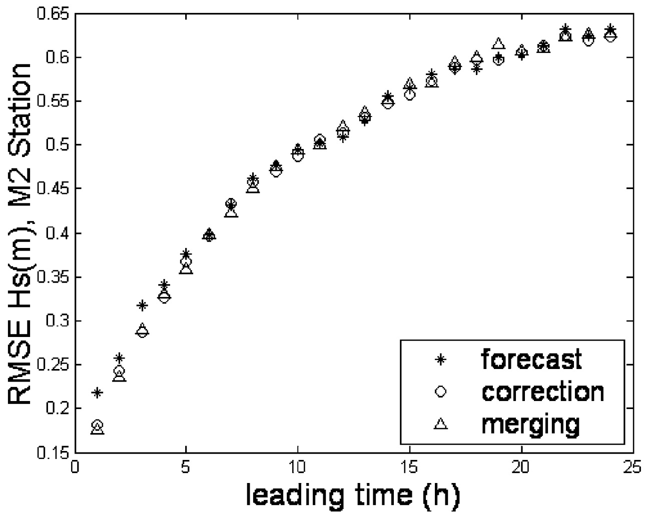

Fig. 8. Comparison of the root mean square error estimated from the results of wave height simulations over different time intervals, M2 station.

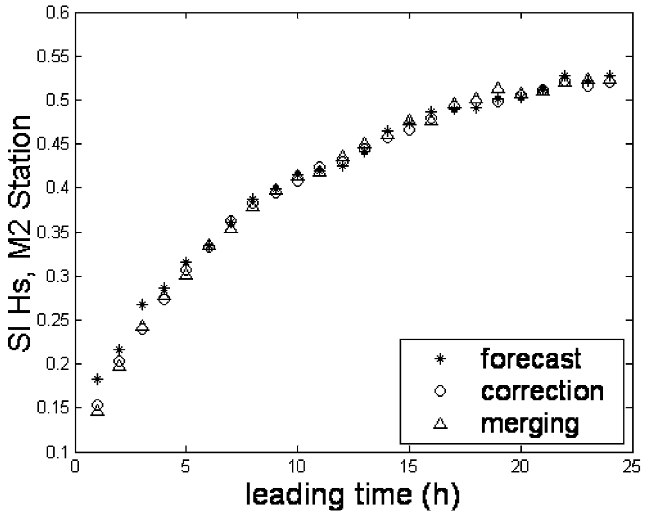

Fig. 9. Comparison of the scatter index estimated from the results of wave height simulations over different time intervals, M2 station.

This dissimilarity in the outcomes of the predicting networks could be explained by taking into account the buoys locations. The buoy M1 undergoes influence of the almost open ocean wave conditions with temporal and spatial scales varying widely. The attempts to train an artificial neural network being able to catch all

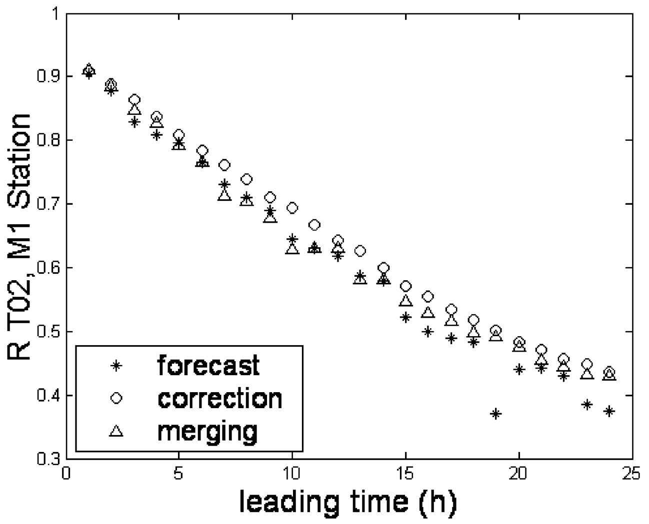

Fig. 10. Comparison of the correlation coefficient estimated from the results of wave period simulations over different time intervals, M1 station.

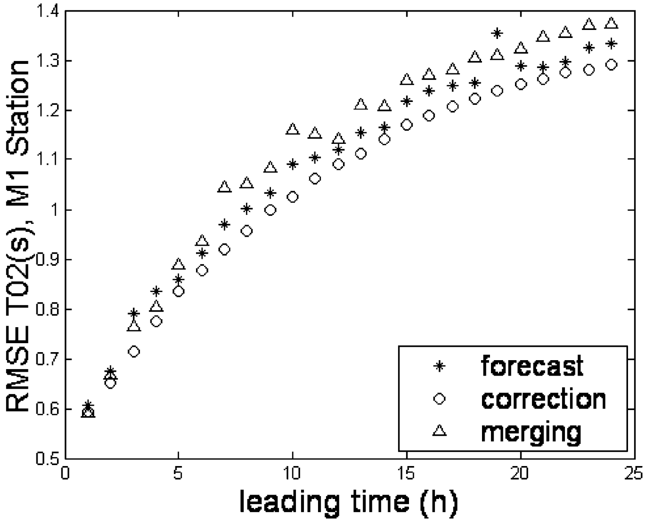

Fig. 11. Comparison of the root mean square error estimated from the results of wave period simulations over different time intervals, M1 station.

these variations at once partially failed. Meanwhile, the M2 site is affected by semi-enclosed sea conditions with lower amplitudes of spatial and temporal variability. Therefore, the networks predicting wave heights and wave periods at the M2 station succeeded in producing smoother results.

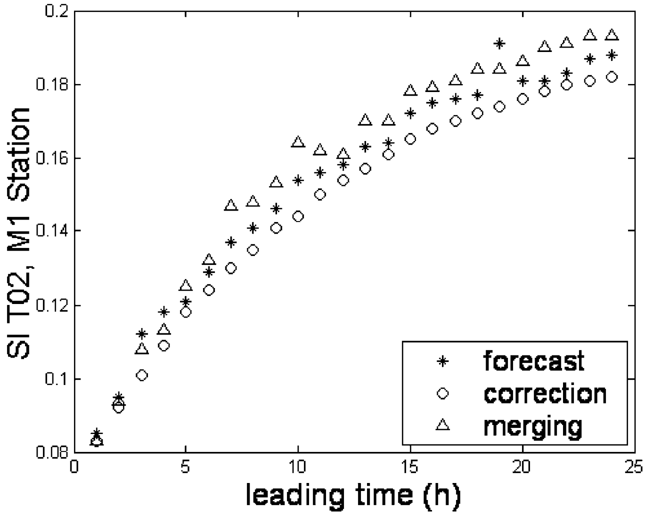

Fig. 12. Comparison of the scatter index estimated from the results of wave period simulations over different time intervals, M1 station.

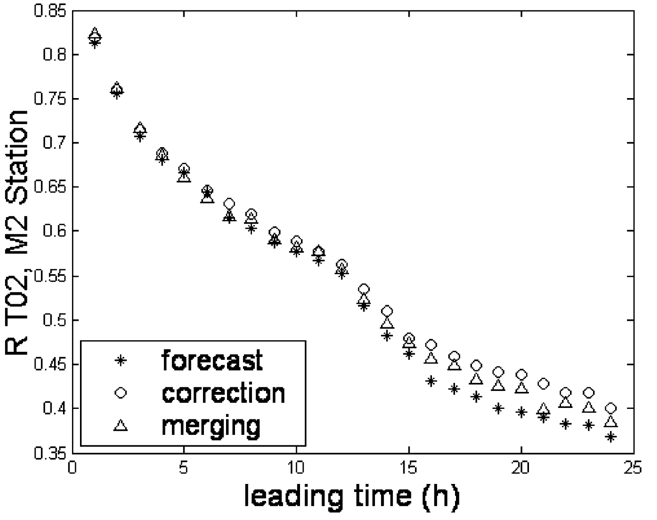

Fig. 13. Comparison of the correlation coefficient estimated from the results of wave period simulations over different time intervals, M2 station.

In order to raise the accuracy of the forecasts at these locations, two approaches described in the previous section were examined.

It clearly follows from an analysis of Figs. 4–6 that applying the correcting and merging procedures significantly improves wave height predictions for the M1 site.

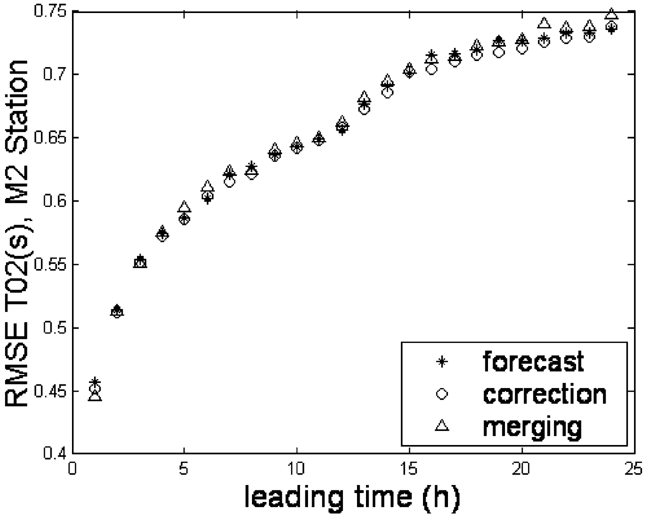

Fig. 14. Comparison of the root mean square error estimated from the results of wave period simulations over different time intervals, M2 station.

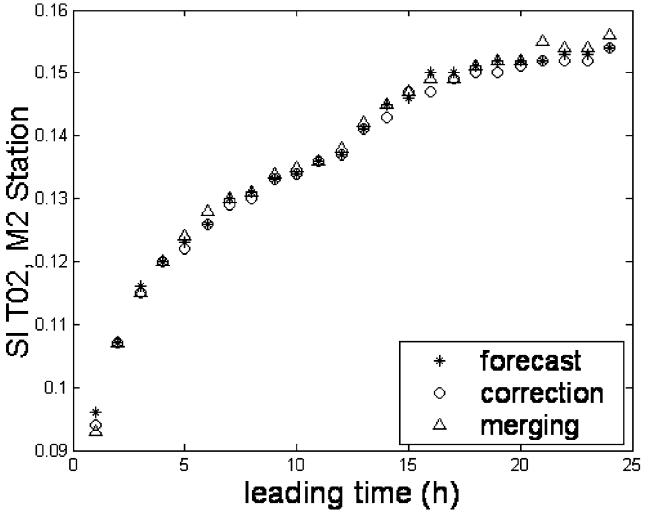

Fig. 15. Comparison of the scatter index estimated from the results of wave period simulations over different time intervals, M2 station.

Accuracy of the amended estimates reduces gradually with longer intervals of forecasting that is reflected in the changes of the verification statistics. The correlation coefficient decreases from 0.98 to 0.62–0.64. The root mean square error and the scatter index increase from 0.24 to 0.92 m and from 0.11 to 0.41, correspondingly. The scatter diagrams presented in Fig. 16 give an example of the achieved improvements. It appears that the correcting network reveals the links existing between the initial simulations and observations for the same 24 h. The network additionally assimilating the last day observations recognizes even more persistence in the merged data patterns.

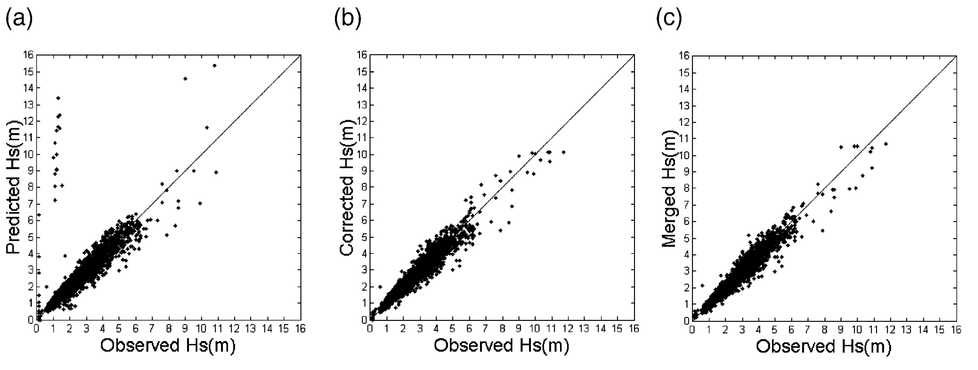

Fig. 16. Scatterplots of the simulated with 2 h leading time vs. observed wave heights and the line of exact fit, M1 station.

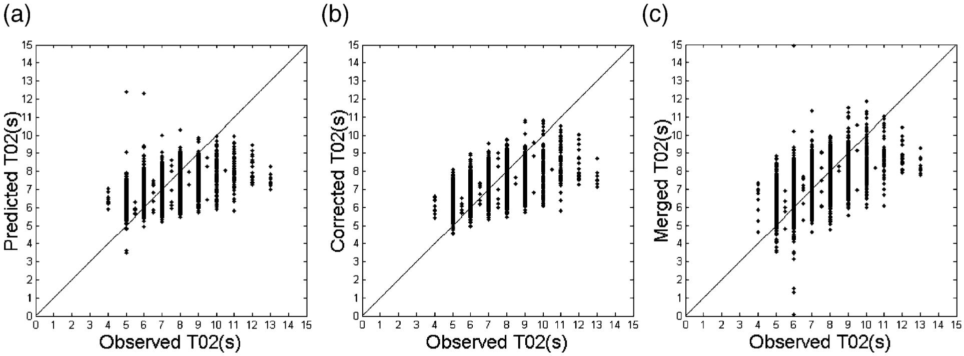

Fig. 17. Scatterplots of the simulated with 15 h leading time vs. observed wave periods and the line of exact fit, M1 station.

The application of the correcting neural network to the initial forecasts of wave periods at the M1 station eliminates the fluctuations in the statistics and raises the accuracy, although these improvements are less pronounced (Figs. 10–12). The correlation coefficient changes from 0.91 to 0.44. The root mean square error increases from 0.59 to 1.29 s. The values of the scatter index are within limits 0.08–0.18. Meanwhile, the network merging the last day observations of this wave parameter with the next day simulations does not provide any considerable betterment of the initial forecasts. For an additional clarification of this point, see the scatterplots in Fig. 17.

An intercomparison of the initial predictions of wave heights and wave periods for the M2 station with the results of the correction and merging does not exhibit any significant differences between them (Figs. 7–9 and 13–15). The correcting networks provide the statistics as follows. The correlation coefficient decreases from 0.97 to 0.51 in the wave height estimations and from 0.82 to 0.40 in the wave period computations. The root mean square error grows from 0.18 to 0.62 m and from 0.45 to 0.74 s, respectively. The scatter index shows an increase from 0.15 to 0.52 in the predictions of the first wave parameter and from 0.09 to 0.15 in the forecasts of the second. The employment of the artificial neural networks at this location reveals that the persistence and correlation tendencies in the Irish Sea are weaker than those at the previously considered North Atlantic site. This might be a sequence of higher temporal inconstancy of wave conditions within this semi-enclosed sea when compared to the ocean.

6. Concluding remarks

The technique of artificial neural networks was applied to predict significant wave heights and zero-up-crossing wave periods over hourly intervals from 1 h up to 24 h ahead, and to amend the forecasts by employing two different approaches.

The observations used to train neural nets were obtained from two ODAS buoys moored at an oceanic and a sea sites offshore the Irish coast.

It was found that both the accuracy of the simulations and the ability of neural nets to improve the initial forecasts, estimated in terms of the correlation coefficient, root mean square error and scatter index, depend on buoy location. The neural networks employed to form the initial predictions of wave heights and periods at the oceanic site demonstrated sparse values of the estimating statistics when compared to the sea site at which the accuracy reduces gradually with longer prediction intervals. However, this problem at the oceanic location was successfully solved and the accuracy of the forecasts was increased through the implementation of the correcting or data merging neural nets. This was not the case when the same procedures were applied at the sea site.

The main reason behind it might be that a single relatively simple network cannot catch the wide range of oceanic variations properly while predicting fairly well lower variability of a semi-enclosed sea. The employment of the additional correcting/merging networks reveals stronger persistence and correlation tendencies inherent to the oceanic wave conditions rather than to the temporally inconstant sea waves.

Acknowledgements

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