One-Day Wave Forecasts Based on Artificial Neural Networks

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ABSTRACT

Sophisticated wave models like the Wave Model (WAM) and Simulating Waves Nearshore (SWAN)/WAVEWATCH are used nowadays along with atmospheric models to produce forecasts of ocean wave conditions. These models are generally run operationally on large ocean-scale domains. In many coastal areas, on the other hand, operational forecasting is not performed for a variety of reasons, yet the need for wave forecasts remains. To address such cases, the production of forecasts through the use of artificial neural networks and buoy measurements is explored. A modeling strategy that predicts wave heights up to 24 h on the basis of judiciously selected measurements over the previous 7 days was examined. A detailed investigation of this strategy using data from six National Data Buoy Center (NDBC) buoys with diverse geographical and statistical properties demonstrates that 6-h forecasts can be obtained with a high level of fidelity, and forecasts up to 12 h showed a correlation of 67% or better relative to a full year of data. One limitation observed was the inability of the artificial neural network model to correctly predict the magnitude of the highest waves; although the occurrence of high waves was predicted, the peaks were underestimated. The inclusion of several years of data and the judicious selection of the training set, especially the inclusion of extreme events, were shown to be crucial for the model to recognize interannual variability and provide more reliable forecasts. Real-time simulations performed for April 2005 demonstrate the efficiency of this technology for operational forecasting.

1. Introduction

Recent years have witnessed a significant increase in the number of instruments deployed in coastal areas to make hydrodynamic measurements. This increase is partly due to the expansion of efforts to develop “ocean observing systems” [such as the Gulf of Maine Ocean Observing System (GOMOOS), the Texas Coastal Ocean Observing Network, the Prince William Sound Ocean Observing System, etc.] and to the National Oceanic and Atmospheric Administration’s (NOAA) Physical Oceanography Real Time System (PORTS) that is intended to aid navigation. While many of these instruments provide hourly measurements of water levels, waves, and other oceanographic parameters in near real time, efforts are required to obtain a forecast from these instrumental data.

This paper attempts to enhance the value of the expanding base of measurements by providing a forecast through the use of artificial neural networks. Of course, forecasts can be obtained through the continuous operation of numerical models such as the Princeton Ocean Model for water levels and velocities and the Simulating Waves Nearshore (SWAN)/WAVEWATCH wave model (Chu et al. 2004; Li and Panchang 2005) for wave conditions. However, in many regions, the continuous implementation of these numerical models is rendered difficult by the unavailability of (future) forcing functions such as offshore boundary conditions and wind stresses at adequate resolution on the model domain. While regional forecasts are successfully made in the GOMOOS project by interfacing local high-resolution models to outer-ocean model forecasts made by NOAA’s National Centers for Environmental Prediction, factors like the corruption of NOAA’s wind forecasts by nearshore topographic features (such as islands), the need for multiple levels of nesting as one goes from offshore to the very near shore, and the complete absence of outer ocean forecasts (forcing functions) in several parts of the world are a major impediment to the use of numerical models (in some cases).
Here we address the issue of forecasting significant wave heights (called wave heights here for brevity) for the next 24 h at the location of a buoy where measurements are available. Since the emphasis is on using the ANN for forecasting. Inspired by biological neural networks, artificial neural networks have been developed as self-learning mechanisms that may be used to map complex mathematical (or random) phenomena using a data-driven approach. In recent years, ANNs have found an increasing application to oceanic and atmospheric sciences and engineering (Hsieh and Tang 1998). Some examples include investigations pertaining to the estimation of salinity and density (Krasnopolsky et al. 2002), phytoplankton production (Scardi and Harding 1999), temperature profiles (Churnside et al. 1994), ocean color (Gross et al. 1999), precipitation (Hong et al. 2004; Liu et al. 2001; Marzban and Witt 2001), wind speeds (Kretzschmar et al. 2004; Lee and Jeng 2002; More and Deo 2003), tidal water levels (Lee et al. 2002; Cox et al. 2002), radiative flux (Loukachine and Loeb 2003), wind and wave loads on structures (Haddara and Soares 1999; Mase and Kitano 1999), barge motions (Mafous and Haddara 2003), scour depths near pilings (Kambekar and Deo 2003), etc.

In the context of wave modeling, Tolman et al. (2005) investigated the use of ANNs as an alternative to the complex Boltzmann integral calculations associated with wave–wave interaction. Of particular relevance to our work, though, are the early efforts of Deo and Naidu (1999), who used ANNs along with measurements from a wave buoy moored off the east coast of India to correlate pairs of wave height data and to estimate a future value based on the current value. Later, Agrawal and Deo (2002) enhanced these efforts by correlating three pieces of data: those at time steps $t - \Delta t$ (past), $t$ (current), and $t + \Delta t$ (future). While their predictions yielded a very high correlation relative to the targets in validation tests for $\Delta t = 3$ h, they used averages for $\Delta t > 3$ h; for example, the average of the current day’s wave heights was used to predict the next day’s average wave height. Using such averages diminishes the value of the forecast for practical applications such as navigation, planning of offshore installation and maintenance works, etc. Furthermore, both studies were based on data from a single location off the east coast of India and covered a limited duration (16 months). The data used for validation covered only 3 months and displayed extremely limited wave height variability. [Wave heights used by Agrawal and Deo (2002) were all less than 1.4 m.] Although the more recent efforts of Makarynskyy (2004) off the Irish coast included much larger waves, these efforts also were accompanied by comparably short datasets that precluded the incorporation of interannual variability. [Medina (2005) has noted that the modeling strategies of Makarynskyy (2004) can be inherently problematic owing to their susceptibility to overfitting and also the correlation between too many values.] Nevertheless, these studies succeeded in demonstrating both the potential of ANNs as well as their superiority over other stochastic prediction methods like those based on autoregressive moving averages that are also used to correlate individual wave heights (e.g., Sobey 1996). This superiority has been noted in the case of wind speed prediction as well (e.g., Kretzschmar et al. 2004).

In this paper, we have attempted to more comprehensively explore the value of ANN technology for predicting significant wave heights from buoy measurements. First, we have used data from six buoys in three areas (the Gulf of Mexico, the Gulf of Maine, and the Gulf of Alaska) where the wave height environments are statistically different (Panchang et al. 1999; Palao et al. 1994). Second, the lengths of the data used are much greater than those in previous efforts and as long as 12 years in some cases. At some of these locations, extreme wave events with recurrence intervals of the order of 100 years or more are included in the data. Third, we explore the possibility of obtaining time-specific forecasts rather than averages over long time intervals in order to enhance the practical usefulness of the predictions. Fourth, to eliminate numerical problems associated with overfitting or excessive data, we have devised a strategy for recognizing wave height patterns that permits a judicious selection of data points to cover a period typical of a storm length without creating enormously large matrices. Finally, in addition to the usual validation with historical data, we examine the performance of these models in real-time predictions starting from 1 March 2005.

The outline of the paper is as follows: section 2 describes the salient features of the data used to “train” and test the ANN model. In section 3, we provide a brief review of the modeling strategy. Modeling results are presented in section 4 along with a discussion of the reliability of the predictions and the identification of the limitations of this technology. Section 5 provides some results of a real-time implementation of the model with a view to providing operational online forecasts in the future. Concluding remarks are given in section 6.

2. Study area and data

For the present work, data from six buoys maintained by the National Data Buoy Center are used. We
have given some preference to buoys in coastal waters, because ANN forecasts are more likely to be beneficial in nearshore areas where traditional model-based forecasting programs do not exist or are difficult to implement. Hourly data from 91 buoys around the United States were obtained and analyzed for the purpose of estimating the extreme wave statistics (to be reported elsewhere). This was done by fitting the monthly maxima to the Gumbel distribution and the three-parameter Weibull distribution via the method of maximum likelihood (e.g., Panchang et al. 1999). Among other quantities, the 50-yr wave heights or, in other words, the wave heights corresponding to a 2% chance of occurrence in any given year ($H_{2\%}$), were estimated.

To explore the applicability of ANN technology to data with sufficiently different statistical qualities, we chose two buoys off the northeast coast in the Gulf of Maine, two in the northern Gulf of Alaska (including one in Prince William Sound), and two in the northern Gulf of Mexico. The locations and data availability for these buoys are depicted in Table 1 along with values of $H_{2\%}$ ($H_{2\%}$ was not estimated for buoy 46082 since the measurements are available only for 3 years, which is an inadequate duration for such an analysis). The maximum quantity of data for about 12 years was available at the location of two buoys, namely, 44007 and 44013 in the Gulf of Maine. Some of the $H_{2\%}$ values shown in Table 1 are confirmed by earlier studies (Panchang et al. 1999; Palao et al. 1994). It can be seen that the distance of the buoys from the coast varies between 22 and 156 km and $H_{2\%}$ varies between 5.53 and 9.56 m. It is remarkable to note that the estimated $H_{2\%}$ is the largest for the buoy closest to the coast (44007). The value is similar for buoy 42040, which is much farther from the coast (118.5 km). Although $H_{2\%}$ is the largest for buoy 44007 near Boston, the maximum wave height (15.9 m) was recorded in the eastern Gulf of Mexico by buoy 42040 in September 2004. In view of these differences, it is reasonable to describe the data from these six buoys as representing a wide range of geographical and statistical properties.

Table 2 shows the total available hourly data at all locations divided into five wave height ranges. It may be noted that the percentage of small wave heights (less than 3 m) is very high as compared to that of very large wave heights (larger than 9 m). In general, the percentage of wave heights greater than 3 m is fairly small.

3. ANN modeling strategy

A detailed background of ANN models may be found in Wasserman (1993) and Bose and Liang (1996). In brief, ANNs essentially involve an input layer and an output layer, which are used for supervised training. In between the input and output layers, one or more hidden layers connected by weights, biases, and transfer functions are often used. The input layer data are multiplied by initial trial weights and a bias is added to the product. This weighted sum is then transferred through either linear or sigmoidal transfer functions to yield an output. This output then becomes the input for the following hidden layers and the procedure is continued until the output layer is reached. The difference between the network output and the target is used and transformed by an error function, and the resulting error is propagated back (“back propagation”) to update the weights and the biases using an optimization technique like the gradient descent, which strives to minimize the error. The entire procedure is repeated for a number of epochs until the desired accuracy in the outputs or other specified conditions is achieved (“training”). Once the network is trained, it can be used to validate against unseen data using the trained weights and biases. In the present work, three-layered “feed forward back propagation” networks were developed for each location for forecasting the wave heights for a maximum lead time of 24 h.

A major issue in this type of forecasting is the selection of appropriate input data patterns that are likely to influence the desired output. In the context of wind speeds, this has been investigated in detail by Kretzschmar et al. (2004). For wave prediction, it is intuitive that the early approach of correlating only two or three pieces of data (e.g., Agrawal and Deo 2002) is suitable only for very small time steps or for long-term averages and may break down with greater variability in the data. Therefore, Makarynskyy (2004) attempted to predict wave heights for lead times up to 24 h (on an hourly basis) using the previous 48-hourly values. However, as noted earlier, his approach can be vulnerable to

<table>
<thead>
<tr>
<th>Buoy No.</th>
<th>Location</th>
<th>Available data</th>
<th>$H_{2%}$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>46082</td>
<td>Cape Suckling, 155.6 km southeast of Cordova, AK</td>
<td>2 yr</td>
<td>6.37</td>
</tr>
<tr>
<td>46060</td>
<td>West Orca Bay, 66.6 km southwest of Valdez, AK</td>
<td>8 yr</td>
<td>9.56</td>
</tr>
<tr>
<td>44007</td>
<td>Portland, 22.2 km southeast of Portland, ME</td>
<td>12 yr</td>
<td>9.10</td>
</tr>
<tr>
<td>44013</td>
<td>Boston, 29.6 km east of Boston, MA</td>
<td>12 yr</td>
<td>9.10</td>
</tr>
<tr>
<td>42040</td>
<td>Mobile South, 118.5 km south of Dauphin Island, AL</td>
<td>7 yr</td>
<td>9.15</td>
</tr>
<tr>
<td>42035</td>
<td>Galveston, 40.7 km east of Galveston, TX</td>
<td>11 yr</td>
<td>5.53</td>
</tr>
</tbody>
</table>
overfitting and other numerical problems because of the correlation between too many values (e.g., Medina 2005).

We therefore considered the following strategy for recognizing wave height patterns. We assume that the wave height information over the 24 h for which the forecast is made is a function of the wave heights over the previous 7 days, which in turn are assumed to have a decreasing influence as the measurements become more remote relative to the onset of the forecast. This permits a judicious selection of data points to cover a period typical of a storm length without creating very large matrices. To be specific, the input layer had 28 neurons representing 7 days of wave heights (at 12 and 24 h on days −7; at 8, 16, and 24 h on days −6 and −5; at 6, 12, 18, and 24 h on days −4 and −3; at 4, 8, 12, 16, 20, and 24 h on days −2 and −1). The output layer had 4 neurons pertaining to wave heights predicted on the eighth day at 6, 12, 18, and 24 h. Sets of 32 data pieces (28 input wave heights and 4 output wave heights) can in fact be created in this fashion at increments of 1 h. This creates over 8000 datasets per year. For the first buoy examined in our research (buoy 46082), the network was trained with all these sets. As the length of the data available for training was considerably greater for the other buoys, we examined the possibility of constructing the required input and output datasets on a daily basis rather than an hourly basis with the first forecast at 0500 local time (LT) on day zero. Thus, 358 sets were prepared for 1 yr of data. For buoy 46082, the results obtained by both methods were practically indistinguishable. For convenience, therefore, in training the network, we used datasets prepared on a daily basis. For testing, pairs of input and output sets were constructed on an hourly basis.

A separate network was developed for each location. Each network had one hidden layer for which the neurons were fixed after trial and error. Trials were done for each network by varying the number of neurons in the hidden layer, and the number of neurons yielding the highest correlation between the model predictions and the testing data was identified for each network. Table 3 provides the details of network architecture (defined by the number of input neuron, the number of neurons in the hidden layer, and the number of output neurons in the table) at all six locations along with the quantity of training and testing data. The data were normalized in the range from 0 to 1. A log-sigmoidal transfer function was used in between both the input layer and the hidden layer, and between the hidden layer and the output layer. The conjugate gradient algorithm with the Fletcher–Reeves update (CGF) was used to optimize the performance function represented

### Table 2. Data analysis. The top number in each data row is the number of measurements and the bottom number is the percentage.

<table>
<thead>
<tr>
<th>Buoy No.</th>
<th>No. of hourly measurements</th>
<th>Wave height measurements in 3-m intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.0–3.0</td>
</tr>
<tr>
<td>46082</td>
<td>17304</td>
<td>12813</td>
</tr>
<tr>
<td></td>
<td></td>
<td>74.06</td>
</tr>
<tr>
<td>46060</td>
<td>67608</td>
<td>67465</td>
</tr>
<tr>
<td></td>
<td></td>
<td>99.79</td>
</tr>
<tr>
<td>4007</td>
<td>105216</td>
<td>103659</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.52</td>
</tr>
<tr>
<td>44013</td>
<td>105216</td>
<td>103302</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.18</td>
</tr>
<tr>
<td>42040</td>
<td>58824</td>
<td>57840</td>
</tr>
<tr>
<td></td>
<td></td>
<td>98.32</td>
</tr>
<tr>
<td>2035</td>
<td>94224</td>
<td>94086</td>
</tr>
<tr>
<td></td>
<td></td>
<td>99.85</td>
</tr>
</tbody>
</table>

### Table 3. Network architecture.

<table>
<thead>
<tr>
<th>Buoy No.</th>
<th>Network architecture</th>
<th>No. of training datasets</th>
<th>No. of testing datasets</th>
</tr>
</thead>
<tbody>
<tr>
<td>46082</td>
<td>28–15–4</td>
<td>348</td>
<td>359</td>
</tr>
<tr>
<td>46060</td>
<td>28–9–4</td>
<td>2438</td>
<td>358</td>
</tr>
<tr>
<td>44007</td>
<td>28–4–4</td>
<td>3997</td>
<td>359</td>
</tr>
<tr>
<td>44013</td>
<td>28–4–4</td>
<td>4004</td>
<td>359</td>
</tr>
<tr>
<td>42040</td>
<td>28–9–4</td>
<td>2177</td>
<td>253</td>
</tr>
<tr>
<td>42035</td>
<td>28–7–4</td>
<td>3539</td>
<td>359</td>
</tr>
</tbody>
</table>
The details of the algorithm can be found in Hagan et al. (1996). All networks were trained for a variable number of epochs ranging from 50 to 5000. The testing results with training for 500 epochs were found to produce the highest correlation; the results presented here hence pertain to 500 epochs.

4. Results and discussion

All six networks were tested using data for 1 yr, generally for the last year (i.e., 2004), except for buoy 46060 where the data for the year 2003 were used (because the data for 2004 are largely missing). The predictions were made for the period between 8 January and 31 December at all locations except at buoy 42040, where measurements after 16 September 2004 were not available. A subset of the results, pertaining to four different months for four different buoys, is shown in Figs. 1 and 2 by way of a representative sample. It is immediately obvious that the 6-h forecasts agree with the measurements to a very high degree. Not only are the peaks and troughs reasonably captured for the most
part, but the short-term fluctuations in the wave heights are also reproduced remarkably well. The 12-h forecasts, too, despite a minor temporal offset relative to the target, display a fidelity to the measurements that is certainly acceptable for most practical applications. For large forecast lead times, the level of agreement with the data deteriorates; however, the inherent trends are correctly captured. These trends are merely readjusted as the lead time decreases (as seen in Figs. 1 and 2), so that the peaks and troughs line up temporally to coincide with the peaks and troughs in the data. Equally remarkable is the reinforcement of most modeled peaks, with decreasing lead time, toward the measured magnitudes.

Consolidated comparisons for the full year are provided in Figs. 3a–d for buoy 44013 (in the Gulf of Maine) and for part of the year in Figs. 4 and 5 for buoys 42035 (in the Gulf of Mexico) and 46060 (in the Gulf of Alaska). (Note that the “target” in Figs. 3a–d is slightly different because only the measurements at these exact times are plotted.) The results shown pertain to forecasts made at 2300 LT every day for 0500, 1100, 1700, and 2300 LT. It is clear that the general patterns of wave height variations are correctly captured by the underlying network and that the predictions are reasonable. The accuracy of the predictions (Table 4) is greater than 84% for all 6-h forecasts, between 67% and 83% for all 12-h forecasts, and between 55% and 71% for all 18-h forecasts. For the 24-h forecasts, although the accuracy is less than 63%, the general trends are again correctly reproduced (as seen in Figs. 1–5).

Looking at the comparison for the whole year highlights one limitation of the ANN model. Even for the case of the 6-h forecasts, which have a high correlation with data, it appears that the highest peaks are sometimes substantially underpredicted (near day 20 in Fig. 4 and near day 30 in Fig. 5). This behavior of the ANN-based predictions may be due to the possibility of the phenomenon of wave development (during episodes of these high waves) being marred or misrepresented by the chosen pattern of data arrangement. A more likely cause, though, is the relative dominance of the smaller wave heights in the datasets, which results in their greater influence during the training of the ANN and hence better predictions for low wave heights. This hypothesis was tested in two ways. First the target values were divided into 1-m intervals, and for each interval, the coefficient of correlation between the predicted and measured wave heights was determined. It was found that the correlation coefficient generally increased with the percentage of wave heights in each interval (Fig. 6) and, as indicated in section 3 (and Table 2), the percentage of wave heights in the 0–3-m range is the highest in all datasets. Thus, the networks are necessarily trained with smaller wave heights as a result of which
higher correlation coefficients are achieved for these wave heights.

The second test consisted of incorporating larger wave heights in the training. In most cases, the largest wave heights were contained in the data used to train the model (and not for testing). However, buoy 42040 in the Gulf of Mexico experienced extreme wave conditions during Hurricane Ivan; on 16 September 2004, the buoy recorded significant wave heights as large as 15.96 m before it was rendered nonfunctional. An examination of all wave data from all buoys around the United States revealed that this wave height was the largest ever recorded in the Gulf of Mexico and that wave heights exceeding this magnitude have only been recorded twice—16.32 m at buoy 46006 in the northeast Pacific Ocean on 27 October 1999 and 16.9 m at buoy 46003 in the southern Gulf of Alaska on 16 January 1991. The ANN model was trained with and without the data from 2004 and tested against data for 1998.

This testing period was selected because it contained 3 episodes where the largest significant wave height exceeded 6 m with an absolute maximum of 10.88 m, which was the largest wave event recorded by this buoy prior to Hurricane Ivan and is of the order of a 300-yr wave condition. Figures 7a,b show 6-h predictions for buoy 42040 for the year 1998, obtained by including and excluding the 2004 data for training. The results of the network that included the 2004 data for training show a greater tendency toward catching the peaks relative to the network that omitted these data for training. At point D in Fig. 7, the predicted wave height increases from 5 to 10 m (the target being 10.88 m). The rising trend is correctly reinforced for peaks A, B, and C also, although the predictions are somewhat greater than the target wave heights (6.95 versus 5.25 m, 8.58 versus 6.71 m, and 7.75 versus 5.96 m at A, B, and C, respectively). This overprediction may be attributed to the extreme nature of the 2004 data. The probability of occurrence
of the 15.96-m wave height, based on the Gumbel distribution, has been estimated to be as low as 0.0025% in any given year (Panchang and Li 2006). This is not merely a large event, rather it is an extraordinarily large event whose effect in network training appears to be particularly significant. That the overprediction at A, B, and C was attributable to this rare event was confirmed by artificially modifying the wave heights for 48 h during Hurricane Ivan by a factor of 0.9 while training the network. These resulting predictions (not shown) were practically indistinguishable everywhere except at the peaks where the predictions were 5.22, 5.77, 5.53, and 6.08 m. Clearly the overprediction at A, B, and C has been reduced and the results match the measurements better. Understandably, the peak at D is now underpredicted, but this test demonstrates the effect of the extreme events on the prediction technology.

The general underprediction noted above (e.g., Figs. 3–5) has not been explored in previous studies and appears to be related to the variability of data patterns and the length of the data (which are generally proportional). As mentioned earlier, the data used by Agrawal and Deo (2002) covered only 16 months and the wave height variability was small (between 0 and 1.4 m). In all of our results, the ANNs have predicted wave heights in this range very well. The duration of the data used by Makarynskyy (2004) was only slightly longer, namely, 21 months. To examine the effect of the length of the data used for training, we trained the ANN model for buoy 42040 using data for 1 yr (1997) and 2 yr (1996 and 1997) and attempted to forecast waves for 1998. The results, shown in Figs. 8a,b, show that the predictions improve as the training data length increases, but many of the large waves are still underpredicted (see points A, B, C, and D). When a greater level of interannual variability is introduced in the training by adding data from the years 1999–2004, the large waves are predicted even better (as was shown in Fig. 7b). However, judging from the similarity between Figs. 8b and 7a, one can conclude that the additional years 1999–2003 had a rather small effect relative to the year 2004. These tests clearly indicate that the variability of the data is critical to obtaining reliable predictions.
The above result also suggests that the accuracy of our predictions (Table 4) for buoy 46082 off the coast of Alaska may be fortuitous, because the training dataset was of only 1-yr duration. Had the waves in 2004 displayed a different character and contained much larger waves than those actually observed, the predictions in general would perhaps still exhibit a high correlation to the measurements, but it is entirely likely that the largest waves would be underpredicted. Possibly the same inference can be drawn of the results presented by previous researchers as well.

One aspect of data-based forecasting is the possibility of the dominance of the latest measurements on the forecast. This was examined to a certain extent by comparing the results of the ANN prediction with a persistence forecast, where the last observation was regarded as the forecast. A sample result is shown in Fig. 9 for a lead time of 24 h. Clearly, the ANN model does more than merely replicate the last observation. As the lead time decreases, the difference between the two models tends to diminish; this is understandable since the wave conditions do not generally change much in short time intervals.
We also tried to use wind speeds (available with the buoy measurements) as an additional input along with wave heights in an attempt to increase the accuracy of the forecasts. Unfortunately, a large improvement in the results was not observed.

5. Real-time implementation

Real-time wave prediction was performed at the location of one buoy in each geographic area (buoy 42035 near Galveston, buoy 46060 in Prince William Sound, and buoy 44013 near Boston) using the weights and biases obtained by training their respective networks. The models were run continuously from 1 April 2005 using the previous 7 days of wave height measurements selected according to the pattern described earlier. Predictions were made from 1 to 30 April 2005. These are shown in Fig. 10 (for buoy 44013) along with buoy measurements that were retrieved after the forecasts were made. The 6-h forecasts are observed to be highly reliable for most applications. The results also display the same trends noted earlier, that is, that the 6- and 12-h forecasts are more accurate than the 18- and 24-h forecasts (these latter forecasts are not shown). The repeated implementation of these models required for operational forecasting was rendered possible by the very small simulation time. Once trained, the ANN models required less than 1 s (on a Pentium 4 processor with 1 GB RAM) to provide a forecast.

6. Concluding remarks

We examined the use of ANN-based models for the forecasting of significant wave heights at six locations with diverse geographical and statistical properties. The chosen model, which uses the previous 7 days of significant wave height data, provided predictions that had a correlation of over 67% relative to the observed wave heights for lead times of 12 h and over 84% for a lead time of 6 h in a full year of validation. For larger lead times, the trend was correctly forecast, but the actual wave heights or the timing of peaks showed (usually) a delay relative to the data. Even for shorter lead times, the actual peaks were occasionally underpredicted; however, the inclusion of greater variability in the data used to train the model resulted in a significant improvement in its ability to reproduce the large peaks. Future investigations will involve efforts to better predict the correct magnitude of the peaks associated with the highest waves. It is also seen that once trained, the implementation of the ANN model is extremely rapid. It is possible, therefore, to consider the ANN-based models as value-added software to complement the basic software that converts the raw water level data into significant wave heights.
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