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Artificial neural network to translate offshore satellite wave data to coastal locations

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Abstract

Owing to the spatial averaging involved in satellite sensing, use of observations so collected is often restricted to offshore regions. This paper discusses a technique to obtain significant wave heights at a specified coastal site from their values gathered by a satellite at deeper offshore locations. The technique is based on the approach of Artificial Neural Network (ANN) of Radial Basis Function (RBF) and Feed-forward Back-propagation (FFBP) type. The satellite-sensed data of significant wave height; average wave period and the wind speed were given as input to the network in order to obtain significant wave heights at a coastal site situated along the west coast of India. Qualitative as well as quantitative comparison of the network output with target observations showed usefulness of the selected networks in such an application vis-à-vis simpler techniques like statistical regression. The basic FFBP network predicted the higher waves more correctly although such a network was less attractive from the point of overall accuracy. Unlike satellite observations collection of buoy data is costly and hence, it is generally resorted to fewer locations and for a smaller period of time. As shown in this study the network can be trained with samples of buoy data and can be further used for routine wave forecasting at coastal locations based on more permanent flow of satellite observations.

Keywords: Wave data; Wave mapping; Artificial neural networks; Multiple regression

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1. Introduction

Considerable amount of data pertaining to wave heights, wave periods and wind speeds are routinely collected by satellites like European Remote Sensing (ERS), Topography Experiment (Topex), Jason and Environmental Satellite (EnviSat). Corresponding observations normally pertain to deeper locations in the ocean, typically 30 km away from the shoreline. This is because of the manner in which data are sensed and averaged. For operational planning of any coastal activity, like arriving at a clear-weather window for construction or for navigational movements, values of wave heights at locations much closer to coasts are needed. Waves propagating from deeper water to shallower region undergo considerable change in their magnitudes because of shoaling, refraction and diffraction. Currently the problem of obtaining waves at coastal locations is solved either by adopting empirical methods, like drawing refraction diagrams and using simplified equations, or by employing complex numerical schemes aimed at integrating shallow water equations. These techniques are mainly oriented towards works like harbor design and planning exercises rather than forecasting waves on real time or short-term basis at specific stations as envisaged in this study. A need exists to explore new techniques to translate the deep-water observations to shallow water regions in order to meet such requirement. Transformation of waves into shallower depths is a highly non-linear and uncertain process and hence, this was done in the present work with the help of artificial neural networks (ANN). ANN basically maps any input vector to the corresponding output vector without going into the physical process involved. This is achieved by following the process of cognition working in human brains.

2. The networks

Neural networks derive their strengths from a ‘model-free’ processing of data and a high degree of freedom associated with their architecture. A neural network consists of interconnected nodes or neurons, each acting as an independent computational element. Most common type of network for engineering applications is multi-layered perceptron (MLP) shown in Fig. 1, which has the ability to approximate any continuous function. It has three basic layers of neurons: input, hidden and output with the flexibility that the hidden layers could be more than one, if need be. Each neuron or node sums up the weighted input, adds a bias term to it, passes on the result through a squashing function and transmits the product to neurons in a subsequent layer. Details of concepts involved in neural networks could be seen in books like Kosko (1992), Wu (1994) and Wasserman (1998). Typical applications in problems related to water flows could be seen in The ASCE Task Committee (2000). Some of the recent studies involving wave analysis and forecasting are given in Deo and Naidu (1999), Krasnopolsky et al. (2002), Huang et al. (2003), DelBalzo et al. (2003), Deo et al. (2001), Deo and Jagdale (2003), Makarynsky (2004), Tolman et al. (2004) and Altunkaynak and Ozger (2004).

A neural network is trained from examples before its actual application. Training comprises presentation of input and output pairs to the network and derivation of the values of connection weights, bias or centres. The training may require many epochs

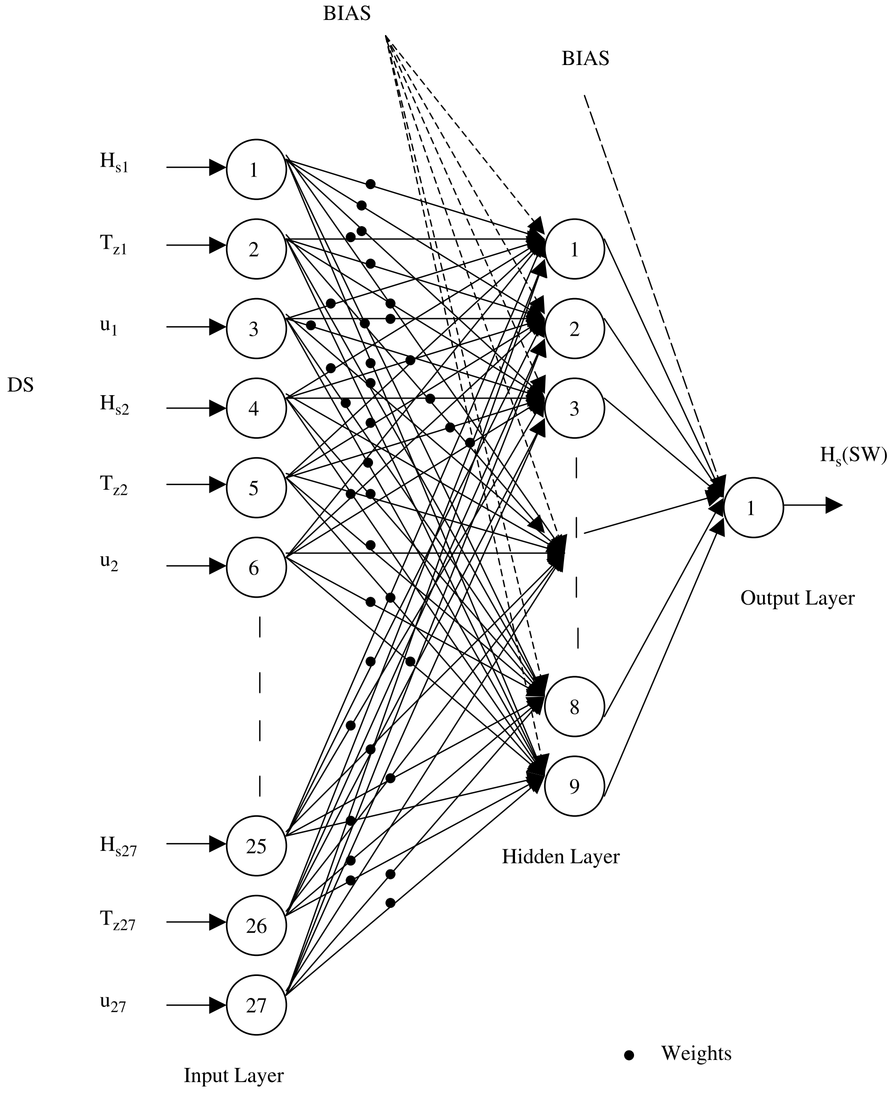


Fig. 1. The MLP network.

(presentation of complete data sets once to the network). Generally the network is presented with an input and output pair till the training error between the target and realized outputs reaches the error goal.

In the present study the multi-layered perceptron (MLP), (Fig. 1) configured as per the relatively recent and advanced architecture called radial basis function (RBF), was used along with the general and basic feed forward back-propagation (FFBP) network. The radial basis function has been found to be more useful than the FFBP by some investigators of hydrology (The ASCE task committee, 2000; Kisi, 2004). It was decided to see if it works well for this application involving ocean waves as well.

Like a general MLP the RBF is also a feed forward network, but has only one hidden layer and involves an unsupervised training component in it. This is unlike the FFBP where only supervised learning is intended. Further, it differs from the latter in treating the data non-linearity through the hidden nodes. While the FFBP affects this through a fixed function such as a sigmoid, the latter captures the same directly from the training examples. Mathematical expressions behind the training of FFBP can be seen in The ASCE Task Committee (2000).

The input to each RBF neuron is treated as a measure of the difference between data and a ‘centre’, which is a parameter of its transfer function. (Fig. 2). The transfer function of the neuron indicates the influence of data points at the centre. Generally this function is Gaussian and its centres can be chosen either randomly from the training data or they are iteratively trained or derived using techniques like K-means, Max–min algorithms, Kohonen self organizing maps. After this unsupervised learning and cluster formations the weights between the hidden and output layer neurons are determined by multiple regression in a supervised manner. The concept of such a fragmented learning is borrowed from certain biological neurons (doing say visual recognition), which function on the basis of ‘locally tuned response’ to sensing. The RBF does not involve iterative training and hence much of the training time is saved. Mathematically the output y of an RBF network corresponding to input x (Refer to Fig. 2) is computed by the equation:

$$y = f(x) = \sum_{i=1}^{n} w_i \varphi \|x - c_i\| + w_0 \tag{1}$$

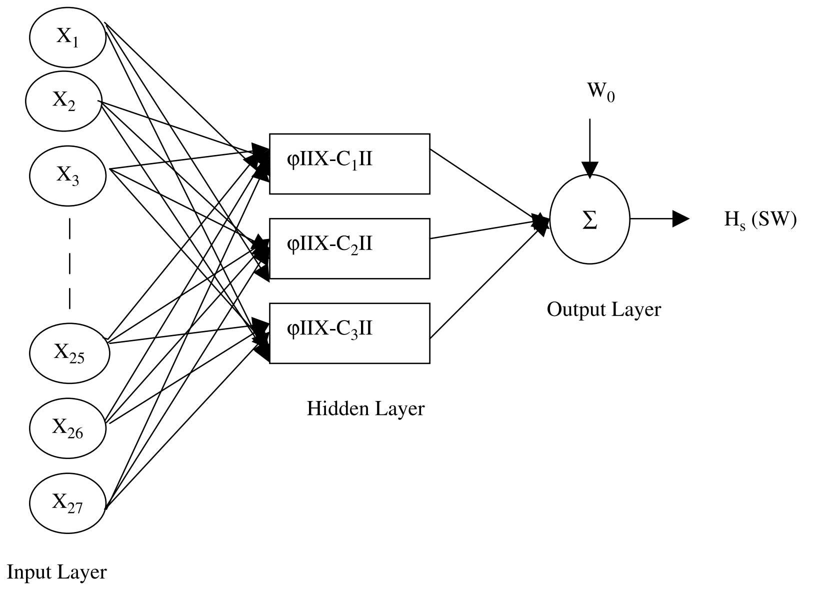


Fig. 2. RBF neural network architecture.

where w_i, connection weight between the ith hidden neuron (of n number) and output neuron; w_0 = bias. $\phi\|x - c_i\|$ indicates a radial basis function which is normally Gaussian having following expression:

$$\varphi\|x - c_i\| = -\exp\left(-\sum_{i=1}^{n} \frac{\|x_i - c_i\|^2}{2\sigma_i^2}\right) \tag{2}$$

where c_i are centres of the receptive field; and σ_i, widths of the Gaussian function which indicates the selectivity of a neuron.

The present study also involved use of the basic FFBP type of network. In its simplest form such a network involves minimization of the error between realized and target outputs according to the steepest or gradient descent approach. However, in order to make sure that adequate training was imparted five different varieties of the MLP training schemes were employed to train such network. These were Resilient back-Propagation (RP), Scaled Conjugate Gradient (SCG), Conjugate Gradient Powell-Beale (CGB), Broyden, Fletcher, Goldfarb (BFG), and Levenberg-Marquardt (LM). In any training schemes the difference or the error between the network-yielded and the target or actual output is minimized using a particular mathematical algorithm. The rate of change of error with respect to the connection weights, i.e. the error gradient is used as a path to do so. The RP algorithm is aimed at eliminating problems arising out of smaller magnitudes of the error gradients. A general conjugate gradient scheme involves performing a search along the conjugate or orthogonal direction in order to determine the step size to minimize the performance function. There are different versions of such an algorithm as per the technique of finding a new search direction like the SCG and CGB. The BFG scheme is a variant of the Newton's method of iteration and involves updating the Hessian matrix at iteration. The need to compute such a matrix is eliminated in the LM algorithm, which is designed to approach the second order training speeds. The details of these algorithms can be found in Demuth et al. (1998).

3. The data base

Data collected by the TOPEX satellite off the west coast of India along with the wave rider buoy measurements at locations DS1, DS2, SW3 and SW4 (as shown in Fig. 3) were available for a period of about 4 years during 1998–2001. From the satellite data base so obtained daily values of the significant wave height, average wave period and wind speed were extracted at selected locations around DS1 and DS2. Wave rider buoy data were 3-hourly from which daily averages were made and used for this study.

4. Network development and testing

The spatial mapping underlying this study was made based on the input of satellite observations over a series of locations around the offshore site DS1 and over the track followed by the satellite. (See Fig. 3). Such input was translated to the coastal location

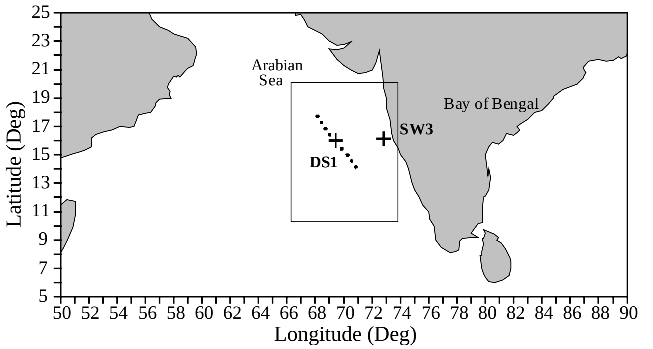


Fig. 3. The site map.

SW3 noting that the major direction of wave approach is westerly. Initial trials showed that at the most nine offshore stations could be used otherwise the network become too large to effectively train and generalize. It was also found that instead of giving values of significant wave heights only as input those of associated average wave period and wind speed as well were necessary for a better generalization and flexible data mining. Hence, the RBF network consisting of 27 input nodes of daily significant wave height, wave period and wind speed sensed by the satellite at the selected nine offshore stations and the single output node of the significant wave height recorded by the wave rider buoy at the coastal location SW3 was developed. It is to be noted that the buoy data has been used only for training purpose and that in the case of actual applications on routine basis in future no buoy measurements would be required. Wave rider buoy measurements are very costly, especially for a developing country like India and hence they cannot be resorted to for long-time unlike the satellite observations, which are available at much cheaper cost. The network was trained with the help of the main processor available in the NN toolbox under MATLAB. The number of hidden nodes in the single hidden layer was 3. The total length of available time history of simultaneous observations at the offshore as well as coastal locations was divided into two segments in the proportion of 70:30%. The former 70% was used for training the network while the remaining 30% was used for testing the accuracy of the learning process carried out. The number of input–output pairs was 319 during training while the same was 90 in the testing work.

Fig. 4(a) shows the comparison (in respect of testing data that were not involved in network training) between the network output and the target one, based on the rider buoy measurements, in terms of a scatter diagram. Fig. 4(b) shows the same through the time history comparison. It may be seen that the networks predictions are close to their true values, although they have a tendency to smoothen out the time series rather than perfectly following the rising and falling trend of the time series for initial low wave activity. The exact reason why initial predictions were not very good was not clear; but this indicates that too much averaging took place during clustering of closely spaced smaller waves during the unsupervised learning step. Nonetheless, the overall accuracy of predictions was found to be good when quantitative measures were applied. Three error criteria were

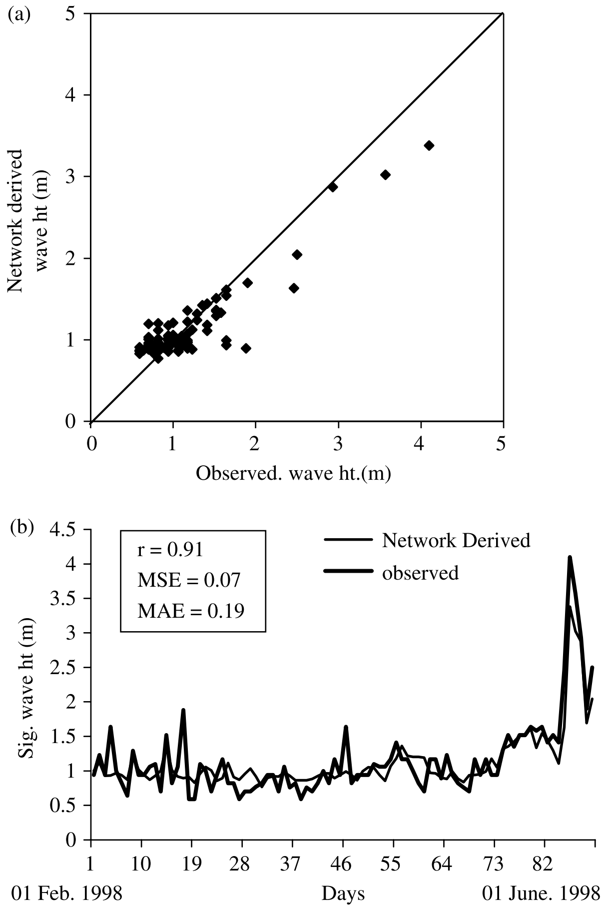


Fig. 4. Validation of RBF network mapping between TOPEX satellite measurements and SW3: multi-series input: (a) scatter plot; (b) time history plot.

evaluated. They were (i) the correlation coefficient, *r*, which measures the degree of linear association between the two quantities being compared, but which is very sensitive to very high or very low values, (ii) the mean square error, MSE, which is an appropriate measure when iterative procedures are involved and (iii) the mean average error, MAE, which is more commonly understood in engineering analysis. In the present case the correlation coefficient was 0.91, while the MSE and MAE were 0.07 and 0.19, respectively. Higher magnitude of *r* and lower one of MSE and MAE thus indicate satisfactory performance of the RBF network.

In order to see how the above RBF network performed vis-à-vis the traditional and basic feed forward back propagation type of network, the latter one was developed with the same input, output as that of the RBF. The number of hidden neurons in this case was calculated by trials aimed at getting the minimum value of MSE at the end of a sufficiently large number of training iterations. This was nine. The FFBP network was trained not only by one but by at least five different schemes namely, RP, SCG, CGB, BFG and LM mentioned earlier in order to ensure that adequate training was imparted and also to see if better training was possible through the options available. It was found that the conjugate gradient method CGB produced most accurate results. This is in line with observations in some other studies (e.g. Thirumalaiah and Deo, 1998, 2000) where efficient search technique underlying general conjugate gradient was found to be advantageous. Fig. 5(a) and (b) show the results of this exercise and compare the target wave heights at the coastal location with the network-derived ones. It may be seen that the lower-value predictions were fairly oscillatory as required, rather than averaging type in case of the earlier RBF network, and that the higher values beyond 2 m were better predicted by this network.

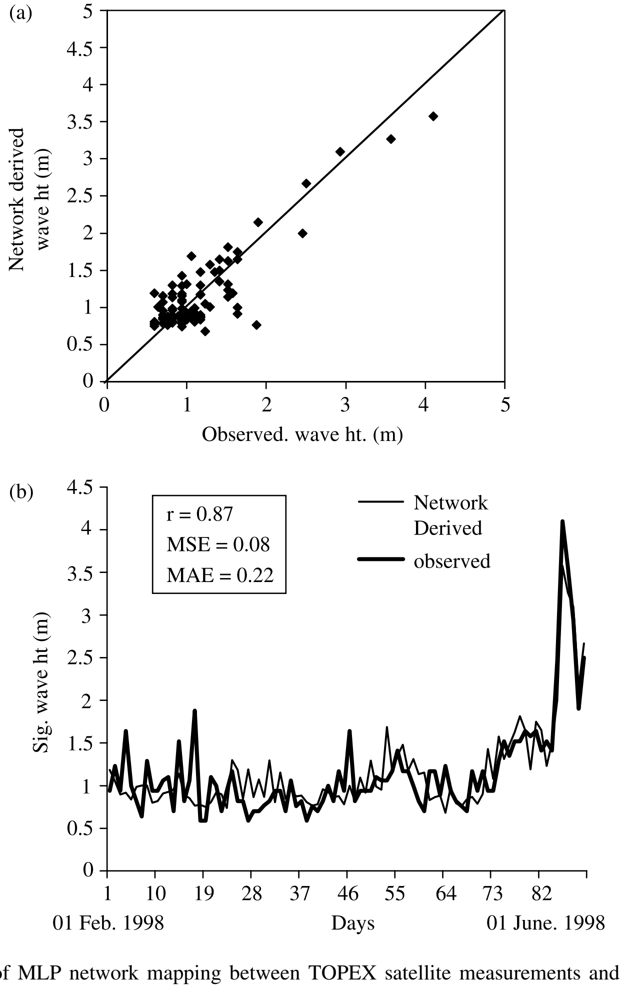


Fig. 5. Validation of MLP network mapping between TOPEX satellite measurements and SW3: multi-series input: (a) scatter plot; (b) time history plot.

Quantitatively however the FFBP had a lower overall accuracy as reflected in relatively smaller values of $r = 0.87$, MSE $= 0.08$ and MAE $= 0.22$ than the RBF.

It is to be noted that the FFBP handles data non-linearities through fixed sigmoid function while the RBF does so directly through data clustering. The former processing scheme modeled higher waves in a better way and also showed good tendency to pick up rises and falls of lower values, but its overall accuracy was somewhat lower than the latter.

Finally, considering that the above comments should be viewed in the light of limitations on data quality and size it can be suggested that for the locations under consideration it would be more prudent to use both the networks for forecasting and take operational decisions after jointly viewing the forecasted values.

5. Checking adequacy of the input

Instrumental observations by wave rider buoys can be expected to be more accurate and reliable than remotely sensed satellite information. In order to see how far the error in predictions could be relegated to accuracy of the satellite input a study was made where offshore buoy measurements were mapped with coastal buoy observations. The wave rider buoy measurements of wave height, period and wind speed at the offshore site DS1 (15.236°N, 69.371°E) and at the coastal location SW3 (18.367°N, 73.751°E) were involved.

A FFBP network with three input nodes of daily values of significant wave height, wave period and wind speed at the deep-water location and one output node of daily values of shallow water significant wave heights was developed. Note that all measurements involved in this exercise were collected through wave rider buoys. The number of hidden nodes was found by trials and it was two. The training pairs corresponded to the 70% segment of recorded wave time series and they were 596 in number. The developed network was validated with remaining 30% of input–output pairs occurring in a sequence and numbering 90. The testing results are shown in Fig. 6(a) and (b), where the network-yielded values were compared with actual observations in terms of a scatter diagram as well as a time history plot. The scatter diagram, as expected, much better match between the network output and the target one qualitatively than the earlier satellite-based mapping. This was further confirmed by the underlying high values of the correlation coefficient (r) of 0.96 as well as low values of the mean square error (MSE) of 0.06 and mean average error (MAE) of 0.20. This compares favorably with the earlier (satellite input case) values of $r = 0.91$, MSE $= 0.07$ and MAE $= 0.19$ and shows viability of satellite based projection of offshore waves.

6. Checking necessity of the neural approach

Traditional method of data mining in the case of current application would be the statistical technique of multiple regression. In order to check necessity of the RBF network

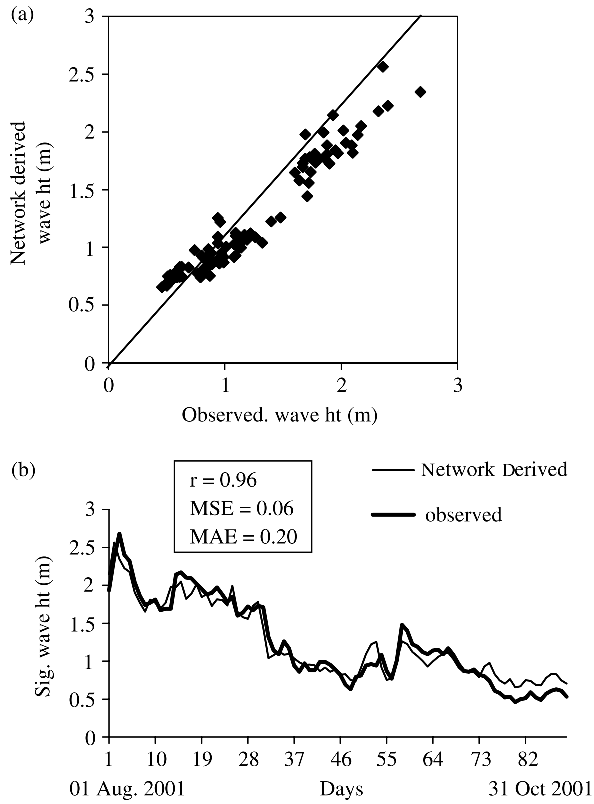


Fig. 6. Validation of network mapping between buoy measurements at DS1 and SW3: (a) scatter plot; (b) time history plot.

it was decided to see how it performed vis-à-vis the regression. The statistical methods are model-oriented and assume a fixed form of a mathematical model beforehand to which the data are fitted. As against this neural networks are data-oriented and come up with their own form of the dependency structure between the input and the output. A multiple regression model of the following type was fitted to the data:

$$\mathbf{y} = [\mathbf{A}]_{1\times 27}[\mathbf{X}]_{27\times 1} + \mathbf{B} \tag{3}$$

where y, significant wave height at the coastal station. $[A]$, coefficient matrix determined by least squares approach, $[x]$, matrix of 27 input (variables) of the offshore region (sensed by the satellite) namely, wave height, Hs in m at station 1, wave period, T_z in s at station 1, wind speed, U in m/s at station 1 and so on for all the nine offshore locations sequentially. B is a constant. The above equation was established with the help of the same training set of data as used earlier.

The coefficient matrix so resulted was as follows:

$$X = [0.1285 - 0.0019 - 0.0117 + 0.1495 - 0.0235 + 0.0583 + 0.1812 + 0.0445 - 0.0880 - 0.8834 + 0.0482 + 0.1460 + 0.8479 - 0.0698 - 0.1407 - 0.1286 - 0.0519 + 0.0362 - 0.1780 + 0.0789 + 0.1359 + 0.3571 + 0.0167 - 0.0286 + 0.7873 - 0.1030 - 0.3623] \quad (4)$$

$$B = 1.3833 \quad (5)$$

This regression when validated with respect to the testing pairs indicated a high level of discrepancy between the predicted and the observed wave heights at the coastal location. This can be seen in the scatter diagram of Fig. 7(a). As well as the time history comparison of Fig. 7(b). A visual qualitative comparison as well as the error measures of 0.59 for the correlation coefficient and of 0.30 and 0.46 for the mean square and the mean average errors confirm relatively very poor performance of the regression compared to the neural networks which corresponded to $r=0.91$, MSE=0.07 and MAE=0.19. It may thus be

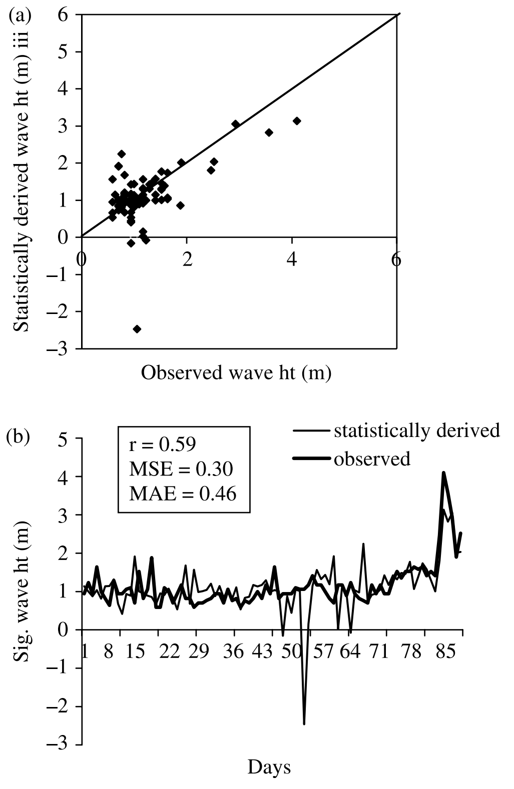


Fig. 7. Validation of statistical (linear regression) mapping between TOPEX satellite measurements and SW3 (multi-series input): (a) scatter plot; (b) time history plot.

admitted that the complexity of neural networks was indeed necessary to solve the problem of translating offshore satellite observations to coastal locations as envisaged in this study.

7. Checking necessity of the multivariate input

The previous results made on the basis of TOPEX observations included input coming from a series of stations along the path of the satellite. It was decided to see if the same mapping between the offshore and the coastal water could be done equally correctly if a single (offshore) location series was instead employed. Another FFBP network was accordingly developed, where the input was values of the TOPEX-sensed Hs, T_z and U at the location DS1 and the output was the translated significant wave heights at the coastal site SW3. As earlier the first 70% segments of the time series was used for training while the remaining 30% served the purpose of testing. The testing window was slided along the available data base till most accurate results were realized. The resulting input–output

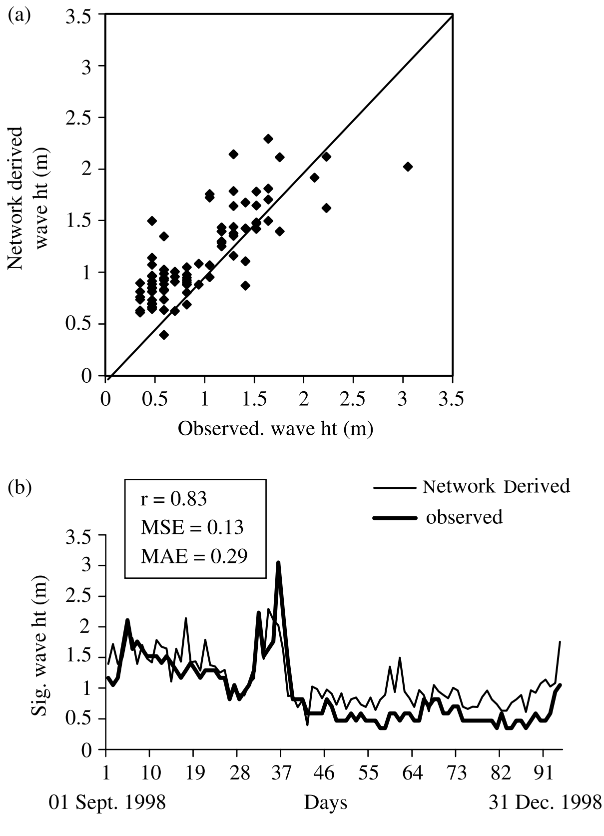
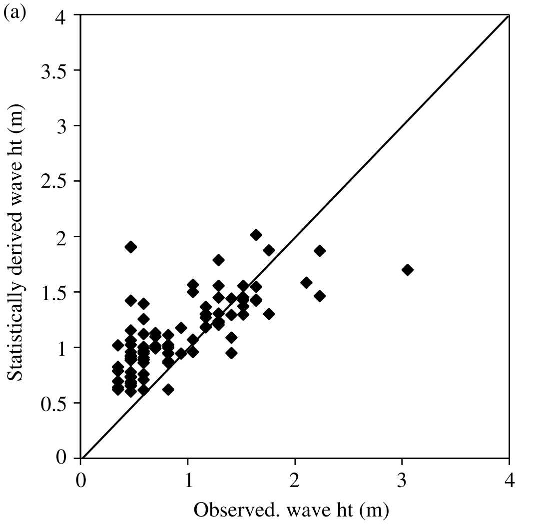


Fig. 8. Validation of MLP network mapping between TOPEX satellite measurements and SW3: single series input: (a) scatter plot; (b) time history plot.

pairs were thus 438 and 94, respectively. Results of testing are shown in Fig. 8(a) and (b). It may be seen that the outcome was poorer compared to Fig. 5(a) and (b) where input from several series was given. The associated error measures ($r=0.83$, MSE$=0.13$ and MAE$=0.29$) confirm this. The scatter diagram further shows systematic over-prediction by the network in this case. It appears that the network does require the flexibility in data mining associated with the multiple site input discussed in Section 6

It was also decided to see if the traditional multiple regression works equally well for the above simple mapping. The least squares fit to the training data yielded following equation in this regard to predict the significant wave height $(Hs)_s$ at the location SW3 from the satellite-sensed values of the significant wave height $(Hs)_0$, average wave period,



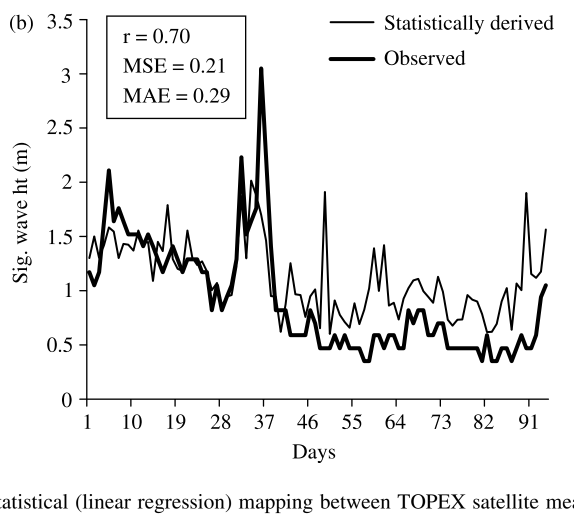


Fig. 9. Validation of statistical (linear regression) mapping between TOPEX satellite measurements and SW3: single series input: (a) scatter plot; (b)time history plot.

T_z and average wind speed, U at DS1.

$$(\mathrm{Hs})_s = 0.29 \quad (\mathrm{Hs})_0 + 0.02 \quad T_z + 0.04 \quad U + 0.04 \tag{6}$$

A comparison of such prediction with the actual rider buoy measurements is shown in Fig. 9(a) and (b). This again indicates a very poor performance by the regression. Quantitatively, this was seen in the values of the correlation coefficient $r = 0.70$, MSE = 0.21 and MAE = 0.29.

If performances of the two regression models, Eq. (3) for the multiple series input and Eq. (6) for the single series input are compared it would appear that the difference between the neural networks and the statistical models becomes large when the complexity of the mapping (multiple series) increases. This confirms the belief, often rarely proved, that the usefulness of neural networks increases with increasing non-linearities in the underlying phenomenon.

8. Necessity of trials to arrive at initial weight matrix

In line with the above observations and during the course of the studies it was also found necessary to have adequate trials with varying initial weight space if proper training convergence is desired. In case of the single series input hardly two or three such trials were found to be sufficient while in case of the complex mapping with multiple series several such simulations were needed. This can be seen from Table 1, which shows how the testing accuracy changes with varying matrix of initial weight and bias values, in case of the multiple series input.

Table 1
Changes in testing accuracy with varying initial weights and biases

Simulations	Correlation coefficient	MSE	MAE
1	0.73	0.16	0.29
2	0.80	0.12	0.24
3	0.79	0.14	0.27
4	0.77	0.14	0.27
5	0.72	0.18	0.29
6	0.79	0.13	0.28
7[a]	0.87	0.08	0.22
8	0.75	0.16	0.27
9	0.62	0.27	0.33
10	0.68	0.24	0.30
11	0.82	0.11	0.26
12	0.85	0.09	0.23
13	0.78	0.13	0.27
14	0.74	0.16	0.29
15	0.61	0.28	0.31

[a] Maximum correlation.

9. Conclusions

The foregoing sections discussed a technique based on the RBF and FFBP type of neural networks to obtain significant wave heights at a specified coastal site from their values sensed by a satellite at deeper offshore locations. The need to do so arise from the spatial averaging involved in sensing data by satellites.

The RBF network yielded output with 19% error on average. Although the overall performance of the FFBP was somewhat lower than that of the RBF, it predicted higher waves more satisfactorily.

Complexity of neural networks was found to be necessary vis-à-vis traditional and simpler statistical regression, which produced highly unacceptable results. Neural networks were proved to be more useful when the underlying mapping becomes more non-linear and complex.

The required number of simulations of the initial weight matrix needed to achieve training convergence increased with the underlying complexity of mapping.

Neural networks provide a useful tool to project deep-water waves sensed by satellites to desired coastal locations. They can be effectively employed to carry out such a correlation on on-line mode. Unlike the satellite observations, collection of buoy data is costly and hence, it is generally resorted to fewer locations and for a smaller period of time. As shown in this study the network can be trained with samples of buoy data and can be further used for routine wave forecasting at coastal locations based on more permanent flow of satellite observations.

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