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Artificial Neural Networks for Coastal and Ocean studies

Pooja Jain
Reasearch Scholar, Dept. of Civil Engineering, Indian Institute of Technology Bombay, Mumbai, India

M. C. Deo
Professor, Dept. of Civil Engineering, Indian Institute of Technology Bombay, Mumbai, India

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ABSTRACT: Artificial neural network (ANN) is a major tool in artificial intelligence computing and it is also extensively used across all disciplines of coastal and ocean engineering including offshore, deep-ocean and marine engineering. A review of important research studies reported so far in these areas is presented. ANN in general has provided either substitutive or complementary option to traditional computational schemes of statistical regression, time series analysis, pattern matching and numerical methods. A reduced data requirement in case of ANN applications was also noticed in some cases. In future advanced and hybrid ANN architectures are likely to be applied in new and unexplored areas of applications. Similarly attempts are likely to be made to tackle issues such as large variations in input, longer prediction intervals and prediction of extremes by extrapolation beyond the sample time. A recent application of the ANN technology to forecast waves in real time sense over the vast coastline of India has been briefly described.

1 Introduction

An artificial neural network (ANN) follows the cognition process of the biological neurons of our brain and develops the intelligence from communications between different artificial neurons. It is basically suited to map any random input vector with corresponding output vector and can be applied to carry out tasks such as function approximation, optimization, system modeling and pattern recognition. A major advantage of the ANN is that it does not call for knowledge of the underlying physical process a priori and does not assume any mathematical model beforehand. Further the ANN is required neither to omit a large number of input variables nor use them after making simplifications. Any exogenous input other than the input-output patterns is also not necessary to build the ANN.

Readers may be referred to text books like Wu (1994), Kosko (1992) and Wasserman (1993) to understand the theoretical details of working of a neural network. It should suffice here to say that the basic computational element in the network is a neuron or a node. It combines the input, determines its strength by comparing the combination with a bias or alternatively by passing it through a non-linear transfer function and sending out the result in proportion to such a strength, i. e.,

$$O = 1 \ / \ [\, 1 + e^{-S} \,] \qquad \text{where, } S = (x_1 w_1 + x_2 w_2 + x_3 w_3 + \ldots\ldots) + \theta \tag{1}$$

In the above equaiton O = output from a neuron; x_1, x_2,..... = input values; w_1, w_2,.......= weights along the linkages connecting two neurons, indicating strength of the connections; θ = bias value. In eq. (1) 'O' indicates a transfer function of Sigmoid nature. There are other forms available, such as, sinusoidal, Gaussian, hyperbolic tangent.

Most of the ANN applications in ocean engineering have involved a feed forward type of the network as against the feedback or recurrent one. Such a feed forward multi-layer network consists of an input layer, one or more hidden layers and an output layer of neurons (Fig. 1). It works as below:

Calculate weighted inputs, i.e.,

$$N_j = \sum_{i=1}^{NIN} (W_{ij} x_i) + \beta_j \tag{2}$$

where, N_j = summation for j-th hidden node, NIN = total number of input nodes, W_{ij} = connection weight i-th input and j-th hidden node, x_i = normalized input at i-th input node, β_j = bias value at j-th hidden node.

Transform the weighted input:

$$O_j = 1/(1+e^{-N_j}) \tag{3}$$

where, O_j = output from j-th hidden node.

Sum up the hidden node outputs:

$$N_k = \sum_{j=1}^{NHN}(W_{jk}O_j) + \beta_k \tag{4}$$

where, N_k = summation for k-th output node, NHN = total number of hidden nodes, W_{jk} = connection weight between j-th hidden and k-th output node, β_k = bias at k-th output node.

Transform the weighted sum:

$$O_k = 1/(1+e^{-N_j}) \tag{5}$$

where, O_k = output at k-th output node.

Before its actual use the network is trained by feeding it with examples of known input-output patterns and the weights are accordingly fixed. The supervised training involves feeding input-output examples till the network develops its generalization capability while the unsupervised one makes classification of the input into clusters by some rule. In the supervised training the network output is compared with the desired or actual one and the error so resulted is processed with the help of a mathematical algorithm. In such a procedure the connection weights and bias are continuously changed by following an iterative process till the desired error tolerance is achieved. For the most common training algorithm of back-propagation (BP), the global error, E, defined below is minimized:

$$\Delta = (1/P)\sum_{p=1}^{P}\Delta_p \quad \text{where} \quad \Delta_p = (1/2)\sum_{k=0}^{N}(O_k - t_k)^2 \tag{6}$$

where, P = the total number of training patterns, Δ_p = error at p-th training pattern; N = the total number of output nodes, O_k = output at the k-th output node, t_k = target output at the k-th output node. The weights over different linkages as well as the bias values are adjusted till the error Δ_p reaches its minimum. For minimizing the global error, the steepest or gradient descent approach is common in which where the correction to a weight, Δw, is made proportional to the rate of change of the error with respect to that weight.

2 General observations from the past studies

In coastal and ocean applications the ANN's have been used mainly to evaluate or forecast some random parameter. These are the wave height, wave period, wave direction, tidal levels and their timings, sea levels, water temperature, wind speeds, estuarine characteristics, coastal currents and sediment movement rate. Additionally forces on structures, including wind and wave loads, structural damage indicators, ship design parameters, barge motions, scour depth and soil liquefaction have also been evaluated with ANN. Table 1 lists such works carried out by different investigators.

It is found that apart from improving the accuracy of the outcome the ANN's have significantly reduced the computational effort as well as time (Krasnopolsky et al. (2002) and Xu and Haddara (2001)) compared with traditional methods.

For network calibration authors have largely used field data as against the laboratory observations, although data generation by mathematical or numerical analysis was seen in a few cases (Mahfouz and Haddara (2003), Zubaydi et al. (2002), Banerji and Datta (1997)). The sample size required for learning was varying, but Tsai et al. (2002), Lee (2004) and Lee and Jeng (2002) found that the ANN can learn with much small sample as compared with traditional methods such as harmonic tide analysis.

Although in most of the applications the feed forward type of network was common, alternatives such as recurrent or Elman type where a 'memory' from the past examples is accounted for have been used by Moreira and Soares (2003), More and Deo (2003), Balas et al. (2004). The training algorithm of the back-propagation is common but alternative efficient algorithms of cascade correlation, conjugate gradient and search based schemes have also been used by More and Deo (2003), Deo and Kiran kumar (2000), Londhe and Deo (2003), although this had not resulted in any large improvement in result accuracy due to the saturated capacity of the network to cater to a fixed sample size of the input. When too much simplification of the underlying physical process by the ANN was not sufficient a hybrid input-output mapping by combining the ANN with statistical regression, genetic algorithms, Kalman Filter and other specific tools like random decrement were also used as in Mahfouz and Haddara (2003), Zubaydi et al (2002), Islam et al. (2001).

The maximum number of input and output nodes used by the different investigators was of the order of 48 by Makarynskyy (2004) or 150 by Huang et al. (2003). But even smaller number of nodes had provided a more accurate alternative to the traditional methods of non-linear regression.

A relatively smooth input and closely spaced data in case of time series analysis provided a satisfactory outcome for wave and wind predictions to Makarynskyy (2004), More and Deo (2003), Deo et al. (2001) and Agrawal and Deo (2002).

When a single ANN architecture was insufficient its combination with another one or with another approach such as genetic programming was found to be rewarding (Singh et al, 2007; Singh et al. 2008).

More details of ANN applications in the ocean and coastal problems can be seen in Jain and Deo (2006).

Table 1. Application of ANN in Coastal and Ocean Problems

VARIABLES	PUBLICATIONS
Scour depth and Soil liquification	Kambekar and Deo (2002), Bhattacharya et. al. (2003), Jeng et. al. (2004)
Forces on structures, including wind and wave loads	Mase et al. (1995), Gent and Boogard (1998), Mase and Kitano (1999), Haddara and Soares (1999), Refaat (2001)
Structural damage indicators	Mangal et al. (1994), Mangal et al. (1996), Banerji and Datta (1997), Lopes and Ebecken (1997), Mynett (1999), Shultz and Fishbeck (1999), Zubaydi et al. (2002).
Ship design parameters	Haddara (1995), Gong (1996),Ray et. al. (1996), Yun and Bahang (1997), Haddara and Xu (1998), Haddara and Soares (1999), Islam et al. (2001), Xu and Haddara (2001), Haddara and Wishahy (2002), Mahfouz and Haddara (2003), Kim and Park (2005)
Barge motions	Haddara and Xu (1998), Rivera and Hinchey (1999), Haddara and Wishahy (2002), Mahfouz and Haddara (2003), Moreira and Soares (2003), Alkan et al. (2004).
Environmental parameters	
(a) littoral drift	Singh et. al.(2007),Singh et. al. (2008)
(b) Sea levels	Vaziri (1997), Cox et al. (2002), Sztobryn (2003),
(c) Estuarine characteristics	Grubert (1995)
(d) Various met-ocean parameters	Krasnopolsky et al. (2002), Mandal et. al. (2005)
(e) Coastal currents	Babovic et al. (2001), Charate and Deo (2007)
(f) Wind speeds	Lee and Jeng (2002), More and Deo (2003), Tolman et. al. (2005)
(g) Tidal levels and timings of high and low water – spatial as well as temporal	Deo and Chaudhari (1998), Tsai and Lee (1999), Lee and Jeng (2002), Huang et al. (2003), Lee (2004), Rao and Mandal (2005)), Rajasekharan et. al. (2006), Chang and Chien (2006), Chang and Lin (2006),
(h) Wave period and spectral characteristics	Deo et al. (2002), Namekar and Deo (2004), Tolman (2004), Naithani and Deo (2005)
(i) Wave height	Deo and Naidu (1999), Dibike and Abbott, (1999), Deo and Kiran Kumar (2000), Deo et al. (2001), Tsai et al. (2002), Agrawal and Deo (2002), Deo and Jagdale (2003), Makarynskyy (2004), Altunkaynak and Ozger (2004), Tolman et al. (2004), Kalra et.al. (2005 a, b).

3 Application to real time forecasting of waves along the Indian coastline

The National Data Buoy Program (NDBP) under the Ministry of Earth Sciences of Govt. of India has deployed a series of moored buoys along the Indian coastline both in deep water and in shallow water for the measurement of met-ocean parameters including the significant wave height, Hs. Three stations covered under this program and located along the western Arabian sea were selected and real time wave forecasting over lead times of some hours was carried out using the ANN.

The observations of wave heights considered in this work were made at locations code named SW2, SW4 and DS1 off Indian coast shown in Fig. 2. Information on the underlying data collection could be seen on the website: http://www.niot.res.in/ndbp/bm.pdf. The 3-hourly significant wave height data used in these locations spanned over 3 years to 7 years. The depths of water over these three stations ranged from 18 m to 3800 m.

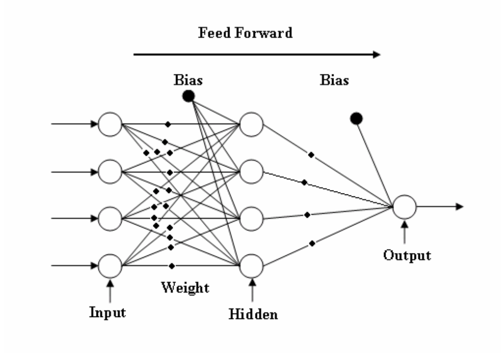

Figure 1. Feed forward backpropagation

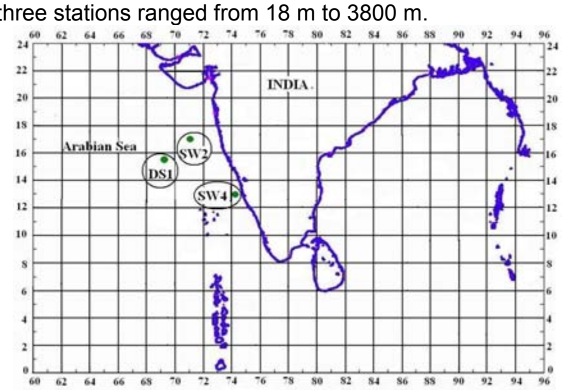

Figure 2. Buoy locations in the Arabian Sea

For developing the ANN usual 3-layer feed forward back-propagation type neural networks were considered. Various input – output combinations were tried to train the network. It was found that the input comprising of four preceding values of the significant wave height, Hs, (i. e., Hs, pertaining to 3^{rd}, 6^{th}, 12^{th} and 24^{th} hour backwards) and the output consisting of the forecasted Hs value for the lead time of 3, 6, 12, 24, 48 and 72 hr –one at a time – constituted the best network architecture. The number of hidden neurons was of the order of 4 to 5 for various networks. The first layer transfer function was 'logsig' and second layer (output layer) transfer function was 'purelin' for all the 24 networks. The data were divided into 2 parts with 60% for training and 40% for testing the network. The best training algorithm turned out to be 'Levernberg- Marquardt'. Details about the training algorithm may be referred to Demuth et al (1998).

The weight and bias matrices of the trained network were retained for testing the network. The prediction accuracy of the networks was judged by calculating the correlation coefficient, R, between the predicted and observed wave heights at these locations along with wave height plots and accompanying scatter plots. Additionally the error measures of root mean square (RMSE) and mean absolute error (MAE) were also used to confirm the findings.

it was found that the measurements involved considerable amount of missing information. For the duration of 3 to 7 years considered for the analysis the gaps varied from as low as 9 % at SW4 to 65 % at SW2 and ranged from few hours to few months at a time. Such lack of continuity in the observations had caused problems in network training due to which lower accuracies were realized. The gaps were filled by using correlation of wave heights between two or more buoys spatially wherein wave heights at one or more buoys worked as 'input buoy(s)' to predict wave heights at another buoy called 'target buoy' at a particular time.

Fig. 3 show an example for location DS1, the comparison between the ANN predicted and observed significant wave heights values through the scatter and time series plots for the testing data. Table 2 shows a similar comparison through the various error measures for all the locations involved up to the lead time of 3 days. Although the accuracy of predictions decreased with the forecast lead time the figures and this Table show a satisfactory work done. Forecasts over the lead time up to 24 hr were indeed very satisfactory in terms of the correlation coefficient while the same over the subsequent higher prediction interval of 48 hr and 72 hr were also acceptable as can be seen in the Table 2.

The techniques developed to carry out real time forecasting of significant wave heights as described in preceding sections can be put into practice through a Graphical User Interface (GUI). The GUI has been developed using the Matlab software background. The buoy data in the form of 3-hourly values of Hs are routinely transmitted to the shore based data reception centre at NIOT, Chennai through a satellite transceiver. These measurements are needed as input for operating on the GUI. The data are processed in the program itself and the model for the forecast is run. These models are based on the selected form of the ANN architecture for different time intervals. The GUI integrates all models for different stations and gives forecast for any of the selected location up to the lead time of 24 hr. A help file is also designed for the user to help in GUI implementation. The forecast results are displayed in the GUI window along with the plot of observed and predicted significant wave heights over the next 24 hrs. The GUI also has the facility to save and print the plots along with the forecasted values (Fig 4).

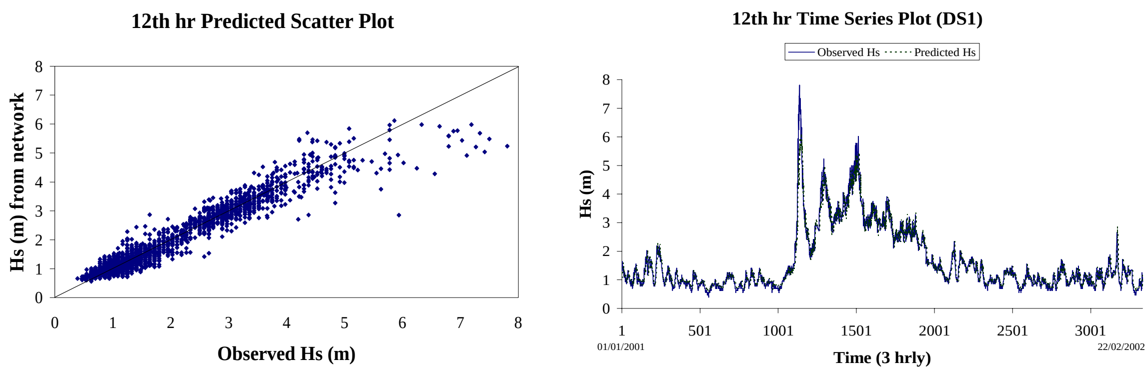

Figure 3. Scatter and Time series plot between observed and predicted wave heights for 12th hour prediction (Station DS1)

Table 2. ANN testing performance in terms of error statistics

		3rd hr	6th hr	12th hr	24th hr	48th hr	72th hr
Station DS1	R	0.99	0.98	0.97	0.95	0.89	0.85
	RMSE(m)	0.19	0.22	0.28	0.36	0.50	0.60
	MAE(m)	0.12	0.14	0.18	0.23	0.31	0.37
Station SW4	R	0.98	0.97	0.96	0.94	0.91	0.88
	RMSE (m)	0.12	0.14	0.18	0.19	0.49	0.52
	MAE (m)	0.08	0.09	0.11	0.13	0.71	0.19
Station SW2	R	0.98	0.97	0.96	0.94	0.89	0.85
	RMSE(m)	0.21	0.23	0.26	0.33	0.46	0.52
	MAE(m)	0.15	0.17	0.19	0.24	0.33	0.38

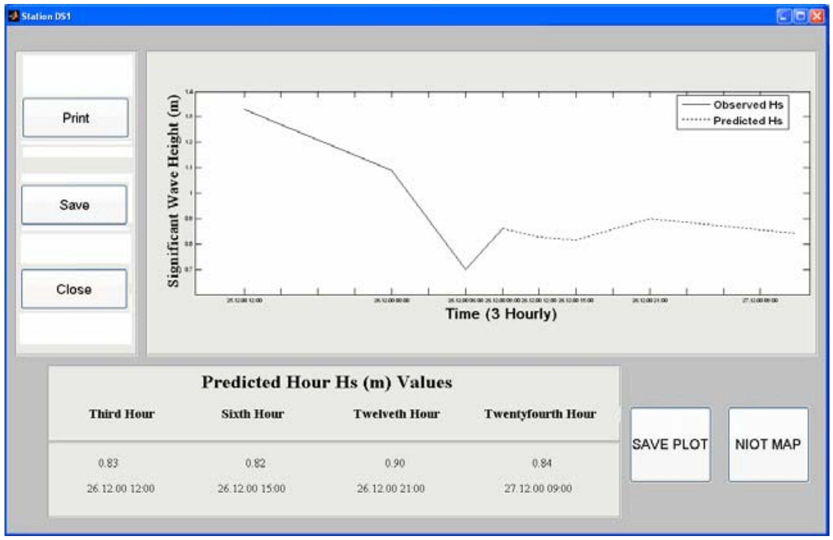

Figure 4. GUI window for station DS1 with the predicted value and plot

4 Concluding Remarks

In coastal and ocean applications ANN's have been used mainly to evaluate or forecast some random parameter. This includes wave height and period, tide and its time, sea level, sea surface temperature, wind speed and direction, estuarine characteristics, coastal current and sediment transport. Environmental loads on structures, structural damage indicators, ship design parameters, barge motions, scour depth and soil liquefaction are some other parameters that have also been evaluated with ANN. Apart from improving accuracy of the outcome the ANN's have significantly reduced the computational effort as well as time compared with traditional methods. ANN's have been calibrated mostly by field observations, but laboratory measurements and mathematical or numerical models have also been employed for this purpose. Some investigators have found that the ANN can learn with much small sample as compared with traditional methods such as harmonic tide analysis. Most of the applications had employed the feed forward type of network and the training algorithm of back-propagation along with its variants. When too much simplification of the underlying physical process by the ANN was not sufficient a hybrid input-output mapping by combining NN with statistical regression, genetic algorithms, Kalman Filter and other specific tools like random decrement were also used. Trained ANN's can be employed to satisfactorily carry out real time forecasting of waves at a number of locations in the sea as shown by the case study briefly presented in this paper.

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6 References

Agrawal J.D. and Deo M.C. 2002. Online wave prediction, *Marine Structures*, Elsevier, Oxford, U.K., **15**(1), 57-74.

Alkan A.D., Gulez K. and Yilmaz H. 2004. Design of a robust neural network structure for determining initial stability particulars of fishing vessels, *Ocean Engineering*, **31**(5-6), 761-777.

Altunkaynak A. and Ozger M. 2004. Temporal significant wave height estimation from wind speed by perceptron Kalman filtering, *Ocean Engineering*, **31**(10), 1245-1255.

Babovic V., Kanizares R., Jenson H.R., Klinting A. 2001. Neural networks as routine for error updating of numerical models, *Journal of Hydraulic Engineering*, *ASCE*, **127**(3), 181-193.

Balas C.E., Koc L. and Balas L. 2004. Predictions of Missing Wave Data By Recurrent Neuronets, J*. Wtrwy., Port, Coast., and Oc. Engrg*., **130**, 256-265.

Banerji P. and Datta T.K. 1997. Integrity monitoring of offshore platforms using artificial neural nets. Proceedings, *ISOPE-97,* Honolulu, **4**, 439-444.

Bhattacharya B., Deibel I.K., Karstens, S.A.M., Solomatine D.P. 2003. Neural ntetworks in sedimentation modeling for the approach channel of the port area of Rotterdam. Proceedings of the 7th International conference on nearshore and estuarine cohesive sediment transport processes, (INTERCOH), Virginia Institute of Marine Science, Virginia, USA, October 2003.

Chang Hsien-Kuo and Chien Wei-An 2006. A fuzzy–neural hybrid system of simulating typhoon waves, *Coastal Engineering*, **53** (9), 737-748.

Chang Hsien-Kuo and Lin Li-Ching 2006. Multi-point tidal prediction using artificial neural network with tide-generating forces, *Coastal Engineering*, **53** (10), 857-864.

Charhate S.B., Deo M.C.and Sanil Kumar V. 2007. Soft and Hard Computing Approaches for Real Time Prediction of Currents in a Tide Dominated Coastal Area, *Journal of Engineering for the Maritime Environment*, Proceedings of the Institution of Mechanical Engineers, London, Part M, **221**, M4, pp147-163.

Cox D.T., Tissot P., Michaud P. 2002. Water level observations and short-term predictions including meteorological events for entrance of Galveston Bay, Texas, *Journal of Waterways, Port, Coatsal and Ocean Engineering Division, ASCE,* **128**(1), 21-29.

Demuth, H., Beale, M., Hagen, M., 1998. Neural Networks Tool Box, User's guide. The Mathworks Inc., Natick,MA.

Deo M.C., Gondane D.S., and Sanil kumar V. 2002. Analysis of wave directional spreading using neural networks, *ASCE Journal of Waterways, Port and Ocean Division*, **128**(1), 30-37..

Deo M.C., Jha A., Chaphekar A.S., Ravikant K. 2001. Wave prediction using neural networks, *Ocean Engineering*, Elsevier, Oxford, U.K., **28** (7), 889-898.

Deo M.C. and Chaudhari G. 1998. Tide prediction using neural networks, *Journal of Computer-Aided Civil and Infrastructural Engineering,* Blackwell Publishers, Oxford, UK, **13**(1998), 113-120.

Deo M.C. and Jagdale S.S. 2003. Prediction of breaking waves using neural networks, *Ocean Engineering*, Elsevier, Oxford, U. K., **30**(9), 1163-1178.

Deo M.C. and Kiran kumar N. 2000. Interpolation of wave heights, *Ocean Engineering*, Elsevier, Oxford, U.K., **27** (9), 907-917.

Deo M.C. and Naidu C.S. 1999. Real time wave forecasting using neural networks, *Ocean Engineering***,** Elsevier, Oxford, U.K., **26** (3), 191-203.

Dibike Y.B. and Abbott M.B. 1999. Application of artificial neural networks to the simulation of two dimensional flow, *Journal of Hydraulic Research*, **37**(4), 435-446.

Gent M.R.A. Van and Boogard H.F.P. Van Den 1998. Neural network and numerical modeling of forces on vertical structures, MAST/PROVERBS report, *WL Delft Hydraulics*, Delft, The Netherlands.

Gong T. 1996. Using ANN for the recognition of vibration signals of offshore equipments' failure. Proceedings, International conference on signal processing, ICSP'96, Oct. 14-18, 1996, Beijing, China, 1605-1608.

Grubert J.P. 1995. Prediction of estuarine instabilities with artificial neural networks, *ASCE Journal of Computing in Civil Engineering*, **9**(4), 266-274.

Haddara M.R. 1995. On the use of neual network techniques for the identification of ship stability parameters at sea, Proceedings of the International conference on offshore mechanics and arctic engineering, June 18-22, 1995, Copenhagen, Denmark, OMAE, **2**, 127-135.

Haddara M.R. and Soares C.G. 1999. Wind loads on marine structures, *Marine Structures,* **12**(3), 199-209.

Haddara M.R. and Wishahy M. 2002. An investigation of roll characteristics of two full scale ships at sea, *Ocean Engineering*, **29**(6), 651-661.

Haddara M.R. and Xu J. 1998. On the identification of ship coupled heave pitch motions using neural networks, *Ocean Engineering*, **26** (5), 381-400.

Huang W., Murray C., Kraus N. and Rosati J. 2003. Development of a regional neural network for coastal water level predictions, *Ocean Engineering*, **30**(17), 2275-2295.

Islam M.M., Reaz M., Khondoker H. and Chowdhury M.R. 2001. Application of artificial intelligence techniques in automatic hull form generation, *Ocean Engineering,* **28**(12), 1531-1544.

Jain P. and Deo M.C. 2006. Neural networks in Ocean Engineering, *International Journal of Ships and Offshore Structures***,** Wood head publications, Cambridge, UK., **1**(1), 25-35

Jeng D. S., Cha D., Blumenstein M. 2004. Neural network model for prediction of wave-induced liquefaction potential, Ocean Engineering, **31**(17-18), 2073-2086.

Kalra Ruchi, Deo M.C., Kumar Raj and Agarwal Vijay K. 2005 (a). RBF neural network for spatial mapping of wave heights, *Marine Structures*, Elsevier, **18**(3), 289-300.

Kalra Ruchi, Deo M.C., Kumar Raj and Agarwal Vijay K. 2005 (b). Artificial neural network to translate offshore satellite wave data to coastal locations, *Ocean Engineering*, Elsevier, **32**, 1917-1932.

Kambekar A.R. and Deo M.C. 2002. Estimation of pile group scour using neural networks, *Applied Ocean Research*, **25** (4), 225-234.

Kim D. H. and Park W. S. 2005. Neural network for design and reliability analysis of rubble mound breakwaters, *Ocean Engineering*, **32** (11-12), 1332-1349.

Kosko B. 1992. Neural networks and fuzzy systems. Prentice Hall, Englewood Cliffs, New Jersey.

Krasnopolsky V.M., Chalikov D.V. and Tolman H.L. 2002. A neural network technique to improve computational efficiency of numerical oceanic models, *Ocean Modelling*, **4**(3-4), 363-383.

Lee T.L. and Jeng D.S. 2002. Application of artificial neural networks in tide forecasting, *Ocean Engineering*, **29**(1), 1003-1022.

Lee T.L. 2004. Back-propagation neural network for long-term tidal predictions, *Ocean Engineering*, **31**(2), 225-238.

Londhe S.N. and Deo M.C. 2003. Wave tranquility studies using neural networks, *Marine Structures,* **16**(6), 419-436.

Lopes T.A.P. and Ebecken N.F.F. 1997. In-time fatigue monitoring using neural networks, *Marine Structures,* **10**(5), 363-387.

Mahfouz A.B. and Haddara M.R. 2003. Effect of the damping and excitation on the identification of the hydrodynamic parameters for an underwater robotic vehicle, *Ocean Engineering,* **30**(8), 1005-1025.

Makarynskyy O. 2004. Improving wave predictions with artificial neural networks, *Ocean Engineering*, **31**(5-6), 709-724.

Mandal S., Rao Subba and Raju D.H. 2005, Ocean wave parameters estimation using backpropagation neural networks, *Marine Structures*, **18** (3), 301-318.

Mangal L., Idichandy V.G. and Ganapathy C. 1996. ART-based multiple neural networks for monitoring offshore platforms, *Applied Ocean Research*, **18**(2-3), 137-143.

Mangal L., Idichandy V.G. and Ganapathy C. 1994. Neural networks in damage detection of offshore structures, *Indian National Conference on Harbor and Ocean Engineering,* INCHOE-94, CWPRS, Pune, **1**, 21-30.

Mase H. and Kitano T. 1999. Prediction model for occurrence of impact wave force, *Ocean Engineering*, **26**(10), 949-961.

Mase H., Sakamoto M., Sakai T. 1995. Neural network for stability of rubble mound breakwaters, *ASCE Journal of Waterways, Port, Coastal and Ocean Engineering Division*, **121**(6), 294-299.

More A. and Deo M.C. 2003. Forecasting wind with neural networks, *Marine Structures*, Elsevier, Oxford, U. K., **16**(1), 35-49.

Moreira L. and Soares C.G. 2003. Dynamic model of manoeuvrability using recursive neural networks, *Ocean Engineering*, **30**(13), 1669-1697.

Mynett A.E. 1999. Hydroinformatics and its applications in Delft Hydraulics, *Hydroinformatics*, **1**, 83-102.

Naithani Reena and Deo M.C. 2005. Estimation of wave spectral shapes using ANN, *Advances in Engineering Software*, Elsevier, **36**, 750-756

Namekar S. and Deo M.C. 2004. Neural networks to derive wave spectra, ISOPE-2004 Conference, Toulon, France, **3**, Paper 7.

Rajasekaran S., Thiruvenkatasamy K. and Lee Tsong-Lin 2006. Tidal level forecasting using functional and sequential learning neural networks, *Applied Mathematical Modelling*, **30** (1), 85-103.

Rao Subba and Mandal S. (2005). Hindcasting of storm waves using neural networks, *Ocean Engineering*, **32** (5-6), 667-684

Ray T.,Gokarn R.P., Sha O.P. 1996. Neural network applications in naval architecure and marine engineering, *Artificial Intelligence in Engineering*, **1**, 213-226.

Refaat H.A.A. 2001. Utilizing artificial neural networks for predicting shoreline changes behind offshore breakwaters, *Journal of Engineering and Applied Science*, **48**(2), 263-279.

Rivera C. and Hinchey M. 1999. Hydrodynamic loads on subsea robots, *Ocean Engineering*, **26**(8), 805-812.

Shultz J.R. and Fishbeck P. 1999. Predicting risk associated with offshore production facilities: neural network, statistical and expert opinion models. SPE/EPA exploration and production environmental conference, May 1-3, Austin, TX, SPE 52677, 195-208

Singh A.K., Deo M.C. and Sanil Kumar V. 2007. Neural network – genetic programming for sediment transport, *Journal of Maritime Engineering***,** The Institution of Civil Engineers, London, **160**, Issue MA3, 113-119.

Singh A.K., Deo M.C. and Sanil Kumar V. 2008. Prediction of littoral drift with artificial neural networks, *Hydrology and Earth Systems Sciences***,** European Geophysical Union, **12**, 267–275.

Sztobryn M. 2003. Forecast of storm surge by artificial neural networks, Journal of Sea Research, **49** (4), 317-322.

Tolman, H. L., 2004. Inverse Modeling of Discrete Interaction Approximations for Nonlinear Interactions in Wind Waves. *Ocean Modelling*, **6** (3-4), 405-422

Tolman H.L., Krasnopolsky V.M. and Chalikov D.V. 2005. Neural network approximations for nonlinear interactions in wind wave spectra: direct mapping for wind seas in deep water, *Ocean Modelling ,* **8** (3), 253-278.

Tsai C., Lin C. and Shen J. 2002. Neural network for wave forecasting among multi-stations, *Ocean Engineering*, **29**(13), 1683-1695.

Tsai C.P. and Lee T.L. 1999. Back-propagation neural network in tidal level forecasting, *ASCE Journal of Waterways, Port, Coastal and Ocean Engineering*, **125** (4), 195-202.

Vaziri M. 1997. Predicting Caspian Sea Surface Water Level by ANN and ARIMA models, *ASCE Journal of Waterways, Port, Coastal and Ocean Engineering Division,* **123**(4), 158-162.

Wasserman P.D. 1993. Advanced methods in neural computing, *Van nostrand Reinhold,* New York.

Wu K.K. 1994. Neural networks and simulation methods, *Marcel Decker*, New York.

Xu J. and Haddara M.R. 2001. Estimation of wave induced ship hull bending moment from ship motion measurements, *Marine Structures,* **14**(6), 593-610.

Yun C. and Bahang E.Y. 1997. Substructural identification of offshore structures using neural networks, Proceedings of the International Offshore and Polar Engineering Conference, **4**, 210-215.

Zubaydi A., Haddara M.R., Swamidas A.S.J. 2002. Damage detection in a ship's structure using neural networks, *Ocean Engineering*, **29**(10), 1187-1200.