

AN OVERVIEW OF THE NUMERICAL AND NEURAL NETWORK ACCOSTS OF OCEAN WAVE PREDICTION

by

Mandal S¹ and Prabakaran, N²

ABSTRACT

This paper presents an overview of the development of the numerical wave prediction models and recently used neural networks for wave hindcasting and forecasting. The numerical wave models express the physical concepts of the phenomena. The performance of the numerical wave model depends on how best the phenomena are expressed into the numerical schemes, so that more accurate wave parameters could be estimated. There are still scopes for improving the numerical wave models. When exact input-output parameters are known for the same phenomenon, it can be well defined by the neural network. Hindcasting of ocean wave parameters using neural networks shows its potential usefulness. It is observed that the short-term wave predictions using neural networks are very close to the actual ones. Ocean wave forecasting using recurrent network yields very high correlation coefficients. The correlation coefficients for the lead of 3, 6, 12 and 24 hours are 0.95, 0.90, 0.87 and 0.73 respectively. It is also observed that the neural network simplifies not only the complex phenomena, but also predicts fairly accurate wave parameters.

1. INTRODUCTION

The importance of the ocean wave prediction was first felt in early 1940's for the planning of Naval fleet operations during the second world war. The wave prediction method was first developed by Sverdrup and Munk (1947) based on the simple empirical formulations. Subsequently, many numerical models were developed during last few decades and presently, a few operational wave models exist for wave forecasting. With the rapid developments in the computer technology, the success of complicated numerical wave prediction models was possible. Unless the phenomena are exactly expressed the uncertainty of accurate prediction of outputs remains. The expressed relation between winds and other outputs and wave parameters may need further improvement for these numerical wave models.

The numerical wave models developed were based on energy balance equation with various inputs. One of the inputs, which could not be fully analyzed till late 1970's, was the non-linear wave-wave interaction (Hasselmann *et al*, 1985). The third generation operational wave models use the source terms with out any prior restrictions on the spectral shape (Tolman and Chalikov, 1996). Even though the present generation wave models fairly predict waves, one can still improve the models by better representation of extremely complex physical processes of wind generated waves (Vledder, 2000).

The neural network has the ability to recognize the hidden pattern in the data and accordingly estimate the values. Provision of model-free solutions, data error tolerance, built in dynamism and lack of any exogenous input requirement makes the neural network attractive. A neural network is an information processing system modelled on the structure of the dynamic process. Its merit lies in the ability to deal with information whose interrelation is ambiguous or whose functional relation is not clear. Some applications of neural networks in wave hindcasting and forecasting are described based

¹Dr.-Eng, Scientist, National Institute of Oceanography, Dona Paula, Goa 403 004, INDIA,
smandal@darya.nio.org,

²Technical Officer, National Institute of Oceanography, Dona Paula, Goa 403 004, INDIA,
prabha@darya.nio.org

on recent work carried out by various authors (Deo *et al*, 1999, 2001; Tsai *et al*, 2002; Mandal *et al*, 2002, Subbarao *et al*, 2001). Krasnopolsky *et al* (2001) have used neural network to develop a computationally cost effective and accurate approximation for non-linear wave-wave interaction source term of the energy balance equation.

Recent trend of neural networks in ocean wave prediction shows that it has potential usefulness. In numerical models, we have many assumptions, boundary conditions, simplification of nonlinear wave-wave interaction, etc. Whereas there are no priori-restrictions in the neural network. The neural network does not recognise the physical phenomena. It establishes the relationships between inputs and outputs based on learning processes. The wave predictions using numerical models and neural networks are briefly described in this paper. Some recent results on predictions of ocean wave parameters using neural networks are also presented.

2. NUMERICAL WAVE MODELS

Numerical wave prediction models which were developed can be divided into three categories, i.e., First generation, Second generation and Third generation wave models.

2.1 First generation models

The first generations wave models are developed based on constant wind fields. The first empirical wave model was developed by Sverdrup and Munk (1947). Thereafter, Pierson, Nueman and James (1955) developed a model called PNJ-model for estimating wave conditions created by the distance storm. This is based on the generated wave energy spreads over the ocean as distance to the generating storm increases. A modified version of PNJ- model was used by Darbyshire (1961). In this model it was assumed that the sea state was fully developed after 12 hours and 200 nm of constant wind. A model for ideal condition was proposed by Wilson (1955) and it was further extensively studied by Bretschneider (1963) and Trajer (1966). This is published in form of a handbook by WMO (1976). Seymour (1977) proposed a directional de-coupling model where a stationary homogeneous wind field is considered over a deep-water basin with an arbitrary geometry of the coastline. Ross and Cardone (1978) developed the wave model, which is applicable to tropical hurricanes where non-dimensional radial distance from the point of the forecast to the eye of the hurricane is one among the characteristic wind parameters.

2.2 Second generation models

The second generation wave models are used under varying wind fields. Here, the sea surface is defined as the sum of a large number of individual wave components, each wave propagating with constant frequency according to the linear wave theory. The path of wave components (from origin to the forecast point) are calculated by the conventional methods. After leaving the origin, the wave component interacts with the other wave components. Thus at regular interval of time the energy gained or released in the process can be evaluated till it reaches the forecast point. This procedure can be repeated for a large number of wave components of different frequencies and directions at a given time so that the total energy is obtained at the point of forecast. A large group of wave experts on wave models made an attempt to interpret all the available models for inter-comparison (SWAMP, 1985).

The numerical wave prediction model DOLPHIN is a deep water hybrid point model, a combination of the parametric wind-sea and spectrally treated swells (Mandal, 1985). The development of this model is based on the directionally decoupled energy distribution of wind generated waves. Inputs to the model are wind field and coastal boundary. Outputs are significant wave height H_s , variance density spectra giving information on the two-dimensional distribution of wave energy. By using this model wave parameters were computed over period where observed data is also available (Anand *et al*, 1994). Three hourly values of Significant wave height (H_s), zero-crossing period, Maximum energy and peak period computed by hindcast model and those based on measured data seems to be quite

good between computed and measured H_s values. The spectra predicted by the model and the measured spectra seem to be reasonably in good agreement.

2.3 Third generation models

Third generation wave models were developed to further improvement of modelling process. In 1985 the Discrete Interaction approximation (DIA) (Hasselmann et al, 1985) was developed. The operational wave models, such as WAM (WAMDI, 1988), SWAN (Booij et al, 1999) and WAVEWATCH III (Tolman, 1999) are the third generations wave models. Even though wave modelling is being carried out for many decades further improvement are being performed by incorporating the updated subroutines in these wave models. One of these is the improved parameterization of nonlinear quadruplet wave-wave interactions for application in operational wave prediction models (Vledder, 2000). The DIA has some shortcomings, which hamper the further development of the third generation wave model. These models use the action balance equation for describing the time and space evolution of wave spectra. Further improvement are being carried out to obtain a fast and accurate method for computing the nonlinear quadruplet wave-wave interactions in deep and shallow water, such that this method can be applied in operational wave prediction models. For reaching a closer values of nonlinear energy transfer, neural network parameterization has been developed by Krasnololsky et al (2001). In this neural network integration approximation (NINA) is considered to estimate nonlinear interactions, $S_{nl}(f, \theta)$ as a function of frequency f and direction θ from the corresponding spectrum, $F(f, \theta)$ in deep water. To train and test this NINA, they used a set of 20,000 simulated realistic spectra for $F(f, \theta)$ and the corresponding exact estimates of $S_{nl}(f, \theta)$. Simulation was based on spectral function of P-M spectra for different peak frequencies oriented randomly in $(0, 2\pi)$ interval. The NINA gives reasonable results and implemented for WAVE WATCH III model.

3. NEURAL NETWORK IN WAVE HINDCASTING

The work carried out by Mandal et al (2002) describes hindcasting of wave heights and periods from cyclone generated wind fields using neural networks. The back-propagation neural network with Rprop updated algorithms used to estimate the wave heights and periods (2 outputs) based on storm parameters (3 inputs), i.e., difference in central and peripheral pressure, radius of maximum wind and speed of forward motion of cyclone. The network structure of $1-3-2$ is shown in Fig-1.

The storm field variables namely central pressure, radius of maximum wind, storm speed, direction of movement of storm, latitude and longitude are extracted for each cyclone from the isobaric charts available with the archives of the Indian Meteorological Department (IMD) at 3/6 hours time intervals. The method based on standard Hydromet pressure profile, presented by Varkey et al (1996) is used for the hindcast of storm wind fields. Young's model (Young, 1988) is used in the estimation of wave characteristics for the cyclones considered. The input parameters to the model are radius of maximum wind, the maximum wind speed and the speed of forward motion. Using the JONSWAP fetch-limited growth relationship, the model estimates the maximum significant wave height and the spectral peak period of the maximum waves in the storm.

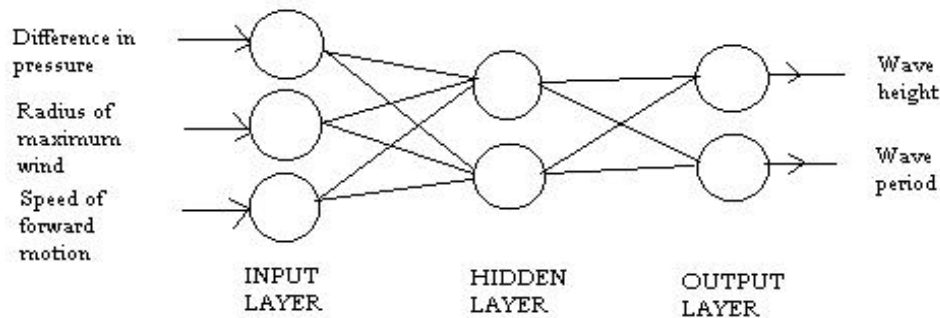


Fig-1 Neural network structure

Correlation between wave height estimated using Young model and neural network yields the correlation coefficient of 0.99 and similarly correlation coefficient for wave period gives a value of 0.97. This shows that neural network with Rprop updated algorithm can be used as an effective tool in estimating cyclone generated wave parameters.

4. NEURAL NETWORKS IN WAVE FORECASTING

The work carried out by Deo and Naidu (1999) describes the application of neural network analysis in forecasting of waves and is carried out for significant wave height (H_s) with 3 hour lead period. They have carried out various combinations of training patterns to obtain the desired output. Also the work of average 12hr and a day wave forecasting are carried out. In this work the back-propagation, cascade correlation and conjugate gradient methods are used with the input layer of one node. The correlation coefficients obtained for the lead of 3 hour, half day and a day are 0.81, 0.78 and 0.71 respectively. Using updated algorithms in back-propagation neural network, the wave forecasting yielded better results as shown in Subba Rao et al (2001). Improved correlation coefficients for the lead of 3 hour, half-day and a day were obtained as 0.93, 0.80 and 0.73 respectively. Deo et al (2001) have demonstrated the use of neural networks for wave forecasting for three different sets of data. It shows that a proper trained network could yield good results in open wider areas, in deep water and also when the sampling and prediction interval are large (say, week).

Significant wave heights are forecasted using recurrent neural networks (Mandal and Prabakaran, 2002). Here Memorization and NARX (Nonlinear AutoRegressive models with exogenous inputs) recurrent algorithms are used in back-propagation neural network.

In the NARX network there is a provision to take values from the input layers and then shift them along the input layer as more patterns are added. For example, if we want to take a hidden unit value or an output unit value and keep them for more than a single time step, in effect a history of what the recent values have been. For the normal network combination of 1-7-1 the NARX network of the following combination is used as 7-7-1 with the input coming from the preceding output values. Figure 2 shows the neural network structure of $7-7-1$, i.e., combination of 7-7-1 where the input value is one and the other values are taken from memorization of earlier sequences.

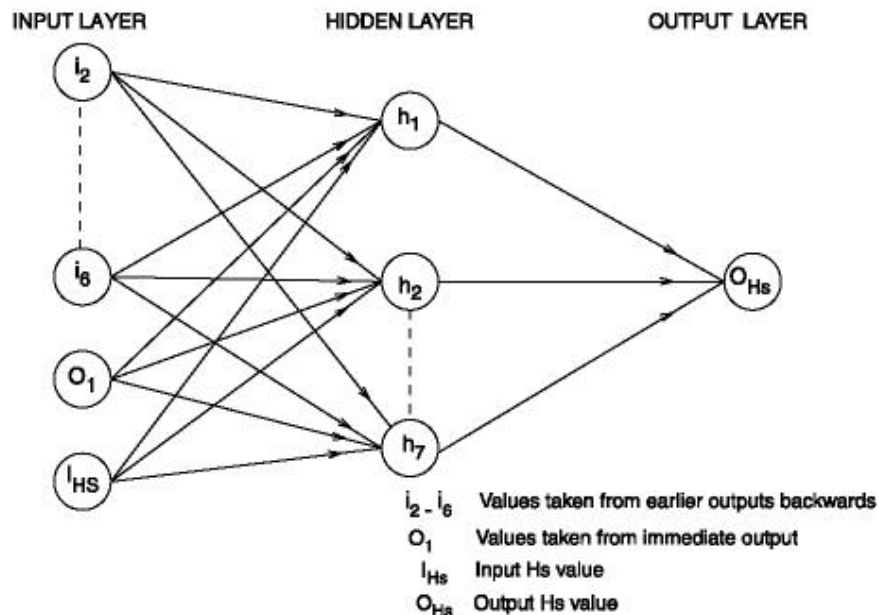


Fig 2. NARX RECURRENT NETWORK

COPEDEC VI, 2003, Colombo, Sri Lanka

The wave data collected off Marmugao, Goa, west coast of India at 23m water depth during February 1996 and January 1997 are used for the present studies. Three hourly significant wave heights (Hs) over the period are considered for the neural network

The time series of the forecasted three hourly Hs (NARX network) with the measured three hourly Hs is shown in Figure 3. It can be seen that the forecasted waves are closely matching with the measured values. The three hourly wave forecasting by memorization network has estimated the CC of 0.94, and the CC for NARX network is 0.95. Figure 3 also shows the correlation for NARX network.

Six hourly averaged significant wave height is forecasted and CCs are 0.88 and 0.90 for memorization and NARX networks respectively. Twelve hourly (half-day) averaged wave forecasting data yields CC of 0.87 for memorization network and 0.87 for NARX network. The time series profile is shown in Figure 4. In this also the up and down of wave profile is picked up by the forecast profile. The corresponding correlation is also shown in Fig 4. The day averaged forecasting Hs yields the correlation coefficient values of 0.72 for memorization network and 0.73 for NARX network.

Results show that the recurrent network predicts much better than the earlier neural network methods. It can also be seen that for even averaged wave data the improved results are obtained. The comparative values of correlation coefficients are shown in Table I. The correlation coefficient for 3 hourly Hs has improved from 0.81 (Deo and Naidu, 1999) to 0.95 (present case).

Forecasting lead time	Cascade corr. Deo & Naidu (1999)	Backprop-rprop Subbarao <i>et al</i> (2001)	Present case
3 hour	0.81	0.93	0.95
6 hour	--	0.88	0.90
12 hour	0.78	0.80	0.87
24 hour	0.71	0.73	0.73

Table-1 Comparison of correlation coefficients

The wave forecasting carried out is the next immediate value based on the present values. The averaged forecasted Hs values for six and twelve hours also give better results. Using this method the Hs can be known in advance up to a period of twelve hours which will be useful for planning operation in the sea, such as pilot deep sea mining in the sea or undertaking any sub sea installation which requires the advance information in sea conditions.

Tsai et al (2002) have used back-propagation neural network to forecast the ocean waves based on learning characteristics of observed waves. The network structure of $1_3H_4O_1$ is used. The network evaluates the interconnection weights among multi-stations based on previous short-term data. Thereafter a time series of waves at a station can be forecasted based on using the neighbour stations data.

The neural network does not explain physical processes taking place for generating ocean waves. To generate ocean waves, if exact input-output parameters were continuously known, the neural network can be trained using known input-output values, similar to validation of the numerical wave model. There after predicting ocean wave parameters could be easier in the case of neural network as compared to the numerical wave model. This is owing to simplicity of neural network connecting where weights are to be fixed based on known input-output values.

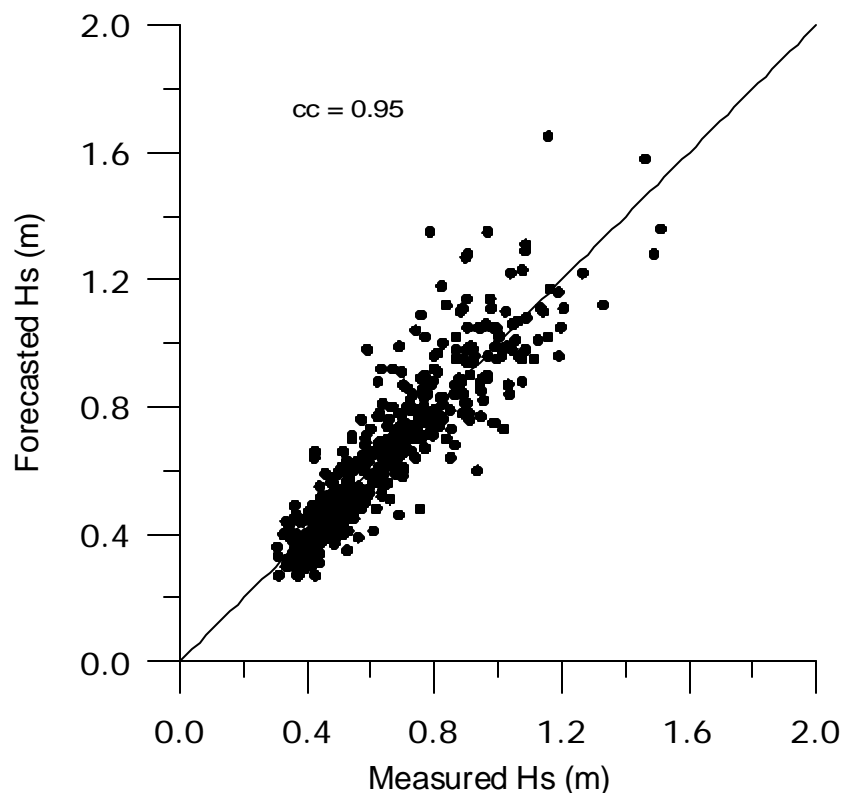
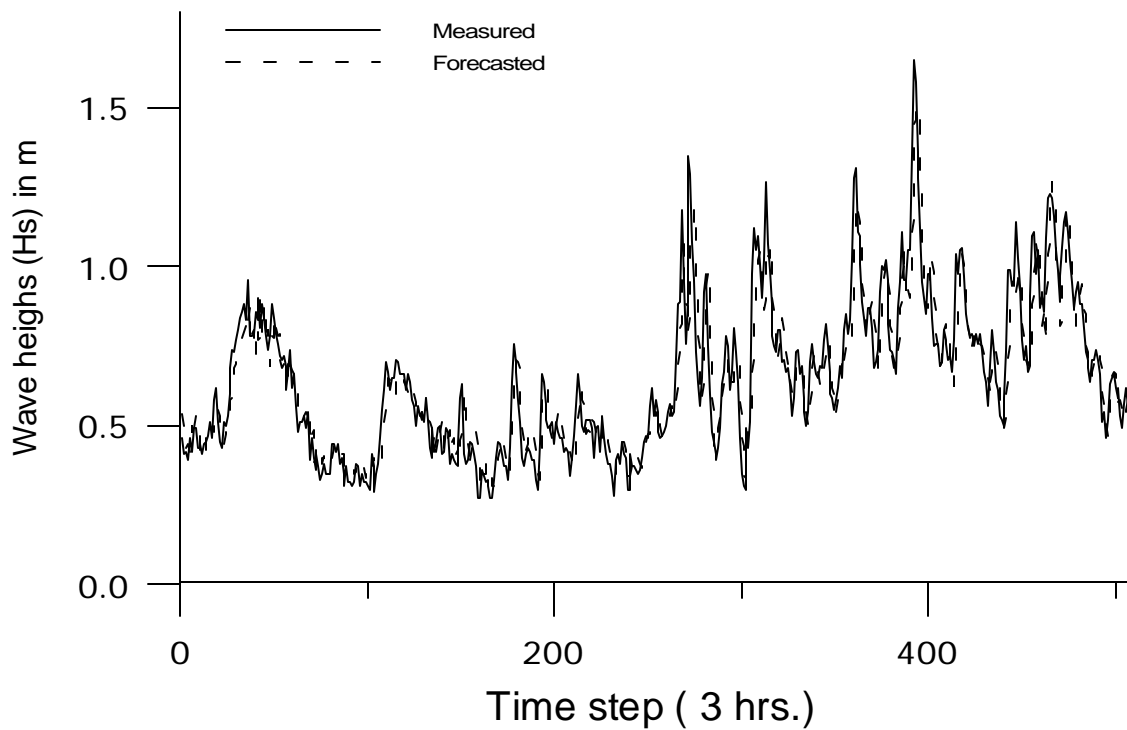


Fig 3. Forecasted (3 hrs) waves off Marmugao by NARX network

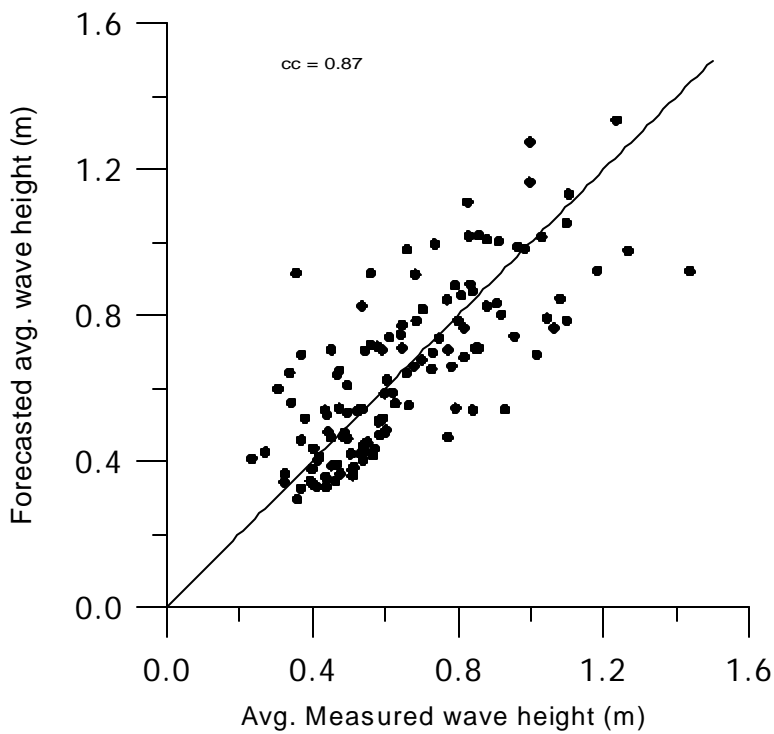
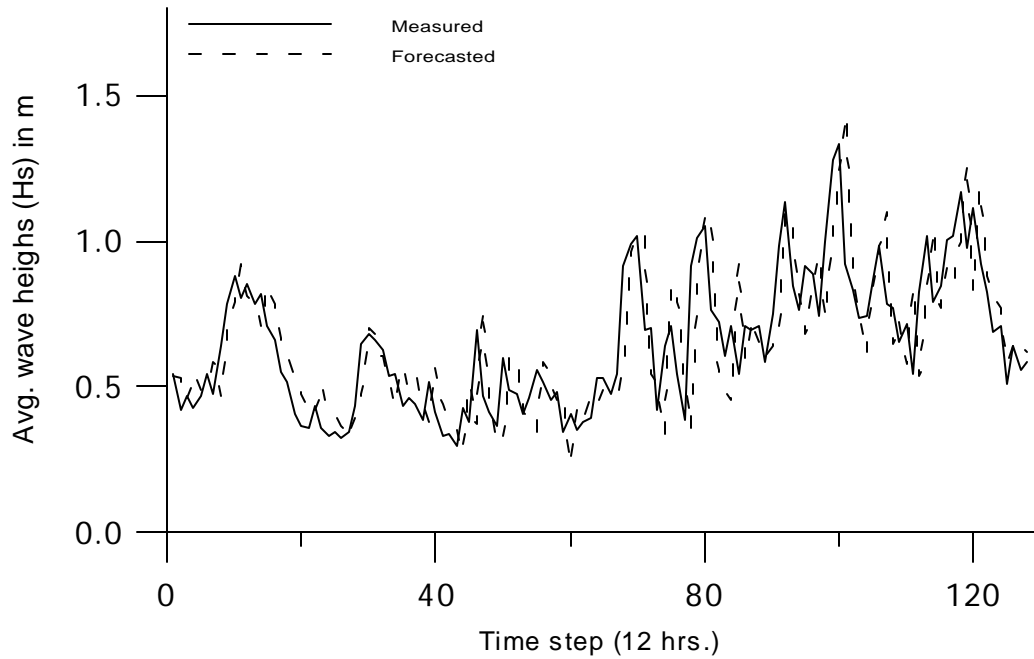


Fig 4 Forecasted (12 hour avg) waves off Marmugao by NARX network

5. CONCLUSIONS

The use of neural network for wave prediction will have future application and the neural work can also be incorporated in the wave modelling for solving complex nonlinear functions in an efficient way. A detail study can be made for a particular location with different modelling estimates and also with the neural network. For a particular location the neural network can be trained based on known inputs-outputs, which is similar to the validation of the numerical wave model. Thereafter, wave prediction can be carried out for unknown inputs. For short term prediction of ocean waves the neural network can be trained for which the data are available during the immediate earlier period and thereafter it can be used for wave forecasting for that location.

Acknowledgements

The authors are grateful to Director, National Institute of Oceanography (NIO), Goa, India for his encouragement. The authors are thankful to staff of Ocean Engineering Division, NIO, Goa for providing the measured waves.

REFERENCES

- Anand NM, Mandal S, Sanilkumar V and Nayak BU (1994) Real time wave measurements and wave hindcasting in deep waters. *Indian Journal of Marine Sciences*, 23, 184-186.
- Booij, N, Holthuijsen, LH and Ris, FC (1999) A third-generation wave model for coastal regions. 1. Model description and validation, *J. of Geophys. Res.*, Vol 104, No-C4, 7649-7666.
- Bretschneider, C.L. (1963) Significant wave hindcast for station I. North Atlantic Storm, Dec. 1959, *Tech Report No.SN-77-1*.
- Darbyshire, J. (1961) Prediction of wave characteristics over the North Atlantic, *J. of the Institute of Navigation*, 14,339-347.
- Deo, MC and Naidu, CS (1999) Real time wave forecasting using neural networks, *Ocean Engineering*, 26, 191-203.
- Deo, MC, Jha, A, Chaphekar and Ravikant, K. (2001) Neural networks for wave forecasting, *Ocean Engineering*, 28, 889-898.
- Fahlman, S.E. (1988) An empirical study of learning speed in back-propagation networks. *Technical report, CMUCS- 88-161*, Carnegie-Mellon Univ, Computer Science Dept, Pittsburgh, PA
- Hasselmann, S and Hasselmann, K (1985) Computations and parameterizations of the nonlinear energy transfer in a gravity wave spectrum, Part I and II, *J. Phys. Oceanography*, 15, 1369-91.
- Krasnopolsky, MV; Chalikov, DV and Tolman, HL (2001) Using neural network for parameterization of nonlinear interactions in wind wave models. *Proc. Of IEEE-INNS Intl. Joint Conf. on neural networks*, 15-19 July 2001, Washington DC, USA.
- Mandal, S (1985) A numerical wave prediction model DOLPHIN: Theory and test results. *Report No 3-85 (Delft Univ of Tech)*, 195pp.
- Mandal, S; Subbarao, and Chakravarty, N (2002) Hindcasting cyclonic waves using neural networks, *International conference in SHOT2002*, 18-20 December, IIT Kharagpur.
- Mandal, S and Prabakaran, N (2002) Recurrent networks for wave forecasting, *National conference in HYDRO2002*, 16-17 December, IIT Bombay.
- Pierson, W.J, Neuman, G. and James, R.W. (1955) Practical method for observing and forecasting ocean wave, *U.S. Navy Hydro. Office Publication No.603*
- Ross, D. and Cardone, V. (1978) A comparison of parametric and spectral hurricane wave prediction products, *Proc. Conf. Turbulent Fluxes than the sea surface, wave dynamics Prediction. Marseille, France, Sept. 12-16*, Plenum Press, 647-665.
- Seymour, R.J.(1977) Estimating wave generation on restricted fetches, *Proc. ASCE J. of Waterway Port, Coastal and Ocean Div.*,103,2,251-264.

- Subba Rao, Mandal, S and Prabakaran, N (2001) Wave forecasting in near real time basis using neural networks, *Proc. International conference in ocean engineering (ICOE' 01)*, IIT Madras, 103-108.
- SWAMP group (1985) Ocean wave modelling. Plenum press, New York.
- WAMDI group (1988) The WAM model- a third generation ocean wave prediction model, *J. Phys. Oceanography*, 18, 1775-1810.
- Sverdrup, HU and Munk, WH (1947) Wind, sea and swell: Theory of relation for forecasting. H.O. Publication 601, US Naval oceanographic office, Washington DC, USA.
- Tolman, HL and Chalikov, DV (1996) Source terms in a third-generation wind wave model. *J. Phys. Oceanography*, 26, 2497-2518.
- Tolman, HL (1999) User manual and system documentation of WAVEWATCHIII version 1.18, NOAA/NWS/NCEP/OMB technical note 166, 100pp
- Trajer, F.L. (1966). Program NEPTUNE, Bur. Mat. Australia.
- Tsai, C-P, Lin, C and Shen, J-N (2002) Neural network for wave forecasting among multi-stations. *Ocean Engineering*, 29, 1683-1695.
- Varkey, M.J., Vaithyanathan, R. And Santanam, K., (1996) Wind fields of storms from surface isobars for wave hindcasting, *Proc. International conference in ocean engineering (ICOE' 96)*, IIT Madras, 502-506.
- Vledder, G Ph van (2000) Improved method for obtaining the integration space for the computation of nonlinear quadruplet wave-wave interactions. *Proc. Intl. Workshop on Wave Hindcasting and Forecasting*, 6-10 November, Monterey, California, USA.
- Wilson, B.W. (1955) Graphical approach to the forecasting of waves in moving fetches, Beach Erosion Board Corps. of Engineers, Dept of the Army Techn. Memo 73.
- WMO (1976) Handbook on wave analysis and forecasting, World Met. Orgn. Geneva. WMO. No. 446
- Young, I.R., (1988) Parametric Hurricane wave prediction model, *Journal of Waterways Port Coastal and Ocean Engineering*, 114(5), 637-652