



WAVE FORECASTING IN NEAR REAL TIME BASIS BY NEURAL NETWORK

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Abstract

In modern age, the human settlements and activities are very much increasing near the ocean front. In order to cope up with the need such as construction of jetties, harbours, offshore berths, offshore platforms, navigation and recreation etc., forecasting of waves become an important aspect of marine environment. This paper presents application of the neural network (NN) with better update algorithms, namely rprop, quickprop and superSAB for wave forecasting. Measured waves off Marmagao, Goa are used for this study. The forecasting of 3, 6 and 12 hourly wave heights are carried out using the NN model. Here the NN with rprop algorithm yields very good results.

INTRODUCTION

The increase in marine operational activities has resulted in increasing demand for wave forecasting. With an accurate advanced knowledge of wave conditions, it is possible to conduct activities such as offshore drilling, nearshore construction, naval operations, merchant vessel routing, commercial fishing etc. more efficiently and safely. Wave data can be forecasted based on the meteorological conditions or hindcasted from the existing charts. However such method may not give forecast close to the observed values. The parametric equation or differential equation based on wind wave relationships and a differential equation of wave energy balance are solved numerically in wave forecasting. This generally employed to give estimate over next 6-72 hours or so. The spatial wave information of numerical wave forecasting schemes is useful and attractive in many applications, but it needs elaborate meteorological and oceanographic data and involves an enormous amount of computational effort. Apart from this translation of wind to waves results in an element of uncertainty and approximation of forecasts (Herbich, 1990)

The work carried out by Deo and Naidu (1999) describes the application of neural network analysis in forecasting of waves. This was carried out for significant wave height (H_s) with 3 hour lead period. They have carried out various combination of training patterns to obtain the desired output. Also work of average six hour, half day, and full day wave forecasting were carried out. In their work the backpropagation, cascade correlation and conjugate gradient methods were used with the input layer of one node. The correlation coefficients for the lead of 3 hour, half day and a day were 0.81, 0.78 and 0.71 respectively. This paper describes about forecasting of wave heights directly from observed waves. The backpropagation neural network with update algorithms, namely rprop, quickprop and superSAB are used to predict the future values using the present values.

NEURAL NETWORK

The artificial neural network (ANN) similar to the biological neurons works on the input and output passing through a hidden layer. The ANN used here is a data-oriented modeling technique to find relations between input- and output- patterns without knowing detailed processes. In this work input is the consecutive points of significant wave heights and the output is a predicted wave height. The ANN is organised in the form of layers. The first one is the input layer consisting of nodes equal to the number of input values. The last one is

the output layer and the number of nodes is equal to the number of output values. The layer between input and output layers is called the hidden layer having various number of nodes. The output of nodes is generated using a 'nonlinear function', sigmoid shape. Before neural network is used for prediction it is trained using the available data. The backpropagation neural networks software developed by Tveter(2000) with the update algorithms of superSAB, rprop and quickprop are used in this paper.

Rprop algorithm

Rprop stands for 'resilient propagation' and is an efficient learning scheme, that performs a direct adaptation of the weight step based on local gradient information. In crucial difference to previously developed adaptation techniques, the effort of adaptation is not blurred by gradient behaviour whatsoever. To achieve this, it is introduced for each weight its individual update value Δ_{ij} , which solely determines the size of the weight update. This adaptive update value evolves during the learning process based on its local sight on the error function E, according to the following learning rule: (Riedmiller 1994)

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^+ * \Delta_{ij}^{(t-1)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t-1)} * \frac{\partial E}{\partial w_{ij}}^{(t)} > 0 \\ \eta^- * \Delta_{ij}^{(t-1)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t-1)} * \frac{\partial E}{\partial w_{ij}}^{(t)} < 0 \\ \Delta_{ij}^{(t-1)} & , \text{ else} \end{cases}$$

$$\text{where } 0 < \eta^- < 1 < \eta^+$$

The adaptation rule works as follows. Every time the partial derivative of the corresponding weight w_{ij} changes its sign, which indicates that the last update was too big and the algorithm has jumped over a local minimum, the update value Δ_{ij} is decreased by the factor Δ . If the derivative is positive (increasing error), the weight is decreased by its update value, if the derivative is negative, the update value is added:

$$\Delta w_{ij}^{(t)} = \begin{cases} -\Delta_{ij}^{(t)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t)} > 0 \\ +\Delta_{ij}^{(t)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t)} < 0 \\ 0 & , \text{ else} \end{cases}$$

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)}$$

But, there is one exception: If the partial derivative changes sign, i.e. the previous step was too large and the minimum was missed, the previous weight update is reverted:

$$\Delta w_{ij}^{(t)} = -\Delta w_{ij}^{(t-1)} , \text{ if } \frac{\partial E}{\partial w_{ij}}^{(t-1)} * \frac{\partial E}{\partial w_{ij}}^{(t)} < 0$$

At the beginning, all update values Δ_{ij} are set to an initial value Δ_0 . For Δ_0 directly determines the size of the first weight step, it is preferably chosen in a reasonable proportion to the size of the initial weights. A good choice may be $\Delta_0 = 0.1$. Even for much larger or much smaller values of Δ_0 fast convergence is reached.

SuperSAB

SuperSAB is based on the idea of sign-dependent learning-rate adaptation. The basic of the function is to change its learning-rate exponentially instead of linearly. This is done to take the wide range of temporarily suited learning-rates into account (Riedmiller 1994)

$$\epsilon_{ij}^{(t)} = \begin{cases} \eta^+ * \epsilon_{ij}^{(t-1)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) > 0 \\ \eta^- * \epsilon_{ij}^{(t-1)} & , \text{ if } \frac{\partial E}{\partial w_{ij}}(t-1) * \frac{\partial E}{\partial w_{ij}}(t) < 0 \\ \epsilon_{ij}^{(t-1)} & , \text{ else} \end{cases}$$

$$\text{with } 0 < \eta^- < 1 < \eta^+$$

In case of a change in sign of two successive derivatives, the previous weight is reversed. SuperSAB is considered to be fast converging algorithm. One of the problem with superSAB is the large number of parameters that need to be determined in order to achieve good convergence times, i.e., the initial learning-rate(ϵ), the momentum factor(μ), and the increase (or decrease) factors. Also one more drawback is inherent to all learning-rate adaptation algorithms, is the remaining influence of the size of the partial derivative on the weight step:

$$\Delta w_{ij}(t) = -\epsilon_{ij}(t) * \frac{\partial E}{\partial w_{ij}}(t) + \mu \Delta w_{ij}(t-1)$$

Despite careful adaptation of the learning rate, the derivative itself can have an unforeseeable influence on the size of the weight step. Consider the situation, where a shallow error function leads to a permanent increase of the learning rate. Although the learning rate grows rather large, the resulting weight-step remains small, due to the partial derivative. When suddenly a region of steep descend is reached, probably indicating the presence of a minimum, the resulting large derivative is scaled by the large learning-rate, pushing the weight in a distant region far away from the previous position.

Quickprop

The quick prop algorithm is developed from the Newtons method, but it is more heuristic than formal. The method is similar to normal backpropagation, but the difference is that, for each weight this process keeps storing the error derivative computed during the previous training epoch, along with the difference between the current and previous values of this weight. The value for the current training epoch is also available at weight update time (Fahlman, 1988).

This is a completely different approach to local adaptive learning, in which the total error function for each weight is assumed to be a 'parabola whose arms are opened upward', and the slope of the curve is not affected by changing all other weight in the network. The estimates of the position of the minimum for each weight are obtained by solving the equation given below for two following partial derivatives

$$\frac{\partial E}{\partial w_{ij}}(t-1) \text{ and } \frac{\partial E}{\partial w_{ij}}(t)$$

$$\Delta w_{ij}(t) = \frac{\frac{\partial E}{\partial w_{ij}}(t)}{\frac{\partial E}{\partial w_{ij}}(t-1) - \frac{\partial E}{\partial w_{ij}}(t)} \Delta w(t-1)$$

There is a marked improvement of learning time compared with standard backpropagation

RESULTS & DISCUSSIONS

The wave data collected off Marmagoa at a water depth of 23 m during February 1996 to January 1997 is used for the present studies. Three hourly significant wave height over the period is used for training the algorithm.

The forecasting of waves is carried out based on training data set and predicted values are compared with the test data set. The results from the combination of 1-10-1, 2-10-1, 3-10-1, 4-10-1, 5-10-1 and 6-10-1 were worked out. The first and last values separated by dashes indicate the number of input and output nodes

involved, while the middle value gives the nodes in hidden layer. The forecasted waves are closely matching with the observed values. Initial 80% of data are used to train neural network. Based on this trained neural network (NN), the wave forecasting for next 20% data is carried out. Figure 1 shows the time series Hs values forecasted for the next 3 hours on the basis of current three hourly observation using rprop algorithms with network combination of 1-10-1. The corresponding scatter diagram is also shown. The correlation coefficient, 0.9259 is obtained for this forecast. Results from other combinations and algorithms are given in the Table 1 and 2. The nonstationary nature of time series (Hs) is separately considered for NN modeling. Figure 2 shows that the forecast is closely matching with observed nonstationary data and correlation coefficient, 0.9602 is obtained.

Forecasting information with higher lead time than three hourly predicted wave data will be useful. To arrive at this, the average over a short period like six hour, twelve hour is taken and analysis is carried out with the combination of 1-10-1. Forecasting of the next six hourly average Hs value based on the current six hourly average Hs value is carried out by training with rprop algorithm (1-10-1). The time series profile of predicted wave data is shown in Figure 3 along with the observed wave data. But there is a minor lag for forecasted profile from the observed profile. This is due to the increase in forecast lead time. The correlation coefficient, 0.8807 is obtained.

The forecasting of half day average significant wave height based on the current half day average significant wave height is carried out by rprop algorithm with the network combination of 1-10-1. The forecasted wave profile picks up rise and fall of observed wave profile but with some lag (Fig 4). Also some deviation from the observed wave profile is visible. The correlation coefficient is 0.8045. In the similar way, the forecasting of day average significant wave height is also carried out using rprop algorithm with the network combination of 1-10-1. The correlation coefficient, 0.7254 is obtained. It is observed that there is a pattern of decreasing correlation values with the increase in lead time of forecast.

Table.1 gives the comparison of correlation coefficients from the present with earlier work of Deo & Naidu (1999). It shows that the present study yields improved results while compared to the results obtained by Deo & Naidu (1999). Table 2 gives the correlation coefficients for input layer of one to six nodes with different update algorithms, namely of quickprop, rprop and superSAB. Generally variation of correlation coefficient from these different algorithms is not appreciable. The results of correlation coefficient from one to higher combination of input nodes are shown in Table 2. And it is seen that there is no further improvement in correlation coefficients by increasing the input nodes. This may be due to the random nature of wave data. In earlier work of tide prediction using backpropagation, improvement of results with increase of input nodes might be due to near sinusoidal nature of tidal data (Mandal 2001). In the case of tidal data, large duration can be predicted using small amount of training data. Whereas for the waves, large amount of data is required for training to obtain good results.

CONCLUSIONS

The forecasting of waves by neural network is carried out using backpropagation. The results also show that updating algorithm of rprop gives good results. The input layer node of one also gives good results. The forecasted significant wave heights closely agree with the observed wave heights. In the present work, neural network with rprop algorithm for three hourly wave forecasting yields correlation coefficient of 0.93. The forecasting of waves from the average data of various periods is carried out and for a day average wave data correlation coefficient, 0.73 is obtained. This shows that the wave forecasting can be carried out using neural network effectively. The neural network in wave forecasting is a useful method and by adopting the different updating algorithms better correlation coefficients can be achieved.

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Table 1 Comparison of correlation coefficients

Forecasting lead time	AR model Deo&Naidu(1999)	Neural network Deo&Naidu(1999)	Present work NN-rprop
3 hour	0.78	0.81	0.93
6 hour	--	--	0.88
12 hour	0.72	0.78	0.80
24 hour	0.70	0.71	0.73

Table 2 Correlation coefficients for 3 hourly forecasted Hs

No of consecutive wave heights as nodes of input layer	Rprop	Quickprop	SuperSAB
1	0.9259	0.9250	0.9300
2	0.9262	0.9200	0.9190
3	0.8987	0.9104	0.9214
4	0.9134	0.8845	0.9157
5	0.9115	0.9064	0.9177
6	0.9177	0.7183	0.9214

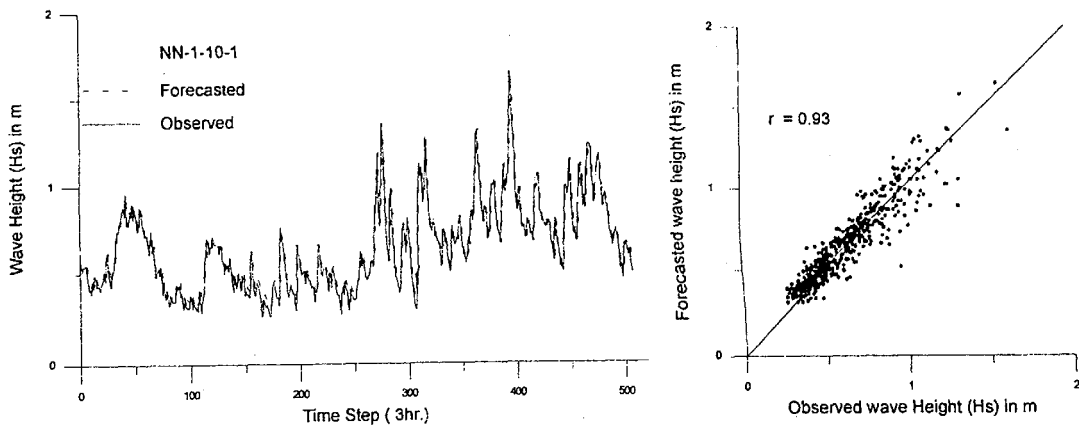


Fig. 1 Wave forecasting off Marmagoa by rprop algorithm

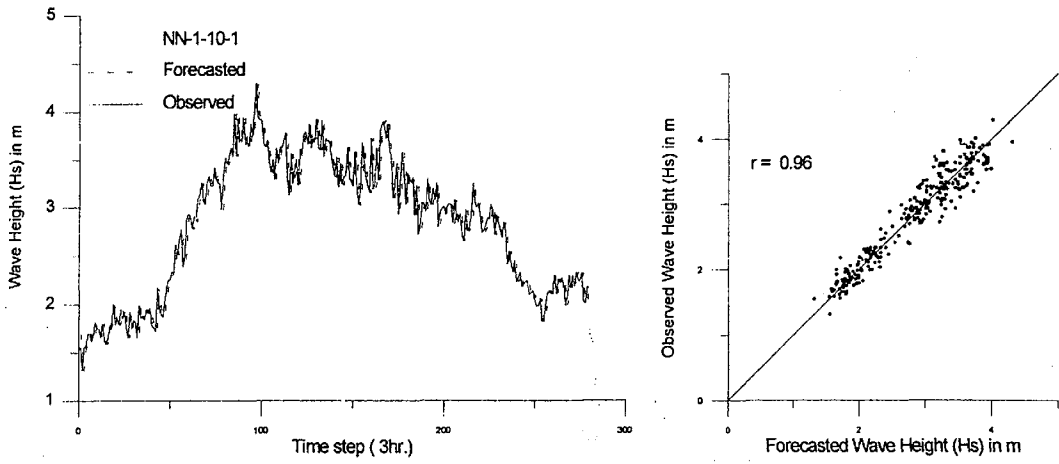


Fig. 2 Wave forecasting (nonstationary) off Marmagoa by rprop algorithm

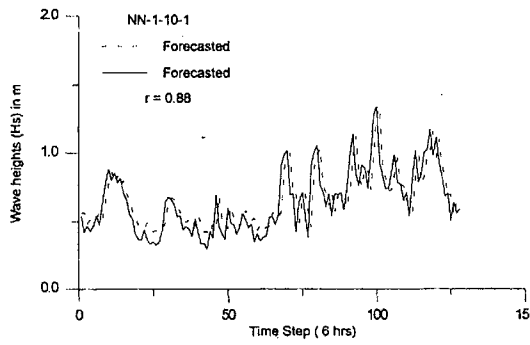


Fig. 3 Wave forecasting (six hourly average) off Marmagoa by rprop algorithm

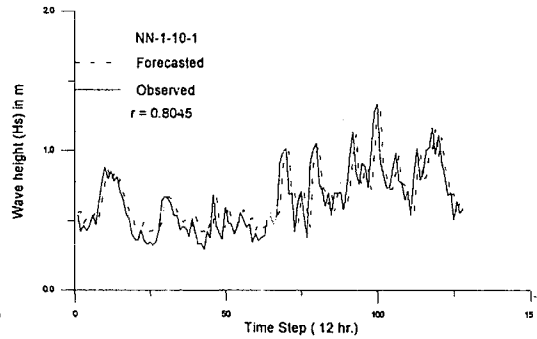


Fig. 4 Wave forecasting (half day average) off Marmagoa by rprop algorithm