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## PREDICTION OF TIDES USING BACK-PROPAGATION NEURAL NETWORKS

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### *Abstract*

*Prediction of tides is very much essential for human activities and to reduce the construction cost in marine environment. This paper presents an application of the artificial neural network with back-propagation procedures for accurate prediction of tides. This neural network model predicts the time series data of hourly tides directly while using an efficient learning process called quickprop based on a previous set of data. Hourly tidal data measured at Gopalpur port - east coast of India was used for testing the back-propagation neural network model. Results show that the hourly data on tides for even a month can be predicted efficiently with a very high correlation coefficient (=0.9984).*

### INTRODUCTION

Accurate tidal prediction is an important problem for construction activities in inlet, coastal and offshore areas. In some coastal areas, the slopes are very gentle and tidal variation makes waterfront distances in the range from hundred meters to a few km. Similarly tidal data is important for the construction of jetties, harbours and navigation. In offshore areas, accurate tidal data is helpful for successful and safe operations, such as platforms being installed, navigation, loading-unloading in the high tide zonal area.

Theoretical expression of tides was first derived by Newton in 1687 and then by Bernoulli in 1741 (Thomas, 1885). The harmonic analysis of tidal prediction made by Thomas was subsequently extended by Darwin (1898). The least-square prediction technique was incorporated by Doodson (1958) for determining the harmonic constants. Thereafter many methods of tide prediction techniques were developed. In a recent paper by Yen et al (1996) Kalman filtering technique was used for the short-term prediction of tides at Kaohsiung Harbour, Taiwan. This has helped in overcoming the problem of conventional harmonic analysis which requires a long period of measured tides. Yen et al have used harmonic tide prediction model with 4 main tidal components namely,  $S_2$ ,  $M_2$ ,  $K_1$  and  $O_1$ . However, the accurate prediction of tides has remained a concern for coastal and offshore engineers.

The artificial neural network (ANN) has been used for predicting some phenomena in marine environment (Williams, 1994; Grubert, 1995; Mase, 1995; Mase et al, 1995). Vaziri (1997) used ANN and ARIMA models for predicting Caspian Sea mean monthly surface water level. Deo and Chaudhari (1998) used ANN which was trained using three algorithms, namely error back-propagation, cascade correlation and conjugate gradient for predicting tides. Tsai and Lee (1999) examined the applicability of the back-propagation neural network (BPN) to forecast the hourly tidal variation.

This study represents the application of ANN to establish a tidal prediction model. The ANN provides the prediction by learning the characteristics of the past data. The BPN is the most popular one among the supervised learning models of ANN. In back-propagation networks, the weights of the connections are adjusted to minimize the measure of the difference between the actual output vector of the network and the desired output vector. This paper applied the BPN technique with quickprop process to predict the hourly

tidal variations. The basic concepts, algorithms and quickprop process of BPN are given below. The proposed model is applied to the tides' prediction at Gopalpur port, east coast of India.

## BACK-PROPAGATION NEURAL NETWORK

ANN is an information processing paradigm inspired by the way the densely interconnected, parallel structure of the mammalian brain processes' information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) and are tied together with weighted connections. The introductory materials of ANN can be obtained from any textbook (Haykin, 1994, Wu, 1994). Back-propagation is, commonly used, one of the self-learning methods of ANN to obtain required answers. A three layered network with an input layer,  $I$ , a hidden layer  $H$ , and an output layer  $O$ , as shown in Figure-1 is considered in this paper. Nodes in input layer receive the measured data values for learning

the network and pass them on to the hidden layer as shown in Figure-1. Here all the input values are multiplied by a weight and then sum them up. This sum value is passed through a nonlinear sigmoid transfer function which is defined by

$$f(x) = 1/(1+e^{-x}) \quad (1)$$

This forms the input to the output layer which operates identically with the hidden layer nodes. Resulting transformed output from each output node yields the network output.

Before we go for actual prediction, the network is to be trained using a set of input-output patterns. In any training process, the objective is to reduce the overall error  $E$  which is defined as

$$E = 1/P \sum E_p \quad (2)$$

where,

$$E_p = 1/2 \sum (T_k - O_k)^2$$

$p$  is the total number of training patterns; the actual output value,  $T_k$  and predicted output value,  $O_k$  at  $k$ th output node.

In the learning process of BPN, the error at the output layer propagates backwards to the input layer through hidden layer in the network to yield the desired outputs. The *gradient descend method* is used to calculate the weight of the network and then adjust the weight of interconnections to reduce the output error. The interconnection weights are adjusted using an error convergence process. There are many such processes available (Deo et al., 1998 and Tveter, 2000). The quickprop (Fahlman, 1988) process which seems to be efficient and consistent in performance, is used in this study.

## QUICKPROP PROCESS

While studying a variety of benchmark problems, Fahlman (1988) developed a new learning process called '*quickprop*' which effectively converges the network and is faster than standard back-propagation. This process is a second order algorithm based loosely on Newton's method. And it also tries to dynamically adjust the learning rate, either globally or separately for each *weight* based in some heuristic way on the history of the computation.

Standard back-propagation and its relatives work by calculating the partial first derivative of the overall error ( $E$ ) with respect to each *weight* ( $dE/dw(t-1)$ ). For each *weight* this process keeps storing  $dE/dw(t-1)$ , the error derivative computed during previous training epoch along with the difference between the current and previous values of this *weight*. The value of  $dE/dw(t)$  for the current training epoch is also used at the *weight* update time.

The *weight* change can be calculated using the expression

$$\Delta w(t) = [S(t)/\{S(t-1) - S(t)\}] \Delta w(t-1) \quad (3)$$

Where  $S(t)$  and  $S(t-1)$  are the current and previous values of the first derivative of the error,  $dE/dw$ . This crude approximation method when applied iteratively is effective.

## RESULTS AND DISCUSSION

The harmonic tide model is commonly used for tides prediction at various coastal/offshore locations. The accuracy of tides prediction depends on the number of component tides used in the harmonic tide model. The well-known main component tides are  $M_2$  and  $S_2$ , and other component tides vary depending on geographical locations. The tides were measured at Gopalpur port (Fig.2) situated on the east coast of India, for the period 8 January to 10 April 1993. The harmonic component tides were estimated based on the above measured tides and then the harmonic tide prediction model was used for future prediction at that location (Chandramohan et al, 1994). However, the need for the accurate prediction of tides led to carry out an alternate method using BPN. The above measured tidal data were used for testing BPN.

The present study considered the neural network structure as  $I_6H_2O_1$ , where  $I_6$  = six input neurons,  $H_2$  = two hidden neurons, and  $O_1$  = one output neuron. The number of training iterations used in the network structure was varied depending on estimated error values. The initial values of the interconnection weights and thresholds were given by uniform random numbers from -1 to 1. Once the learning process is completed from a training set, the final interconnection weights and thresholds were used in the prediction process.

Here a previous time series of tides was generally used to predict the next tidal value. The present neural network model uses six previous consecutive values to predict the next one, for example,  $x_1, x_2, x_3, x_4, x_5, x_6$  tidal data are used to predict next tidal value  $x_7$ . This is similar to the Autoregressive Moving Average (ARMA) process (Mandal, 1996).

In Figs. 3 and 4, 1-day tidal data were used for training and consequently predicted 1-day and 6-days tides respectively. There were hardly any differences which can be observed from the error and the correlation coefficients of 0.9993 and 0.9990 respectively. This implies that reliable tidal prediction can be obtained based on 1 day records of the hourly measured tides used as training set for the BPN model. Now it is better to test whether this 1-day tidal data can also produce useful predictions for 30 days or longer period. Fig-5a used 1-day tidal value as training set where final interconnection weights and values of thresholds were calculated and these values were used to predict for next 30-days tides. The comparison between the measured and predicted tides for 30-days is shown in Fig 5b. Here the correlation coefficient is 0.9984. This shows that a very good agreement between the measured and predicted tides can be obtained using the BPN model.

The root-mean-square (RMS) error of the hourly tides can be defined as

$$RMS = \sqrt{\{\sum (y_{it} - y_{ot})^2 / \sum y_{it}^2\}} \quad (4)$$

Where  $y_{it}$  = measured tides,  $y_{ot}$  = predicted tides. The accuracy improves if RMS value approaches zero. It can be generally shown that a longer period of measured data as training set is required to improve the accuracy of predicted tides for a longer period. This is verified based on the measured data as shown in Table -1. As the duration of training data set increases, the RMS error decreases.

## CONCLUSIONS

The hourly predicted tides can be generally estimated using harmonic analysis. This process requires a large amount of measured data for estimating the approximate harmonic parameters. This paper describes an alternate approach for predicting tides using a small data set. In this study, the BPN model with quickprop algorithm is adopted to predict the tides by learning and recalling processes. Unlike conventional harmonic analysis, the present method predicts directly using a learning process from a training set based on a set of

previous data. The result shows very good long term (one month) prediction using 1-day measured tides as training set, in which the estimated correlation coefficient is 0.9984.

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TABLE 1. RMS errors for different training data set

Type	Training data set	Prediction period	RMS error
1	1 day	6 days	0.0172
2	1 day	30 days	0.0182
3	5 days	30 days	0.0181
4	10 days	30 days	0.0166
5	5 days	60 days	0.0201
6	10 days	60 days	0.0187

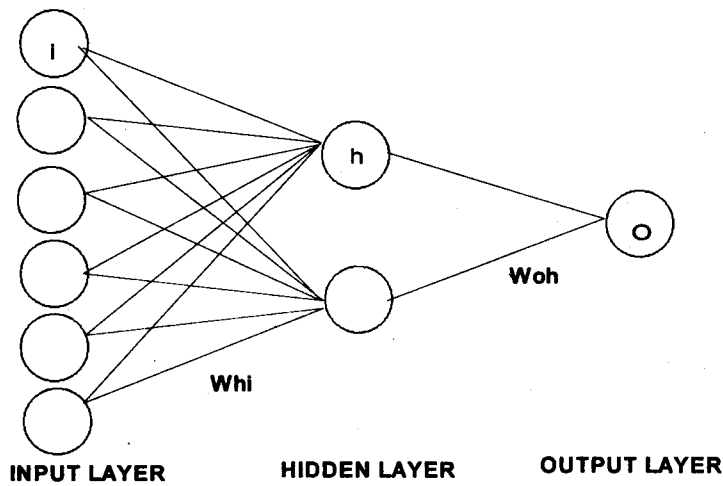


Fig.1 Structure of ANN

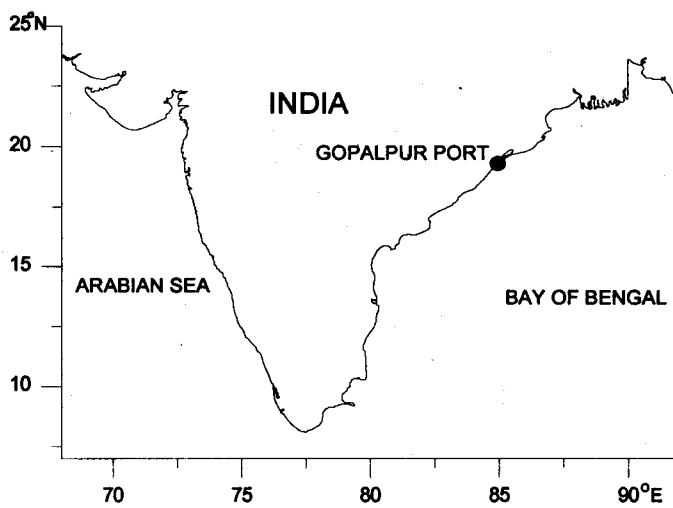


Fig.2 Study Area

Predictions of tides using backpropagation neural networks

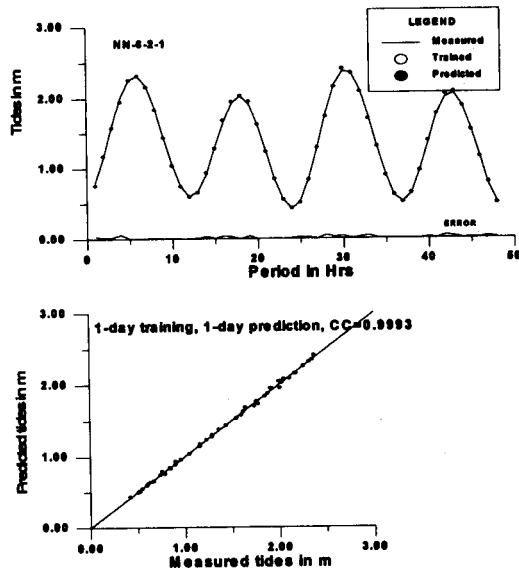


Fig.3 Measured and Predicted tides

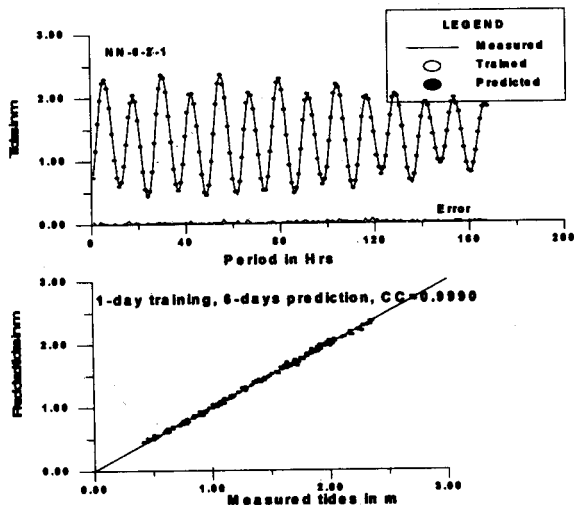


Fig.4 Measured and Predicted tides

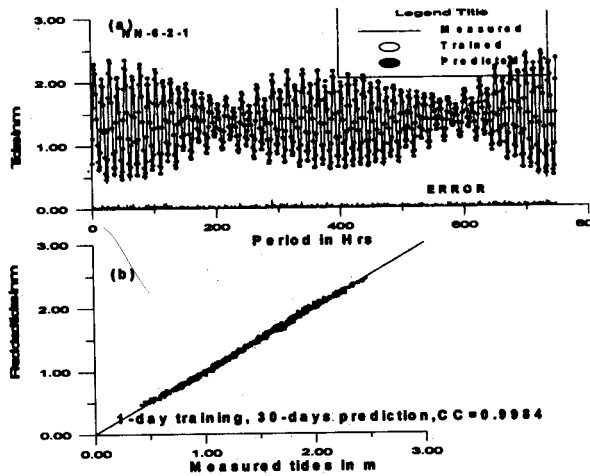


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