TIDAL-LEVEL FORECASTING USING ARTIFICIAL NEURAL NETWORKS ALONG THE WEST COAST OF INDIA

Shetty RAKSHITH¹, G. S. DWARAKISH² and Usha NATESAN³

¹P.G. Student, Dept. of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal (Srinivasnagar P.O., Mangalore, Karnataka 575 025, India)
E-mail: dwaraki.gs@gmail.com

²Professor, Dept. of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal (Srinivasnagar P.O., Mangalore, Karnataka 575 025, India)
E-mail: shettyrakshith@gmail.com

³Professor, Centre for Water Resources, Anna University (Chennai, Tamil Nadu. 600 025, India)
E-mail: u_natesan@yahoo.com

Knowledge of tide level is essential for safe navigation of ships in harbor, disposal and movement of sediments, environmental observations, explorations, and many more coastal and ocean engineering applications. Traditional methods such as harmonic analysis, least mean squares method, and hydrodynamic models have disadvantages in that they require excessive data, are time consuming, and are tedious to carry out. Artificial Neural Network (ANN) has been widely applied in the coastal engineering field in the last two decades for solving various problems related to time series forecasting of waves and tides; predicting sea-bed liquefaction and scour depth; and estimating design parameters of coastal engineering structures. Its ability to learn highly complex interrelationship based on provided data sets with the help of a learning algorithm, along with built-in error tolerance and less amount of data requirement, makes it a powerful modeling tool in the research community. In the present study, an attempt was made to predict tides at Karwar, located at the west coast of India, using a type of network called Non-linear Auto Regressive eXogenous input (NARX). It has an advantage in that the generated output is fed back to the network creating a loop. Conceptually, it differs in the fact that it uses the target given to it also as an input. Predictions were carried out for various durations using the weekly and monthly data sets. It was found that at Karwar, one year’s prediction can be successfully carried out using one month data as an input with correlation coefficient (‘r’) greater than 0.97. The developed model was further applied to predict tides at New Mangalore Port Trust, Panambore, along the west coast of India, which is 260 kms south of Karwar. Results obtained were encouraging with ‘r’ value greater than 0.96.

Key Words: artificial neural network, tides, prediction, non-linear auto regressive, Karwar, correlation coefficient

1. INTRODUCTION

Man has been trying to understand the oceans for a very long time but even after centuries he still knows little about them. It is a complex system that involves physical, chemical, and biological processes being carried out all the time. Physical oceanography involves wave formation, breaking, tidal-level variations, seasonal beach profile changes, to name a few. Various methods have been formulated with advances in mathematical and physical science to demystify each of the phenomena. Methods based on the physics of the event, statistical analysis, spectrum analysis, time series analysis, and empirical equations derived from the laboratory studies have been used. Constant attempts are being made to increase the efficiency and/or accuracy of the model being developed to replicate the process, but with limited success. This is largely due to the sheer size of the system involved and also the highly complex interrelationship between the numerous parameters involved in the occurrence of the single phenomenon. The site-specific and ever changing nature of the oceans adds to the woes.

Tidal level has a major role to play in various activities such as harbor planning, determining Mean Sea Level (MSL) and navigation depth, drawing marine boundaries, storm surge monitoring, and even disposal of sediments. Monitoring and prediction of tidal level are thus important so that activities that are controlled by it are planned and operated properly. Tidal ranges are largely affected by the gravitational pull of the sun and moon on the oceanic water body, the com-
ponent of tide being called ‘the astronomical tide.’ Other factors such as bottom topography, sea-level atmospheric pressure, and wind speed also contribute to the other component called ‘non-astronomical tide.’

The traditional method of tide prediction is done by the harmonic method, which accounts for the parameters or constituents of astronomical tide. It is given by the equation

\[ H = H_o + A \cos(at + \alpha) + B \cos(bt + \beta) + C \cos(ct + \gamma) \]  

(1)

where \( H \) is the height of the tide at location; \( H_o \) is the MSL; \( A, B, \) and \( C \) are the amplitudes of the constituents; and \( (at + \alpha), (bt + \beta), \) and \( (ct + \gamma) \) are the phases of the constituents. Once the harmonic constituents or constants are found out for a location by least mean squares or Kalman Filtering methods, it can be used to predict the tides by reuniting them with the available astronomical relations prevailing at the time for which predictions have to be done. For a detailed account of harmonic analysis and prediction of tides, one can refer to\(^3\). The major drawback of this method is the large amount of continuous tide data that are required to determine the tidal constituents\(^5\). Also, the method does not take into consideration various hydrodynamic and meteorological parameters. Though Kalman filtering requires fewer amounts of data, its prediction are for short-term duration. Numerical models, such as the finite difference method, require accurate boundary conditions and geometric information\(^5\). Although including more number of constituents in the harmonic analysis improves the accuracy, it leads to the problem of growing memory and calculation time. Harmonic analysis and Kalman filtering methods are ineffective in supplementing the lost tide data, especially when tidal-level changes are complex in nature and data available are incomplete\(^5\). Also, it is restricted to the prediction of the tides at a particular station only, as tidal constituents vary from one place to another.

A new model based on the working of human brain has been conceptualized to meet the objective of learning the relationship between complex parameters involved in the interaction without having to know the underlying physics behind it. As it is an attempt to mimic the capabilities of human neural system, it is called Artificial Neural Network (ANN). It imbibes the qualities of exploiting non-linearity, adaptability to adjust free parameters (in this case the connection weights, comparable to synaptic connections in the human nervous system) by mapping input/output data sets using various learning algorithms and fault tolerance. Also, compared to the available techniques in majority of the cases, it gives accurate results. It has been extensively used for solving problems in coastal engineering ever since\(^7\) used it for stationarity analysis of rubble mound breakwaters. Some of the studies that implemented the ANN for tide predictions are reviewed in the following section.

Back Propagation Network (BPN) was used for prediction of tides and the study revealed that long duration predictions can be done using very small duration data set without having to determine the harmonic constants\(^8\). In a similar study conducted to check the applicability of ANN where different tide conditions exist (diurnal, semi-diurnal, and mixed) at three different stations, satisfactory results were obtained at all the stations\(^9\). Further, it was also showed that ANN can be successfully utilized in supplementing missing tide data\(^10,11\). Comparative study was conducted on hydrodynamic and ANN models at Okha and Navlakh, Gujarat, India. Though the results were marginally in favor of hydrodynamic models, the study concluded that ANN can be used as a substitute for hydrodynamic models considering the sparse data requirement and less computational time taken\(^12\). Regional neural network was developed to predict sea water level at a station using data obtained from other stations at distances ranging from 234 kms to 591 kms; the results obtained showed very good ‘r’ value ranging from 0.96 to 0.98\(^13\). A study\(^14\) used functional neural networks (FNN) and sequential learning neural networks (SLNN) to predict tide levels. The FNN uses domain knowledge while the conventional ANN uses data knowledge. FNN learns function as opposed to ANN, which learns weights. Seven parameters affecting the tide-generating forces from the tide theory were used as input in a model developed\(^15\). The model was trained using one-year tidal data and same data were used to find harmonic constants in the harmonic method (HM) consisting of 60 constituents HM (60). The results showed that the ANN model is as powerful as HM (60) when one-year tidal data are used and with 2-hour lead time. ANN and wavelet analyses were combined to extend the predictions for 5-year duration and to improve the prediction quality\(^16\). Feed forward neural network with Resilient Back Propagation (RBP) learning algorithm was used to predict tide levels and supplement missing data with quicker computation\(^16\). To study the effect of meteorological parameters of wind speed and sea-level atmospheric pressure on tidal predictions\(^17\), incorporated three-hour wind speed data and atmospheric pressure data in the input, along with calculated tide data from the harmonic analysis method for the network training. The importance of the meteorological parameters was highlighted by the results obtained, which showed a considerable decrease in prediction error when additional inputs were provided. The detailed review on applications of ANN in tide-level prediction can be found in\(^18\).
The present study utilizes the advantages of Non-linear Auto Regressive eXogenous (NARX) network for the prediction of tide level. It is better than the network used in previous studies as the architecture is such that the input given at a particular point of time will have its effect not only on the corresponding output but also on the forthcoming points. Thus, the information contained in them or the relationship between the current output and previous input is not lost, which is normally the case in other networks. It also has an added advantage of fixing the phase lag values in the creation of network itself by giving the lag values in terms of time delay between the layers.

The present study focuses on creating a model that requires minimum amount of data for the satisfactory prediction of yearlong hourly tide-level predictions to overcome the disadvantage of excessive data requirement in the existing methods. Normally, 369 days of hourly data at a point are required to extract 20 to 30 constituents with adequate separation of closely spaced constituents using the least squares method. The present study also is extended to the prediction of tide levels at nearby locations, which have similar existing tide conditions to that of the location where the model is created. This can be further developed to create a regional neural network for the prediction of tides where similar conditions exist and will help in obtaining a preliminary but reliable tide data for greenfield projects at places where permanent tide gauge stations are not established.

The following section covers the data products and methodology, describing in brief the development of ANN and the basics of NARX network. It is followed by the results and discussion of the study and conclusions that have been drawn from the study.

2. STUDY AREA AND DATA DIVISION

The study is carried out for two stations of Karwar and New Mangalore Port Trust, Mangalore located at the northern and southern tips in the coastal segment of the southern state of Karnataka, respectively. Fig. 1 shows the study locations with respect to the map of India.

The coastal segment along the study region is bounded by Western Ghats in the east and the Arabian Sea in the west. The coast is exposed to the seasonally reversing monsoon winds and the annual rainfall is 3 m. The tides in the Karwar region are mixed semi-diurnal dominant. The average tidal range at Karwar is 1.58 m during springs and 0.72 m during neaps. Tides at Mangalore coast are of the mixed type with the semi-diurnal components dominating. The average tidal range here is 1.68m.

NARX network has been used for the prediction of tides at Karwar, located on the west coast of India. Three years of observed hourly tide-level data (from December 2008 to December 2011) were obtained from the National Institute of Oceanography; Goa is used in the present study. The success of ANN largely depends on the amount and quality of the data that are used for training purposes. The present data used at the Karwar region are void of any missing values. Also, being observed/measured real time data obtained from tide gauge station, the information regarding the meteorological parameters is built in.

The data are divided into weekly and monthly data sets for the prediction of tides using various durations of data sets. In weekly data sets, a row in the input data matrix comprises 168 data points corresponding to an equal number of hours in the week. These rows represent a single node in the input and output layer of the network. Similarly, in monthly data sets, a single row (or a node) consists of 720 data points corresponding to 30 days. In the present study, the yearly data sets are divided into 12 months consisting of 30 days each for the regularity of input data matrix size.

Table 1 briefly describes the data sets fed into the network. The network architecture 1-1-1 indicates

<table>
<thead>
<tr>
<th>Data sets</th>
<th>Network architecture</th>
<th>Input</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>1-1-1</td>
<td>01/01/2009 to</td>
<td>31/01/2009 to</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30/01/2009</td>
<td>01/03/2009</td>
</tr>
<tr>
<td>Simulation</td>
<td>1-1-1</td>
<td>02/03/2009 to</td>
<td>01/04/2009 to</td>
</tr>
<tr>
<td></td>
<td></td>
<td>31/03/2009</td>
<td>30/04/2009</td>
</tr>
</tbody>
</table>
that there are one input node, one hidden layer neuron, and an output layer. The input layer consists of one month’s hourly tide data; hence the input data matrix will be [1x720]. The number of rows (1) represents the number of months and number of nodes represented in the architecture (Fig. 2). Number of columns (720) represents the corresponding hourly data points. For one month’s tide-level prediction using one month’s tide-level data, the output will also have same data matrix size of [1x720]; subsequently, in network architecture, the number of output nodes will be referred to as one. However if one week’s data are used for the prediction of four weeks’ data (Fig. 3), then the input data matrix will be [1x168] and output matrix will be [4x168]. Hence, network architecture representation will be 1-1-4 for a network having a single hidden layer and a single hidden neuron.

Hourly tide-level data from December 2010 to December 2011 were obtained from New Mangalore Port Trust (NMPT), Mangalore to check the model applicability of the one that was developed for Karwar. The data are divided into weekly and monthly data sets in a fashion similar to that of Karwar’s data.

3. METHODS

1) Artificial Neural Networks

The development of Artificial Neural Networks (ANN) can be attributed to the attempt carried out to mimic the working pattern of the human brain. Its success lies in its ability to exploit the non-linear relationship between input and output data by continuously adapting itself to the information provided to it by means of some learning process. ANN can be classified, based on network type, into feed forward and feedback or recurrent networks. The basic difference between the two is that, in feed forward networks, the information is passed from one layer to the other in a forward manner till the output is obtained in the output layer. Whereas, in feedback network, the output obtained in the output layer is fed back into the network through input layer; thus, this type of network will have a minimum of a single loop in its structure. Further, ANN can also be classified based on learning type; i.e., supervised and unsupervised learning. In supervised learning, a set of input and corresponding output is fed into the network and the calculated output is compared with the target output (given output values to the network); the difference between the two is the error in the prediction and through various error correction measures available (learning algorithms), the network adapts itself till the error reaches a minimum value, or fixed number of iterations are complete. In unsupervised learning, the networks are tuned to statistical regularities of the input data by learning rules such as radial basis function and others; here, no input-output data set is presented to the network.

Fig. 4 shows the basic mathematical model of ANN where, \( x_1, x_2, x_3 \ldots x_n \) are the input parameters; \( w_{k1}, w_{k2}, w_{k3} \ldots w_{ki} \) are the weights associated with the connections; i.e., synaptic weight connections from input neuron ‘i’ to neuron ‘k’ and \( i = 1 \) to \( n \). The ‘k’ neuron is the summing junction where net input is given by

\[
 u_k = \sum_{i=1}^{n} w_{ki} \cdot x_i \tag{2}
\]

and

\[
 v_k = u_k + b_k \tag{3}
\]

where \( b_k \) is the bias value at the ‘k’th node. The final output \( y_k \) is the transformed weighted sum of \( v_k \), or in
other words, \( y_k \) is the function of \( v_k \) represented by
\[
y_k = \Phi(v_k) = 1 / [1 + \exp(-a v_k)]
\] (5)
The present study utilizes ‘tansig’ and ‘purelin’ transfer functions mathematically expressed as
\[
y_k = \frac{2}{(1 + \exp(-2 \cdot a v_k))} - 1
\] (6)
and
\[
y_k = a v_k
\] (7)
respectively, where, ‘\( a \)’ is the slope of the curve of respective functions seen in Fig. 5 and Fig. 6 showing the graphical representations of the transfer functions.

The most commonly used learning algorithm in coastal engineering applications is the gradient descent algorithm. In this algorithm, the global error calculated is propagated backward to the input layer through weight connections, during which the weights are updated in the direction of the steepest descent or in the direction opposite to gradient descent.

However, the overall objective of any learning algorithm is to reduce the global error \( E \) defined as
\[
E = \frac{1}{p} \sum_{p=1}^{P} E_p
\] (8)
and
\[
E_p = \frac{1}{2} \sum_{k=1}^{N} (o_k - t_k)^2
\] (9)
where \( E_p \) is the error at the \( p^{th} \) training pattern, \( o_k \) is the obtained output from network at the \( k^{th} \) output node and \( t_k \) is the target output \( k^{th} \) output node, and \( N \) is the total number of output nodes. The Levenberg-Marquardt algorithm\(^{20,21} \) used in this study can be written as
\[
W_{\text{new}} = W_{\text{old}} - [J^T J + \gamma I]^{-1} J^T E_{\text{old}}
\] (10)
where \( J \) is the Jacobian of the error function \( E \), \( I \) is the identity matrix, and \( \gamma \) is the parameter used to define the iteration step value\(^{22,23} \). It minimizes the error function while trying to keep the step between the old weight configuration \( W_{\text{old}} \) and the new updated one \( W_{\text{new}} \) small.

The major drawback of the Feed Forward Back Propagation (FFBP) is that the network gets trapped in the local minima. The overlearning phenomenon due to high learning rate may lead to oscillatory behavior of the network. Very large number of neurons in the hidden layer will lead to complex learning and might take large number of iterations to terminate the process. Less number of input data makes it difficult for the network to learn all the relationship involved between the input and target parameters. Too many variations in the involved data set also diminish the accuracy of the network. The mentioned setbacks can, however, be overcome by selecting the optimum architecture of the network using various techniques, such as sensitivity analysis, to select the most effective input parameters and reduce network size to decrease the computational time required. Using generalization techniques, such as Principal Component Analysis (PCA), to improve the quality of the input data, will also help improve prediction quality. Other ANN models based on conjugate gradient algorithm, radial basis function, cascade correlation algorithm, and recurrent neural networks can be used to overcome this drawback\(^{24} \). Recently, many studies have been carried out combining ANN with statistical and other Artificial Intelligence (AI) methods of Genetic Programming (GP) and Fuzzy Logic (FL) systems to improve forecasting accuracy and duration as well.

(2) NARX Network

In the present study along with FFBP, a recurrent type of network, namely, Non-linear Auto Regressive network with eXogenous inputs (NARX) has also
been used. In recurrent networks, the output depends not only on the current input to the network but also on the previous input and output of the network. The response of the static network at any point depends only on the value of the input sequence at that time instant; whereas, the response of the recurrent networks lasts longer than the input pulse. Its response at any given time depends not only on the current input, but also on the history of input sequence. This is done by introducing a tapped delay line in the network, which makes the input pulse last longer than its duration by an amount that is equal to the delay given in the tapped delay. This makes the network have a memory of the input that is fed. If the network has feedback connections, then the effect of the first input sequence will be passed on to all the upcoming outputs.

In relevance to the time series prediction of tidal data, recurrent dynamic network can be effectively put to use in order to reduce the input data requirement without the loss of information from the initial data feeds. The advantage of NARX network lies in the very fact that it does not necessarily require target data for the prediction. It generates the outputs based on provided input and reuses those output as the input for further prediction. In case of availability of target data, the loop required can also be omitted from the network architecture. However, the present study uses the target output for training and creation of the model. During simulation the input data are fed equivalent to the size of training data sets and obtained results are validated against the observed tide-level data for that period.

NARX is a recurrent network, with feedback connections enclosing several layers of the network. It is based on the linear ARX model, which is commonly used in time series modeling. The defining equation for the NARX model is:

$$ y(t) = f[y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)] $$

(11)

where $y(t-1)$ to $y(t-n_y)$ are the time series data of the precedent outputs and $u(t-1)$ to $u(t-n_u)$ form the data of precedent inputs; $n_y$ and $n_u$ form the value of the input and output at the first instant. The subsequent value of the dependent output signal $y(t)$ is regressed on previous values of an independent (exogenous) input signal. The output of NARX network can be considered to be an estimate of the output of some nonlinear dynamic system that is being modeled. The output is fed back to the input of the feed forward network as part of standard FFBP architecture. The standard back propagation algorithm is now used for training the network instead of dynamic back propagation, which has complex error surfaces, exposing the network to higher chances of getting trapped in local minima and hence requiring more number of training iterations. Also, it is computationally intensive, which takes more time to train.

In relevance to the present study, since the attempt is to predict larger duration of tide-level data using minimum input, the input data set as such will be shorter. NARX network, which also uses target output as its input during training, helps in preserving the information contained regarding seasonal variations.

The non-linear data-driven self-adaptive approach, as opposed to the high data requirement of the numerical models along with requirements of the initial boundary and geometry of the study area in case of ocean engineering applications, makes ANN attractive and a powerful tool for modeling when underlying data relationship is unknown. Many studies have shown that once the network is validated for a partic-
ular task, they can be successfully used for field applications as well\textsuperscript{\texttt{[20]}}. The detailed account of theory and mathematics basics behind ANN can be found in\textsuperscript{\texttt{[27]}}.

(3) Network Parameters

Three-layered NARX network with single input layer, hidden layer, and output layer was used. Tangent sigmoid (‘tansig’) was used in the hidden layer as transfer function since data were normalized to fall in the range of -1 to 1; while purely linear (‘purelin’) transfer function was used in the output layer, as this combination of ‘tansig’ and ‘purelin’ transfer function is capable of approximating any function\textsuperscript{[27]}. The training was carried out using the aforementioned network architecture for various data size matrices. The time delay (phase lag) is taken as two hours in the present network for all the predictions done. The number of neurons in the hidden layer kept on increasing starting from one, till the best combination was found in terms of network performance indicators. The mean squared error (‘mse’) and correlation coefficient (‘r’) were taken as the performance indicators in the present study. One thousand iterations were set as the stopping criteria for the training of the network.

(4) Network Performance Indicators

The performance of the network is measured in terms of various performance functions such as sum squared error (SSE), mean squared error (MSE), root mean squared error (RMSE) and Correlation coefficient (‘r’) between the predicted and the observed values of the quantities. In the present study, ‘mse’ and ‘r’ are used as performance indicators; the lower value of MSE and higher value of CC indicate better performance of the network.

a) Mean squared error (MSE)

It is given by the formula

\[ \text{mse} = \frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2 \]  \hspace{1cm} (12)

b) Correlation coefficient (‘r’)

It measures the strength of association between the variables and is given by the formula

\[ r = \frac{\left( \sum_{i=1}^{n} x_i \cdot y_i \right)}{\sqrt{\left( \sum_{i=1}^{n} x_i^2 \right) \cdot \left( \sum_{i=1}^{n} y_i^2 \right)}} \]  \hspace{1cm} (13)

(5) Simulation of developed model at NMPT

To check the prediction adaptability of the developed model at Karwar in nearby locations with similar tide conditions, the model was applied for predictions at New Mangalore Port Trust (NMPT), which is more than 260 kms from Karwar.

The observed tide gauge data obtained from NMPT had a total of 126 missing values due to faulty working of the tide gauge at various points during the time span from 1/1/2011 to 31/12/2011. The missing values were imputed by using simple linear regression.

The simulation of the developed network at Karwar providing the most accurate prediction results is used to carry out yearlong predictions at NMPT, using the weekly and monthly data sets of Karwar. Enough care has to be taken that the input data sets being used for the simulations should fall within the range of input data sets, which are used for training purposes, to ensure that the new data fed are well within the information that has been gained by the network during the training stage. This will ensure sensible prediction of values by the network during simulation stage.

The network predictions are validated against the observed tide levels at NMPT and the results of the same are shown in Fig. 14, Fig. 15, and Fig. 16, respectively.

4. RESULTS AND DISCUSSION

(1) Prediction at Karwar

a) Weekly predictions

In the present study, weekly predictions are carried out using one week’s data to predict tide levels for 4, 12, 26, and 52 weeks, respectively. The results obtained in terms of ‘mse’ and ‘r’ values were very good from 0.99 for one week’s prediction to greater than 0.92 for 25 weeks’ prediction. However, the accuracy dropped to 0.78 for predictions of 52 weeks’ tide-level data using one week’s data as shown in Table 2. The use of target data as one of the input nodes as explained in Fig. 8 helped in improving the efficiency of the network and also in the long-term prediction of tide levels using small amount of data. The best performance for the prediction of 25 weeks was obtained when the hidden layer consisted of seven neurons. The variations in ‘r’ values for the case are shown in Table 3. Scatter plot for training and simulation of the network for 25 weeks’ prediction are

<table>
<thead>
<tr>
<th>Network structure</th>
<th>mse</th>
<th>r</th>
<th>Training</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-1-1</td>
<td>23.53</td>
<td>37.07</td>
<td>0.99663</td>
<td>0.99632</td>
</tr>
<tr>
<td>1-7-4</td>
<td>7.23</td>
<td>78.84</td>
<td>0.99861</td>
<td>0.98406</td>
</tr>
<tr>
<td>1-6-12</td>
<td>12.68</td>
<td>232.41</td>
<td>0.99742</td>
<td>0.95521</td>
</tr>
<tr>
<td>1-7-25</td>
<td>13.93</td>
<td>349.80</td>
<td>0.99718</td>
<td>0.92706</td>
</tr>
<tr>
<td>1-7-52</td>
<td>31.51</td>
<td>977.16</td>
<td>0.99358</td>
<td>0.78813</td>
</tr>
</tbody>
</table>
Table 3 Variations in ‘r’ values with increase of neurons in the hidden layer of NARX network with 1 input and 25 output nodes.

<table>
<thead>
<tr>
<th>Neurons</th>
<th>Training</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.61321</td>
<td>0.39808</td>
</tr>
<tr>
<td>3</td>
<td>0.92729</td>
<td>0.73679</td>
</tr>
<tr>
<td>5</td>
<td>0.98327</td>
<td>0.86614</td>
</tr>
<tr>
<td>7</td>
<td>0.99718</td>
<td>0.92706</td>
</tr>
<tr>
<td>8</td>
<td>0.99771</td>
<td>0.90610</td>
</tr>
<tr>
<td>9</td>
<td>0.99799</td>
<td>0.89096</td>
</tr>
</tbody>
</table>

Fig. 9 Scatter plot of training of NARX network during 25 weeks’ predictions done using one-week’s data set.

given in Fig. 9 and Fig. 10, respectively. The ‘r’ value will be one when the plot of observed versus predicted values follow a perfect straight line pattern passing through the origin. The plots in Fig. 9 for training and Fig. 10 for simulation prove the same with simulation plot being more scattered than the former, hence the higher value of ‘r’ for training and comparatively lower ‘r’ value during simulation. The time series plot of the observed versus predicted tide levels are shown in Fig. 11 and Fig. 12. Fig. 12 shows the more detailed time series plot of Fig. 11 itself for the first 500 hours of prediction. It is evident from the graph that there is no phase lag observed in prediction. Also the semi-diurnal dominant-mixed type of tide has been captured very well.

The maximum and minimum error in prediction is found to vary from 16.62 cms to -15.03 cms with a standard deviation of 3.733. The average absolute error calculated by averaging the sum of absolute error (irrespective of overestimation/positive error or underestimation/negative error) between the predicted and observed values, sums up to 15.00 cms.

A considerable amount of overestimation of low tide levels is observed in Fig. 12. Though overestimation of low tide levels is considered to be on the safer side for navigation purposes, the present model provides mere satisfactory results near the extreme values. The existence of steep slopes near the extreme
The advantage of the NARX network over the conventional ANN can be established by comparing the results of the present study with the results of the earlier study\(^{28}\) conducted by the authors to prove the superiority of ANN model over statistical methods. The study\(^{28}\) was carried out for the Karwar station using similar data sets and division. However, the outcome of the study revealed that satisfactory prediction could be achieved only when yearlong data sets were used as input in training as well as simulation. The prediction accuracy was relatively low; ‘r’ value of 0.89 for data sets divided in weeks and 0.95 for data sets divided in months was achieved, keeping in view the amount of data sets that were given as input.

Due to the increase in input data size, the model has been successful in reducing the amount of overall prediction error near the extreme values (Fig. 16). It is justified by the reduced average absolute error observed in this case, of 7.78 cms when compared to the average absolute error of 15.00 cms that was obtained during prediction using a week’s data. The minimum and maximum error value obtained in this case is -16.31 cms and 16.16 cms, respectively.

Table 4 ‘mse’ and ‘r’ values for tide-level predictions of one month, 3, 6, and 12 months’ duration using one month’s tide level as input.

<table>
<thead>
<tr>
<th>Network structure</th>
<th>mse (Training)</th>
<th>mse (Simulation)</th>
<th>r (Training)</th>
<th>r (Simulation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-1-1</td>
<td>21.99</td>
<td>31.71</td>
<td>0.99539</td>
<td>0.99574</td>
</tr>
<tr>
<td>1-5-3</td>
<td>13.97</td>
<td>32.38</td>
<td>0.99705</td>
<td>0.99389</td>
</tr>
<tr>
<td>1-7-6</td>
<td>13.62</td>
<td>105.89</td>
<td>0.99745</td>
<td>0.97875</td>
</tr>
<tr>
<td>1-10-12</td>
<td>12.49</td>
<td>110.13</td>
<td>0.99772</td>
<td>0.97775</td>
</tr>
</tbody>
</table>

Table 5 Variation of ‘r’ values with increase of neurons in the hidden layer of NARX network, with one month as input and 12 months’ data as output.

<table>
<thead>
<tr>
<th>Neurons</th>
<th>Training mse</th>
<th>Simulation mse</th>
<th>Training r</th>
<th>Simulation r</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.70012</td>
<td>0.63587</td>
<td>0.97012</td>
<td>0.97563</td>
</tr>
<tr>
<td>3</td>
<td>0.94818</td>
<td>0.88623</td>
<td>0.94850</td>
<td>0.96447</td>
</tr>
<tr>
<td>5</td>
<td>0.98927</td>
<td>0.94850</td>
<td>0.99464</td>
<td>0.96447</td>
</tr>
<tr>
<td>7</td>
<td>0.99464</td>
<td>0.96447</td>
<td>0.99627</td>
<td>0.97620</td>
</tr>
<tr>
<td>9</td>
<td>0.99627</td>
<td>0.97620</td>
<td>0.99772</td>
<td>0.97775</td>
</tr>
<tr>
<td>10</td>
<td>0.99772</td>
<td>0.97775</td>
<td>0.99801</td>
<td>0.97563</td>
</tr>
<tr>
<td>11</td>
<td>0.99801</td>
<td>0.97563</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The advantage of the NARX network over the conventional ANN can be established by comparing the results of the present study with the results of the earlier study\(^{28}\) conducted by the authors to prove the superiority of ANN model over statistical methods. The study\(^{28}\) was carried out for the Karwar station using similar data sets and division. However, the outcome of the study revealed that satisfactory prediction could be achieved only when yearlong data sets were used as input in training as well as simulation. The prediction accuracy was relatively low; ‘r’ value of 0.89 for data sets divided in weeks and 0.95 for data sets divided in months was achieved, keeping in view the amount of data sets that were given as input.

Table 5 Variation of ‘r’ values with increase of neurons in the hidden layer of NARX network, with one month as input and 12 months’ data as output.

<table>
<thead>
<tr>
<th>Neurons</th>
<th>Training mse</th>
<th>Simulation mse</th>
<th>Training r</th>
<th>Simulation r</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.70012</td>
<td>0.63587</td>
<td>0.97012</td>
<td>0.97563</td>
</tr>
<tr>
<td>3</td>
<td>0.94818</td>
<td>0.88623</td>
<td>0.94850</td>
<td>0.96447</td>
</tr>
<tr>
<td>5</td>
<td>0.98927</td>
<td>0.94850</td>
<td>0.99464</td>
<td>0.96447</td>
</tr>
<tr>
<td>7</td>
<td>0.99464</td>
<td>0.96447</td>
<td>0.99627</td>
<td>0.97620</td>
</tr>
<tr>
<td>9</td>
<td>0.99627</td>
<td>0.97620</td>
<td>0.99772</td>
<td>0.97775</td>
</tr>
<tr>
<td>10</td>
<td>0.99772</td>
<td>0.97775</td>
<td>0.99801</td>
<td>0.97563</td>
</tr>
<tr>
<td>11</td>
<td>0.99801</td>
<td>0.97563</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
(2) **Prediction at Mangalore**

Using the observed hourly tide-level data obtained from NMPT, the model developed at Karwar with network architecture of 1-10-12 was simulated at NMPT. December 2010’s hourly tide-level data were given as input and the predictions obtained for the entire year 2011 were compared with those of the observed values of tide at NMPT for the year 2011. The results showed a very good ‘r’ value greater than 0.96 between the observed and predicted values and mean squared error was 121.98. **Fig. 17, Fig. 18, and Fig. 19** show the scatter plot and the graph of observed versus the predicted values. The average absolute error observed in this case was 8.22 cms and the extremes were -15.67 cms to 15.77 cms with a standard deviation of 3.528.

The existence of similar tide types and ranges is instrumental in replicating the results obtained by the model at one station for other stations, which has also been the case in the present study. Also, the slight reduction in ‘r’ might also be due to the fact that the

**Fig. 15** Graph showing the predicted and observed hourly tide-level values for 12 months using one month’s data.

**Fig. 16** Graph showing the predicted and observed hourly tide-level values for first 500 hours of 12 months’ prediction using one month’s data.

**Fig. 17** Scatter plot of simulation of NARX network during 12 months’ predictions done using one month’s data set at NMPT using Karwar’s model.

**Fig. 18** Graph showing the predicted and observed hourly tide-level values for 200 hours of 12 months’ prediction using one month’s data at NMPT.

**Fig. 19** Graph showing the predicted and observed hourly tide-level values for 200 hours of 12 months’ prediction using one month’s data at NMPT.
ACKNOWLEDGMENT: The authors would like to thank the National Institute of Oceanography, Goa and New Mangalore Port Trust, for providing us with the data required for the execution of this study.

REFERENCES


(Received July 11, 2013)