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Application of Artificial Intelligence to Schedule Operability of Waterfront Facilities in Macro Tide Dominated Wide Estuarine Harbour

A. Basu, A. A. Purohit, M. M. Vaidya, M. D. Kudale

***Abstract*—**Mumbai, being traditionally the epicenter of India's trade and commerce, the existing major ports such as Mumbai and Jawaharlal Nehru Ports (JN) situated in Thane estuary are also developing its waterfront facilities. Various developments over the passage of decades in this region have changed the tidal flux entering/leaving the estuary. The intake at Pir-Pau is facing the problem of shortage of water in view of advancement of shoreline, while jetty near Ulwe faces the problem of ship scheduling due to existence of shallower depths between JN Port and Ulwe Bunder. In order to solve these problems, it is inevitable to have information about tide levels over a long duration by field measurements. However, field measurement is a tedious and costly affair; application of artificial intelligence was used to predict water levels by training the network for the measured tide data for one lunar tidal cycle. The application of two layered feed forward Artificial Neural Network (ANN) with back-propagation training algorithms such as Gradient Descent (GD) and Levenberg-Marquardt (LM) was used to predict the yearly tide levels at waterfront structures namely at Ulwe Bunder and Pir-Pau. The tide data collected at Apollo Bunder, Ulwe, and Vashi for a period of lunar tidal cycle (2013) was used to train, validate and test the neural networks. These trained networks having high co-relation coefficients (R= 0.998) were used to predict the tide at Ulwe, and Vashi for its verification with the measured tide for the year 2000 & 2013. The results indicate that the predicted tide levels by ANN give reasonably accurate estimation of tide. Hence, the trained network is used to predict the yearly tide data (2015) for Ulwe. Subsequently, the yearly tide data (2015) at Pir-Pau was predicted by using the neural network which was trained with the help of measured tide data (2000) of Apollo and Pir-Pau.

The analysis of measured data and study reveals that: The measured tidal data at Pir-Pau, Vashi and Ulwe indicate that there is maximum amplification of tide by about 10-20 cm with a phase lag of 10-20 minutes with reference to the tide at Apollo Bunder (Mumbai). LM training algorithm is faster than GD and with increase in number of neurons in hidden layer and the performance of the network increases. The predicted tide levels by ANN at Pir-Pau and Ulwe provides valuable information about the occurrence of high and low water levels to plan the operation of pumping at Pir-Pau and improve ship schedule at Ulwe.

***Keywords*—**Artificial neural network, back-propagation, tide data, training algorithm.

I. Introduction

Mumbai harbor is one of the oldest harbor of India and is situated in Thane estuary on the west coast having an access to the Arabian Sea through its wide entrance. Mumbai being traditionally the epicenter of India's trade has two major ports in the region namely Mumbai and Jawaharlal Nehru (JN). Mumbai port being on the leeside of Salsette Island and JN port being well inside from wide estuarine entrance, wave tranquility is not a main concern from operational consideration. However, the presence of macro tide (tidal range of 5.0m) of semi-diurnal in nature, strong tidal currents (1-2 m/sec) prevail in the harbour. The entrance to these harbors is ultra-wide (10 km) and the tidal water spreads/extends 30-40 km north resulting in huge exchange of tidal flux during flood/ebb phase of tide. Due to various developments over the past several decades in this estuarine region there is significant advancement of shoreline on west side of estuary and the tidal flux entering/leaving has changed considerably. In view of this various water front facilities such as intakes at Pi-Pau and jetty at Ulwe Bunder are facing the problem of inadequacy of water supply for cooling of condensers and operability of berths respectively. In order to cope with this problem, it is inevitable to have accurate information about tide data for longer duration (over the years) by actual field measurement. However, the collection of tide data over a long duration is not only tedious but acostly affair. In order to overcome these problems and to improve the operability of both waterfront structures, application of Artificial Intelligence to predict water levels based on the actual field measurements for a lunar tidal cycle is made.

Artificial Neural Network had been used for predicting/ forecasting several oceanographic phenomena such as tides, waves, etc. The past studies, dealing with ANN involved either estimation or forecasting of several parameters such as wave heights/period, spectral shapes and directional characteristics and has been summarized by [1]. Back propagation neural network has been used by several researchers [2], [3] to predict tide data. The present study represents the application of a two layered feed-forward ANN for prediction of yearly (2015) tide data at Ulwe and Pir-Pau. Actual tide data which have been collected at 10 minutes' interval for a lunar cycle (15 days) for the year 2013 at Apollo, Ulweand Vashi have been used to form the two-layered feed forward neural networks. Matlab 7.11.0 (R2010b) software was used to operate the model. Back-propagation training algorithms have been used to train the network, where network weights and bias get updated to minimize the difference between actual output of network and the desired output. Two different training algorithms such as gradient

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decent (traingd) and Levenberg-Marquardt (trainlm) have been used for training the network. The trained networks were used to predict the measured tide data for the year 2013 and 2000 for Ulwe and Vashi for its comparison with the measured tide. Finally, the trained networks have been used to predict yearly (2015) tide data at Ulwe Bunder. Similarly, the measured tide data (year 2000) for the period of ten days at Apollo and Pir-Pau was used to form two layered feed forward neural networks. The networks were trained by the same back propagation training algorithms (traingd and trainlm). The trained networks are used to predict the yearly tide data (2015) at Pir-Pau. The location plan of Mumbai Harbour wherein data collected is shown in Fig. 1.

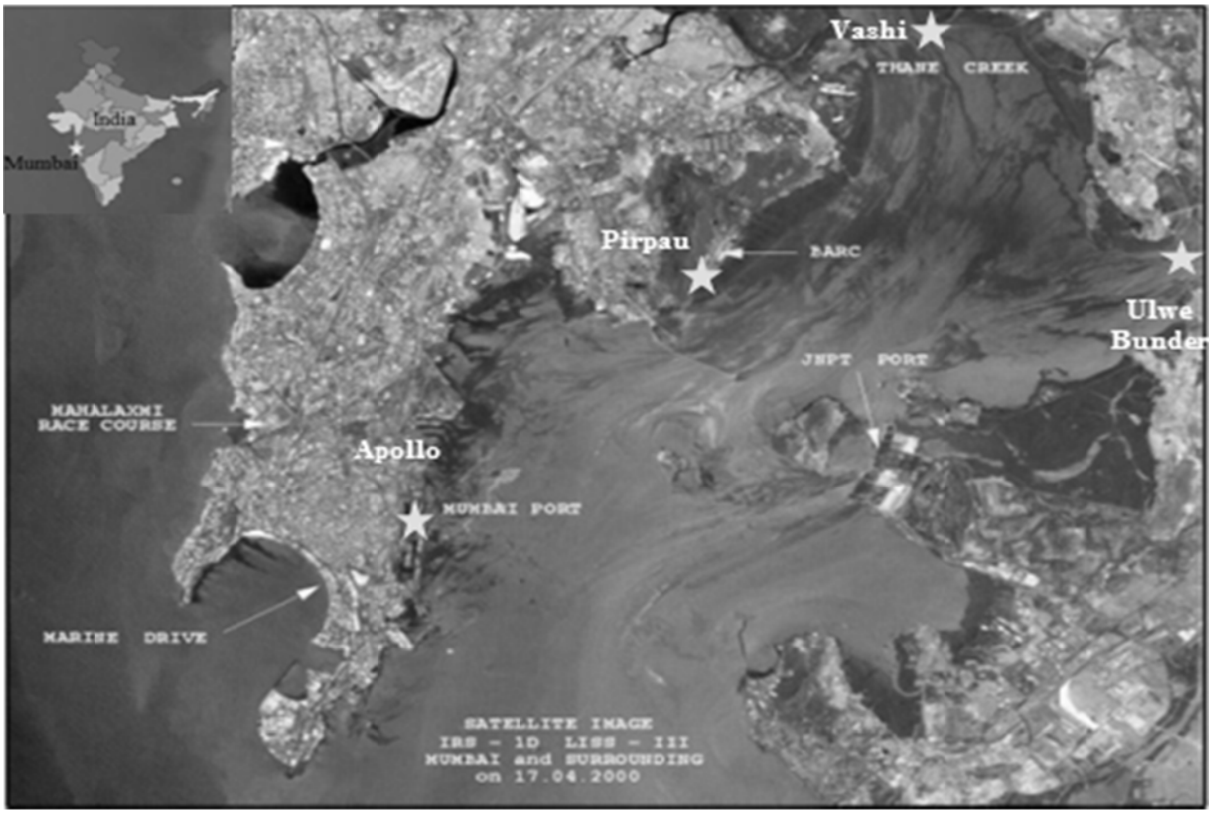


Fig. 1 Layout plan of Mumbai harbor

II. Salient Features of Mumbai Harbour

The Mumbai harbor situated on leeside has an ultra-wide entrance of about 10 km and tidal water spreads 30-40 km north up to Thane city. The main navigational channel was maintained to a depth of about 10.8 m for past several decades. The channel has total length of about 28 km. and inside the estuary and takes turn at 90^0 towards Mumbai port and thereafter bifurcates into two branches; one goes towards the waterfront structures of Pir-Pau and other part goes towards JN Port. Beyond JN port the depths are shallow and are about 1- 5 m. In Mumbai harbor macro semi-diurnal tide (tidal range of 5 m) prevails. Hence small self-propelled barges by taking the advantages of tidal window can only ply up to the Ulwe Bunder. During flood/ebb phase of tide, barges can sail during high waters only and as such limits the number of trips due to non-availability of accurate information on tides at Ulwe. The number of barges plying is more during spring and less during neap tides. Also in view of presence of shallow patch between JN port and Ulwe [4], ships cannot ply till sufficient water level is reached. Presently, the ships which are plying up to Ulwe Bunder have draft requirement of 3-4.5 m. This results in loss of valuable business hours.

In Mumbai Harbour area, the suspended sediment concentration being high (0.5-1.3gm/lit) and material being of cohesive in nature, sedimentation rates are high. This is due to the fact that for many developmental activities such as reclamations, bridges, colonies etc. in Thane, Panvel has resulted in decrease of tidal flux over decades and increase in siltation. Thus advancement of shoreline at various waterfronts near western side such as intake at Pir-Pau is facing problem of inadequate supply of water. Hence, in order to improve the number of ship trips to Ulwe Bunder and to plan the operation of pumping for the intake structures at Pir-Pau, it is essential to have tidal data at Ulwe and Pir-Pau for the entire year. For the present study, Artificial Neural Network (ANN) has been used to predict the yearly tide data at Ulwe Bunder and Pir-Pau.

III. Artificial Neural Network

The concept of Artificial Neural Network was developed several decades ago; it was found in the biological neural system of human beings. The human brain is highly complex, non-linear, parallel information processing system. It has the capability to organize its structural constituents known as neurons, so as to perform several computations such as pattern recognition, perception etc., many times faster than today's digital computer [5]. The basic structure of Artificial Neural Net is very simple and is shown in Fig. 2.

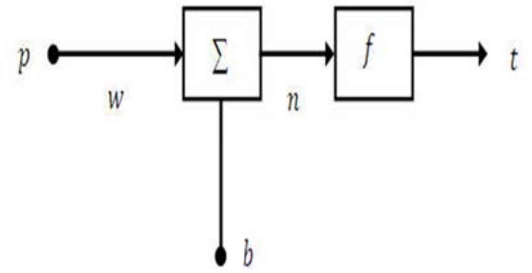


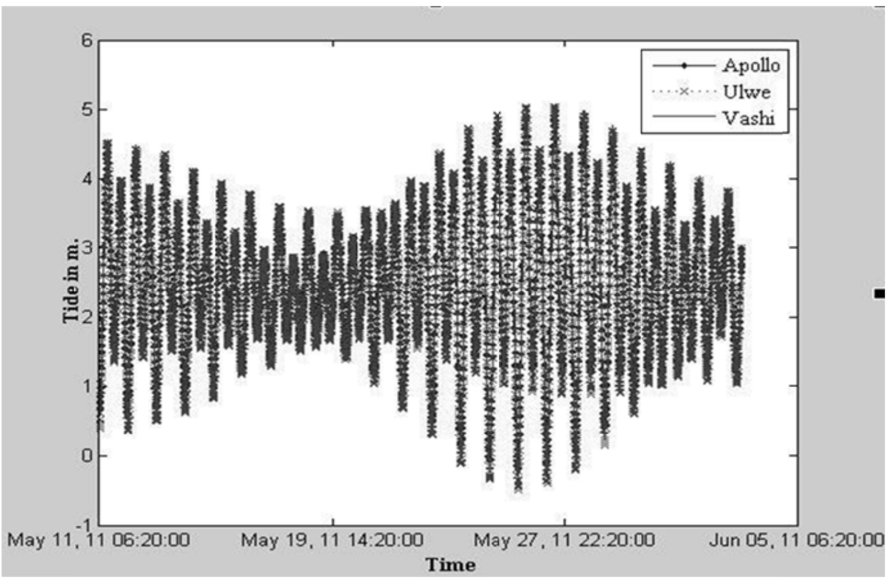
Fig. 2 Schematic of single input neuron

A neural net has three components such as weight (w), bias (b) and transfer function (f). As shown in Fig. 1; p and t are input and output to a neural. This neural takes an input argument (n), which is formed by the summation of weighted input (wp) and a bias (b), i.e. $n = wp + b$. This input argument is subjected to a transfer function$(f)$to produce output (t) of the network; i.e.; $t = f(n)$. There are several transfer functions available in the field of artificial neural network such as linear, log-Sigmoid, hyperbolic tangent-sigmoid etc. Depending on the number of inputs for the corresponding output, there can be several numbers of input-weight pair to form a particular argument for the transfer/activation function.

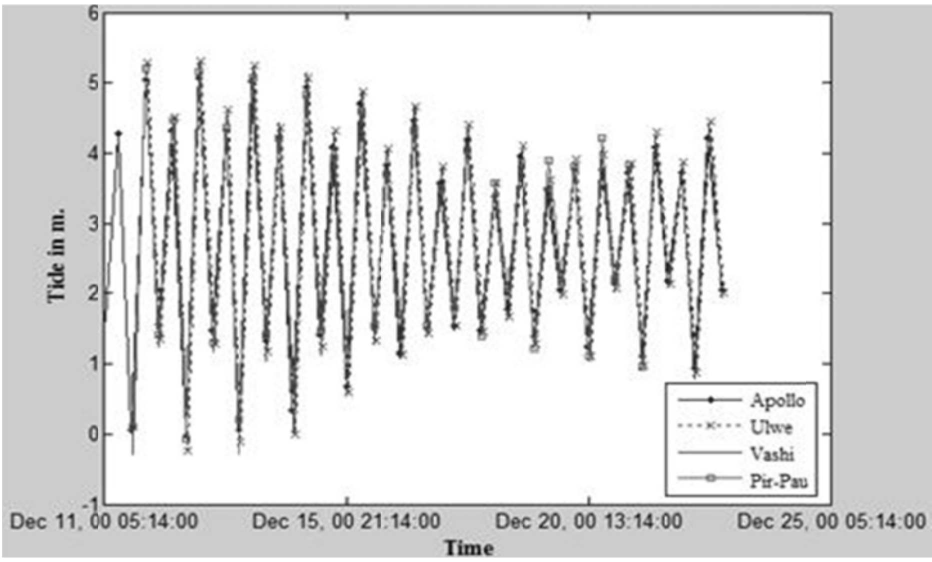
A. Data Employed

For the present study two types (A and B) of measured tide data which were collected at different time interval, have been used to form two layered feed forward artificial neural networks. The tide data which were collected at every 10 minutes' interval, for the period of a lunar cycle (6.30 AM of 11th May 2013 to 6.20 AM of 26th May 2013), are referred as tide data of type A. The tide data sets of type-A, were collected at Apollo Bunder, Ulwe and Vashi. Similarly, the tide data which were collected based on the occurrence of high/low tide for ten days (from1.19 AM of 13th Dec 2000 to 3.48 PM of 22nd Dec 2000), are referred as tide data of type B. These tide data were collected at Pir-Pau and Apollo. The Apollo Bunder is located near the entrance of Mumbai harbor whereas Ulwe Bunder, Vashi and Pir-Pau are located around 24, 22, 12 km. north of Apollo, respectively. All the tide data was collected with respect to the chart datum of Apollo Bunder. The plot of measured tide data for the year 2000 and 2013 are shown in Figs. 3 (a) and (b).

The analyzed as well as plotted tide data for Ulwe, Vashi and Pir-Pau; indicate that there is maximum amplification in tidal level by around 10-20 cm with a phase lag of 10-20 minutes with respect to the tide at Apollo Bunder.



(a)



(b)

Fig. 3 (a) Plot of tide data (2013) for a lunar cycle at Apollo Bunder, Ulwe Bunder and at Vashi, (b) Plot of tide data (2000) for ten days at Apollo, Ulwe Bunder, Vashi & at Pir-Pau

B. Two Layered Feed Forward Neural Network

The architecture of Two Layered Feed Forward Network is shown in Fig. 4. It contains input, hidden layer, output layer and the output. Output of hidden layer is the input to the output layer. The transfer/activation functions for hidden and output layer are hyperbolic tangent sigmoid and linear respectively.

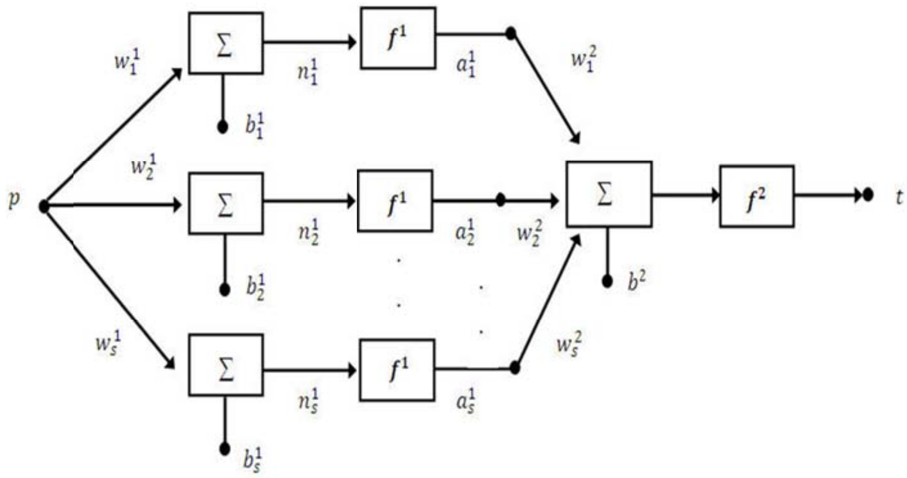


Fig. 4 Two layered feed-forward neural network

As it is indicated in Fig. 4; p is the input to the network, s is the number of neurons in the hidden layer and $W^1$and $W^2$are the weightmatrices for hidden and output layer respectively. The transfer functions for hidden and output layers are $f^1$and f^2. Therefore, for this feed forward two layer network;

$$a^1 = f^1\,(W^1 * p + b^1)$$

and

$$t = \ a^2 = f^2\,(W^2 * a^1 + b^2)$$

The input/output relationship for the hyperbolic tangent sigmoid transfer function, f^1 is as:

$$a = \frac{e^n - e^{-n}}{e^n + e^{-n}}$$

Similarly, the input/output relationship for the pure-linear transfer function f^2 is as:

$$a = n$$

where n and a are the input and output to the transfer function.

C. Method of Analysis

The aim of this study is to use two layered feed forward neural networks to predict yearly (2015) tide data at two water front facilities such as Pir-Pau and Ulwe. Initially, two types (I and II) of two layered feed forward artificial neural network were formed. The two layered feed forward neural networks of type-I were formed by using two sets of 2160 tide data (covering spring-neap-spring tide) which were collected at every 10 minutes interval for a lunar cycle in the month of May2013, at Apollo and Ulwe. Similarly, the network of type-II were also formed by using two sets of 2160 tide data (covering spring-neap-spring tide) which were collected at every 10 minutes' interval for a lunar cycle in the month of May 2013; at Apollo and Vashi. For both the types (I and II) of network, out of each 2160 data sets, 70% of this data were used for training the network, 15% for validation of network and remaining 15% was used for the testing of network.

The architecture of two layered feed forward neural network which is shown in Fig. 4, indicates that for the network of type I and II, the hidden layer receives the tide data of Apollo Bunder as the input data. Each of the input value will then be multiplied by the weight and added to the bias. These summation values are passed through a non-linear transfer function which is hyperbolic tangent sigmoid (tansig). The output from hidden layer will be treated as input to the outer layer, where the input will once again be multiplied by the weight and it will be added to the bias. Thereafter, all these summed up values are added and finally the summation value will be passed through the linear transfer function (purelin) and it produces the network output. The desired outputs for two types (I and II) of network are tide data of Ulwe and Vashi, respectively. Once the network is formed, it is trained to minimize the overall error of the network. For the present study two kinds of back-propagation training algorithm ('trainlm' and 'traingd') were used.

The 'traingd' is gradient decent back-propagation algorithm where the network weight and bias are updated based on the errors of the network. If the weight and bias variable are denoted by a variable Y, these variables are adjusted according to the gradient decent. The amount of adjustment (dY) to these variables for an iteration is expressed as:

$$dY = lr * \frac{d(perf)}{dY}$$

where *lr* is the learning rate and *perf* is a function of the network error. For 'traingd' algorithm the specified value for *lr* is 0.01. One drawback of this training function is that, because of its lesser learning rate, its rate of convergence is slow but it is a stable training function.

The 'trainlm' is a training algorithm where the network weight and bias are updated based on the Lavenberg-Marquardt optimization technique. This algorithm is faster than 'traingd'. In Lavenberg-Marquardt algorithm, the amount by which the weight/bias (Y) get adjusted after an iteration is given as

$$dY = [\boldsymbol{J}^\wedge\boldsymbol{T}\,\boldsymbol{J} + \mu\boldsymbol{I}]^{-1}\boldsymbol{J}^{\boldsymbol{T}}\boldsymbol{e}$$

where $\boldsymbol{J}$ is Jacobian matrix that contains derivatives of the network error with respect to the weights, biases and **e** is the vector of network errors and μ is a scalar called as the combination co-efficient and $\boldsymbol{I}$ is the identity matrix. In this training algorithm, the value of combination co-efficient (μ) gets updated during the training process. The value of μ is decreased after each step of iteration, if total error of the network, decreases after that iteration step. Similarly, the value of combination co-efficient (μ) increases if total error of the network, increases after the iteration step.

The performance of the neural network is evaluated by the calculation of mean square error (MSE) and co-relation co-efficient (R). The expressions for MSE and R are as:

$$MSE = \frac{\sum_{i=1}^{n}(y_i - z_i)^2}{n}$$

and

$$R = \frac{\sum_{i=1}^{n}(y_i - Y)(z_i - Z)}{\sqrt{\sum_{i=1}^{n}(y_i - Y)^2 \sum_{i=1}^{n}(z_i - Z)^2}}$$

where y_i is the actual observed value at i^{th} time step and z_i is the predicted value at i^{th} time step; n is the number of samples. Y and Z are mean of observed and predicted value respectively.

During the training of neural networks (Type I and II) by different back-propagation training algorithms (traingd, trainlm), the number of neurons in the hidden layer was increased to improve the performance of the network. Once the desired performance of the network was achieved, it was used for the prediction of eight days of tide data (for the year 2013 and 2000) at Ulwe and Vashi. The predicted tide data at these two locations were compared with the measured water levels and it indicates that the predicted data compares well with the measured data. Hence, the network was used to predict yearly (2015) tide data of Ulwe Bunder, with the help of yearly (2015) predicted tide data of Apollo Bunder. Subsequently, by using ten days of measured tide data (1.19 AM of 13th Dec 2000 to 3.48 PM of 22nd Dec 2000), at Apollo and Pir-Pau, the two layered feed forward artificial neural networks (of type-III) were formed. The network was trained by the same back-propagation training algorithms ('traingd', 'trainlm') where the number of neurons in the hidden layer was increased to improve the performance of the network. Once the desired performance of the network was achieved, it was used to predict yearly (2015) tide data of Pir-Pau, with the help of yearly (2015) predicted tide data of Apollo Bunder.

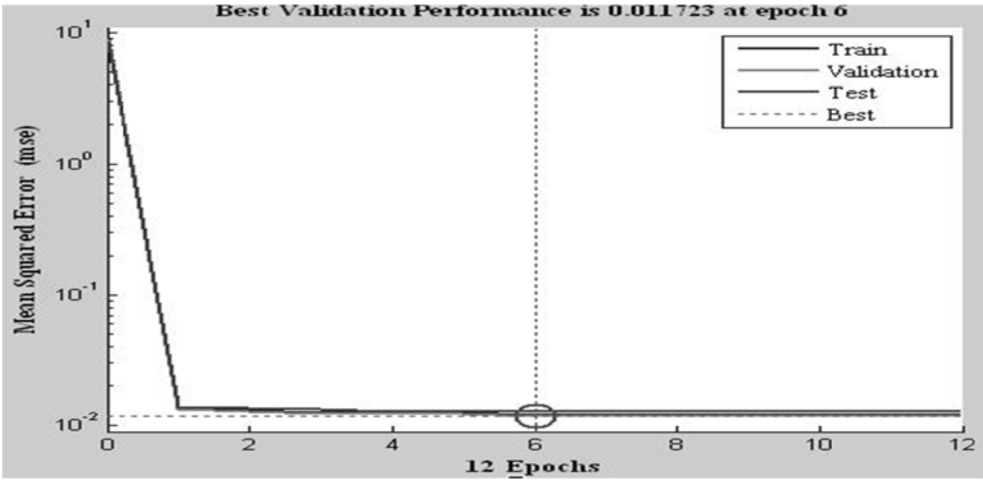
D. Results and Discussions

Basically, three types (Type I, II & III) of two layered feed forward neural network had been developed by using the measured tide data at Apollo, Ulwe, Vashi and Pir-Pau. These networks were trained by training algorithms such as 'traingd'& 'trainlm'. It has been observed that 'traingd' function is little slower in convergence compared to the 'trainlm' function. The overall performances of these networks are evaluated by the calculation of mean square error (MSE) and co-relation co-efficient (R). The number of neurons in the hidden layer has been increased to improve the performance of the network. The variations in the performance of the networks with the increase of number of neurons in the hidden layer are shown in Table I.

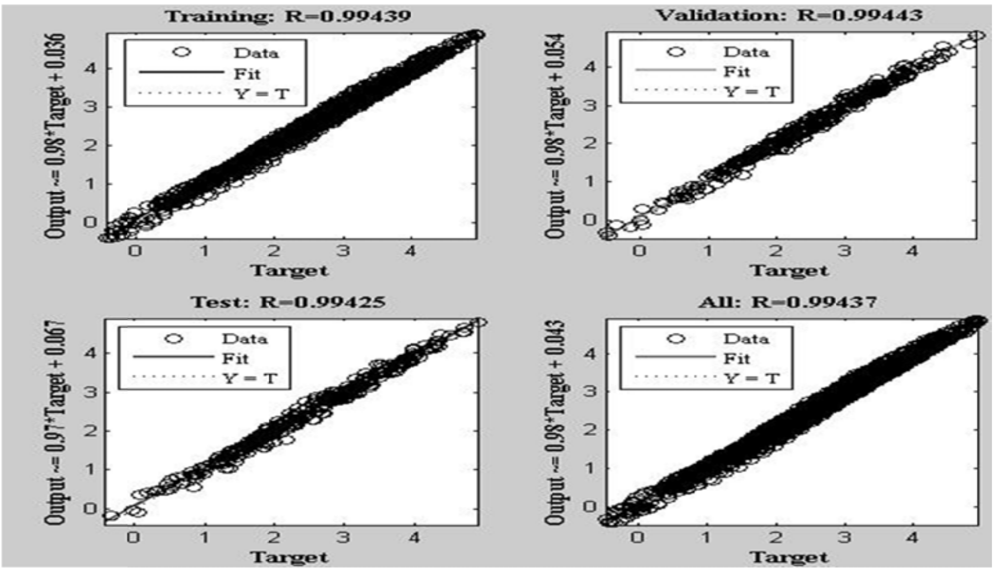
It is observed from Table I that for networks of type I & II, when the number of neuron in the hidden layer increases beyond 12, the performance of the network does not improve significantly. Similarly, for networks for type-III, when the number of neuron in the hidden layer increases beyond 10, the performance of the network does not improve significantly. The plots of performance and regression of network of type-I, II & III are shown in Figs. 5-7.

TABLE I
VARIATIONS OF M.S.E. FOR ALL THE THREE NETWORKS

Sr. No.	Training Function	No. of Neurons in the hidden layer	MSE of Network (type-I)	MSE of Network (type-II)	MSE of Network (type-III)
1	traingd	5	0.0192	0.0245	0.004
2	trainlm	5	0.0123	0.0107	0.003
3	traingd	7	0.0156	0.016	0.0025
4	trainlm	7	0.0121	0.0106	0.0015
5	traingd	10	0.0123	0.0123	0.0016
6	trainlm	10	0.0121	0.0105	0.0015
7	traingd	12	0.0122	0.0122	0.0016
8	trainlm	12	0.0121	0.0105	0.0015
9	traingd	15	0.0122	0.0122	0.0016
10	trainlm	15	0.0121	0.0105	0.0015

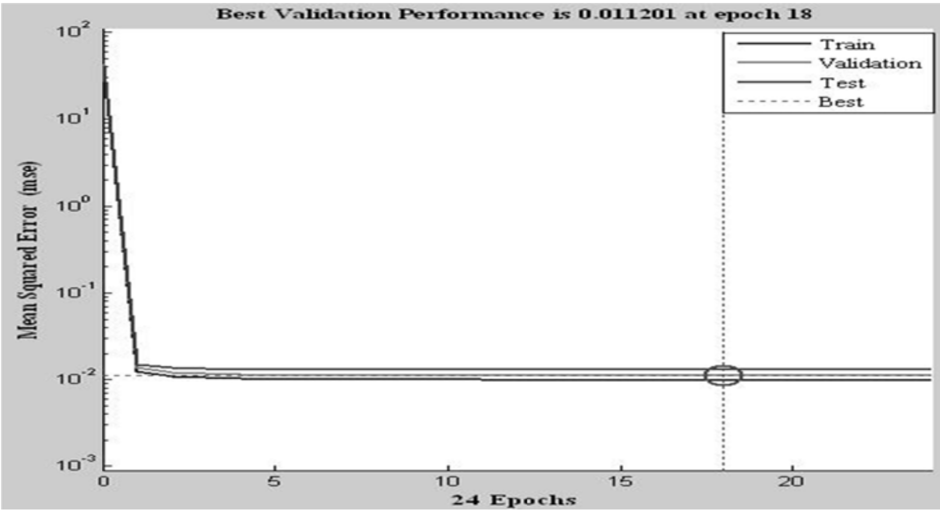


(a)



(b)

Fig. 5 (a) Performance of network of type-I with 'trainlm' as training algorithm & no. of neurons in hidden layer is 7, (b) Regression plot of network of type-I with 'trainlm' as training algorithm& no. of neurons in hidden layer is 7



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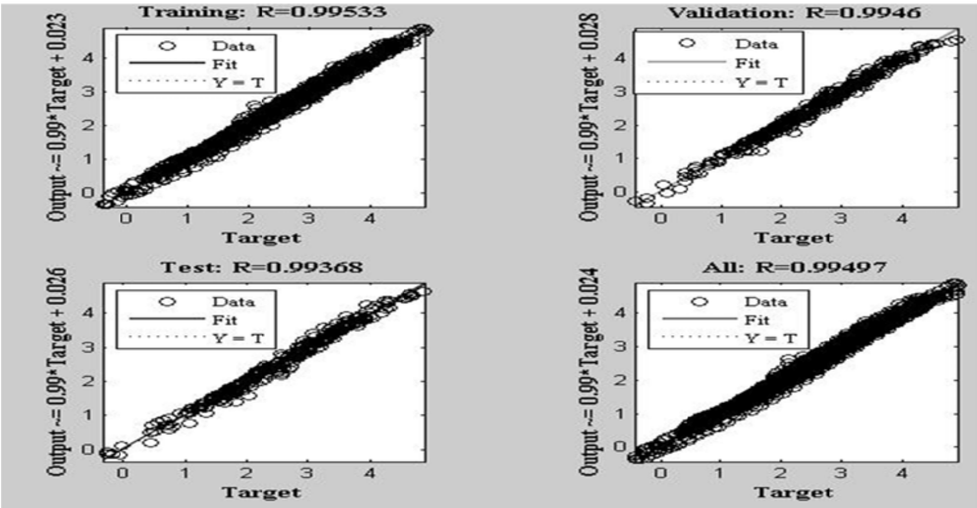
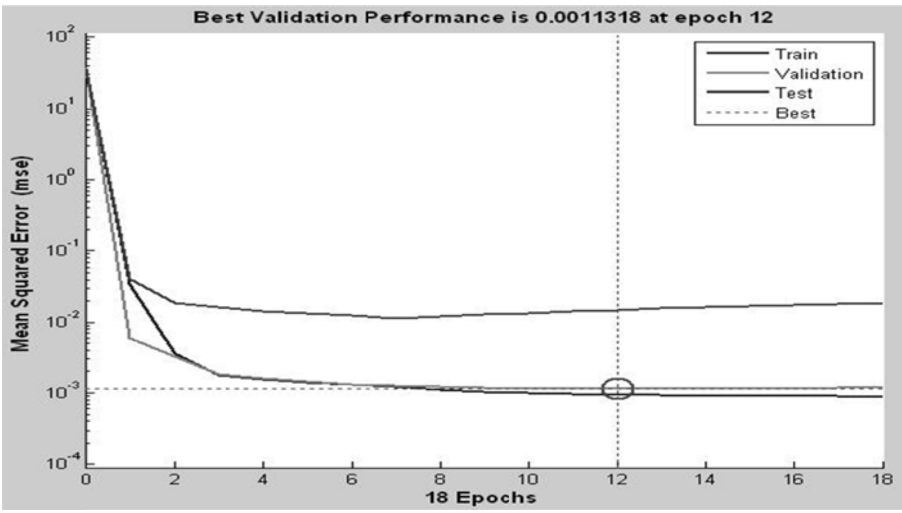


(b)

Fig. 6 (a) Performance of network of type-II with 'trainlm' as training algorithm & no. of neurons in hidden layer is 10, (b) Regression plot of network of type-II with 'trainlm' as training algorithm & no. of neurons in hidden layer is 10



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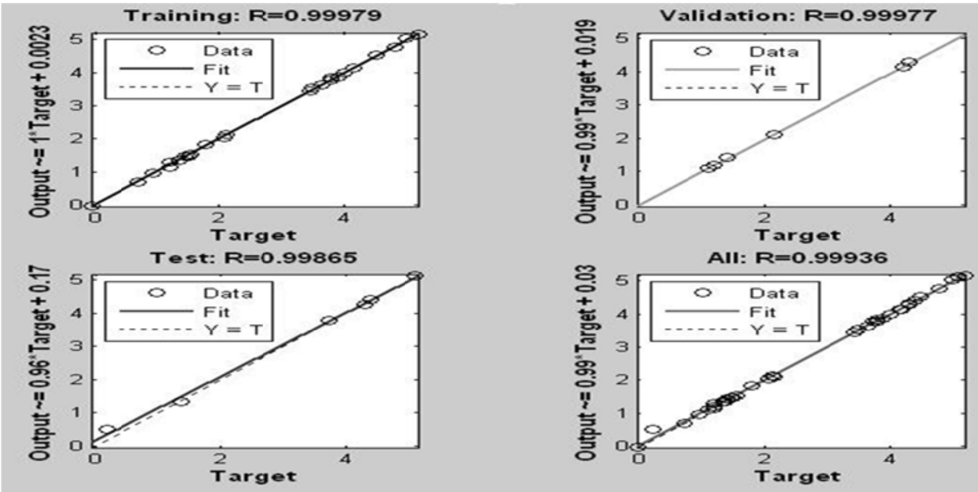
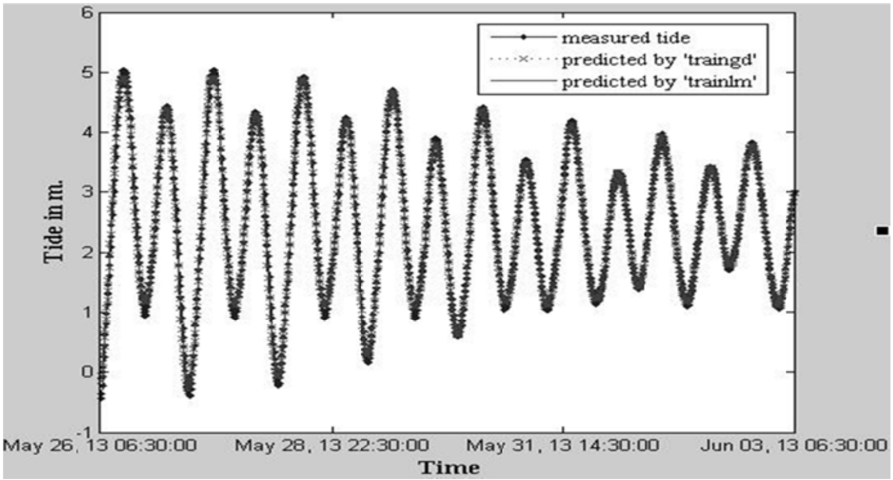


(b)

Fig. 7 (a) Performance of network of type-III with ‘trainlm’ as training algorithm & no. of neurons in hidden layer is 7, (b) Regression plot of network of type-III with ‘trainlm’ as training algorithm& no. of neurons in hidden layer is 7



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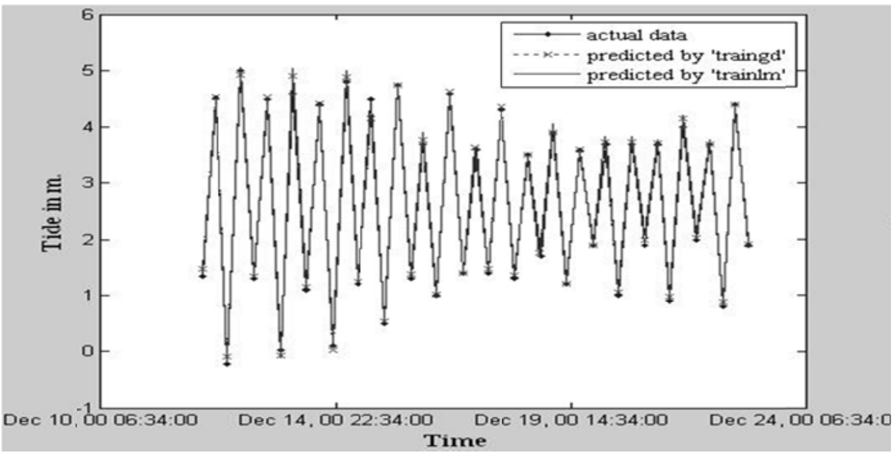
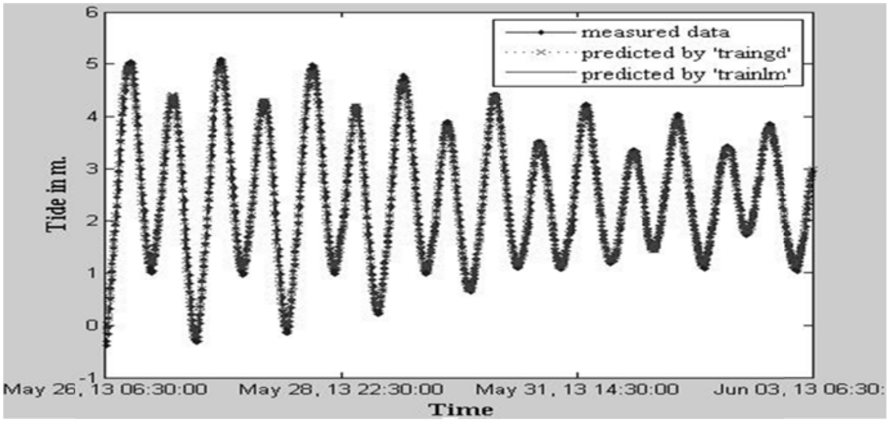
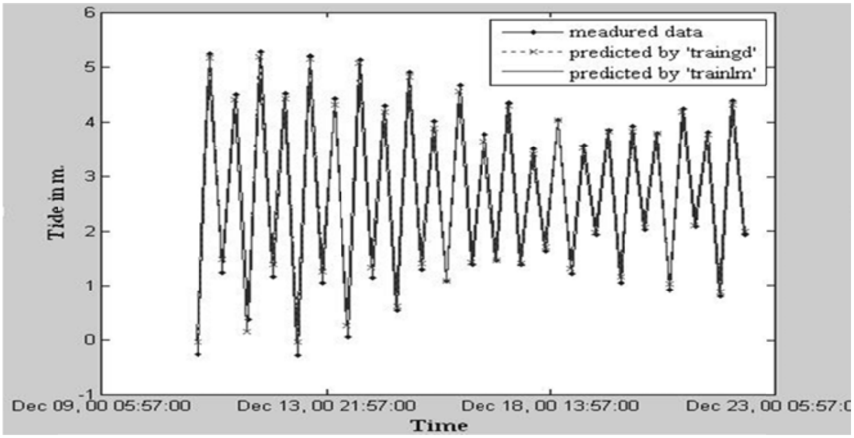


(b)

Fig. 8 (a) Comparison of predicted tide data by ANN with the measured data at Ulwe Bunder for the year 2013, (b) Comparison of predicted tide data by ANN with the measured data at Ulwe Bunder for the year 2000



(a)

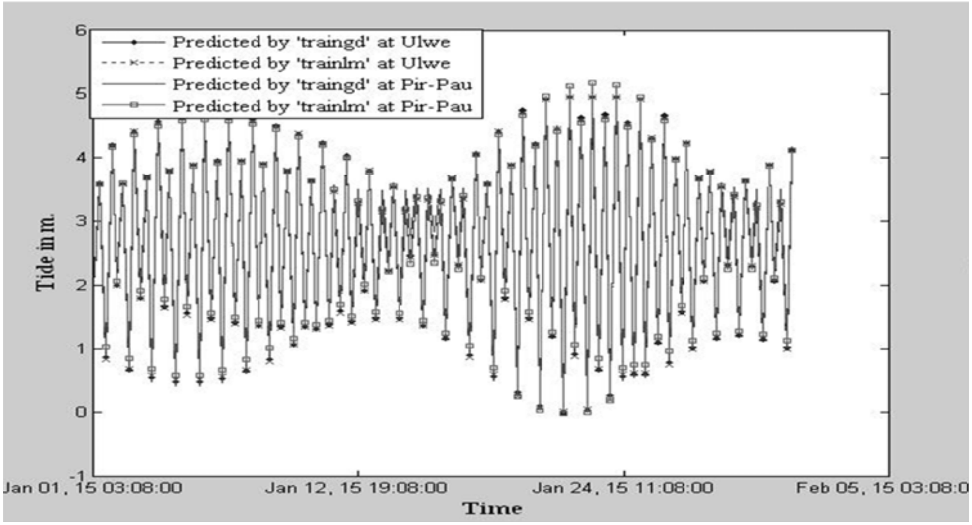


(b)

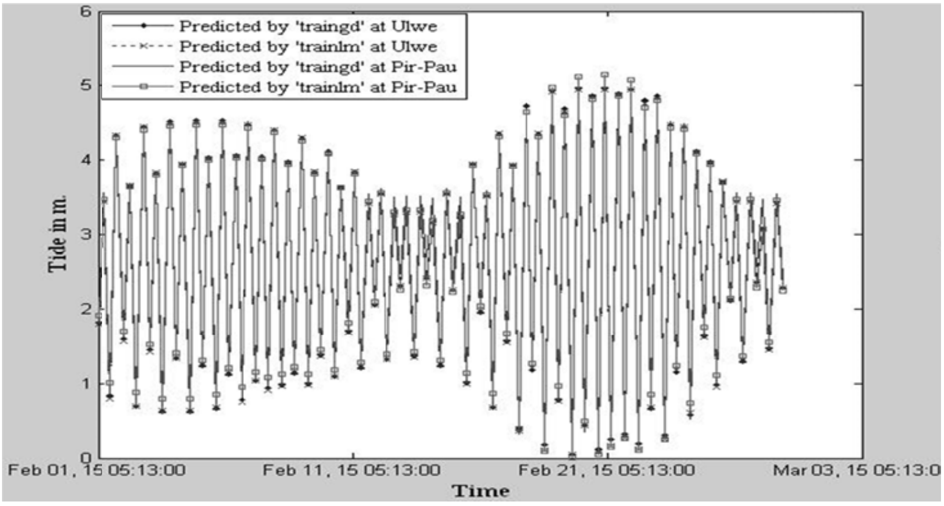
Fig. 9 (a) Comparison of predicted tide data by ANN with the measured data at Vashi for the year 2013, (b) Comparison of predicted tide data by ANN with the measured data at Vashi for the year 2000

Theses plots indicate that even by using measured tide data for a lunar cycle at Apollo, Ulwe and Vashi, the trained networks are capable of predicting the actual tide of Ulwe and Vashi for the year 2013 & 2000 with a good accuracy. Hence, the trained networks have been used to predict yearly (2015) tide data of Ulwe Bunder by using the predicted tide data (2015) of Apollo Bunder. It is to mention that the predicted tide at Apollo Bunder is in good agreement with measured tide at Apollo Bunder (2015) and hence was used for predicting tide levels at Ulwe and Pir-Pau for year 2015. The plots of yearly predicted tide data of Ulwe by using both the training algorithms 'traingd' and 'trainlm' are shown in Fig. 10.

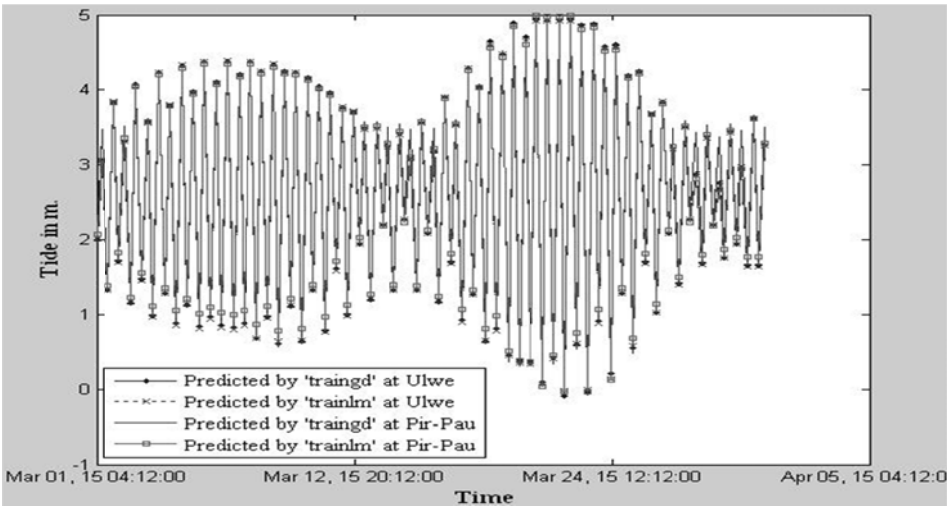
Similarly, the trained neural networks of type III, with the number of neurons in the hidden layer as 7,10 (for 'trainlm'& 'traingd' respectively) have been used to predict the yearly tide data (2015) of Pir-Pau and the plot of yearly predicted tide data of Pir-Pau are shown in Fig. 10. Hence by using ANN, the yearly tide data at Ulwe and Pir-Pau can be predicted. Depending upon the time at which high/low water will occur during spring/neap tide; the ship scheduling can be done at Ulwe Bunder. During the high waters of spring tide, ships requiring draft of about 4-4.5 m should be allowed to ply in/out of Ulwe Bunder. Whereas, during the high waters of neap tide, ships requiring draft of about 3-3.5 m should be allowed to ply in/out of Ulwe Bunder. It will reduce considerable downtime for ships waiting unnecessarily at berths near Panvel estuary mouth for water level to increase and at the same time it will also avoid the congestion of ships anchored at JN Port. Similarly, after having the information about the occurrence of high/low water during spring/neap tide, the pumping operation/maintenance of pumps for the intake structures at Pir-Pau can be scheduled.


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Jan 01, 15 03:08:00
Jan 12, 15 19:08:00
Jan 24, 15 11:08:00
Feb 05, 15 03:08:0

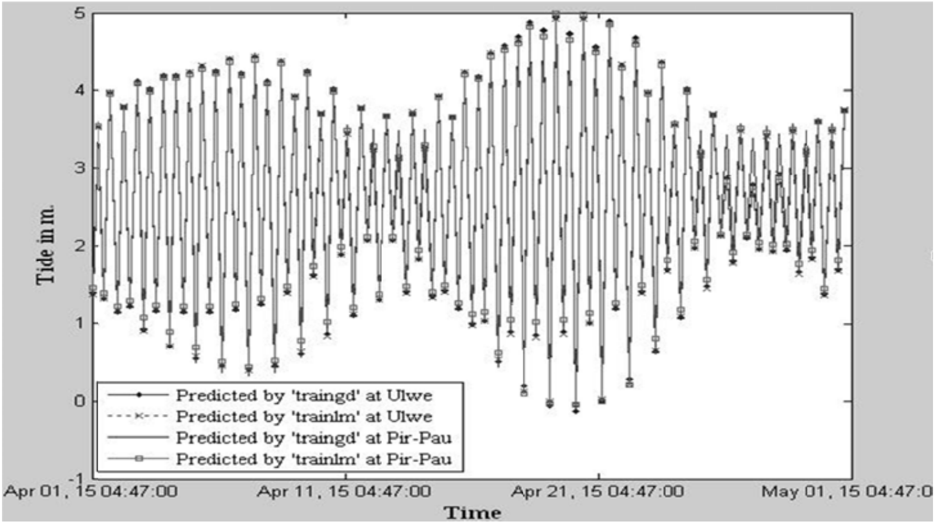
(a)


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Feb 01, 15 05:13:00
Feb 11, 15 05:13:00
Feb 21, 15 05:13:00
Mar 03, 15 05:13:0

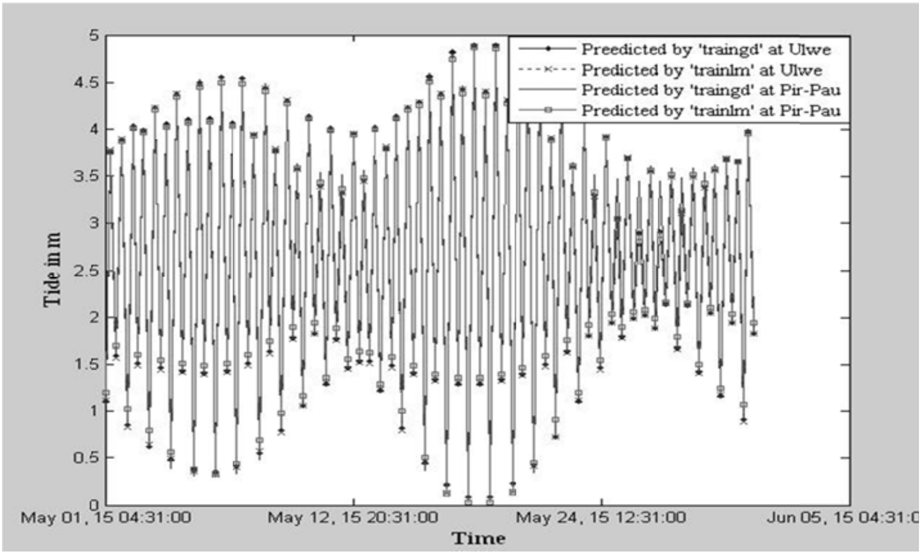
(b)


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Mar 01, 15 04:12:00
Mar 12, 15 20:12:00
Mar 24, 15 12:12:00
Apr 05, 15 04:12:0

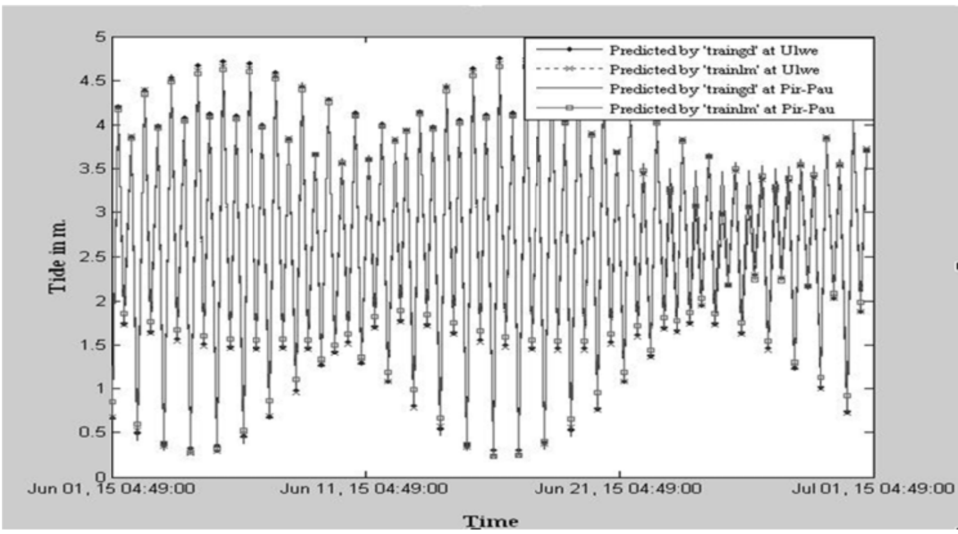
(c)


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Apr 01, 15 04:47:00
Apr 11, 15 04:47:00
Apr 21, 15 04:47:00
May 01, 15 04:47:0

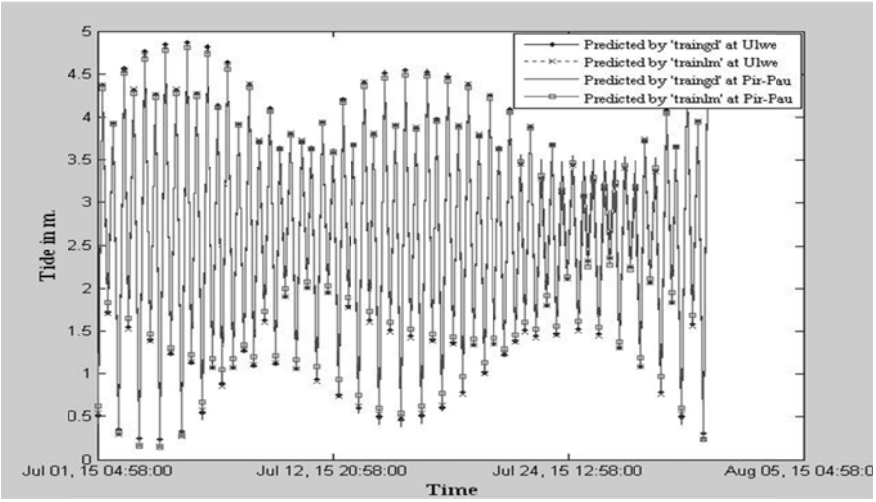
(d)


Preedicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m
Time
May 01, 15 04:31:00
May 12, 15 20:31:00
May 24, 15 12:31:00
Jun 05, 15 04:31:0

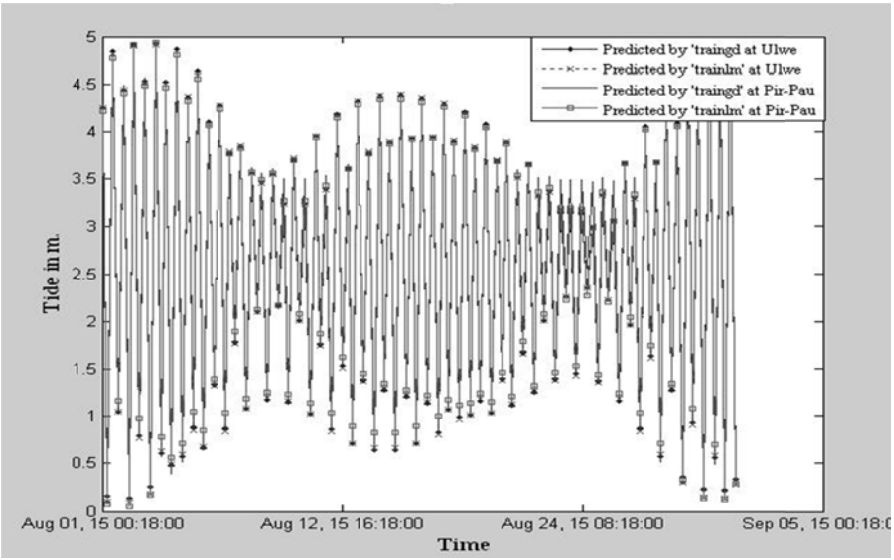
(e)


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Jun 01, 15 04:49:00
Jun 11, 15 04:49:00
Jun 21, 15 04:49:00
Jul 01, 15 04:49:00

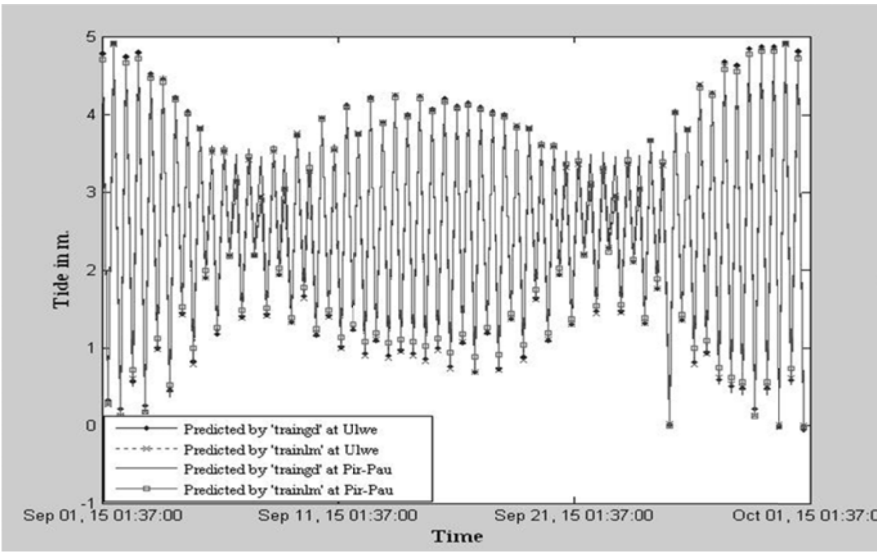
(f)


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Jul 01, 15 04:58:00
Jul 12, 15 20:58:00
Jul 24, 15 12:58:00
Aug 05, 15 04:58:0

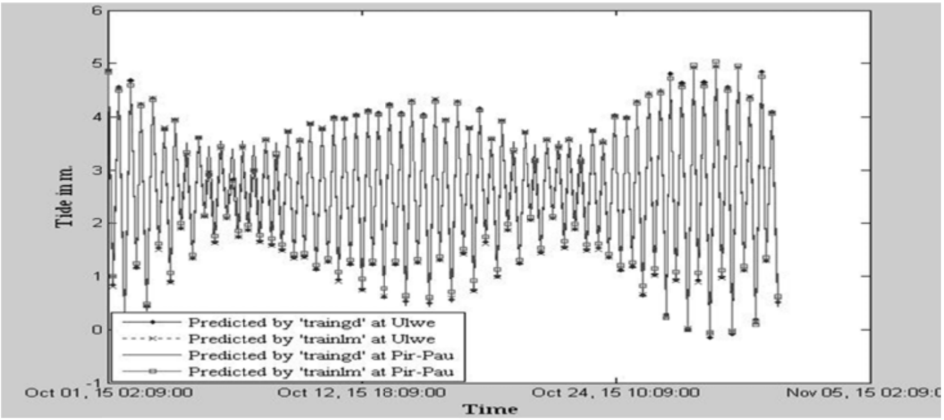
(g)


Predicted by 'traingd at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Aug 01, 15 00:18:00
Aug 12, 15 16:18:00
Aug 24, 15 08:18:00
Sep 05, 15 00:18:0

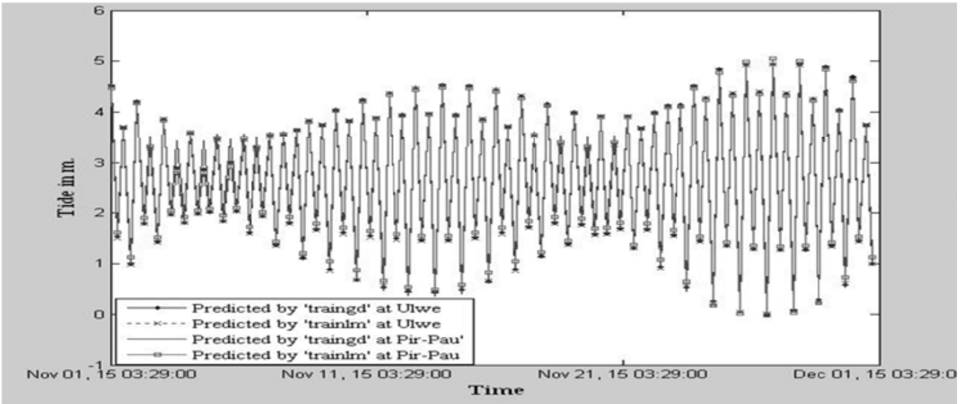
(h)


Predicted by 'traingd' at Ulwe
Predicted by 'trainlm' at Ulwe
Predicted by 'traingd' at Pir-Pau
Predicted by 'trainlm' at Pir-Pau
Tide in m.
Time
Sep 01, 15 01:37:00
Sep 11, 15 01:37:00
Sep 21, 15 01:37:00
Oct 01, 15 01:37:0

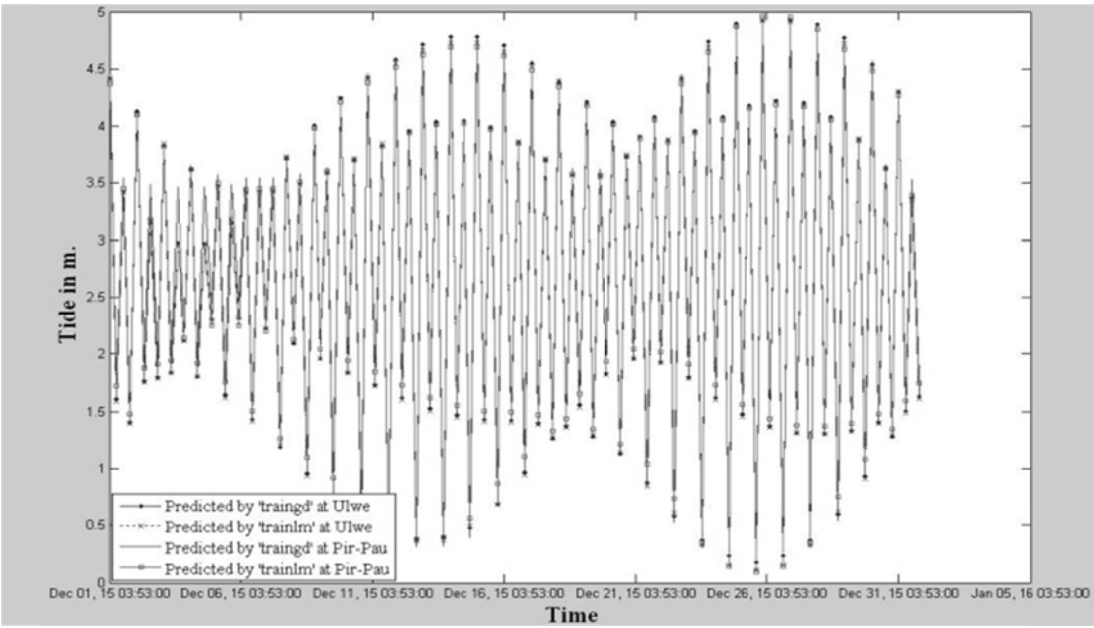
(i)



(j)



(k)



(l)

Fig. 10 Predicted tide data for months of 2015 by ANN at Ulwe Bunder and Pir-Pau(a) January 2015, (b) February-2015, (c) March-2015, (d) April-2015, (e) May-2015, (f) June-2015, (g) July-2015, (h) August-2015, (i) September-2015, (j) October-2015, (k) November-2015, and (l) December-2015

IV. Conclusion

The present study attempted to investigate the applicability of two layer feed-forward artificial neural networks, having one hidden layer and one output layer, in the prediction of yearly tide data at two waterfront facilities viz. Ulwe Bunder and Pir-Pau of Mumbai harbor. Two types of training function (traingd and trainlm) have been used to train the network. The number of neurons in the hidden layer has been increased to improve the performance of the network. Once the desired performances of the networks are achieved, they are used to predict the tide data of Ulwe Bunder and Pir-Pau. From this experimental study several observations are made, such as:

- The measured tidal data at Apollo Bunder, Pir-Pau, Vashi and Ulwe indicate that there is maximum amplification of tide by about 10-20 cm with the phase lag of 10-20 minutes with reference to the tide at Apollo Bunder (Mumbai).
- In a two layer feed forward network, if the training function ‘traingd’ is used, more number of neurons in the hidden layer are required to improve the overall performance of the network compared to the training function ‘trainlm’.
- The training function ‘traingd’ is little slower in training the network, compared to the ‘trainlm’.
- The comparison of predicted tide data and the actual tide data of Ulwe, Vashi and Pir-Pau, indicate that a two layer feed forward neural network with sufficient number of neurons in the hidden layer is capable of predicting the tide data with a good accuracy.
- Depending on the timing at which high/low tide will occur; the timing at which ships/barges of different drafts should ply up to Ulwe Bunder can be decided and the waiting time of ships at JNP/Panvel mouth can be substantially reduced.
- Similarly, based on the predicted tide data at Pir-Pau, the pumping operation/maintenance of pumps for the intake structures at Pir-Pau can be planned efficiently.

Acknowledgment

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