

Comparative Analysis of Tidal Data Using FLSM ANN and Hybrid Model

A. Bhavani Shankar

**M.Tech,
Embedded Systems,
GITAM University,
Visakhapatnam, India.**

Dr.D.Elizabeth Rani

**Professor,
Embedded Systems,
GITAM University,
Visakhapatnam, India.**

Abstract:

The need of alternative source of power has become necessary in these days, dependency for power by the consumption of fossil fuels has led us to polluted environment, apart from solar energy the tidal energy can be a vital resource for the power production and this can be done by the study of the tidal behavior. The hybrid model contains the Fourier least squares method (FLSM) and artificial neural network (ANN). With the help of tidal data collected from weather station for one month the tidal behavior can be monitored and we are able to predict the behavior of the tides in the future.

I. Introduction:

Tides are the rise and fall of the sea water due to the gravitational effects of sun, moon and some natural phenomenon like air speed, geological effects. The tides can be predicted accurately with the help of data collected for a period of one month, this data is help full for not only for producing tidal energy but also for towing the boats at the harbor and maintenance works. The accuracy of the model directly reflects on the production of stable and controlled tidal power and allows us to predict the occurrence of cyclones depending on the tidal behavior.

II. PREVIOUS RESEARCH ON TIDAL FORECASTING:

Sir G. H. Darwin was the first person who had come up with the idea of representing the tidal oscillations in the form of harmonic waves, later Dood son developed the concept of Darwin into a model and he later suggested that least squares method is suitable for the estimation of the parameters of the model.

The ANN is used at the areas where the relations between the values in a model are nonlinear. Lee and Jeng used ANN model for tidal level forecasting, Lee used back propagation with descent algorithm for forecasting tidal levels at the harbor of Taiwan. Vijay and Govil stated that the fourier series which is used alone cannot produce accurate results. The above methods have their unique way of forecasting the tidal data and have their limitations. The hybrid model uses ANN for forecasting the results observed with the use of FLSM. The model depends on the time series data provided to the model. The model is used for the data collected for a month.

III. THE PROPOSED MODELS FOR FORECASTING:

A. THE NEURAL NETWORK:

A neural network comes in handy for forecasting in many areas of science and engineering. ANN has one input layer, which in our case time series data, one output layer, which in our case the tidal forecasting data and one or more hidden layers. Each layer consists of a set of neurons. Performance of the ANN depends on the number of neurons, layers, input and the activation function used. Back propagation algorithm is dependent on gradient descent function for adjusting the weights in a feed forward network. Fig. 1(a) shows the general structure of ANN. The system used for the work has one input and one output layer.

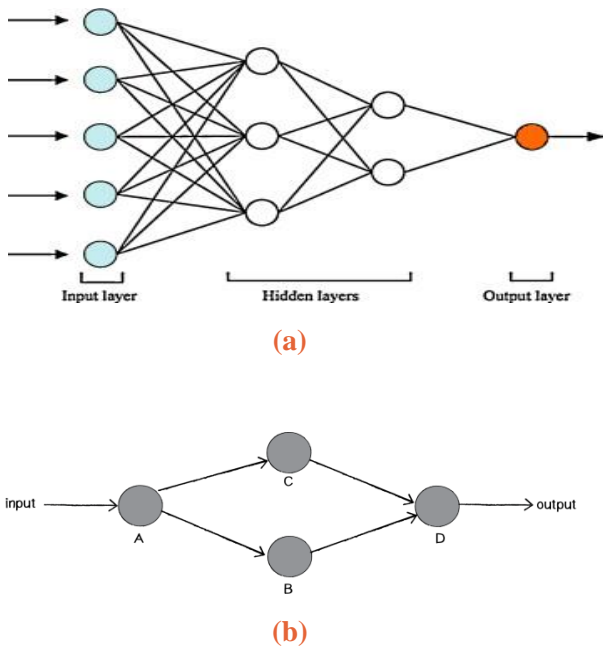


Fig. 1. Neural network structure (a) general structure of ANN (b) structure used in the model.

B. The FLSM structure:

The least squares method is useful for estimating the parameters to fit a function to a set of data, this method finds a line that best fits a set of data points.

The estimated data may be represented using fourier series as:

$$Z_{estimated}(k) = DC + \sum_{i=1}^N (a_i \sin(w_i * k + \theta_i))$$

$$= DC + \sum_{i=1}^N (a_i \sin(w_i * k) \cos \theta_i + a_i \cos(w_i * k) \sin \theta_i)$$

Where DC is the value obtained from averaging the time series data; k is discrete time; a is amplitude; i is the number of harmonics in the wave; and θ is the phase shift. The above parameters may be determined by using LSM. The actual data may be defined as

$$Z = DC + HX + \epsilon(k)$$

Where $\epsilon(k)$ is the error, the FLSM may be implemented as

$$\hat{X} = (H^T H)^{-1} H^T Z$$

$$Z_{estimate} = DC + H\hat{X}$$

$$Z_{innovation} = Z - Z_{estimated}$$

$$H = \begin{pmatrix} \sin w_1 & \cos w_1 & \sin w_2 & \dots & \sin w_i \\ \cos w_i \\ \sin 2w_1 & \cos 2w_1 & \sin 2w_2 & \dots & \sin 2w_i \\ \cos 2w_i \\ \sin 3w_1 & \dots & \dots & \dots & \dots \\ \cos 3w_i \\ \dots & \dots & \dots & \dots & \dots \\ \sin n w_1 & \cos n w_1 & \dots & \dots & \sin n w_i \\ \cos n w_i \end{pmatrix}$$

$$X = \begin{pmatrix} a_1 \cos \theta_1 \\ a_1 \sin \theta_1 \\ a_2 \cos \theta_2 \\ \dots \\ a_i \sin \theta_i \end{pmatrix}$$

C. The Hybrid Model of ANN and FLSM:

The model consists of a tidal magnitude prediction using the FLSM at first, where the error between the actual and predicted values is measured. This error is called innovation. The innovations are passed to the ANN where it gets reduced even more resulting in our Hybrid model. The flow chart shown in Fig.2 describes the steps of the hybrid model.

IV Tidal data prediction

a. The FLSM model:

In this section, FLSM model for predicting the tidal magnitude. We use percentage of error (P.E) for

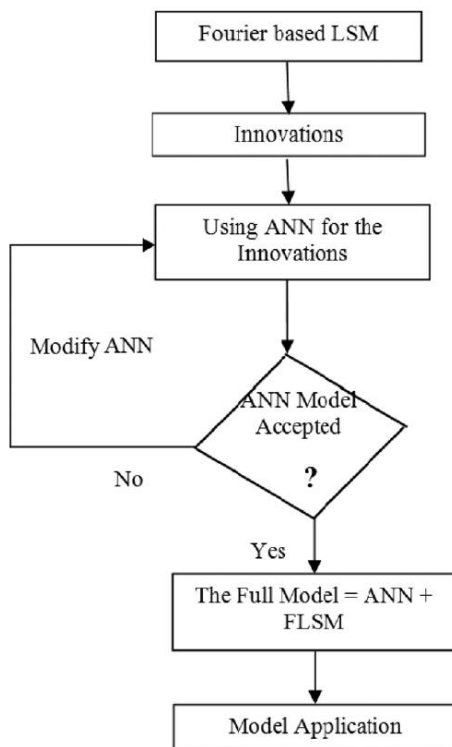


Fig. 2. Hybrid model flowchart.

Comparison between actual and predicted data. The percentage of error (P.E) = $\frac{(Z_{actual} - Z_{predicted})}{Z_{actual}} * 100$.

After using FLSM, the P.E for trained data is 0.7471% this means that the error depends on number of data points and vary and the time that the data were taken, the shape will be different for time to time. Fig.3 shows the exact and estimated data using FLSM. The time for the collected data is measured for every 10 minutes for a period of one month that is 3000*10 min, the height in the graph is in meters.

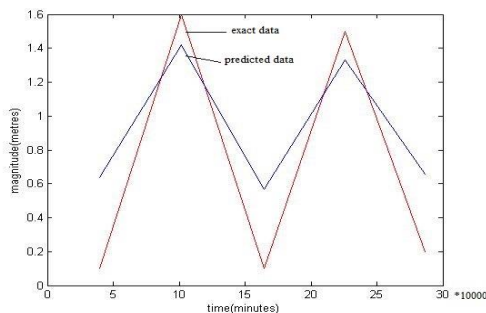


Fig. 3 The relation between time and height using FLSM

b. The ANN model:

The data used for FLSM is directly used for ANN without any modification. After 1000 epochs and 60 neurons in the first layer the P.E became 0.6432%, we would get a small deviation at the beginning and as the data progresses the error gets reduced. Fig.4 shows the exact estimated data using ANN.

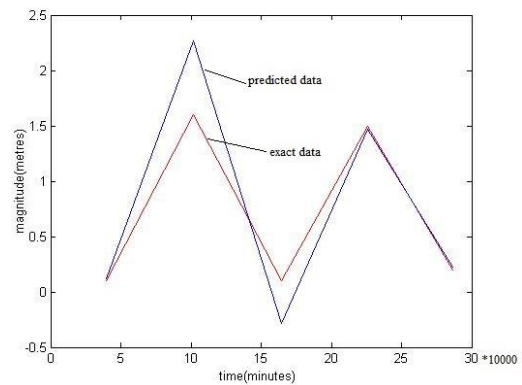


Fig. 4 The relation between time and magnitude using ANN

c. The Hybrid Model:

In here the innovations found using FLSM are forwarded along with the FLSM data and ANN is used to reduce the P.E present in FLSM data so that we could get readings close to exact data. The P.E using Hybrid model is 0.3328. Fig. 5 shows the relation between time and magnitude data using Hybrid model.

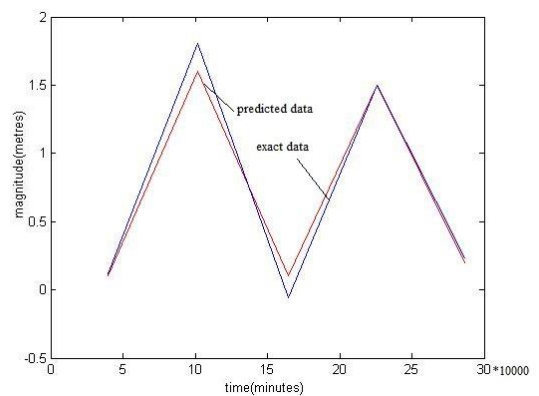


Fig.5 The relation between time and magnitude using

Hybrid model:

TABLE: Comparison between the models used

Percentage of error for different models		
FLSM	ANN	Hybrid model
0.7471%	0.6432%	0.3328%

From the available information so far we can say that the percentage of error for the Hybrid model is less when compared to ANN, FLSM used alone. So we can conclude that it is better to use hybrid model for the prediction of tidal magnitude data.

VI CONCLUSION:

Harmonic tidal magnitude constituent analysis and hydrodynamic models are most common models used for tidal magnitude prediction. Recently ANN has been widely used for its capability to solve nonlinear models effectively. Here a Hybrid model is used in this project has proven its effectiveness. The usage of back propagation algorithm for adjusting the weights has reduced the percentage of error effectively, leading us a better way of predicting the tidal data.

REFERENCES:

[1] G. H. Darwin, "On an apparatus for facilitating the reduction of tidal observations," *Proc. Roy. Soc. A*, vol. 52, pp. 345–376, 1892.

[2] A. T. Doodson, "The harmonic development of the tide-generating potential," *Proc. Roy. Soc. Lond.*, vol. 100, pp. 305–329, 1923.

[3] A. T. Doodson, "The analysis and predictions of tides in shallow water," *Int. Hydrographic Rev.*, vol. 33, pp. 85–126, 1958.

[4] V. John, "Harmonic tidal current constituents of the Western Arabian Gulf from moored current measurements," *Coastal Eng.*, vol. 17, pp. 145–151, 1992.

[5] T. L. Lee and D. S. Jeng, "Application of artificial neural networks in tide forecasting," *Ocean Eng.*, vol. 29, no. 9, pp. 1003–1022, Aug. 2002.

[6] T.-L. Lee, "Back-propagation neural network for long-term tidal predictions," *Ocean Eng.*, vol. 31, no. 2, pp. 225–238, Feb. 2004.

[7] T. L. Lee, C. P. Tsai, and R. J. Shieh, "Applied the back-propagation neural network to predict long-term tidal level," *Asian J. Inf. Technol.*, vol. 5, no. 4, pp. 396–401, 2006.

[8] R. Vijay and R. Govil, "Tidal data analysis using ANN," *J. World Acad. Sci. Eng. Technol.*, no. 24, pp. 872–875, 2006.

[9] B.-F. Chen, H.-D. Wang, and C.-C. Chu, "Wavelet and artificial neural network analyses of tide forecasting and supplement of tides around Taiwan and South China Sea," *Ocean Eng.*, vol. 34, no. 16, pp. 2161–2175, Nov. 2007.

[10] J. F. Adamowski, "River flow forecasting using wavelet and crosswavelet transform models," *J. Hydrol. Processes*, vol. 22, no. 25, pp. 4877–4891, 2008.

[11] P. G. Remya, R. Kumar, and B. Sujit, "Forecasting tidal from tidal levels using genetic algorithm," *Ocean Eng.*, vol. 40, pp. 62–68, Feb. 2012.

[12] D. M. Burrage, C. R. Steinberg, and K. P. Black, "Predicting long-term currents in the Great Barrier Reef," in *Proc. 11th Australasian Conf. Coastal Ocean Eng.*, 1993, pp. 573–581.