Asian Journal of Information Technology 5 (4) : 396-401, 2006

Applied the Back-propagation Neural Network to Predict Long-term Tidal Level

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Abstract: Prediction of tide levels is rather an important task in determining constructions and human activities in coastal and oceanic area. Accurate predictions of tide levels could not be obtained without a large length of tide measurements by conventional methods. The Back-Propagation Neural Network (PBN) was applied to predict long term semi-diurnal tidal level. Based on the model, the different tide types for other two field data, referred as the diurnal and mixed types, are further to test the performance of PBN model. The results also present that one-year tidal level forecasting can be satisfactorily achieved using a half-month length of observed data for these two tide types.

Key words: Back-propagation neural network, long term, prediction

INTRODUCTION

In the past few decades, considerable efforts have been devoted to the prediction of tidal level in coastal engineering. It has been well known that the method of least-squares analysis in determining harmonic parameters has been widely used to predict the tidal level since 1958. Yen *et al.*[1] proposed the Kalman filtering method in determination of parameters in the harmonic tide-level model as well. The estimation of harmonic parameters could predict accurately the tide level using the Kalman filtering method, which solved by the covariance matrix. Tsai and Lee[2] applied the back-propagation neural network to predict the real-time tidal level using the historical observations of water levels without determining the harmonic parameters. Lee and Jeng[3] extend the diurnal and semi-diurnal tide to the mixed tides, which are more likely to occur in the field.

Recently, the Artificial Neural Network (ANN) has been widely applied to various areas and applied to a variety of areas due to overcome the problem of exclusive or (XOR) and the nonlinear relationships. The Back-Propagation Neural Network (BPN) developed by Rumelhart *et al.*[4] is the most representative learning model for the artificial neural network. The procedure of the BPN repeatedly adjusts the weights of the connections in the network so as to minimize the measure of the difference between the actual output vector of the net and the desired output vector. The BPN is widely applied in a variety of scientific areas especially in applications involving diagnosis and forecasting.

For example, in water resources, French *et al.*[5] used the ANN to predict the rainfall intensity. Campolo *et al.*[6] applied ANN for river flood forecasting. Other successful examples of the application of neural network in water resources, hydraulics and earthquake induced liquefaction have been reported in the literature[7-9].

In coastal engineering, Mase *et al.*[10] applied the ANN algorithm to assess the stability of the armor unit and the rubble-mound breakwater and estimate the wave forces acting on the structures. Tsai *et al.*[11] used ANN models to predict the wave heights. Lee and Jeng[12] extend the diurnal and semi-diurnal tide to the mixed tides, which are more likely to occur in the field. At the same year, Lee *et al.*[12] applied the PBN to predict long term tidal level for the semi-diurnal type.

In this study, the different tide types for other two field data (the diurnal and mixed types) are further considered. Based on the BPN model, two fields data of tide at the Keelung and Kaohsiung harbor will be test the performance of PBN model.

NEURAL NETWORKS

The Artificial Neural Network (ANN) is an information-processing system mimicking the biological

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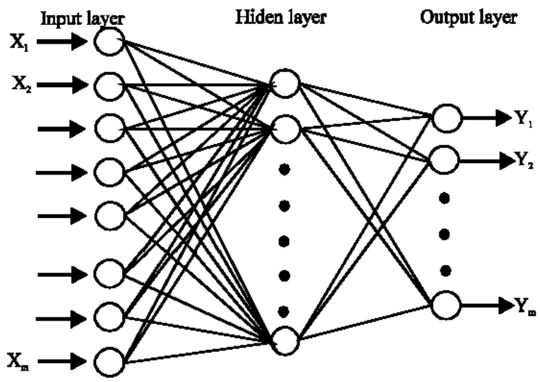

Fig. 1: Structure of an artificial neural network

neural network of the brain by interconnecting many artificial neurons. Since the principle of ANN has been well documented in the literature, only a brief is given in this section.

A typical three-layered network with an input layer (I), a hidden layer (H) and an output layer (O) is adopted in this study, which shown in Fig. 1. Each layer consists of several neurons and the layers are interconnected by sets of correlation weights. The neurons receive inputs from the initial inputs or the interconnections and produce outputs by transformation using an adequate nonlinear transfer function. A common transfer function is the sigmoid function expressed by $f(x)=(1+e^{-x})^{-1}$, it has a characteristics of $df/dx = f(x)[1-f(x)]$. The training processing of neural network is essentially executed through a series of patterns. In the learning process, the interconnection weights are adjusted within input and output value.

The Back-Propagation Neural Network (BPN) is the most representative learning model for the artificial neural network. The procedure of the BPN is the error at the output layer propagates backward to the input layer through the hidden layer in the network to obtain the final desired outputs. The gradient descent method is utilized to calculate the weight of the network and adjust the weight of interconnections to minimize the output error. The error function at the output neuron is defined as

$$E = \frac{1}{2}\sum_{n}(T_j - A_j)^2 \tag{1}$$

in which T_j and A_j are separately the actual and predicated values of output neuron, respectively and is the output neuron. Further details of the BPN algorithm can be found in Rumelhart *et al.*,[4].

The normalized Root Mean Squared error (RMS) and Correlation Coefficient (C.C.) were used for the agreement index to present the accuracy of the present model, given as

$$\text{RMS} = \sqrt{\sum_{k=1}^{n}(y_k - \hat{y}_k)^2 / \sum_{k=1}^{n}\hat{y}_k^{\,2}} \tag{2}$$

$$\text{C.C.} = \frac{\sum_{k=1}^{n}(y_k - \bar{y}_k)(\hat{y}_k - \bar{\hat{y}}_k)}{\sqrt{\sum_{k=1}^{n}(y_k - \bar{y}_k)^2 \sum_{k=1}^{n}(\hat{y}_k - \bar{\hat{y}}_k)^2}} \tag{3}$$

in which is the v alue of observation and denotes the value of prediction. is the mean of observation ($\bar{y}_k = \frac{1}{n}\sum_{k=1}^{n} y_k$) and is the mean value of prediction ($\bar{\hat{y}}_k = \frac{1}{n}\sum_{k=1}^{n}\hat{y}_k$)

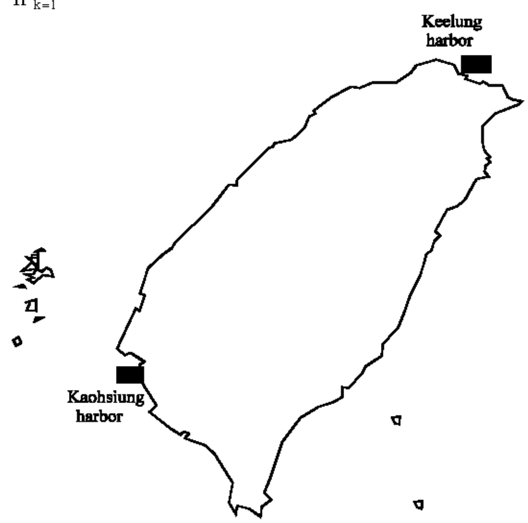

Fig. 2: Locations of Keelung and Kaohsiung harbor, Taiwan

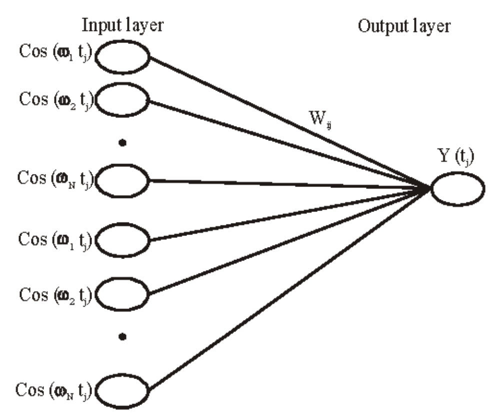

Fig. 3: Structure of the major tidal constituents for BPN without the hidden layer

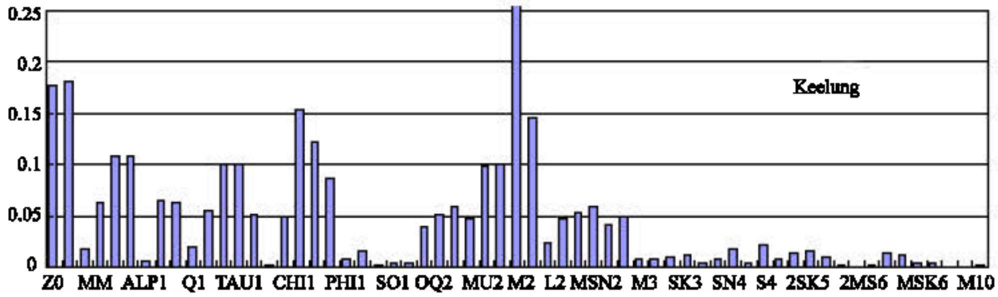

Fig. 4: The results of the main components of tide using one month of tidal data for the ANN model

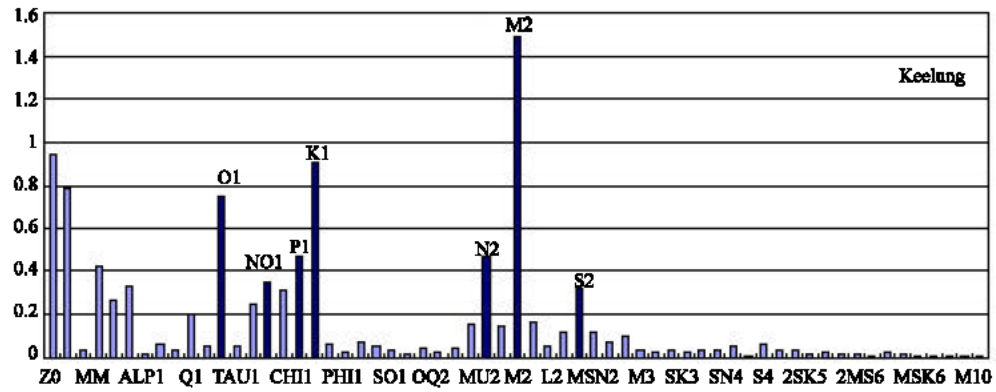

Fig 5: The results of the main components of tide using two months of tidal data for the ANN model

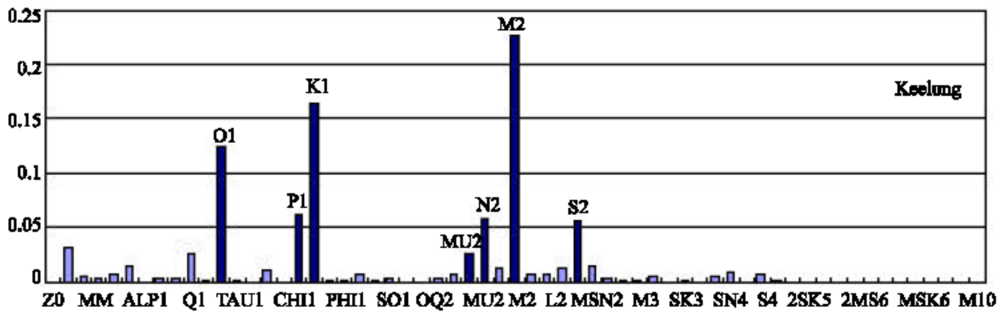

Fig. 6: The results of the main components of tide using the spectral method (Liu, 1996)

Illustrative examples: To illustrate the capability of the proposed model, the hourly tide levels taken from the Keelung and Kaohsiung harbor, Taiwan, at 1996~1998 were used. The locations of these tidal gauge stations are shown in Fig. 2. According to the past record, the main components of tides should be concluded in tide analysis are M2, K1 and O1 in Keelung harbor, which is a diurnal tide type that the regular rise and fall of the tide twice a day. In the Kaohsiung Harbor port, the main components of tides are M2, K1, S2 and O1 and the irregular rise and fall of the tide once a day is belongs to the mixed tide type.

An application of the BPN associated with the harmonic equation to forecast the long-term tide level will be proposed in this study. Firstly, we examine the connection weights in the learning process of the artificial neural network to assess the relative importance of the various input component tides. To show the correction weights between the input and output data, the structure of no hidden layers will be adopted. In other words, the variables of input layer are 138 neurons used $\cos(\omega_i t)$ and $\sin(\omega_i t)$ corresponds to the 69 meteorological tide (Fig. 3) and one neuron of output layer was given the tidal level Y (t).

Figure 4 and 5 show the correction weights between the input and output data with one month and two months as a training set at Keelung harbor in Taiwan. From the result of Fig. 4, one month tide records can not shown the major constituent of component tides owing to the effect of diurnal components or semi-diurnal components. However, we can easily see the 5~7 peak value, such as M2, K1, O1, P1, S2, N2 and NO1, in the Fig. 5 which trained with two months of tide measurements. The result is same with the spectral analysis using two years of tidal data, as shown in the Fig. 6[13]. The major constituent of component tides for Kaohsiung harbor is presented in Table 1.

Generally speaking, the optimal number of component tides will effect the accurate tidal predictions. Table 2 depicts that the RMS for various input number of component tides for these two harbors. It shows that forecasting performance of the BPN can be improved with the number of component tides increases. However, a large number of neuron in the input layer will result too the more complex of neural network to increase the error. From the Table, we can found that the five number of component tide, such as M2, K1, O1, S2 and N2, was selected for Keelung harbor.

Based on the determined the total number of component tides, the basic structure of the ANN tide forecasting model is depicted in Fig. 7, in which the variables will be used as input data for the input layer, N is the total number of component tides. Each tide components corresponds to $\cos(\omega_i t)$ and $\sin(\omega_i t)$. There is only one variable for output layer, i.e., the tidal level Y (t).

An optimized neural network structure is used to illustrate the performance for the storm surge tidal-level forecasting. Since the neural network is a non-linear procedure and the network parameters will affect each other, the adjustment of each parameter to optimize the whole network is not an easy task. The determination for how the neural network structures effect the performance of the forecasting model, which includes the number of neurons hidden layers, the learning rate (η), the momentum factor(α) and the number of training iterations(Epochs) as follows Lee *et al.*,[12]. After some preliminary tests, the optimized neural network structure of these two cases is tabulated in Table 3.

Table 1: The former 7 tidal components using the ANN

Harbor	The name of tidal components						
Keelung	M2	K1	O1	P1	S2	N2	NO1
	(1.35)	(0.91)	(0.69)	(0.41)	(0.40)	(0.37)	(0.21)
Kaohsiung	M2	K1	O1	S2	N2	P1	CHI1
	(1.55)	(1.23)	(1.20)	(0.54)	(0.52)	(0.28)	(0.26)

Table 2: The effect of the number of tidal components using the ANN

Harbor	The name of input tidal components	Number	RMS
Keelung	M2、K1、O1、P1	4	0.1386
	M2、K1、O1、P1、S2	5	0.1250
	M2、K1、O1、P1、S2、N2	6	0.1252
	M2、K1、O1、P1、S2、N2、NO1	7	0.1931
Kaohsiung	M2、K1、O1、S2	4	0.1152
	M2、K1、O1、S2、N2	5	0.1110
	M2、K1、O1、S2、N2、P1	6	0.1404
	M2、K1、O1、S2、N2、P1、CHI1	7	0.1456

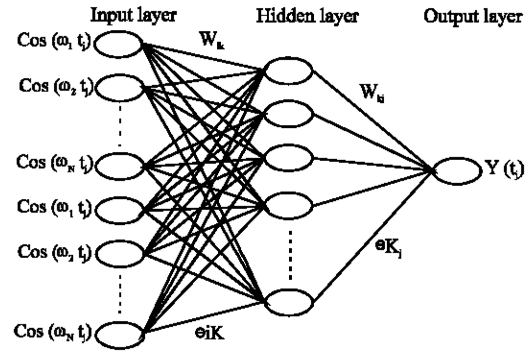

Fig. 7: Structure of the main components of tidal forecasting for an artificial neural network

Table 3: The structure of the ANN for two harbors

Harbor	hidden layers	η	α	Epoch	
Keelung		1	0.1	0.8	1000
Kaohsiung		1	0.01	0.5	1000

Table 4: The performance of the one year for three harbors using the different day's measurements

Harbor	Training sets	RMS	CC
Keelung			
	1 day (13/4/1996)	0.2117	0.6499
	7 days (13~19/4/1996)	0.2032	0.6932
	15 days (13~27/4/1996)	0.1234	0.8931
	30 days (13/4~12/5/1996)	0.1237	0.8947
Kaohsiung			
	1 day (2/10/1997)	0.2486	0.4127
	7 days (2~8/10/1997)	0.1583	0.8202
	15 days (2~16/10/1997)	0.1091	0.9127
	30 days (2/10~1/11/1997)	0.1107	0.9111

Based on the optimized neural network structure stated above, we applied different days hourly tidal observations as a training set to predict the long term tide levels of next year for various harbor. Table 4 show that one year of hourly tidal predictions at these two harbors, respectively, when using different days hourly tidal observations as a training set. These results imply that the tidal forecasting is able to use only 15 days hourly tidal observations when utilizing the present ANN model.

The one-year predication of tidal level against the observation is illustrated in Figs. 8 and 9 (only show some days) using the 15-day collected data, which the solid lines represent the observation and dashed-symbols are forecasting results. Good agreement between the predictions and the observations are found in the

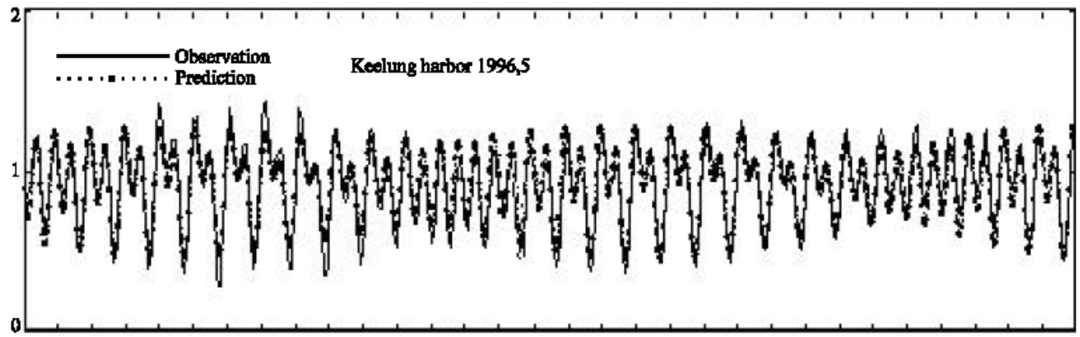

Fig. 8: Comparison for one year of predictions with observed data at Keelung harbor with the observations using 15 days of hourly records

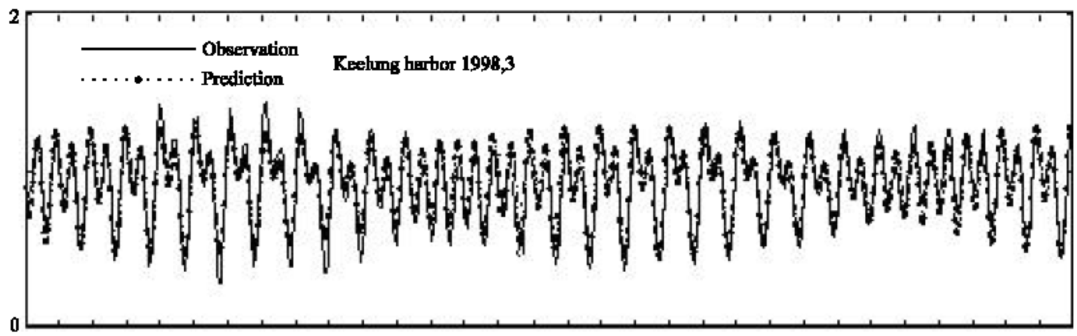

Fig. 9: Comparison for one year of predictions with observed data at Kaohsiung harbor with the observations using 15 days of hourly records

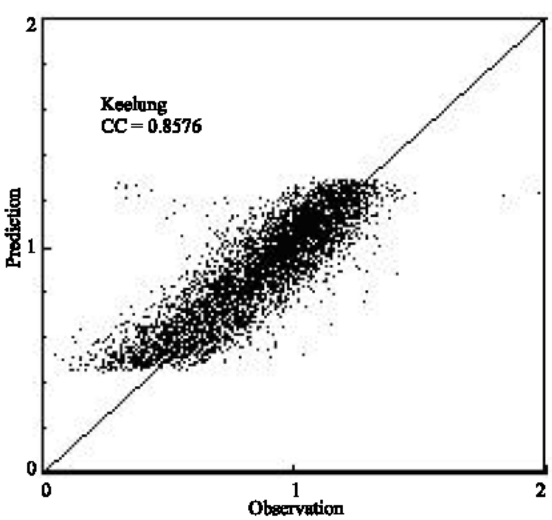

Fig. 10: Comparisons for one year of predictions between the measured and predicted tidal level for Keelung harbor

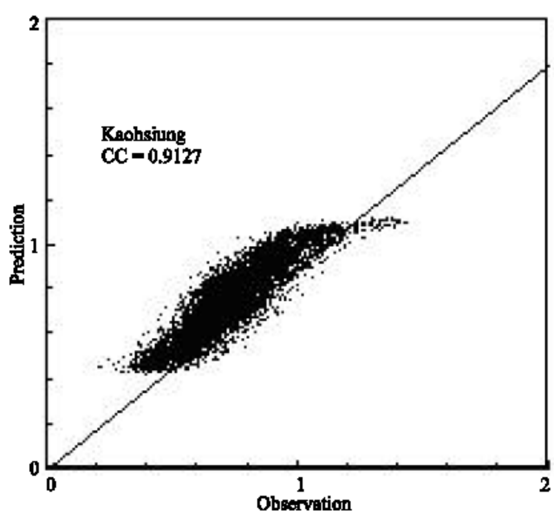

Fig. 11: Comparisons for one year of predictions between the measured and predicted tidal level for Kaohsiung harbor

comparison. As seen from the Fig. the results of tidal prediction for Keelung and Kaohsiung harbor are less than the Taichung harbor, because these two harbors have the complex variation of the tide level affected by the diurnal components, K1, O1 and the semi-diurnal component, M2. The correlation of the observation data and prediction over one year is presented in Figs. 10 and 11. The correlation coefficients are more than 0.85, which is quite good. These results also indicate that the artificial neural network is capable of learning the level variations for forecasting tide using only very short-term observations.

CONCLUSION

In this study, the artificial back-propagation neural network with gradient descent algorithm is adopted to predict the long-term tidal level by learning processes is proposed. Based on the present results, the following conclusions can be drawn:

- Unlike the conventional method of the harmonic analysis, which requires a large amount of observed tidal data for estimating the total number of component tides and the harmonic parameters, this paper describes an alternative method (the artificial neural network) for forecasting the tidal level variations.
- The results show that the major constituents can be obtained only using a two months measured data.
- This BPN model can predict one-year tidal level using a half-month length of observed data for diurnal and mixed types.

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