TIDAL FORECASTING IN THE BAHIA BLANCA ESTUARY, ARGENTINA

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SUMMARY

In recent years, the availability of accurate ocean tide models has become increasingly important, as tides are the main contributor to disposal and movement of sediments, tracers and pollutants, and also due to a wide range of offshore applications in engineering, environmental observations, exploration and oceanography. Tides can be conventionally predicted by harmonic analysis, which is the superposition of many sinusoidal constituents with amplitudes and frequencies determined by a local analysis of the measured tide. However, accurate predictions of tide levels could not be obtained without a large number of tide measurements by the harmonic method. An application of the back-propagation artificial neural network using long-term and short-term measuring data is presented in this paper. On site tidal level data at Ingeniero White harbor in the inner part of Bahia Blanca estuary, Argentina, will be used to test the performance of the present model. Comparison with conventional harmonic methods indicates that the back-propagation neural network model also predicts accurately the long-term tidal levels.

The knowledge of future sea level height in the nearshore environment is of great importance for the monitoring and prediction of changes in complex marine ecosystems, as well as for planning and constructing coastal and offshore structures. The instantaneous measurements, as well as time averaged values of sea level, are not stationary either spatially or temporally. They vary under the synergetic influence of changing tides, atmospheric forcing, and currents (Pierini, 2007). To solve the tasks of nearshore sea level predictions, the least-squares method or an alternative artificial intelligence approach, such as genetic algorithms, fuzzy logic or artificial neural networks, can be employed.

The modern view of artificial neural networks (ANNs) began in the 1940's. McCulloch and Pitts (1943) showed that networks of artificial neurons could compute any arithmetic or logical function. Following their work, Hebb (1949) proposed a mechanism for learning in biological neurons. In the late 50's and 60's the first practical ANN, the 'perceptron' network and the associated learning rule were invented (Rosenblatt, 1958). Widrow and Hoff (1960) introduced a new learning algorithm and used it to train adaptive linear ANNs. These basic perceptrons could solve only a limited class of problems. Thereafter, some important work like that of Kohonen (1972) continued during the 1970's, although for a decade neural network research was suspended. This was mainly due to the belief that the research had reached a dead end and no powerful digital computers were available. During the 1980's the number of studies in the field of ANNs increased dramatically; important new concepts were introduced, two of which are the most significant in the rebirth of ANNs. The first was the use of statistical mechanics to explain the operation of a certain class of recurrent network described by Hopfield (1982). The second was the back-propagation algorithm (BPN) for training multilayer perceptron (MLP) networks discovered independently by several researchers, the most influential among them being Rumelhart and McClelland (1986). Since the mid 1980's thousands of papers have been published, and ANNs have spread, with new theoretical and practical applications.

The applications, software and hardware related to ANNs have grown. Neural networks are also gradually showing their abilities to solve different problems in oceanography. The study by Wong and Wilson (1984) of 30-day data indicated that sub-tidal sea level variation

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plays an important role in the column exchange between estuary and ocean through the inlets in the Long Island south shore. ANNs have been applied to an increasing number of real-world complex problems, including those of ocean engineering. ANNs have been covered by many authors including Haykin (1999), Hagan (1996) and Fausett (1994). Various authors have recently applied these systems to provide reliable predictions of sea currents (Babovic, 1999), problems related to the quality of the data series (Reusch and Alley, 2002), wave parameters (Makarynskyy, 2004), sea level data (Makarynskyy *et al*., 2004), wind wave data (Makarynskyy, 2006), tidal prediction (Lee *et al*., 2007), wind wave forecasts with field observation (Makarynskyy, 2007), as well as predicting sea level variations (Makarynska and Makarynskyy, 2008). These and many other scientific contributions exploited the ANN capability to determine interrelations among the elements within a complex estuary system.

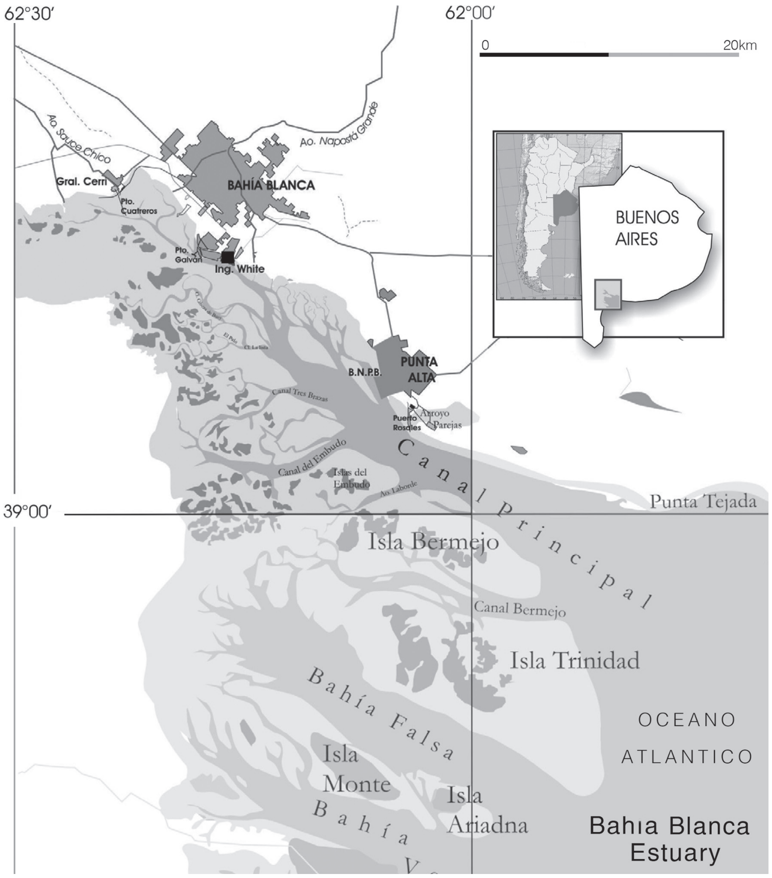

Figure 1. Bahia Blanca estuary and Ingeniero White tide gauge location.

A tidal level record is a determinant factor in constructions or activities in coastal areas. Doodson (1957) employed the least-squares method in determining harmonic parameters and it has been widely used to predict the sea level. In contrast to traditional harmonic analysis, which is used only in the prediction of periodic tidal components, the neural network model can be trained to recognize and predict both nonlinear and nonperiodic signals. The traditional harmonic analysis method is unable to provide accurate predictions of long-term water level variations where non-tidal sea level variations are significant. Besides the prediction of the sea level, a supplement of the tidal record is also important for a complete observation of the sea level database. The interruption in observations may come from a damage of recording facilities, inappropriate operation, natural disasters, etc. This paper proposes the application of the back-propagation algorithm (BPN) combined with the harmonic analysis equation for the short and long-term prediction of the tidal level. The BPN model is applied to two different types of tide level prediction for Ingeniero White harbor, Argentina.

Study Area

Bahia Blanca is a mesotidal coastal - plain estuary located in the south of the Buenos Aires Province, Argentina. It consists of a series of NW-SE channels separated by islands and wide tidal flats (Figure 1), which are the remanents of a late Pleistocene - early Holocene delta, and has an area of 1150km^2 (Melo, 2004). The estuary has an elongated shape with a total length of 68km, being 200m and 4km wide near its head and mouth, respectively. Its mean depth is 10m, although values of the order of 22m are found at the mouth of the estuary (Pierini, 2007). The circulation in the estuary in general, and in the main channel in particular, is dominated by semidiurnal and stationary tides. The mean tidal amplitude is 2.4m and the tidal range and tidal current amplitude increase headward.

Prevailing winds are NW-N for over 40% of the time, while SE-S winds occur ~10% of the time (Piccolo *et al*., 1989). These wind directions are important because they blow parallel to the main channels. Wind is a major factor in the Bahia Blanca Estuary dynamics since it produces strong delays or advances of the tidal wave and large differences between the real and the predicted astronomical tides. The amplitude of the tidal wave increases with a decrease in depth of the channel. Bahia Blanca is a hyper-synchronous type estuary, where the amplitude increases steadily from the mouth to the head, implying that the convergence effect on the tidal wave is larger than the friction effect (Pierini, 2007).

The head of the estuary has a very small freshwater input. Only the Sauce Chico River and Napostá Grande Creek enter the estuary near its head, providing most of the freshwater inflow. The origin of both courses is in Sierra de la Ventana, about 120km north from Bahia Blanca. Other creeks near Ingeniero White (Galván, Saladillo de García and Maldonado) reach the estuary with intermittent flows that become significant only during periods of local precipitation. The Sauce Chico River basin has an area of 1500km^2. The annual mean runoff is 1.87m^3·s^{-1}, but the river has presented runoff peaks >10m^3·s^{-1} reaching on several occasions discharges >50m^3·s^{-1} (Piccolo *et al*., 1989). The maximum and minimum monthly mean rainfall occur in October and August. The complex bathymetry and coastal configuration of the estuary, as well as the continental discharges may affect harmonic analysis results, making ANNs an alternative tool for short term based estimates of sea level.

Data and Methodology

Data in the form of hourly sea level records were obtained from the CGPBB (Consorcio de Gestión del Puerto de Bahia Blanca) station deployed at Ingeniero White harbor (38º47'27.10"S, 62º16'7.42"W) in Bahia Blanca estuary, Argentina. This station (Figure 1) is operated and maintained by CGPBB, and the observations are referenced to the datum plane which is located 2.63m below the mean level tide gauge. The period from Jan 1999 to Dec 2002 was employed for this study (Figure 2). The record of the tide gauge was divided in two data sets; one of them served to train the NN, and the other was used to validate the retrieval procedure but was not used to train the ANN. In this series there are multiple gaps randomly generated in the sea level recordings at Ingeniero White harbor.

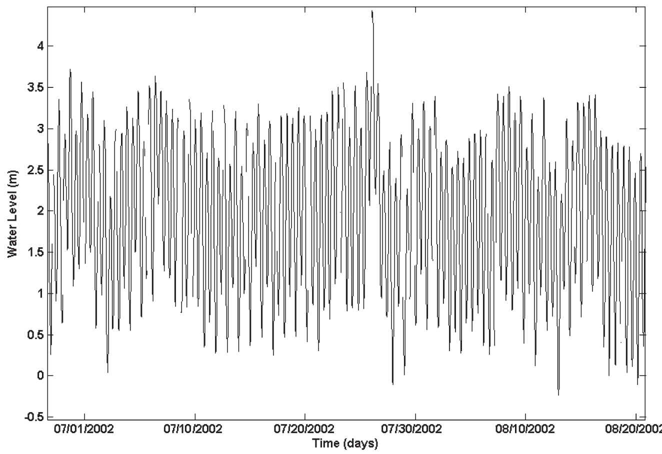

Figure 2. Hourly sea level observations from Ingeniero White harbor tide gauge, partial data from time series (01/01/1999 - 12/31/2002).

When dealing with time series, some treatment for the missing data is essential, since most of the analysis methods cannot be performed otherwise. Classical methods, such as substitution of the gap by the mean value of the series or interpolation from the nearest neighbours, are unable to catch time variations or dependence upon variations in other variables. The alternative method of using neural networks to improve missing values substitution (Makarynskyy *et al*., 2005; Makarynskyy and Makarynska, 2007) and its comparison with harmonic analysis for tide forecasting proposed by Doodson (1957) were evaluated. In his model, widely used because of its simplicity, the least squares method was used to determine the harmonic constants. These constants are further substituted into the harmonic equation to determine the tidal level.

Based on the harmonic theory, the vertical tidal level Y(t) at time t at any place is expressed as

$$Y(t)= A_o + \sum_{i=1}^{N} (A_i \cos w_i t + B_i \sin w_i t)$$

where A_o : mean water level, A_i and B_i : coefficients of tide components, w_i : angular frequency of the tidal components, and N: number of component tides.

In general, the number of main tidal components will directly affect the accuracy of tidal forecasting. Thus, the influence of the number of tidal components on the accuracy is examined through a parametric study. Using the data in Ingeniero White harbor, the tidal components are tabulated in Table I.

TABLE I
PRINCIPAL TIDAL COMPONENT FOR INGENIERO WHITE HARBOR TIDAL GAUGE

Tidal Component	Speed (deg/hr)	H (cm)	Φ (º)
Z_0	0.000	263.544	0.000
M2	28.984	169.123	186.072
L2	29.528	25.475	255.364
N2	28.440	23.983	103.593
M4	57.968	22.764	178.277
S2	30.000	21.589	307.350
K1	15.041	21.151	61.178
O1	13.943	15.528	0.701
MU2	27.968	14.523	291.531
NU2	28.513	10.954	137.915

H: amplitude, ϕ: phase.

The relative root mean squared error (RMSE), skill index (SKI) and correlation coefficient (R) were used to evaluate the accuracy of the ANN model and harmonic analysis method. They are defined by

$$RMSE= \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N} x_i^2}}$$

$$SKI=1-\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{\sum_{i=1}^{N}\left(\left|y_i-\bar{x}\right|+\left|x_i-\bar{x}\right|\right)^2}, \quad \leq SKI \leq 1$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}}$$

in which y_i : value of prediction, x_i : value of the observation, and N: total number of hourly tide levels. The mean value of the prediction is $\bar{y}$ and that of the observation is $\bar{x}$.

Neural networks

The ANN is an information-processing system mimicking the biological neural network of the brain by interconnecting many ANNs. Since the principle of the ANN has been well documented in the literature, only a brief summary is given in this section. The feasibility of a three-layer network for the reproduction of complex system behaviour was proven empirically by a number of applications (Huang *et al*., 2003; Lee, 2004; Makarynskyy *et al*., 2004). Such an ANN (Figure 3) having an input layer (I), a hidden layer (H) and an output layer (O) was adopted in this study. Each layer consists of neurons and the layers are interconnected by sets of correlation weights, which enable the network to process the data. The neurons receive inputs from the initial data or the interconnections and produce outputs by transformation, using an adequate non-linear transfer function. A common transfer function is the sigmoid function expressed by $f(x)= (1+e^{-x})^{-1}$, which has the characteristics $df/dx = f(x)\,[1-f(x)]$. The training process of the ANN is essentially executed through a series pattern. In the learning process, the interconnection weights are adjusted within input and output values. The back-propagation network (BPN) is the most representative learning model for the ANN. The output is compared to the target data, from which the network error is determined. The error is then back-propagated through the network in order to adjust the weights and biases associated with each neuron in the network layers. 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

$$E = \frac{1}{2}\sum_{k}(T_k - O_k)^2 \qquad (1)$$

where T_k and O_k are, separately, the value of target and output. Further details of the BPN algorithm can be found in Rumelhart *et al*. (1986).

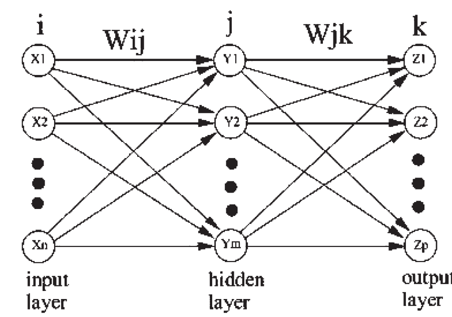

Figure 3. Structure of an artificial neural network.

Results

To illustrate the capability of the BPN model, the hourly tide levels taken from Ingeniero White harbor, Argentina, were used. According to past records, its highest water level is 5.38m, the lowest water level is -0.64m and the average tidal range is 2.63m. In addition, it is a semidiurnal tide type with regular rise and fall of the tide twice a day. RMSE, R and SKI were used for the agreement index to present the accuracy of the current model.

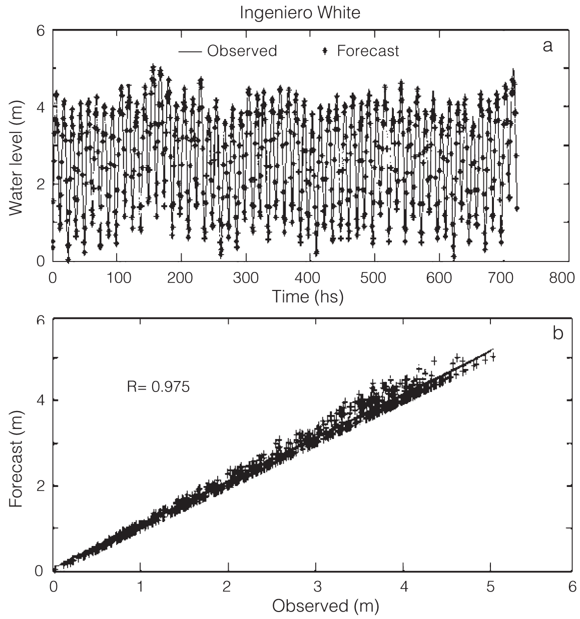

Figure 4. a: Hourly tidal predictions over a months period using different lengths of records using a one day training duration (a), and comparison between observed and predicted data and correlation value (b).

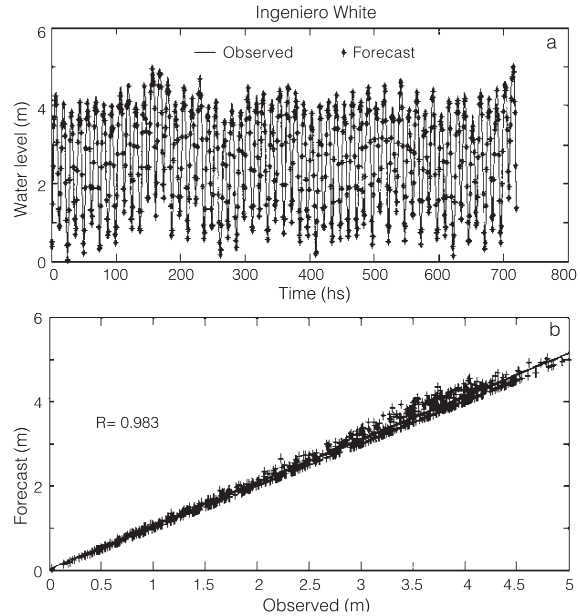

Figure 5. Hourly tidal predictions over a months period using different lengths of records using a seven days training duration (a), and comparison between observed and predicted data and correlation value (b).

Short-term tide forecasting

Figures 4 to 7 present the prediction of the one month tidal level at Ingeniero White harbor with 1, 7, 15 and 21 days training since 07-01-2002. As seen, the predictions of overall hourly data agree with the measured data. The prediction of tidal level with training duration of 21 days is better than that with one day. The correlation for observation and prediction data can also be seen in the figures, and the correlation coefficients (R) are given. The R value confirms that a good agreement between observations and predictions can be achieved by using BPN with short-term tidal data (one day).

Based on the harmonic analysis and number of tidal constituents, Table II shows the RMSE, R and SKI values for various numbers of tidal constituents. RMSE is 0.0705 with six tidal constituents (M2, L2, N2, M4, S2, K1), but the error increases to 0.0983 if another two tidal constituents (O1 and MU2) are included. This implies that O1 and MU2 cannot improve the accuracy of tidal forecasting. Thus M2, L2, N2, M4, S2, K1 are considered as the six main constituents for the Ingeniero White harbor study.

Based on the above results, different numbers of days of hourly tidal observation to predict the tide levels were applied. Table III shows the values obtained in one month of hourly tidal predictions, when using different day hourly tidal records. The results imply that tidal forecasting is unable to use only one day of hourly tidal observations when utilizing harmonic analysis.

Long-term tide forecasting

As mentioned previously, the major shortcoming of conventional harmonic analysis for tidal level forecasting is the large amount of databases required to determine the harmonic constants. On the other hand, the major advantage of the ANN model is to predict tidal level in the long-term with short-term collected data.

The RMSE on a long-term (over one month, one year) prediction and observed data is illustrated in Table IV. As shown, the hourly tidal data during one month can be efficiently predicted using a one-day hourly tidal record. However, to provide an accurate prediction of tidal level, at least 15 days of hourly tidal data is required for a one year tidal level forecasting. The one year prediction of tidal level using

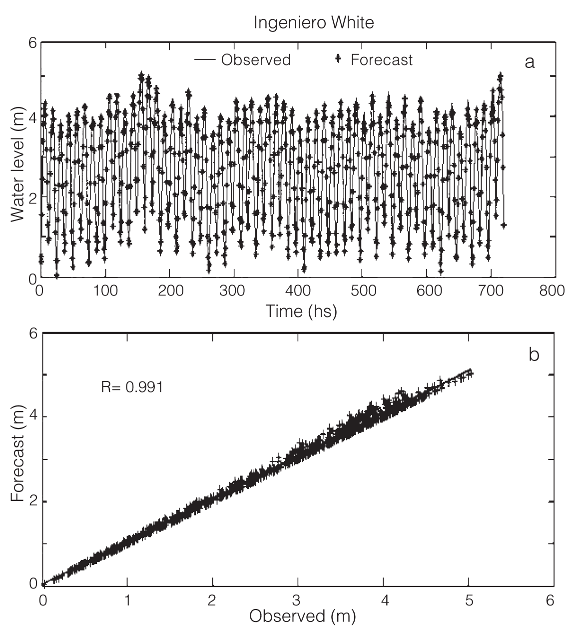

Figure 6. Hourly tidal predictions over a months period using different lengths of records using a 15 days training duration (a), and comparison between observed and predicted data and correlation value (b).

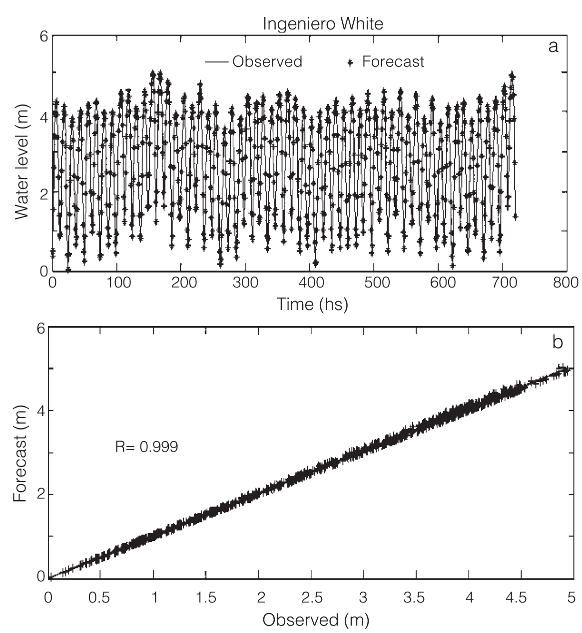

Figure 7. Hourly tidal predictions over a months period using different lengths of records using a 21 day training duration (a), and comparison between observed and predicted data and correlation value.

TABLE II
TEST OF VARIOUS TIDAL COMPONENTS

Tidal Components	Nº of tidal components	RMSE	SKI	R
M2, L2, N2, M4	4	0.078	0.975	0.984
M2, L2, N2, M4, S2	5	0.071	0.981	0.987
M2, L2, N2, M4, S2, K1	6	0.070	0.984	0.988
M2, L2, N2, M4, S2, K1, O1	7	0.076	0.974	0.979
M2, L2, N2, M4, S2, K1, O1, MU2	8	0.098	0.943	0.946

RMSE: relative root mean squared error, SKI: skill index, R: correlation coefficient.

TABLE III
PERFORMANCE OVER ONE MONTH USING MEASUREMENTS OVER DIFFERENT DAYS HARMONIC ANALYSIS SINCE 07/01/2002

Training sets	RMSE	SKI	R
1 day	0.545	0.484	0.502
7 days	0.354	0.850	0.883
15 days	0.178	0.908	0.891
21 days	0.084	0.921	0.907

TABLE IV
PERFORMANCE OVER ONE YEAR USING MEASUREMENTS OVER DIFFERENT DAYS BPN SINCE 07/01/2002

Training sets	RMSE	SKI	R
1 day	0.254	0.981	0.975
7 days	0.164	0.989	0.983
15 days	0.094	0.997	0.991
21 days	0.052	1.000	0.999

the 15 day collected data *versus* the observation and the results of harmonic analysis are illustrated in Figure 8, where solid lines denote the results of BPN, dashed lines are the predicted values using harmonic analysis, and symbols are measured data. As seen in the figure, the prediction of the BPN agrees overall with the observation and the harmonic analysis. These results also indicate that the BPN is capable of learning the level variations to predict the tidal variation using only very short-term observations. In other words, to reach a reasonable accuracy of the prediction data for a one year period, 15 day training data are required. Figures 8 and 9 ilustrate the scatter data over one year between the BPN model and harmonic analysis against the observational data. Comparing the correlation coefficient (Tables III and IV) of the BPN (R=0.991) with the harmonic analysis (R=0.895), it is found that the BPN is more accurate.

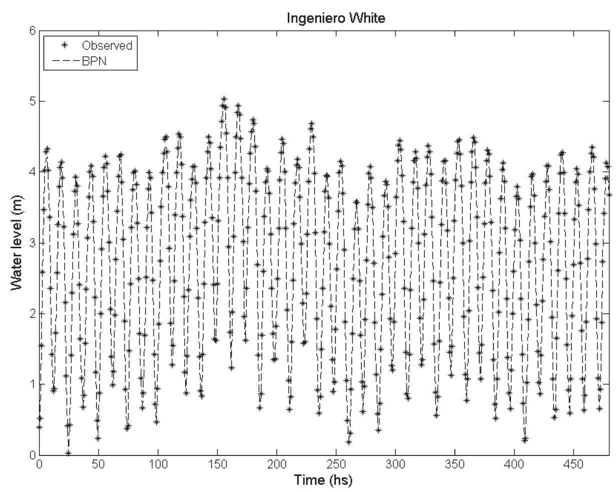

Figure 8. Comparison of observed tide levels with a BPN model over a years period, using a 15 days training duration. Here are represented only twenty days since 07/01/2002.

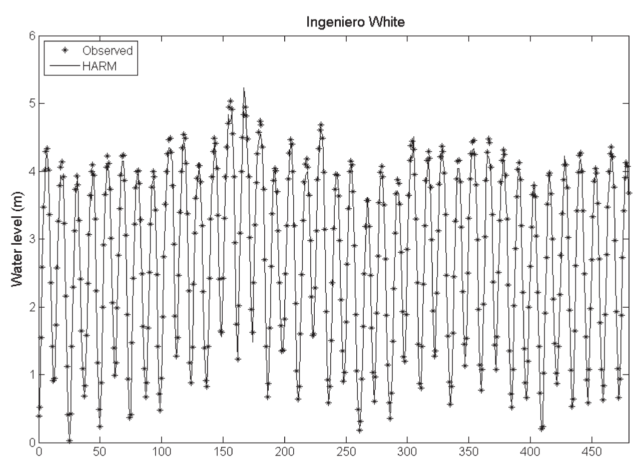

Figure 9. Comparison of observed tide levels with a HARM model over a years period, using a 15 days training duration. Here are represented only twenty days since 07/01/2002.

Discussion

In order to demonstrate the enhanced performance of the ANN, it was compared to other algorithms. In comparing harmonic analysis and an ANN modelled algorithm developed with sea level data, the values produced by the ANN model were significantly better than those from the other model. Tables III and IV show the statistical performance parameters of the two algorithms, and that of the validation set and the training set of the study's BPN. The scattered plots of the BPN model and the harmonic analysis model further illustrate the dramatic difference in performance (Figures 8 and 9). The most notable difference between the two is the range of values reported. The BPN model ranges from 0.254 to 0.052m, whereas the harmonic analysis spans values ranging from 0.545 to 0.084m. Thus, this locally trained optimal BPN model is a significant improvement over the current harmonic analysis algorithm. Since the local sea level data was used in the harmonic analysis, the results of this algorithm represent a more reasonable data set for comparison with the BPN model. As shown in Table III, the harmonic analysis performance parameters are considerably poorer than the results of the BPN model. The scattered plot of the harmonic analysis model (Figure 9) shows that its performance is similar to that of this study's BPN model while the sea level data remain above 15 days training duration. However, after this point the harmonic analysis model performs significantly poorer.

Reflecting on the performance of the BPN, the size of the data set is likely to have been a primary cause of problems in modelling the transfer function. The relatively small size of the data set primarily affects the BPN results by limiting model complexity and reducing the effectiveness of cross validation. These two effects are not unrelated. The size of the data set limits the number of free variables (weights and biases) in BPN models, which effectively controls the extent to which a BPN structure can grow. Thus, complex relationships that might require a large number of neurons and additional hidden layers in order to achieve very accurate results are stunted and not able to fully simulate the desired relationship.

Conclusions

Unlike the conventional method of harmonic analysis, which requires a large amount of observed tidal data for estimating the appropriate harmonic parameters; this article describes an alternative method (BPN) for forecasting the hourly tidal level variations. With the numerical examples presented it is demonstrated that the present model is applicable and, furthermore, it has the capability to predict the hourly tidal levels with over one month duration with one day observations. Also the prediction over a longer duration (such as a year) can be effectively performed with a 15 days collected tidal data. The application of this validated methodology over the complex bathymetry and coastal configuration of the Bahia Blanca estuary, could possibly be successfully achieved to gauge tides in other parts of the estuary. For this, a necessary condition would be the availability of sufficiently long and continuous sea level records.

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PREDICCIÓN DE MAREAS EN EL ESTUARIO DE BAHÍA BLANCA, ARGENTINA

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RESUMEN

Durante los últimos años, la disponibilidad de modelos oceánicos cada vez más exactos han aumentado en importancia, por ser las mareas el principal contribuyente para la disposición y movimiento de trazadores, sedimentos y contaminantes, y por una amplia variedad de aplicaciones en ingeniería, observaciones ambientales, exploración y oceanografía. Las mareas pueden ser pronosticadas mediante análisis armónico, que es la superposición de funciones sinusoidales con amplitudes y frecuencias determinadas en un análisis local de registros mareográficos. Sin embargo, la exactitud de las predicciones del nivel de marea por el método armónico no puede obtenerse sin un gran número de mediciones. En este trabajo se presenta una aplicación del método propagación hacia atrás (back-propagation) de redes neuronales empleando datos de corto y de largo plazo. Para medir la precisión del presente modelo se utilizan mediciones de nivel de marea correspondientes al Puerto Ingeniero White, en la parte interna del estuario de Bahia Blanca, Argentina. La comparación con métodos armónicos convencionales indica que las redes neuronales empleando back-propagation también predicen eficientemente los niveles de mareas a largo plazo.

PREVISÃO DE MARÉS NO ESTUARIO DE BAHIA BRANCA, ARGENTINA

Jorge O. Pierini e Eduardo A. Gómez

RESUMO

Durante os últimos anos, a disponibilidade de modelos oceânicos cada vez mais exatos têm aumentado em importância, por ser as marés o principal contribuinte para a disposição e movimento de traçadores, sedimentos e contaminantes, e por uma ampla variedade de aplicações em engenharia, observações ambientais, exploração e oceanografia. As marés podem ser prognosticadas mediante análise armônico, que é a superposição de funções sinusoidais com amplitudes e frequências determinadas em uma análise local de registros maregráficos. Entretanto, a exatidão das previsões do nível da maré pelo método armônico não pode obter-se sem um grande número de medições. Neste trabalho se apresenta uma aplicação do método propagação para atrás (back-propagation) de redes neuronais empregando dados de curto e de longo prazo. Para medir a precisão do presente modelo se utilizam medições de nível de maré correspondentes ao Puerto Ingeniero White, na parte interna do estuario de Bahia Branca, Argentina. A comparação com métodos armônicos convencionais indica que as redes neuronais empregando back-propagation também predizem eficientemente os níveis de marés a longo prazo.