Available online at www.sciencedirect.com
SCIENCE DIRECT®
ELSEVIER
OCEAN ENGINEERING
Ocean Engineering 30 (2003) 2275–2295
www.elsevier.com/locate/oceaneng

Extended Technical Note

Development of a regional neural network for coastal water level predictions

Wenrui Huang [a,*], Catherine Murray [a], Nicholas Kraus [b], Julie Rosati [b]

[a] Civil Engineering Department, FAMU-FSU College of Engineering, 2525 Pottsdamer Street, Tallahassee, FL 32310-6046, USA
[b] US Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory, 3909 Halls Ferry Road, Vicksburg, MS 39180-6199, USA

Received 21 August 2002; received in revised form 27 November 2002; accepted 5 March 2003

Abstract

This paper presents the development of a Regional Neural Network for Water Level (RNN—WL) predictions, with an application to the coastal inlets along the South Shore of Long Island, New York. Long-term water level data at coastal inlets are important for studying coastal hydrodynamics sediment transport. However, it is quite common that long-term water level observations may be not available, due to the high cost of field data monitoring. Fortunately, the US National Oceanographic and Atmospheric Administration (NOAA) has a national network of water level monitoring stations distributed in regional scale that has been operating for several decades. Therefore, it is valuable and cost effective for a coastal engineering study to establish the relationship between water levels at a local station and a NOAA station in the region. Due to the changes of phase and amplitude of water levels over the regional coastal line, it is often difficult to obtain good linear regression relationship between water levels from two different stations. Using neural network offers an effective approach to correlate the non-linear input and output of water levels by recognizing the historic patterns between them. In this study, the RNN—WL model was developed to enable coastal engineers to predict long-term water levels in a coastal inlet, based on the input of data in a remote NOAA station in the region. The RNN—WL model was developed using a feed-forwards, back-propagation neural network structure with an optimized training algorithm. The RNN—WL model can be trained and verified using two independent data sets of hourly water levels.

The RNN—WL model was tested in an application to Long Island South Shore. Located about 60–100 km away from the inlets there are two permanent long-term water level stations,

* Corresponding author. Tel.: +1850-410-6199; fax: +1-850-410-6236.
E-mail address: whuang@eng.fsu.edu (W. Huang).

doi:10.1016/S0029-8018(03)00083-0

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **27 NOV 2002**	2. REPORT TYPE	3. DATES COVERED **00-00-2002 to 00-00-2002**
4. TITLE AND SUBTITLE **Development of a regional neural network for coastal water level predictions**		5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **U.S. Army Engineer Research and Development Center,Coastal and Hydraulics Laboratory,3909 Halls Ferry Road,Vicksburg,MS,39180-6199**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR'S ACRONYM(S) 11. SPONSOR/MONITOR'S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT **Approved for public release; distribution unlimited**		
13. SUPPLEMENTARY NOTES		

14. ABSTRACT

This paper presents the development of a Regional Neural Network for Water Level (RNN- WL) predictions, with an application to the coastal inlets along the South Shore of Long Island, New York. Long-term water level data at coastal inlets are important for studying coastal hydrodynamics sediment transport. However, it is quite common that long-term water level observations may be not available, due to the high cost of field data monitoring. Fortunately, the US National Oceanographic and Atmospheric Administration (NOAA) has a national network of water level monitoring stations distributed in regional scale that has been operating for several decades. Therefore, it is valuable and cost effective for a coastal engineering study to establish the relationship between water levels at a local station and a NOAA station in the region. Due to the changes of phase and amplitude of water levels over the regional coastal line, it is often difficult to obtain good linear regression relationship between water levels from two different stations. Using neural network offers an effective approach to correlate the nonlinear input and output of water levels by recognizing the historic patterns between them. In this study, the RNN-WL model was developed to enable coastal engineers to predict long-term water levels in a coastal inlet, based on the input of data in a remote NOAA station in the region. The RNN-WL model was developed using a feed-forwards, back-propagation neural network structure with an optimized training algorithm. The RNN-WL model can be trained and verified using two independent data sets of hourly water levels. The RNN-WL model was tested in an application to Long Island South Shore. Located about 60-100 km away from the inlets there are two permanent long-term water level stations, which have been operated by NOAA since the1940s. The neural network model was trained using hourly data over a one-month period and validated for another one-month period. The model was then tested over year-long periods. Results indicate that, despite significant changes in the amplitudes and phases of the water levels over the regional study area, the RNN-WL model provides very good long-term predictions of both tidal and non-tidal water levels at the regional coastal inlets. In order to examine the effects of distance on the RNN-WL model performance, the model was also tested using water levels from other remote NOAA stations located at longer distances, which range from 234 km to 591 km away from the local station at the inlets. The satisfactory results indicate that the RNN-WL model is able to supplement long-term historical water level data at the coastal inlets based on the available data at remote NOAA stations in the coastal region.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**21**	

which have been operated by NOAA since the1940s. The neural network model was trained using hourly data over a one-month period and validated for another one-month period. The model was then tested over year-long periods. Results indicate that, despite significant changes in the amplitudes and phases of the water levels over the regional study area, the RNN—WL model provides very good long-term predictions of both tidal and non-tidal water levels at the regional coastal inlets. In order to examine the effects of distance on the RNN—WL model performance, the model was also tested using water levels from other remote NOAA stations located at longer distances, which range from 234 km to 591 km away from the local station at the inlets. The satisfactory results indicate that the RNN—WL model is able to supplement long-term historical water level data at the coastal inlets based on the available data at remote NOAA stations in the coastal region.

Keywords: Neural networks; Tides; Water level; Coastal inlet

1. Introduction

Coastal inlets are important due to their navigation links between inland waterway and coastal ocean, and because of their effects on shoreline and beach stability. For example, on the South Shore of Long Island (Fig. 1) there are several inlets that are

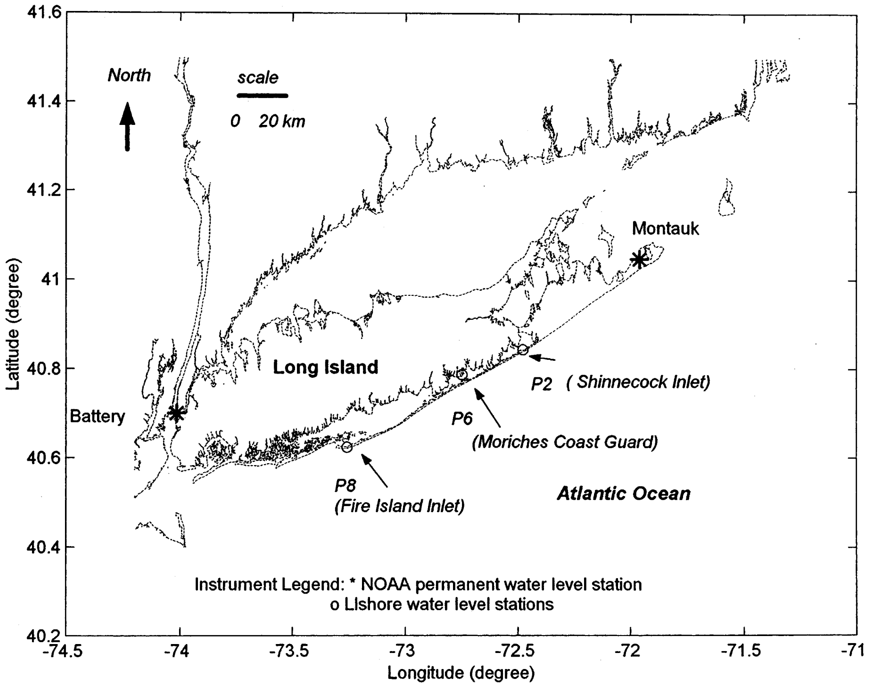

Fig. 1. South Shore of Long Island, New York.

important to both commercial and recreational navigation. Sediment deposition in the inlets requires costly dredging to maintain sufficient navigation depth. According to Grosskopf et al. (2000) and Rosati et al. (1999), representative average annual dredging requirements, in cubic meters, for the inlets are as: Shinnecock—100,000; Fire Island—500,000; and Jones—100,000. US Army Corps of Engineers' New York District and the State of New York have as an objective regional sediment management program for the South Shore. This program effectively integrates operation cost by linking dredging, sand bypassing, breach-contingency plans, and protection of beaches vulnerable to storm erosion. Monitoring and prediction of long-term water level variations in the coastal inlets are important elements in this long-term regional sediment management program. For example, historic water levels are needed in the analysis of aerial photos to determine coastal line changes, and in the boundary conditions for coastal hydrodynamic models. Since 1999, several water level stations have been established in Shinnecock Inlet, Moriches Coast Guard, and Fire Island Inlet. However, long-term historic water level data are often not available in the inlets along the South Shore except those at stations maintained by the US National Ocean and Atmospheric (NOAA). About 60–100 km away from the inlets, are two NOAA permanent water level stations that have been operating since the 1940s, one located at Montauk at Long Island and another at the Battery in lower Manhattan. Water level data from the Montauk and the Battery stations starting from the 1940s have been processed and verified by NOAA and are available online from the NOAA web site (http://co-ops.nos.noaa.gov/coastline.shtml?region=ny). If the relationship of water levels between NOAA stations and local stations in coastal region can be established, valuable historical water level data at NOAA stations can be supplemented for the study of long-term circulation and sediment transport in Long-Island South Shore. In addition, the verified data at NOAA stations can be used for the prediction of water level data at the temporary stations at the coastal inlets in future operations so that expensive measurement instruments can be relocated to other study areas.

Artificial Neural Networks (ANN) have been widely used in multivariate nonlinear time series modeling in the many research areas such as electronics, aerospace, and manufacturing engineering. ANN is capable of directly correlating the time series of multiple input variables to the output variables through the interconnected nodes using trainable weights and bias signal (Hagan et al., 1995). In this study, our objective was to develop a Regional Neural Network for Water Level (RNN—WL) model to correlate the time series of water levels at a local station with water levels at a remote NOAA station in the coastal region. The model was firstly tested in the Southern Shore of Long Island using input data from NOAA stations at the Montauk and the Battery. Then, the model was further tested using input data from other remote water level stations located 60—500 km away. Because the RNN—WL model requires only the time series inputs and outputs, it can also be applied to other coastal areas in US. Therefore, the RNN—WL model developed in this study can benefit researchers and engineers in the coastal engineering community.

2. Review of artificial neural network applications

Artificial neural networks (ANN) have proven their usefulness in a number of research areas such as electronics, aerospace, and manufacturing engineering (Hagan et al., 1995). An ANN can correlate multiple input variables with the output signal through nodes or neurons. It is capable of directly correlating input time series of forcing functions to the output variables through the interconnected nodes with trainable weights and bias. In contrast to traditional harmonic analysis (Ippen, 1966), which is used only in the predictions of periodic tidal component, the neural network model can be trained to recognize and predict both nonlinear and non-periodic signals. Wong and Wilson's (1984) study of 30-day data indicates that sub-tidal sea level variation plays an important role in the column exchange between estuary and ocean through the inlets in the Long Island South Shore. The traditional harmonic analysis method is unable to provide accurate predictions of long-term water level variations along Long Island where non-tidal sea level variation is significant.

In applying a trained and validated ANN, output variables are directly calculated without iteration from the input variables and the vectors of weights and bias in the network nodes. This functioning is similar to directly find the output from a linear regression function. Therefore, applying an ANN model takes much less computational time than the traditional fluid mechanic models, as long as data is available to establish the ANN model. For this reason, some researchers have combined fluid mechanics modeling with neural networks to improve the efficiency of model applications (Bibike and Abbot, 1999). Greenman and Roth at the NASA Ames Research Center incorporated neural networks with finite element fluid mechanics models to optimize airfoil design (Greenman and Roth, 1999). A fluid mechanics model can be used to provide time series outputs of system responses under a few study scenarios for a period of time. The time series outputs from fluid mechanics model simulations and forcing functions can then be used as "data" for neural network model development. A validated neural network model can serve as a cost-effective tool in quickly assessing the system response to the input factors.

The application of neural networks in oceanographic study is relatively new due mainly to highly nonlinear characteristics. Hsieh and Tang (1998) discussed several typical obstacles and provided some suggestions to incorporate neural networks with other time series forecasting approaches. There are some successful ANN applications in coastal engineering. For example, Bibike et al. (1999) used ANN to encapsulate numerical hydrodynamic model simulations for cost-effective forecasting of water levels. Mase et al. (1995) adopted ANN to assess the stability of armor unit and rubble-mound breakwater and found satisfactory agreement between observations and model predictions. Huang and Foo (2000) employed neural networks to directly correlate time series of salinity to the forcing functions of winds, water levels, and freshwater inputs in a multiple-inlet estuary of Apalachicola Bay, Florida. Deo and Naidu (1999) applied ANN to perform real-time wave forecasting. Tsai and Lee (1999) conducted a study that applied ANN in tidal-level forecasting using historic data at the same station, which did not address the non-periodic sub-tidal sea levels and the correlation with tidal data at other stations. Tsai et al's (2002) ANN application for wave forecasting dealt with three stations in the vicinity of a harbor that are within a relatively small spatial scale.

In the study described in this paper, the long-term water levels consist of both tidal and non-tidal signals. Because of shallow water effects and the long distance (above 60 km) between the south shore inlets and the remote NOAA tidal stations, there are substantial differences in the amplitude and phases of water levels between NOAA stations and local stations at south shore (Fig. 2). The nonlinearity and phase difference were considered as major obstacles in the application of ANN by Hsieh and Tang (1998). Hagan et al. (1995) describe several different algorithms in neural network development. Using adequate network structure and training algorithm has effects on the ANN model performance. The following sections present the techniques in the development of an ANN model to predict water levels in large regional coastal waters where considerable differences exist in the phase and amplitude of the water levels, and non-periodic sea level variations.

3. Backpropagation neural network methodology

In analogy to the biological nervous system, ANN technology is being applied to solve a wide variety of complex scientific, engineering, and business problems. Neural networks are ideally suited for such problems because, like their biological counterparts, ANNs can learn, and therefore be trained to find solutions, recognize patterns, classify data, and forecast future events. Hagan et al. (1995) and Haykin (1999) provide detailed explanations of the theories and engineering applications of the neural networks. In a neural network model, the outputs are correlated to the inputs through the neurons (or nodes) with weights and bias. The behavior of a neural network is defined by the way its individual computing elements are connected and by the strength of those connections or weights. The weights are automatically adjusted by training the network according to a specific learning rule until it performs with the desired error rate.

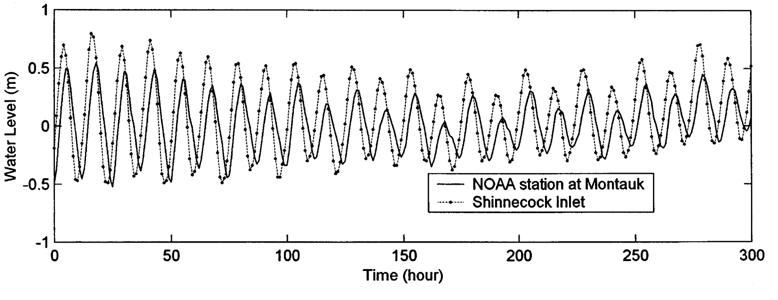

Fig. 2. Time series of water levels in the region of Long Island south shore show the difference of magnitude and phases between inlet station and NOAA station.

3.1. One-neuron model

By starting with a one-neuron model, it may be easier to understand the neural network structure. A neuron is defined as an information-processing unit that is fundamental to the operation of a neural network. Fig. 3 shows a simple one-neuron model to illustrate the neural network structure.

As shown in Fig. 3, there are three basic elements in an ANN:

(a) A set of *connecting links*, *w*, each of which is characterized by a *weight* of its own. The weights on the connections from the input X_i ($i = 1, ..., n$) to the neuron Y are w_i ($i = 1, ..., n$).

(b) An *adder*, Σ', for summing the weighted input signals; the operation constitute a linear combiner, v:

$$v = w_1x_1 + w_2x_2 + ... + w_nx_n \quad (1)$$

(b) An *activation function*, *f(.)*, for limiting the amplitude of the output of a neuron. The output from the neuron model can be described by

$$y = f(v) \quad (2)$$

There are several types of activation functions. Examples of activation functions related to this study are given below.

i) linear function:

$$f(v) = 0 \quad (3)$$

ii) sigmoid function:

$$f(v) = \frac{1}{1 + \exp(-av)} \quad (4)$$

where a is the slope parameter

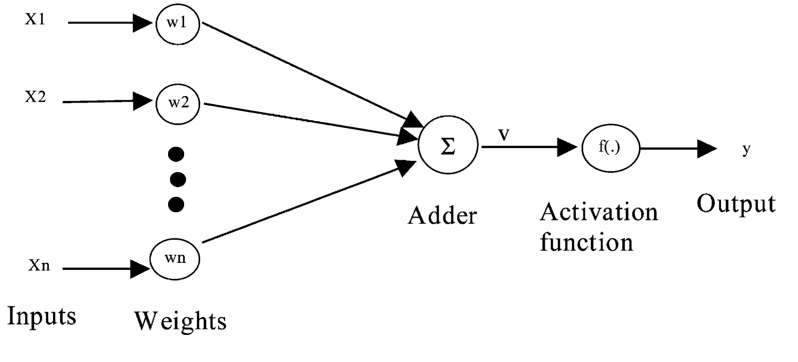

Fig. 3. One neuron structure.

iii) hyperbolic tangent function:

$$f(v) = \tanh(v) \tag{5}$$

3.2. Multiple-layer model

In practical applications, a neural network often consists of several neurons in several layers. A schematic diagram of a three-layer neural network is given in Fig. 4**,** where X_i (i = 1, ..., n) represents the input variables (such as boundary forcing functions of wind and water levels); Y_i (i = 1, ..., m) represents the outputs of neurons in the hidden layer; and Z_i (i = 1, ..., p) represents the outputs of the neural network such as water levels and currents in and around coastal inlets. The layer that produces the network output is called the *output layer*, while all other layers are called *hidden layers*. The weight matrix connected to the inputs is called the *input weight* ($\mathbf{W_{ij}}$) matrix, while the weight matrices coming from layer outputs are called *layer weights* ($\mathbf{W_{jk}}$).

3.3. Standard network training using gradient descent method

Multiple-layer neural networks using backpropagation training algorithms are popular in neural network modeling (Hagan et al., 1995) because of their ability to recognize the patterns and relationships between nonlinear signals. The term back-propagation usually refers to the manner in which the gradients of weights are computed for non-linear multi-layer networks. A neural network must be trained to determine the values of the weights that will produce the correct outputs. Mathematically, the training process is similar to approximating a multi-variable function, $\boldsymbol{g}(\boldsymbol{X})$, by another function of $\boldsymbol{G}(\boldsymbol{W},\boldsymbol{X})$**,** where $X = [x_1,x_2,\ldots,x_n]$ is the input vector, and $W = [w_1,w_2,\ldots w_n]$ the coefficient or weight vector. The training task is to find the weight

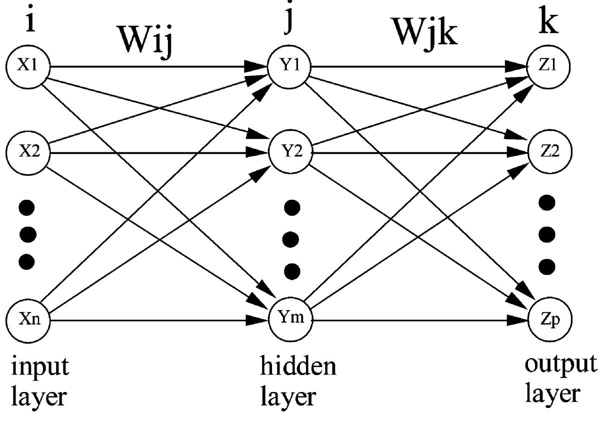

Fig. 4. A three-layer feed-forward neural network for multivariate signal processing.

vector W that provides the best possible approximation of the function $g(X)$ based on the training input $[X]$.

The standard or basic training method is the *Gradient Descent Method.* In this method, weight changes move the weights in the direction where the error declines most quickly. Training is carried out by assigning random initial weights to each of the neurons (usually between 0.1 and 1.0) and then presenting sets of known input and *target* (*output*) values to the network. The network estimates the output value from the inputs, compares the model predicted output to the target value, and then adjusts the weights in order to reduce the mean squared difference between the network output and the target values. The complete input–output sets are often run through the network for several iterations (or epochs) until either the mean square error is reduced to a given level or reaches a minimum, or until the network has been trained for a given number of iterations.

If we let w_m represent the value of weight w after mth iteration in a neuron, then

$$w_m = w_{m-1} + \Delta w_m \tag{6}$$

where Δw_m is the change in the weight w at the end of iteration m. It is calculated by

$$\Delta w_m = -\varepsilon d_m \tag{7}$$

where ε is the user-specified parameter controlling the proportion by which the weights are modified. The term d_m is given by

$$d_m = \sum_{n=1}^{n} \left(\frac{\partial E}{\partial w_m}\right) \tag{8}$$

where N is the total number of examples and E is the simulation output error.

3.3.1. Network development processes

In neural network model development, the first step is to design a specific network architecture that includes a specific number of layers, each consisting of a certain number of neurons. The size and structure of the network needs to match the nature of the investigated phenomenon. Because it is usually not well known at the early stage, the task is not easy and often involves a trial and errors approach. The new network is then subjected to the training process. In that phase, neurons apply an iterative process to the number of inputs (variables) to adjust the weights of the network in order to optimally predict (in traditional terms one could say, find a fit to) the sample data on which the training is performed. After learning from an existing data set, another new data set is used to validate or verify the performance of the trained neural network. If the neural network performance is satisfactory in model verification, it is capable in model predictions using other new data inputs.

3.4. Advantages of the ANN approach

One of the major advantages of neural networks is that, theoretically, they are capable of approximating any continuous function (Haykin, 1999). The resulting network developed in the "learning" process represents a pattern detected in the data. Thus, in principle, ANN methods can be applied to many research issues such as those in coastal engineering and oceanography. Theoretically, as long as the training data set covers the maximum range of the forecasting boundary data, a short-term data set can be used to train an ANN model for long-term predictions. A trained neural network can provide a much faster simulation for forecasting long-term events than traditional hydrodynamic models since its calculation requires no computational iteration. The implementation of an ANN model is similar to calculating a multiple variable linear regression function: Output $Y(t)$ = ANN [$w1*X1(t)$, $w2*$ $X2(t)$ $\ldots wn*Xn(t)$], where w_i (i = 1, …, n) are the weights of the ANN network, X_i (i = 1, …, n) are input signals, and Y is output signal.

3.5. ANN optimization and improvement

The standard gradient-descent training method sometimes suffers from slow convergence due to the presence of one or more local minima. This is generally a characteristic of the particular error surface, which is often composed of several flat and steep regions. There are, however, several optimization methods, that can be used to improve the convergence speed and the performance of network training. Details of the optimization algorithms have been described by Haykin (1999). Huang and Foo's (2002) study shows that training speed increases by almost three times when the conjugated optimization technique is used.

Overfitting is another problem that may occur during neural network training. The error on the training set is driven to a very small value, but when new data is presented to the network, the error is large. In this case, the network has memorized the training examples, but has not learned to generalize to new situations. One useful approach for improving network generalization is to use an adequately sized network that is just large enough to provide an adequate fit. The larger a network is, the more complex the functions that the network can create, which may lead to overfitting. If a small enough network is used, it will not have enough power to overfit the data. Mathworks (1999) provides examples that show how reducing the size of a network can prevent overfitting. However, it is difficult to know beforehand just how large a network should be for a specific application. In general, the optimal network size to prevent overfitting can be determined through model sensitivity experiments.

4. RNN—WL model design

In this study, the standard three-layer feed-forward backgropagation network (Haykin, 1999) with a nonlinear differentiable log-sigmoid transfer function in the hidden layer (Fig. 5) was employed. The network programming was done using the Matlab computer software (MathWorks, 1999). Huang and Fu's (2002) study indicates that using an optimized conjugated training method results in improvement of both training speed and accuracy. In general, the network training speed using conjugated training method is about three times faster than when the standard gradient

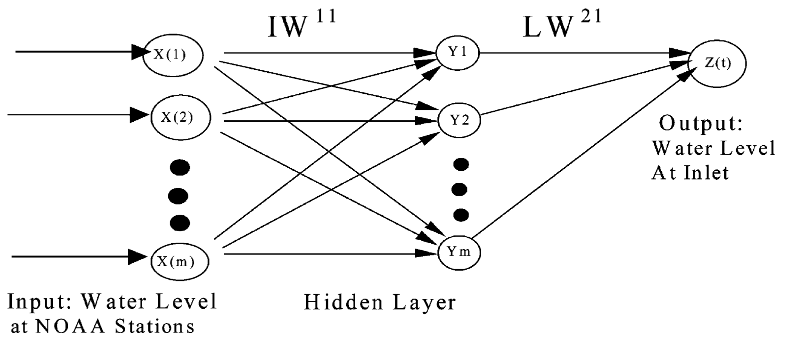

Fig. 5. (a) Schematic diagram of RNN—WL model for the coastal region of Long Island south shore, where the distance between local inlet and remote NOAA station is above 60 km. (b) A simple graphic-user-interface in Matlab environment allows users to easily load data files from Windows menu, and then run the model program.

descent training method is used. Therefore, the conjugated training algorithm was used in this study to improve the model performance. To avoid network overfitting, Fletcher and Goss's (1993) approximation was applied to approximately estimate the number of neurons in the hidden layer. The network was trained using the data set and then validated with another data set. Through sensitivity study, the optimal network size was selected as that size which resulted in the minimum error and maximum correlation in the validation data set.

In order to account for the phase difference of water levels between inputs and outputs, the last 4 hourly data points from the input time series of water levels at the NOAA stations at each time step were used to predict water level at an inlet at the given time step. This is similar to the autoregressive and moving average variables in stochastic modeling. The neural network relationship between water level at inlet, $\eta(t)_{\text{inlet}}$, and at NOAA permanent station, $\eta(t)_{\text{NOAA}}$, in the RNN—WL neural network model can be illustrated by the following equation

$$\eta(t)_{\text{inlet}} = \text{RNN—WL}[\eta(t),\eta(t-1),\eta(t-2),\eta(t-3)]_{\text{NOAA Station}} \quad \text{(a)}$$

After a series of sensitivity tests, a network with 25 neurons in the hidden layer was adopted. A schematic diagram of the RNN—WL model is given in Fig. 5(a). The model is generalized for convenient user input. A simple graphic-user-interface was developed for users to easily load data files in Windows environment (Fig. 5(b)). Data sets required for model training and verification in Table 1. Default model parameters are given in Table 2.

Table 1
Input file names of hourly data required for RNN—WL model training and verification

	Remote NOAA station	Local inlet station
1. Model training	*Dataset—1—NOAA*	*Dataset—1—Local*
2. Model verification	*Datatset—2—NOAA*	*Dataset—2—Local*

Table 2
Default parameters in the RNN—WL model for network training

Parameters	Description
Optimized training method	Conjugated gradient training
Number of nodes in hidden layer	25
Training goal	0.001
Training epoches	500

Note: When applying RNN—WL to different coastal regions, users may adjust these parameters to in model training and verification.

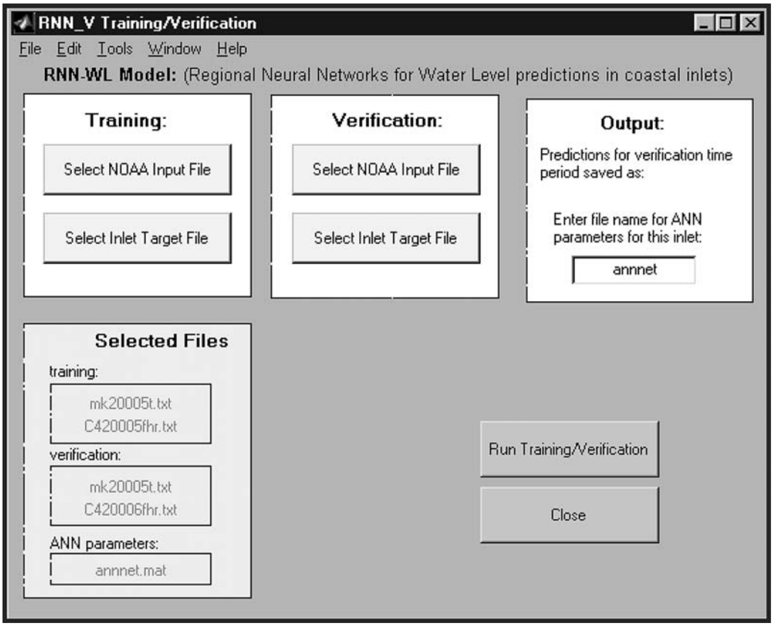

Fig. 6. RNN—WL model training and verification at Station P2 of Shinnecock Inlet. The distance between input NOAA station at Montauk and the inlet is about 60 km.

5. Model training, verification, and long-term predictions

5.1. Training and verification

In the model training and verification phases, two independent data sets of input and output time series are required in the RNN—WL model. The first data set is used for model training to determine the weight values of the interconnected network, while the second data set is used for model verification by comparing the model predictions with observations. Model parameters can be adjusted until model accuracy is satisfactory. After training and verification have been successfully completed, the model weights and bias parameters can be saved for future application. The data set used for model training should be continuous and without gaps. Due to missing data gaps in the Long Island field observation data, we were able to use only short-term continuous data sets for about 30 days in model training.

Comparison of model predictions and observations during training and verification phases are given in Fig. 6 for Station P2, and Fig. 7 for Station P8. Results show that the RNN—WL neural network model was satisfactorily trained to determine the weight parameters in the network so that the inputs match well with the target time series. Moreover, the backpropagation neural network was trained to recognize the time series pattern. Keeping the same weight parameters determined in the training phase, the model was able to provide satisfactory predictions for an independent data set during the verification phase. The correlation coefficients between model predictions and observations ranged from 0.968 to 0.985 during the verification phase for all the stations. The root mean square errors (RMSE) were all approximately 0.06. A summary of the statistics of the model performance is given in Table 3. As shown in Fig. 7b, the neural network model provides good predictions of water levels that consist of both tidal and non-tidal signals.

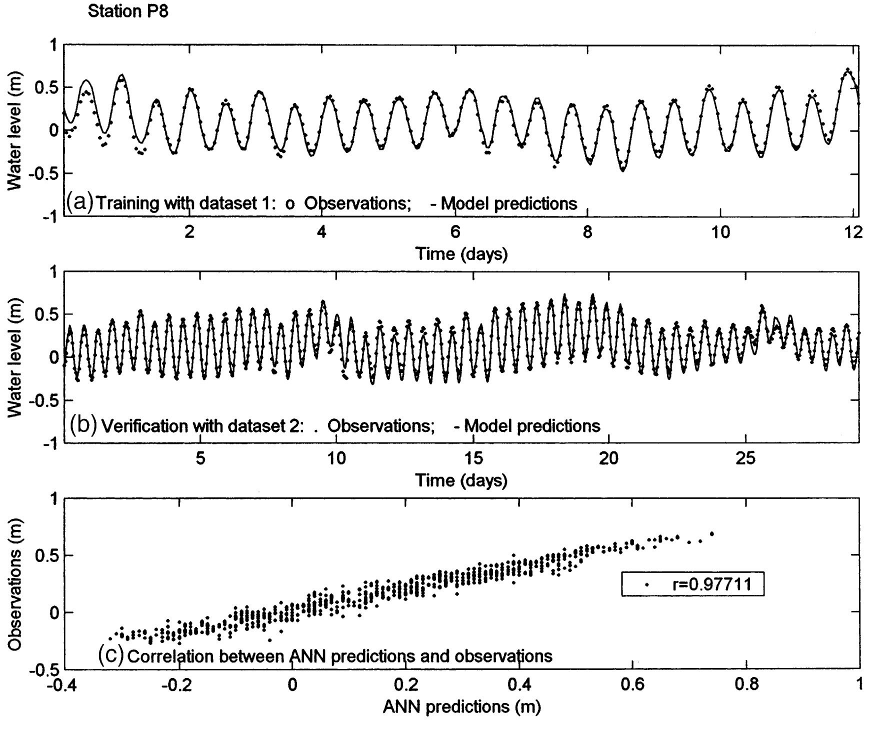

Fig. 7. RNN—WL model training and verification at Station P8 of Fire Island Inlet. The distance between input NOAA station at Montauk and the inlet is about 90 km.

Table 3
Statistical summary of comparison between model predictions and observations of water levels

Output Station	Input NOAA station	Training period	Verification period	Correlation value (r)	Root-mean-square error (m)
P2	Montauk	12/1999	04/1999	0.985	0.0667
P8	Battery	11/2000	03/2000	0.977	0.0529

5.2. Model testing in predicting water levels over yearlong periods

After the model had been satisfactorily trained and verified over a short period, the model is capable of predicting long-term water levels at the coastal inlets of Long Island South Shore. Water level data from NOAA stations at Montauk and Battery are available from the 1940's to the present. Therefore, using the RNN—WL neural network model, long-term water levels over several decades in the inlets of Long Island's south shore can be predicted. These long-term model predictions will be very helpful in studying the long-term circulation and shoreline change in the region. Comparisons between model predictions and observations for yearlong periods are given in Fig. 8 for Station P2, and Fig. 9 for Station P8. Results indicate very good correlation (above 0.95) between model predictions and available yearlong data (excluding missing data gaps). This good correlation using data over yearlong

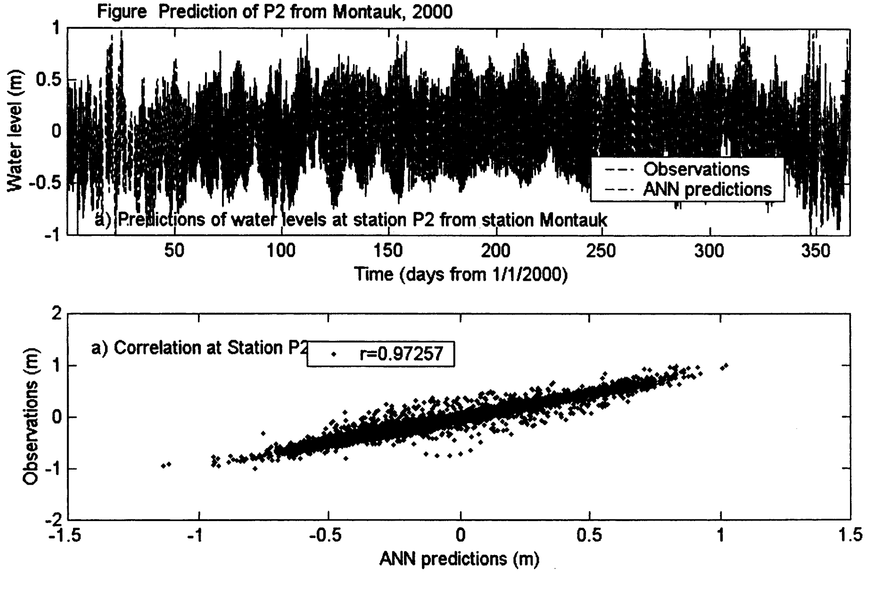

Fig. 8. Comparison of water levels between model predictions and observations at station P2 of Shinnecock Inlet for year 2000. The distance between input NOAA station at Montauk and the inlet is about 60 km.

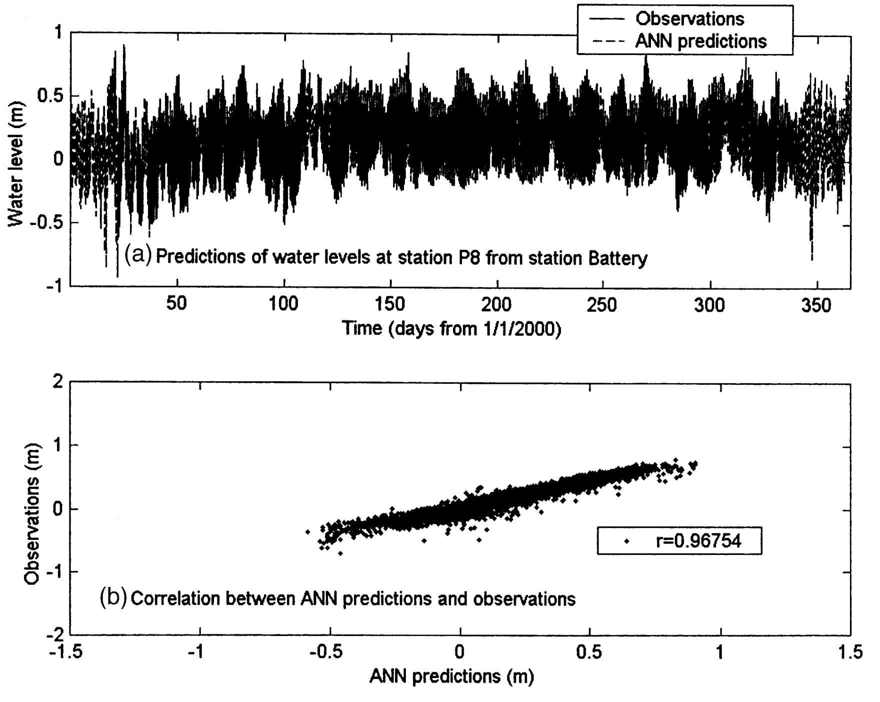

Fig. 9. Comparison of water levels between model predictions and observations at station P8 Fire Island Inlet for year 2000. The distance between input NOAA station at Battery and the local station is about 90 km.

period should provide confidence in the RNN—WL neural network model's ability to hindcast other periods when historic data is not available.

6. Model testing for subtidal water level predictions

Unlike periodic tidal fluctuations caused by astronomical forcing, subtidal sea level variations are non-periodic signals induced by atmospheric pressure and remote wind forcing. Wong and Wilson's (1984) study using 30-day data indicated that subtidal sea level fluctuations along the Long Island South Shore were forced primarily by longshore winds through coastal Ekman effects. Time series of water levels in Figs. 6 and 7 also show the low-frequency fluctuations of non-tidal water level variations. Because patterns of non-periodic signals are difficult to visually observe, there may be some concerns about the capability of neural network models to recognize the patterns in subtidal sea level fluctuations when new data sets are presented. In this study, subtidal sea level variations obtained using 36-h low-pass filtering were used to examine the neural network model's predictions of non-tidal water level variations.

Comparisons of model predictions and observations of time series subtidal sea level variation are given in Fig. 10 for Station P2, and Fig. 11 for station P8. The model predictions match well with observations and are able to reproduce the nonlinear and non-periodic characteristics such as the magnitudes and phases. A summary of the comparison statistics is given in Table 4. The correlation between model predictions and observations is very high. The correlation values are 0.99 at Station P2, 0.98 at Station P6, and 0.98 at Station P8, respectively. The RMSE error is 0.028 at Station P2, 0.027 at Station P6, and 0.017 at Station P8, respectively.

7. Model testing using water levels from remote NOAA stations

As described above, the RNN—WL model provides very good predictions of water levels in a local station when inputs of water levels is given in a NOAA station within about 100 km of the region of Long Island south shore. However, in some other coastal study sites, the distance between a local station and a NOAA station may be longer than 100 km. Therefore, the RNN—WL model would be more convincing if it was further validated using inputs of water levels from remote NOAA stations located over several hundred kilometers from the local station.

Three NOAA stations (NOAA Water Level Network Web Site) distributed in New Jersey, Virginia, and North Carolina as given in Fig. 12 were selected to validate the model performance using remote water level inputs. Among these three stations,

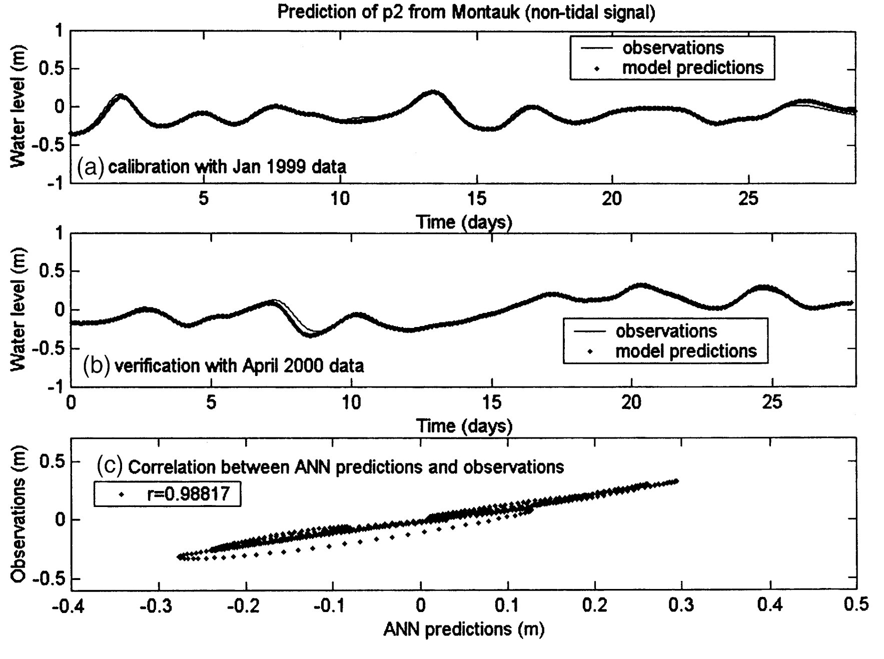

Fig. 10. Model test for non-tidal water level predictions at station P2. The distance between input NOAA station at Montauk and the inlet is about 60 km.

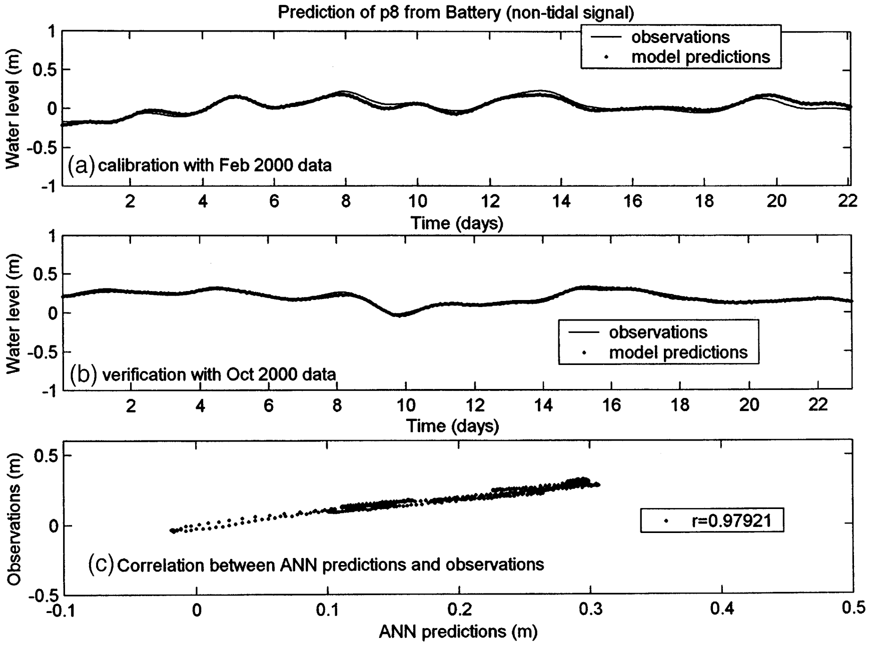

Fig. 11. Model test for non-tidal water level predictions at station P8. The distance between input NOAA station at Battery and the local station is about 90 km.

Table 4
Statistics Summary of comparison between model predictions and observations of low-frequency, non-tidal water levels

Output Station	Input NOAA station	Training period	Verification period	Correlation value (r)	Root-mean-square error (m)
P2	Montauk	01/1999	04/1999	0.988	0.0280
P8	Battery	02/2000	10/2000	0.979	0.0170

the minimum distance to the local station P2 at Shinnecock Inlet is about 234 km from Atlantic City, New Jersey; and the maximum distance is 591 km from Duck, North Carolina. Stations of Atlantic City and Duck are located on the coast. The Lewisetta Station is located in the Chesapeake Bay Estuary, in which estuarine topography has an effect on tidal waves.

A summary of validations of model performance is given in Table 5. Using inputs of water levels from the coastal station at Atlantic City (234 km away from the local station), model predictions are very good, with a 0.98 correlation value and 0.05 m root-mean-square error. As the distance increase, the prediction accuracy slightly decreases. Using inputs from the farthest station at Duck (591 km away), the RNN—WL model give reasonable predictions, with a 0.97 correlation value and 0.08 m

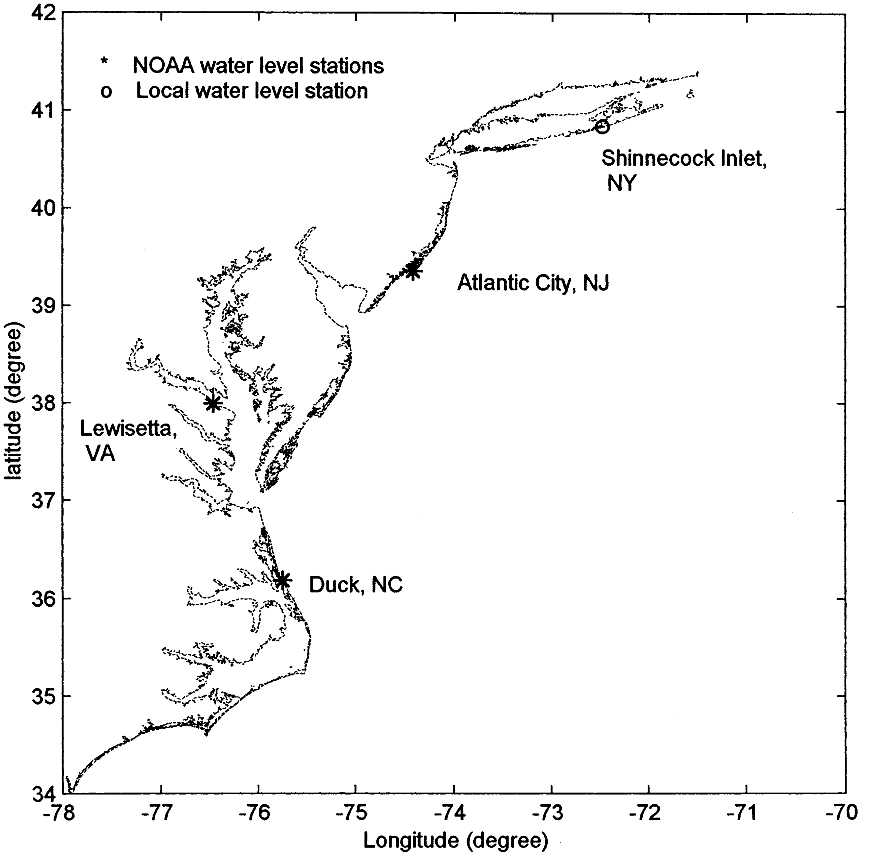

Fig. 12. Locations of remote NOAA water level stations along US East Coast.

Table 5
RNN—WL model test using inputs of water levels from remote NOAA stations in the East Coast of USA

Input water level location of remote NOAA stations	Distance to local station at Shinnecock Inlet, NY (km)	Comparing ANN predictions and observations at Shinnecock Inlet, NY	
		Correlation **r**	Root-mean-square error (m)
Atlantic City, NJ. (Coast)	234	0.98	0.05
Lewisetta, VA (Estuary)	466	0.96	0.09
Duck, NC (Coast)	591	0.97	0.08

root-mean-square error (Fig. 13). Model predictions using inputs from the Lewisetta station are not so accurate as those using input from Duck and Atlanta City stations. As given in Fig. 14, there is about a 180 degree phase difference between water levels at local coastal station at Shinnecock Inlet and NOAA station at Lewisetta in Chesapeake Bay, which may be caused by the reflection of tidal waves in the estuary of Chesapeake Bay. Despite the significant difference of amplitude and phase between the input and output stations, model predictions using inputs from the Lewisetta Station match well with observations, resulting in a correlation value of 0.96 and a root-mean square error of 0.09 m. Based on the information given in NOAA Water Level Network Web site, NOAA water level stations are distributed along the coastline of USA. The distance between most of NOAA stations range from 50 km to 200 km. Therefore, the validation of RNN—WL model in this study for the distance up to 591 km provides good confidence that the RNN—WL model can be used in regional coastal studies at other sites.

8. Conclusion

A Regional Neural Network for Water Level (RNN—WL) has been successfully developed in this study for water level predictions at coastal inlets. Using the inputs

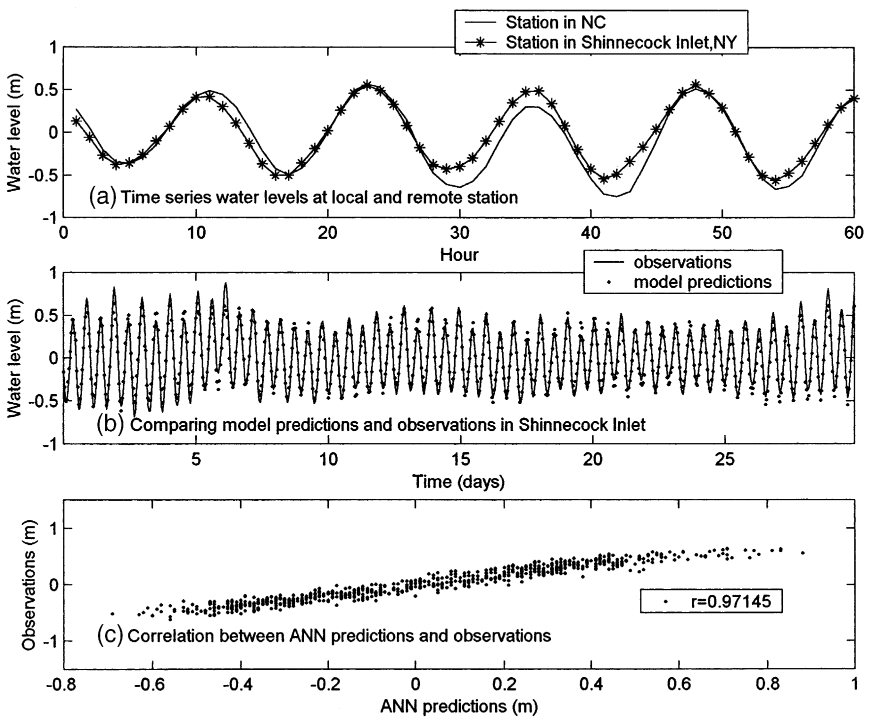

Fig. 13. Model test using water level inputs from a remote NOAA station located 591 km away in coastal of Duck, North Carolina.

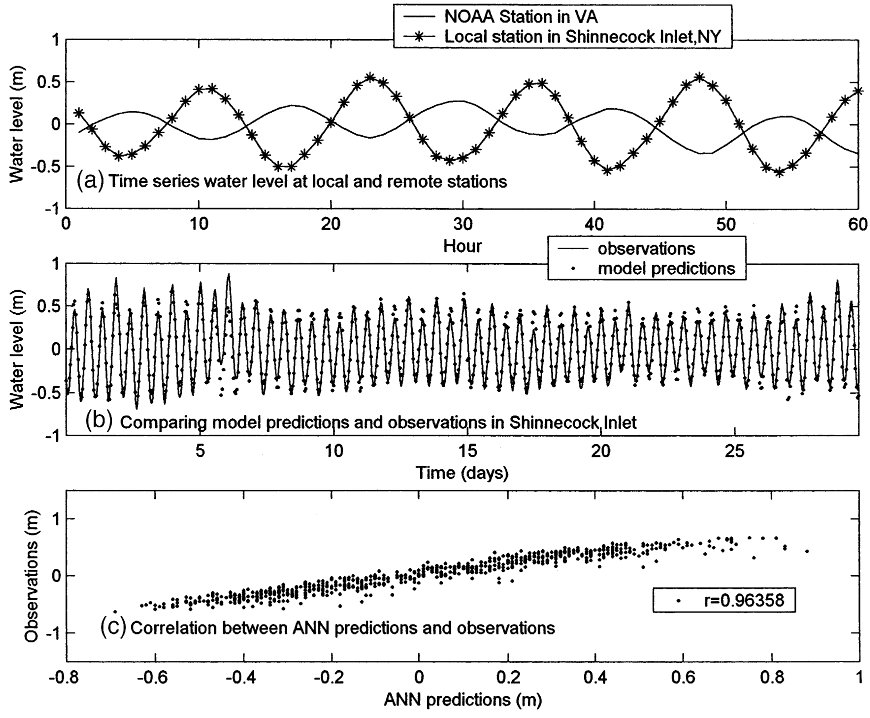

Fig. 14. Model test using water level inputs from a remote NOAA station located 466 km away in the coast of Lewisetta, Virginia.

of time series water levels in a NOAA station in the region, the RNN—WL model is capable of predicting water levels in a local station at coastal inlets. The RNN—WL neural network model employs three-layer feed-forward, backpropagation structure with optimized training method using conjugated training algorithm. The model requires the input of the last 4-h values of the hourly water levels from a permanent NOAA station to predict the hourly water levels in an inlet station. The model was successfully tested in a case study in the Long Island south shore using input data from NOAA water level station ranging from 60 to 591 km away. Field data indicate that water levels change substantially in both amplitude and phase over the coastal region due to the complex coastal and estuarine topography and shallow water effects. In addition, low-frequency non-tidal water levels also vary due to wind effects. Using short-term data sets (two months), the model was trained using a month-long data set, and verified using another independent data set for another month-long period. The model was then successfully tested using yearlong data sets. The predicted tidal signals matched well with observations. The model was also successfully validated in predicting non-periodic subtidal sea levels. Because there are several decades of hourly water level data available since the 1940s in NOAA permanent stations located at the Montauk and Battery stations in the region, the successful development of the RNN—WL model in this study will supplement cost-effective long-term water level data for the study of coastal hydrodynamics and shoreline change in the Long Island's South Shore. In addition, because water levels at temporary field stations can now be predicted by the RNN—WL model, expensive data monitoring instruments can be relocated to other new sites.

NOAA has a national water level observation network that covers all the coastal regions in USA (http://co-ops.nos.noaa.gov/usmap.html). Within a scale ranging from 60 to 591 km as given in this study, one can always find one or more NOAA water level stations along the US coast. For many NOAA stations, long-term data over a period of several decades have been processed and are available for online download from the NOAA Web site. However, due to the long distance between a local station and a NOAA station, the differences of phase and amplitude of water levels are usually significant. This disparity often makes it difficult to apply conventional regression method to transfer the valuable data at a NOAA monitoring station to a local station in a specific study site. The regional neural network model (RNN—WL) developed in this study will provide a practical tool for coastal engineers and researchers to predict long-term historic water level data at a local station from a remote NOAA station. The RNN—WL model has been programmed for application to general coastal regions. Two sets of hourly water level data are needed in model training and verification. Because field data collection is usually expensive, the RNN—WL model provides a cost-effective alternative for coastal engineers to obtain long-term data in the regional coastal study area.

Acknowledgements

This study was supported by the Coastal Inlet Research Program, US Army Corps of Engineers (USACE). The views expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agency. The authors would like to thank Thomas C. Wilson, Stony Brook University, for providing the data for this study. Permission was granted by Headquarters, U.S. Army Corps of Engineers, to publish this information.

References

Bibike, Y., Solomatine, D., Abbott, M., 1999. On the encapsulation of numerical-hydraulic models in artificial neural network. Journal of Hydraulic Research 37 (2), 147–161.

Deo, M.C., Naidu, C.Sridhar, 1999. Real time wave forecasting using neural networks. Journal of Ocean Engineering 26, 191–203.

Fletcher, D., Goss, E., 1993. Forecasting with neural networks: an application using bankruptcy data. Inf Management 24, 159–167.

Greenman, R., Roth, K., 1999. High-lift optimization design using neural networks on a multi-element airfoil. Journal of Fluids Engineering, ASME 121, 434–440.

Grosskopf, W.G., Aubrey, D.G., Mattie, M.G., Mathiesen, M., 1983. Field Intercomparison of Nearshore Directional Wave Sensors, IEEE Oceanic Engineering Society. IEEE Journal of Oceanic Engineering 8 (4), 254–271.

Hagan, M.T., Demuth, H., Beale, M., 1995. Neural Network Design. PWS Publishing Company, Boston, MA.

Haykin, S., 1999. Neural Network: A Compressive Foundation. Prentice Hall, New Jersey.

Huang, W., Foo, S., 2002. Neural network modeling of salinity variation responding to multiple forcing functions in Apalachicola River. Water Research 36, 356–362.

Hsieh, W., Tang, B., 1998. Applying neural network models to prediction and data analysis in Meteorology and oceanography. Bulletin of American Meteorological Society 79 (9), 1855–1868.

Ippen, A., 1966. Estuary and Coastline Hydrodynamics. McGraw-Hill, New York.

Mase, H., Sakamoto, M., Sakai, T., 1995. Neural network for stability analysis of rubble-round breakwaters. Journal of waterway, port, coastal, and ocean engineering 121 (6), 294–299.

Mathworks, Inc., 1999. Neural Network Toolbox for Matlab, www.mathworks.com.

Rosati, J.D., Gravens, M.B., and Smith, W.G., 1999. Regional Sediment Budget for Fire Island to Montauk Point, New York, USA. Proc. Coastal Sediments ’99, ASCE, Reston, VA, 802–817.

Tsai, C.P., Lee, T.-L., 1999. Back-propagation neural network in tidal level forecasting. Journal of Waterway, Port, Coastal, and Ocean Engineering 125 (4), 195–201.

Tsai, C.P., Lin, C., Shen, J.N., 2002. Neural network for wave forecasting among multi-stations. Ocean Engineering 29 (13), 1683–1695.

Wong, K.C., Wilson, B., 1984. Observation of low-frequency variability in Great South Bay and relations to atmospheric forcing. Journal of Physical Oceanography 14, 1893–1900.