Application of artificial neural networks model on estimation of sea water levels along the northern Egyptian coast

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Most of different methods and models to predict sea water level require comprehensive exogenous inputs and involve some analysis along with certain assumptions. This paper describes the development of an Artificial Neural Networks (ANN) model to predict the sea water level along the Northern Egyptian Coast by using data of tidal gauges at different stations from Alexandria to El-Arish. A feed foreword back propagation algorithm was used to estimate the sea water level at stations along the coast. Before training could be carried out, the size of the network and the training parameters are assumed. In conclusion, the calculated daily sea water levels agree well with the measured values. The ANN's results gave better results compared with results obtained by other conventional technique based on statistical regression analysis.

تحتاج الطرق المختلفة لحساب منسوب سطح البحر الى معرفة عدد كبير من المتغيرات و الافتراضات مما يجعل هذا الحساب غير دقيق في بعض الأحيان. هذا البحث يتناول طريقة حديثة لحساب منسوب سطح البحر و يطلق على هذه الطريقة شبكة الأعصاب الصناعية و قد تم تطبيق نموذج لشبكة الأعصاب باستخدام طريقة (Feed Foreword Back Propagation) في حساب منسوب سطح البحر في عدد من المحطات المختلفة على طول الساحل الشمالي المصري من الإسكندرية و حتى العريش. و قد تم تحديد العوامل المختلفة المؤثرة على كفاءة النموذج حتى تتناسب مع البيانات المختلفة لسطح البحر. عند تشغيل النموذج لحساب منسوب سطح البحر وجد انه يعطى قيم متقاربة مع المناسيب المقاسة فعليا في الطبيعة. و بمقارنة البيانات الناتجة من تشغيله مع طرق أخرى متعارف عليها مثل وجد أنها متقاربة في الدقة و تعطى نسبة خطأ صغيرة.

Keywords: Sea water level, Artificial neural networks model, Back propagation algorithm, Linear regression analysis model

1. Introduction

Estimation of sea water level constitutes major required information in coastal planning and management. Harbor engineers need the knowledge of the sea water level changes to determine the crest elevations and the optimum forces affecting the structures to be designed. Navigable waterway engineers such as the Suez Canal Authority staff depends on the accurate knowledge of the variation in sea level to determine the required water depth. It is important for coastal constructions and inland works near the coast to know the extreme values for the sea water levels. Coastal planners need reliable estimates for sea water level to evaluate the vulnerability of their decisions to challenge risks. Self-recording tidal gauges collect information of sea water level. Gauges are fixed in different locations along the coast to determine the sea water level variation and its characteristics along the coast. Prediction of future sea water level based on the recorded data is a difficult task because the variety of local and global parameters influences the sea water level in a highly nonlinear manner. Most of different methods and models, which determine the sea water level, require comprehensive exogenous inputs and involve some analysis along with certain assumptions. The prediction of sea water level, being uncertain, may not always be amenable to any specific modeling. Many researchers used the available recorded data of tidal gauges along the Nile Delta Coast to determine the sea water level characteristics and variations along the coast. The tide data is recorded using continuous automatic tide gauge called Marigraph, as shown in fig. 1. This instrument has a float, which move up and down according to water level. The movements of the float draw by a pen on a graph sheet and the curves are analyzed to give the characteristics of the sea water levels. Stations for recording tide data are distributed along the Northern Egyptian Coast. Sharaf El-Din et al. [1] studied the sea water level variation at Alexandria and Port Said with effect of meteorological parameters by using statistical regression analysis technique for tide gauges records at Alexandria for the period from (1958-1988) and Port Said from (1924-1973). El-Fishawi et al. [2] studied the characteristics of sea water level along the Nile Delta Coast by using the available sea water level records data measured by Coastal Research Institute at Alexandria (1944 - 1970), Rosetta (1981-1984), Burullus (1972-1990) and Damietta (1972-1976) and Port Said (1926 - 1973), the total average mean sea water level at each station was illustrated in table 1.

Recently, there has been a growing interest in the class of computing technique that operate in a manner analogous to that of the biological nervous system, Freeman and Skapure [3]. This technique, known as Artificial Neural Networks (ANN), is finding applications in almost of science and engineering branches. A significant advantage of the ANN approach in system modeling is that one does not need to have a well-defined process for algorithmically covering an input to an output. Rather all that is needed for most networks is a collection of representative examples of the desired mapping. The ANN then adopts itself to reproduce the desired output when presented with training sampleinput. Neural Networks have the capability to learn from examples and generalize on novel data. Use of neural networks techniques to solve civil engineering problems began in the late 1980s, Flood and Kartam [4,5]. Neural systems are already being used to compute flood discharges in rivers, Karunanithi et al. [6], forecasting river stage, Konda and Deo. [7], forecasting rainfall in space and time domain, French et al. [8], forecasting runoff from rainfall, Hsu et al. [9], Tokar [10] and Tokar and Peggy [11], prediction of sediment transport, Trent et al. [12, 13], and prediction of sediment load concentration in rivers, Nagy et al. [14].

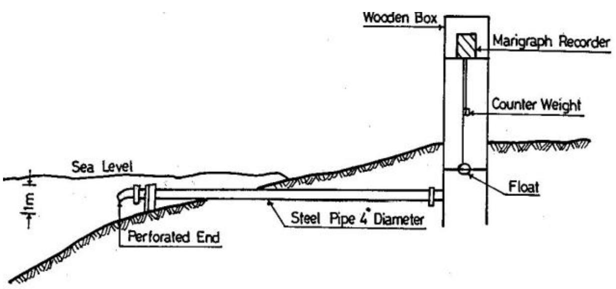


Fig. 1. Water level recorder (Marigraph).

In this paper the development of an Artificial Neural Networks (ANN) model using the back-propagation algorithm was used. Several trials were done to design the suitable architecture of the network. The calibrated magnitudes of various parameters and number of neurons on the hidden layer, which used in the training, were defined to give the estimated sea water level. The model was trained with measured field data of the daily sea water level along the Northern Egyptian Coast at different stations from Alexandria to El-Arish for the year 1997, and 1998. The model was verified with a large number of data for daily sea water level from different stations along the coast. The ANN's results were compared with results obtained by other conventional technique of regression analysis. Mean error analysis and the standard deviation of the errors for obtained results by ANN were carried out, and found that in general it were less than that obtained with regression analysis.

2. Artificial neural networks

An Artificial Neural Networks (ANN) is built of hundreds or thousands of processing elements in much the same way as the hundreds of billions of neurons in the human brain, and for convenience it can be assumed to work in much the same way. The ANN are especially useful for mapping problems, which are tolerant of high error rate, have a lot of example data available, but to which any hard fast rules cannot easily be applied. According to Hecht-Nielsen [15], a neural network can be defined as a computing system made up of a number of highly interconnected processing

Table 1
Total average mean sea water level along the Nile Delta costal referred to the survey department zero level in Egypt

Station	Alexandria	Rosetta	Burrullus	Damietta	Port Said
Mean sea water level (cm)	17.6	18.2	27.6	27.0	14.0

elements (neurons), which process information by its dynamic state response to external inputs. ANN is an information processing system composed of many nonlinear and densely interconnected processing elements or neurons. Neurons in the ANN are arranged in groups called layers or slabs. Each neuron in a layer operates in logical parallelism. Information is transmitted from one layer to others in serial operations, Hecht-Nielsen [16]. A network can be composed of one to many layers; the input layer, where the data are introduced to the network, the number of neurons on the hidden layer or layers, where data are processed, and the output layer, where the results for given inputs are produced, see fig. 2. The neurons at each layer are connected to the neurons in the subsequent layer through weighted interconnections. The net input to each neuron is converted to an activated value (through an activation function) and is compared with the threshold value (bias) to generate the output of each neuron. The architecture of an ANN is designed by weights between neurons, a transfer function that controls the generation of output in a neuron, and learning laws that define the relative importance of weights for input to neuron, Caudil [17].

In this study, a back propagation algorithm accomplished the training of ANN's. The back propagation is the most commonly used supervised training algorithm in the multiplayer feed forward networks. With the development of a back propagation algorithm, minimizing the error between a target and computed outputs modifies the network weights. In back propagation networks, the information is processed in the forward direction from the input layer to the hidden layer (s), and then to the output layer. The objective of back propagation network is to find the weight that approximate target values of output with a selected accuracy.

3. Back propagation learning

In feed forward networks of the back propagation type, neurons in a given layer do not link with each other, and do not take inputs from subsequent layer, or layers before the previous one. The network connections are therefore similar to the arrangement shown in fig. 3, for a network with two hidden layers. The process of training the network is straightforward. Initially, the weights in the networks are randomized, except those weights from the outside world to the input layer, which are set as +1 (Bias). The network is then presented with repeated sets of input patterns together with their correct output patterns. The feed forward operation calculates outputs for each input and then compares it with the desired or corrected output. The difference between the desired and computed output is the error, and this is then propagated backward through the network, using the gradient descent rule to update the weights on the connections as it goes, so that the same error will not occur again. When the total error of the network reaches a minimum then the network is trained. If we think of each layer as a vector of its neuron's outputs, then the connection strengths between any two layers constitutes the elements of a real-valued matrix which we call matrix $W(\omega_{ij})$ represents the weight from neuron j (in some layer) to neuron (I) (in the next higher layer). The weights are the values that are modified by the training algorithm. Using the notation by Lawrence [18], if we have N input/output pairs that need to be learned we can index these pairs with the letter (ρ), where the value of ρ runs from 1 to N. We must force the weights to change so that ultimately achieve a state in which the network maps inputs$_{(p)}$ to pattern$_{(\rho)}$, for all value of ρ. We will designate the output of any individual neuron with the

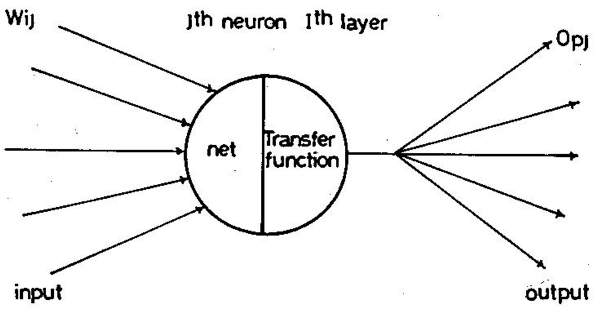


Fig. 2. Artificial neural networks structure.

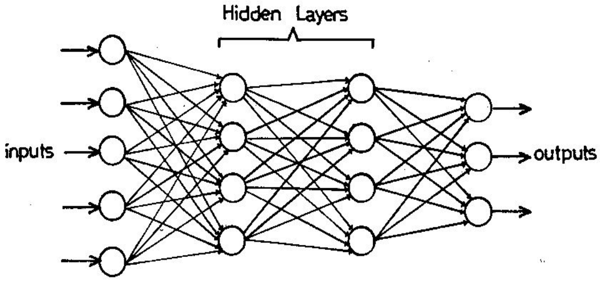


Fig. 3. Feed-Forward networks.

index (i) as output (i). Similarly the activation level of neuron (i) is $A(i)$. There is a transfer (activation) function (f), which must be continuous and differentiable, such that $Output_{(i)}=f\ (A_{(i)})$. $Pattern_{(\rho i)}$ will represent the desired output for the (i) th neuron in the output layer of the network, on the p th input/output pairs. $Output_{(\rho i)}$ initially will not be equal to $pattern_{(\rho i)}$, because the network starts out untrained. We can define the error (E), on pattern (ρ), of the (i)th output neuron as:

$$E_{(\rho i)} = \tfrac{1}{2}\left(Pattern_{(\rho i)} - Output_{(\rho i)}\right)^2 . \quad (1)$$

The total error (E) for all patterns is the sum of the errors on each pattern over all ρ;

$$E_\rho = \sum_\rho E(\rho) = \left(\tfrac{1}{2}\right)\sum_\rho \sum_i \begin{pmatrix} Pattern\ (\rho i) \\ -\ Output\ (\rho i) \end{pmatrix}^2 . \quad (2)$$

The simplest method of finding a minimum is known as gradient descent or steepest descent. Gradient descent involves moving a small step down the local gradient of the scalar field. If the change in weight $\omega_{(ij)}$ on pattern ρ is denoted by $\Delta_{(\rho)}\omega_{(ij)}$, then we have, as the gradient descent in the error $E_{(\rho i)}$, the following:

$$\Delta_\rho\ \omega_{ij} = -\ \zeta\ \frac{\partial E_{\rho\ i}}{\partial\ \omega_{ij}} . \quad (3)$$

Where ζ = a constant called the learning rate

The differential of the transfer function with respect to activation level is defined in terms of the transfer function as:

$$\frac{df}{dA_{\rho i}} = f(A_{\rho i0})\left[1 - f\left(A_{\rho\ i}\right)\right]. \quad (4)$$

In this study a sigmoid transfer function, is used [19].

$$f\left(A_{\rho\ i}\right) = \left(1 - e^{-A}\right)^{-1} . \quad (5)$$

The chain rule is used until error error become:

$$\delta_{\rho i} = f\left(A_{\rho\ i}\right)\left[1 - f\left(A_{\rho\ i}\right)\right]\sum_k \delta_{\rho k}\ \omega_{k i} . \quad (6)$$

Where k is known as the local error signals, and is propagated backward during training.

4. Data collection along the study area

The data used in this study was collected from six tidal gauges along the Northern Egyptian Coast from Alexandria on the west to El-Arish far to the east of the coast. Two of tide gauges at Alexandria Western Harbor and Port Said were fixed under the authorization of the Egyptian Marine Forces; one record every hour along the day. The other four gauges at Abu Quir Bay, El-Burullus, Damietta and El-Arish (at Arish Power Station) were fixed under the control of Coastal Research Institute (CoRI); continuous self-recording all the day. Fig. 4 shows the positions of the tidal gauges along the Northern Egyptian Coast. The recorded data from the gauges gave that;

the datum of the gauges was not the same, so in this analysis the data used for each station was referred to the minimum value of the recording data for each station.

Data sets used in this study for the training of ANN program is the daily average sea water level for the six tide gauges for years 1997 from calendar day 119 to 321 and from day 352 to 365, with number of 217data set. Also records for days from 1 to 11 and from 32 to150 for the year 1998 for the whole gauges were used, with total number of 130 data set. The daily average sea water level at Alexandria and Port Said is calculated by taken the average of the 24 records of sea water level for every day. For the other four tidal gauges the average daily sea water level calculated from the average between higher high, higher low and lower low, lower high levels of sea water surface every day. Table 2 gives the recorded average daily sea water level along the gauges for the years 1997 and 1998.

5. Model development

Successful training depends on the selection of appropriate network parameters including the number of neurons on the hidden layer. The size of the required network has to be decided upon together with the values of training parameters. Also, data sets selected for the training should have a wide range and uniformly distributed.

The number of iteration, number of neurons on the hidden layer, the value of learning rate parameter (ε) and the value of shape factor (α) of the sigmoid function must be assumed before training. To determine the exact model parameters for development of the ANN model, the data of average daily sea water level for the year 1997 from day 119 to 321 and from 352 to 365 for the whole stations along the coast were used. The network was trained with 217 data sets (patterns). The neurons of the input layer in network was set up for the previous periods in the five locations of tide gauges from Abu Quir to El-Arish. The output layer contains one neuron represents the data of daily average sea water level at Alexandria station.

6. Calibration of the model parameters

The performance of the ANN model is tested and validated by using a pool of data sets. In each run, the algorithm is trained by using different number of neurons on the hidden layer, different parameters, and number of iterations. Consequently, the resulting data of the daily sea water level at Alexandria are compared with the observed ones. For each case, a discrepancy ratio, $D_{ri} = Y/X$, is used for comparison, in which, Y is the estimated daily average sea water level at Alexandria and X is the measured one. The mean error, $\overline{D}_r$, and the standard deviation of errors, SD, are calculated to evaluate the results accuracy according to the following expressions.

$$\overline{D}_r = \sum D_{ri} / N , \tag{7}$$

$$SD = \sqrt{\frac{\sum (Y - X)^2 - \left[\sum (Y - X)\right]^2 / N}{N - 1}} \quad . \tag{8}$$

Where N = 217 is the number of the tested patterns.

Several trials are carried out to design the suitable architecture of the network, and to calibrate the model parameters. Fig. 5-a shows that the variation number of neurons on the hidden layer gives good results of training, ($\overline{D}_r \cong 1$), when the number of neurons equal two. Figure (5-b) shows that the good performance of ANN when the iteration number increases until the value of approximately 2,000,000. The variation of $\overline{D}_r$ value is almost constant when the iteration number exceeds 2 million.

Learning rate parameter, ε, affects on the performance of the output results. Fig. 5-c shows that the best results of training are obtained when the learning rate, ε, equals 0.06. For the values higher than 0.06, accuracy of results decreases.

Changing of the steepness parameter α in the sigmoid function affects on the training results. The best results are obtained, when parameter α equals one. The accuracy of results decreases with the increase of α value, as shown in fig. 5-d.

The previous analysis gives the magnitude of the various parameters and number of neurons on the hidden layer applicable for estimating the sea level. The parameters values are summarized in table 2. The obtained network used the measured 217 data sets of year 1997 to estimate sea water level values in Alexandria station. Comparison between measured and estimated temporal variation of sea water level values is shown in fig. 6. The figure shows the agreement between the estimated sea water levels and the measured levels.

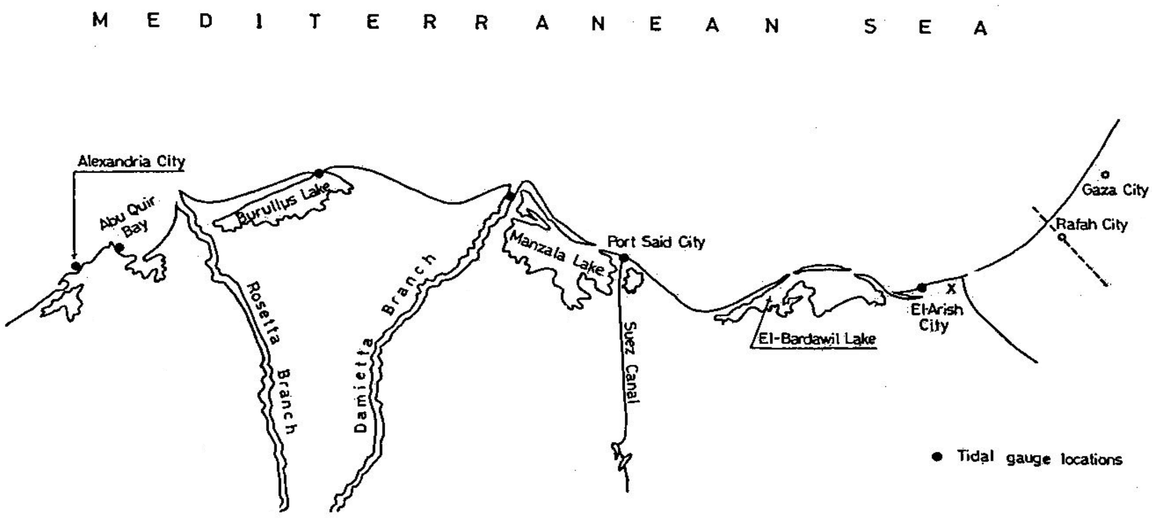


Fig. 4. Tidal gauges locations along the northern coast of Egypt.

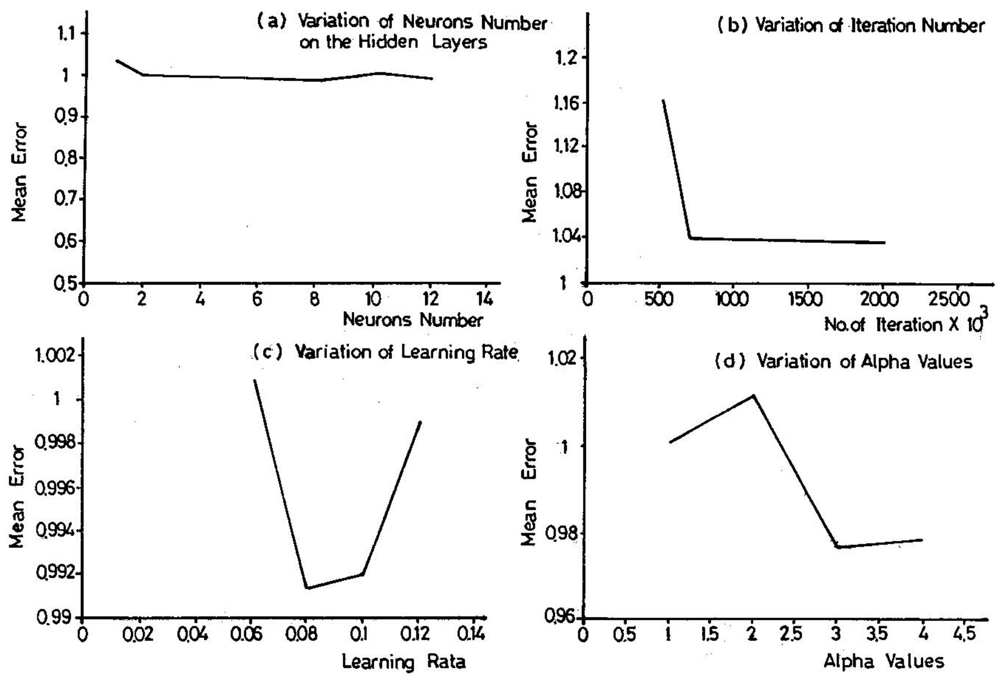


Fig. 5. The effect of changing different parameters on training of neural networks model.

Table 2
Tida gauge recording along the northern coast of Egyptian

Station Calendar	El-Arish	Port Said	Damietta	El-Burrulus	Abu Quir	Alexandria
1-29	√	√	—	—	√	√
30-118	√	√	—	√	√	√
119-321	√	√	√	√	√	√
322-334	√	√	√		√	√
335-351	√	√	√		√	√
3520465	√	√	√			√

Year 1998

Station Calendar	El-Arish	Port Said	Damietta	El-Burrulus	Abu Quir	Alexandria
1-11	√	√	√	√	√	√
12-29	√	√	√	—	√	√
30-151	√	√	√	√	√	√
152-183	√	√	—	√	√	√
184-210	—	√	—	√	√	√
211-227	—	√	—	—	√	√
228-240	—	√	—	√	√	√
241-305	—	√	—	√	—	√
306-365	—	√	—	√	√	√

√ Data record
– No data record

Table 3
Values of different parameters using in training ANN model

Parameter	Value
No. of Neurons of the Hidden layers	2
Iteration number	2,000,000
Learning rate (ε)	0.06
Shape factor (α)	1.0
Error coefficient	0.0001

7. Model validation

The previous calibrated model is used to estimate the sea water level for year 1998. The 217 patterns for year 1997 data are used for learning the model. Additional 130 patterns for the year 1998 from day 1 to 11 and from 30 to 151 are added without target output. Fig. 7 shows the comparison between the measured and estimated values for Alexandria 1998 data.

8. Linear regression analysis model

The method of linear regression analysis is used to determine the relationship between a dependent and independent variables according to the equation:

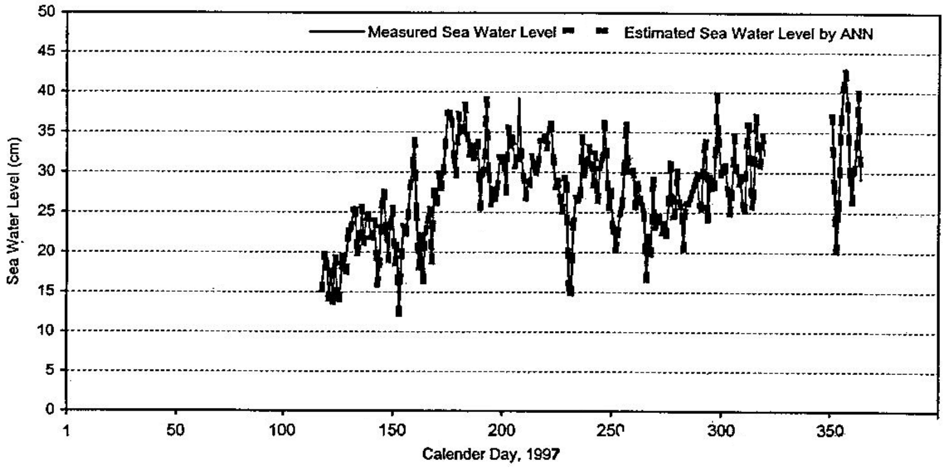
$$Y = a_o + a_1 X_1 + a_2 X_2 + a_3 X_3 + a_4 X_4 + a_5 X_5. \quad (9)$$

Where Y is the estimated values of the average daily sea water level at Damietta, the parameters from a_o to a_5 are the regression constants, and the variables from X_1 to X_5 are the daily average sea water level at El-Arish, Port Said, El-Burullus, Abu Quir and Alexandria, respectively.

First, the data used for training the model of regression analysis were the data of daily average sea water level for the year 1997 from day 119 to 321 and from 352 to 365. Also data from day 1 to 11 and from 30 to 151 for the year 1998 added for the whole gauges along the coast. This data were used to obtain the different parameters of eq. (9). Results of training eq. (9) yield that:

$$Y = -7.55 + 0.035 X_1 - 2.35 X_2 + 0.302 X_3 + 0.415 X_4 + 2.631 X_5. \quad (10)$$

The obtained equation is used to calculate the values of average daily sea water level for the previous periods for Damietta, the results are shown in fig. 8. Also the average daily sea water level for Damietta were calculated using the calibrated ANN model for Alexandria, but in this case the network is set up with the previous periods for the five locations of tide gauges from Alexandria to El-Arish as the input pattern and the data of daily average sea water level at Damietta as the output pattern. The results are shown in fig. 9. Comparing the measured recorded data for Damietta with the results obtained from calculation using both the model of ANN and the regression analysis model by using the mean error ($\overline{D}_r$) and (*SD*), results by ANN gave the value of ($\overline{D}_r$ =1.1947) and (*SD* = 4.6717), while results obtained by statistical regression analysis gave ($\overline{D}_r$ = 0.9250) and (*SD* = 5.113).



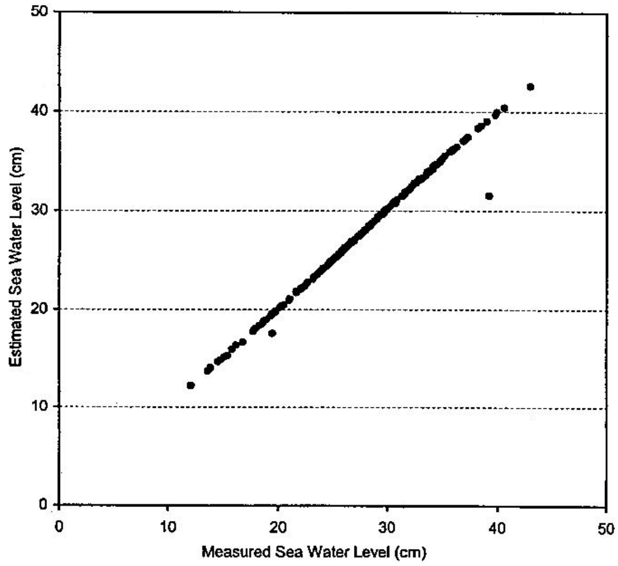


Fig. 6. Comparison between measured and estimated sea water level at Alexandria using ANN fro year 1997 from measured data of all stations for year 1997.

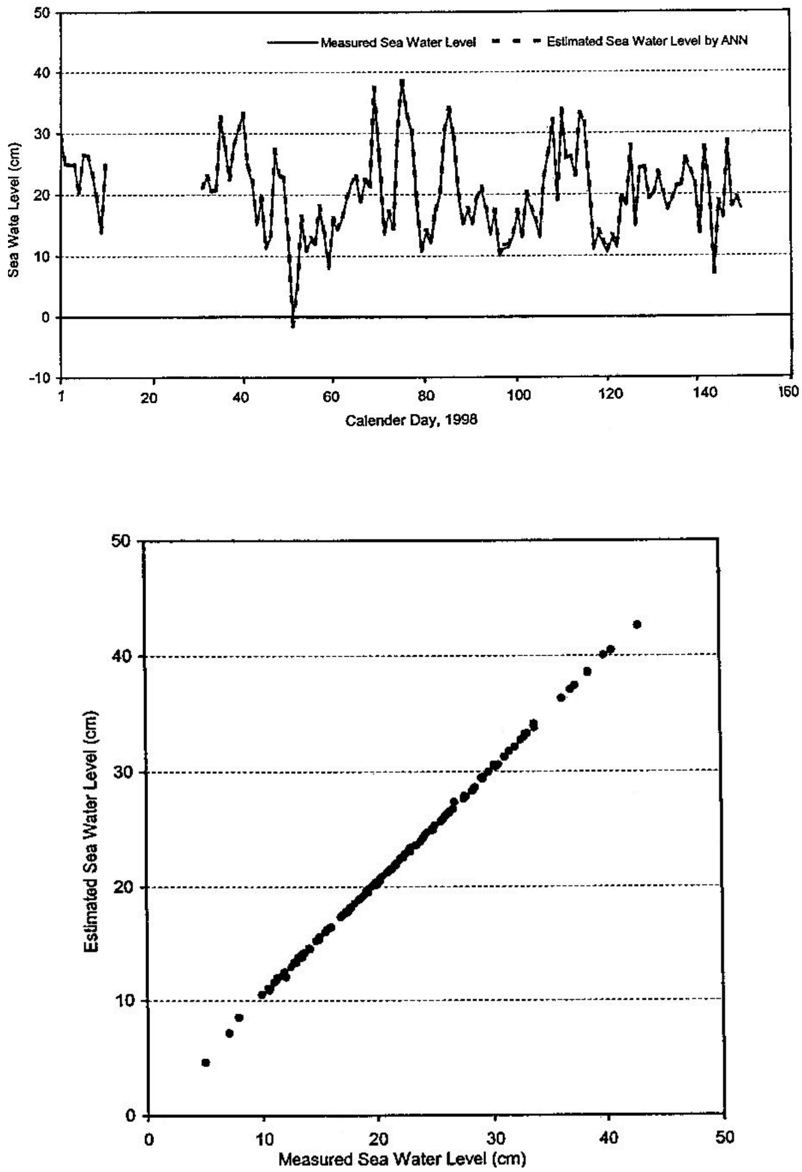


Fig. 7. Comparison between measured and estimated temporal variation of sea water level at Alexandria for year 1998.

9. Estimation of the missing data

The missing data for Damietta for the period from the day 30 to 118 (89 patterns) for the year 1997 were estimated by using the calibrated models of ANN and statistical regression analysis. The resulting values from the ANN are compared with those obtained from the method of linear regression analysis. The obtained values are shown in fig. 10. The figure shows that the resulting values from ANN model are much better than that from regression analysis model, no negative values appears from ANN results. It means that the results from ANN model higher than the referred minimum value for all data, which used as a datum for all data in training the model.

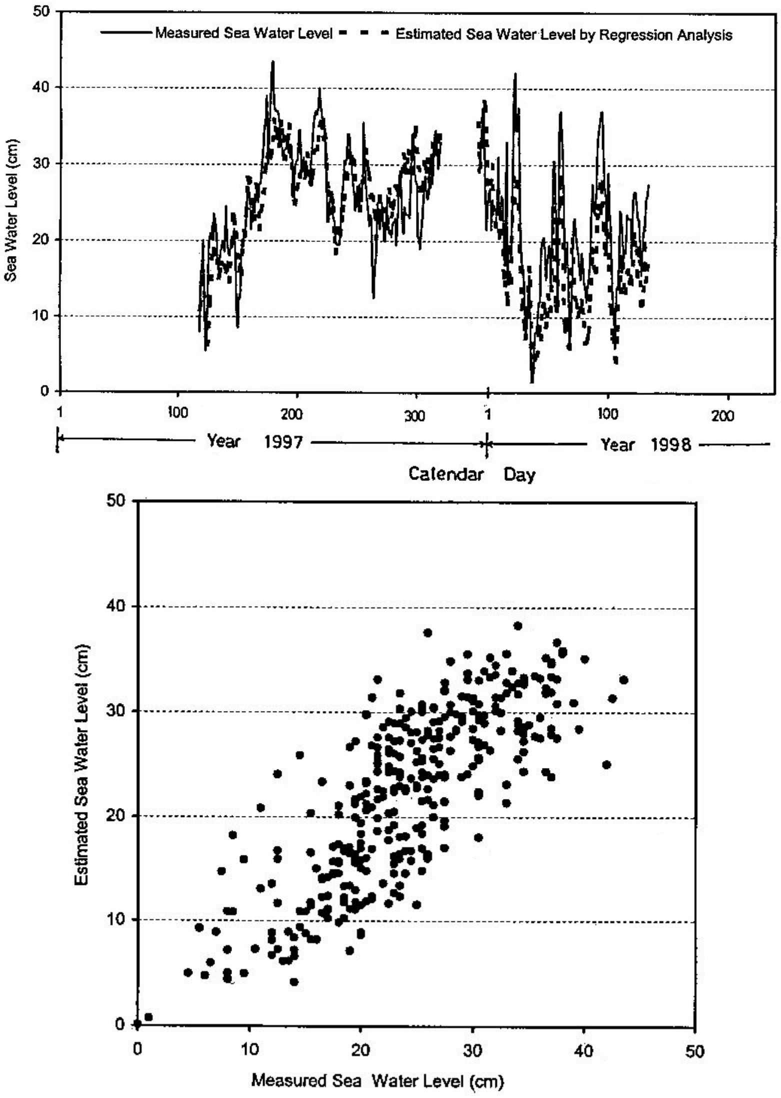


Fig. 8. Comparison between measured calculated sea water level using regression analysis at damietta for years 1997 and 1998.

10. Conclusions

Estimation of the missing data records for sea water level in some stations is a difficult task. Variation of local and global parameters affects on sea water level in a highly nonlinear manner. The estimation of sea water level, being uncertain, may not always be amenable to any specific modeling. The ANN model is useful when the underlying problem is either poorly defined or not clearly understood. A feed forward back propagation algorithm is used to estimate the missing data for daily sea water level along the Northern Egyptian Coast using the available data of tide gauges along the coast during years 1997 and 1998. In verification, the calculated daily average sea water level values agree well with the measured ones. The results from artificial neural network were compared with the results from conventional methods, such as statistical regression analysis method. In general the mean error values of ($\overline{D}_r$) and standard deviation (*SD*) of the errors from the results of artificial neural networks and statistical regression analysis are found to be approximately the same values.

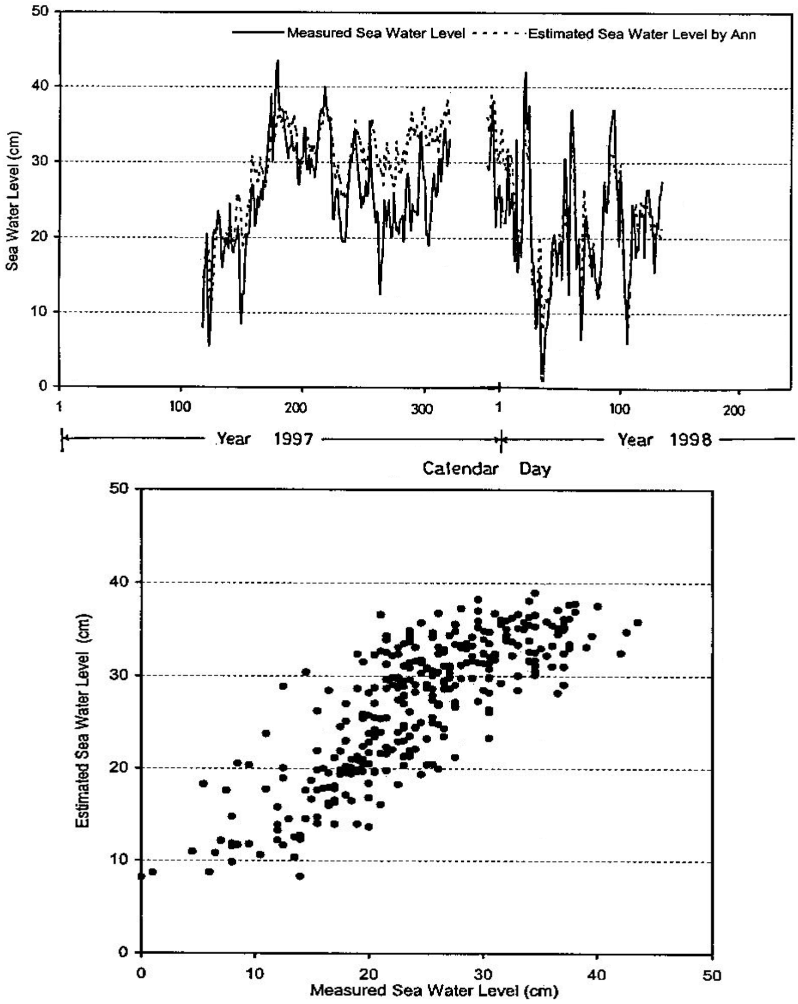


Fig. 9. Comparison between measured and estimated sea water level using ANN at damietta for years 1997 and 1998.

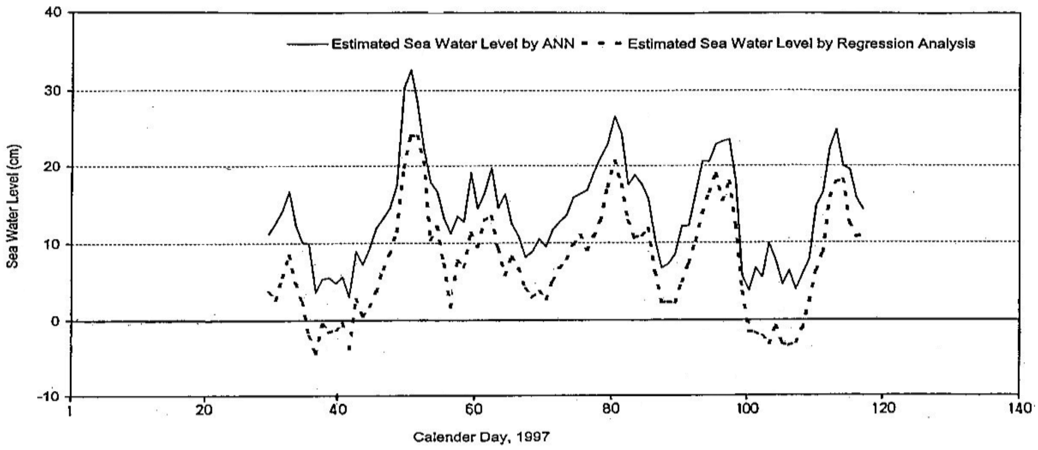


Fig. 10. Comparison between estimated sea level at damietta by regression analysis and ANN models for year 1997.

Nomenclature

$A_{(i)}$ Activation level of neuron (i),
ANN Artificial neural network,
$\overline{D}_r$ The mean error,
E Total error on pattern (ρ),
F Transfer activation function,
SD Standard deviation of errors,
X Measured average daily sea water level,
Y Estimated average daily sea water level,
α Shape factor,
Δ Gradient dscent,
ε Learning rate parameter,
ζ Learning rate constant, and
ω_{ij} Weight from neuron (j) to neuron (i) in the next heigher layer,

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