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Modelling and Prediction of Water Level for a Coastal Zone Using Artificial Neural Networks

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ABSTRACT
Research on Modern Coastal Water level modeling and prediction techniques has attracted growing concern in recent years. The reason for this is not far-fetched, as water continues to be the major contributor to disposal and movement of sediments, tracers and pollutants. This research work presents one of the most potent methods of coastal water level prediction using Artificial Neural Networks (ANNs). The ANNs model provides the prediction by learning the characteristic pattern of the historical event or in our case historical data. Back Propagation (BP) is the most popular supervised learning technique of ANNs. In back-propagation networks, the weights of the connections are adjusted to minimize the measure of the difference between the actual output vector of the network and the desired output vector. The BP technique with feed forward architecture and optimized training algorithm known as Levenberg-Marquardt was used in this work to develop a Neural Network Water Level Prediction model-(NNWLM) in a MatLab programming environment. The model was tested with data from five coastal water level gauge stations. The result revealed great performance with model prediction accuracy ranging from 0.012 to 0.045 in terms of Mean Square Error (MSE) and 0.82 to 0.97 in terms of correlation coefficient (R-value). With this high performance, the NNWLM developed in this work can be deemed as a veritable tool for a wide variety of coastal engineering and development, covering sediment management program: dredging, sand bypassing, breach-contingency plans, and protection of beaches vulnerable to storm erosion and monitoring and prediction of long-term water level variations in the coastal inlets.

Keywords: *Modelling, Prediction, Tide, Coastal Zone, Neural Networks, Analysis,Sigmoid function*

I. INTRODUCTION

The coast can be thought of as an area of interaction between the land and the ocean. It is the band of dry land and adjacent ocean space (water and submerged land) in which terrestrial processes and land uses directly affect oceanic processes and uses, and vice versa.Coastal zones are defined by the extent of territorial waters up to the high water mark. Generally the world's coastal zones are long narrow features of mainland, islands and seas.Coastal zones include the entire continental shelf and occupy about 18% of the surface of the globe, supplying about 90% of global fish catch and accounts for some 25% of global primary productivity while at the same time being some of the most endangered regions on the planet.

1.1 Importance of the Coastal Zone

The coastal zone is of great importance historically for human populations. Two-thirds of the world's cities occur on the coast.Valuable resources such as fish and minerals are considered to be common property and are in high demand for coastal dwellers for subsistence use, recreation and economic development.

Integrated coastal zone management protects habitats, i.e. wetlands, coral reefs and their water quality and also prevents the loss of life, while for others it provides a means of public access to coastal areas (which sometimes causes conflicts with private bodies)

The significance of monitoring and managing the coast has far reaching significance in many areas of human endeavour, some of which include:

- Protection of Coastal and low lying regions' residents.
- Monitoring and prediction of changes in complex marine ecosystems, harvest estimation for the fishery
- Planning and constructing of coastal and offshore structures,
- Development and implementation of ocean-based alternative energy technologies.

1.2 Water Level Observations

Water level observation started in Lagos during the colonial rule and was done primarily for waternavigation especially for commercial shipping activities. The need for water level monitoring has increasedover the years. Water level monitoring is among other things useful for oil and gas exploration andexploitation activities, and construction of ports and harbour works. Water level observations are carried out with the aid of tide gauges. Water level observations can be madewith either automatic or manual tide gages. An automatic tide gage records the water level, mechanically ordigitally, in a continuous manner without the need for a human observer to physically monitor the waterlevel. These types of tide gages are more expensive but produce more reliable results. There are now waterlevel recorders, which use the time of flight of a pulse of radar, rather than sound, to measure level. Water Level measurements are made to meet the needs of mariners, engineers, resource managers,researchers, and the general public. Some of the most important purposes for which they are measured arefor the mariners to estimate draft under keel while in transit, data and datum reference for storm surgemonitoring, data for production of tide and tidal current predictions, data for estuarine studies and numericalhydrodynamic models, for determination of mean sea level, for dredging and sand mining operations, forlaying of underwater oil and gas pipelines and communication cables, for determination of tidal datum andfor surveying and engineering purposes. Information on the variation of the coastal water levels in maintenance and capital dredging which are required in long-term regional sediment management program. It is apparent that continuous collection, analysis of tidal data isimportant for the integrated management of the Nigeria Coastal areas.Water level components are generally important for numerical model calibration(Wegde, 2006) and as such data recovery and prediction for extending measurement data is absolutely necessary. Due to the need for a period of 18.6 years measurement for an ideal water level prediction Forrester (1983) andGhosh (1998) saw the need for alternative methods of water level prediction to save time, labour and cost.One of such methods is the subject matter of this paper.

1.3 Tidal Harmonic Analysis

The traditional method of water level prediction involves tidal harmonic analysis of tidal data covering a period of time ranging from 29 days to 18.6 years.Many authors have made significant contributions to tidal analysis and predictions, and several algorithms of tidal harmonic analysis have been proposed byMunk and Cartwright (1966), Doodson (1941), Godin (1972), Zetler and Cartwright (1979) and Schwiderski (1980),Greenberg, (1977), Stravisi (1983).

The traditional method is accurate but has the following disadvantages:

i. More than 18.6 years of data are needed to resolve the modulation of the lunar tides.
ii. Amplitude accuracy of 10^{-3} of the largest term requires that at least 39 frequencies be determined. Several researches that not less than 400 frequencies are needed for an amplitude accuracy of 10^{-4} of the largest term.
iii. Non-tidal variability introduces large errors into the calculated amplitudes and phases of the weaker tidal constituents. The weaker tides have amplitudes smaller than variability at the same frequency due to other processes such as wind set up and currents near the tide gauge.
iv. At many ports, the tide is non-linear, and many more tidal constituents are needed. For some ports, the number of frequencies is unmanageable. When tides propagate into very shallow water, especially river estuaries, they steepened and become non-linear. This generates harmonics of the original frequencies.

II. ARTIFICIAL NEURAL NETWORKS

This paper presents a veritable approach to water levels prediction using Artificial Neural Networks (ANNs).ANNs have been widely used in multivariate nonlinear time series modelling in many research areas such as electronics, aerospace, and manufacturing engineering.

Some of the merits of the ANN include:

i. Capability 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 (1995).
ii. Ability to achieving non-parametric (or semi-parametric) regression. They share the advantage of the curve-fitting approach: once their internal parameters have been set to appropriate values, they are able to interpolate (and in some cases extrapolate) to values that were not used in setting their parameters.

However, unlike the curve-fitting approach, ANNs are not limited by the choice of any particular mathematical function.A single ANN may therefore be used as a generic prediction tool across a wide range of Coastal data with varied sea-conditions.

ANNs are used to identify unknown multivariate functions from samples of data. This work is particularly concerned with the difference between local transfer functions that only have significant outputs across a small volume of input space and more diffuse transfer functions. Apart from the method used to train artificial neural networks (ANNs), ANNs may be differentiated in many ways.

The following perspectives give alternative ways of classifying ANNs, although the different perspectives are intertwined in complex ways:

- Choice of transfer function
- Selection of assessment function Maierand Dandy (2000).
- Choice of network architecture Maier and Dandy (2000).

2.1 Classificationsof ANNs

ANNs can be classified into three main classes: pattern association, pattern recognition and function approximation.

2.1.1 Pattern Association

A neural network may be trained to act as an 'associative memory'. The process of training stores a set of patterns (vectors), which may be retrieved from the network.

2.1.2 Pattern Recognition

During pattern recognition, an ANN is required to identify the class to which an input pattern belongs. This model is analogous to processes within the human brain, such as the process by which we identify familiar objects despite variation in viewing angle, lighting conditions and other distortions to our visual inputs (Ullman, 1996). There are two ways in which the classification may be performed, i.e. unsupervised learning and the supervised learning.

2.1.3 Function Approximation

Within function approximation, tasks may be divided into modeling and forecasting. In the latter, time series data is available and the aim is to predict future data from past data. The main application investigated within this thesis, water level modeling and prediction, comes into the category of modeling and forecasting.

2.2 Initial Research in ANNs

Hebb (1949) noted that the strength of a synaptic connection is increased if the neurons on either side of the connection are activated synchronously. Later authors Sejnowski (1977) added the converse rule that the connection strength is decreased if the neurons on either side of the synapse fire asynchronously. Widrow and Hoff (1960) introduced a new training rule, i.e. 'least squares rule', and used it to train an ANN they called an adaptive linear element, or 'ADALINE'. The Hopfield network introduced in 1982 is a recurrent network. It contains a single layer of neurons and the output of each neuron is fed back into the ANN as an input to all of the other neurons. Rumelhart and McClelland (1986) presented a training algorithm that would allow the use of one or more hidden layers of neurons and a variety of transfer functions. The only condition was that the transfer function was differentiable, i.e. one could calculate a gradient for the function at all points. This rules out stepwise functions and led to the use of more sophisticated transfer functions. Hybrid neural networks, containing both sigmoidal and radial basis transfer functions in the same layer, have been suggested by Poggio and Girosi (1989).

2.3 Network Design

A number of authors have considered design issues in the context of ANN use for freshwater studies. Some of these authors are Maier et al. (2000). The network design issues fall into the following categories:

- Performance criteria
- Data pre-processing
- Choice of inputs
- Determination of network architecture
- Choice of training algorithm
- Stopping and validation criteria

2.4 Mathematical Approaches in Neural Networks

The mathematical approaches in ANNs include:

i. Transfer of functions commonly used by neural networks.
ii. Identification of algorithms and equations used to perform gradient descent optimisation, including back-propagation (BP) and several improvements to the basic BP.

2.5 Coastal Applications of ANNs

Mase*et al* (1995) predicted the stability of rubble-mound breakwaters using structural parameters, such as a permeability parameter, as well as sea-state information including water depth and wave steepness.Deo and Sridhar Naidu (1999) used previous wave heights to predict their future values. Overall, research on coastal applications has been more varied than that on freshwater applications. There have been more attempts to predict dependent variables from independent variables, rather than using time-series data, authors have been more adventurous in their choice of network architecture. Due to the paucity of research in this area however, a consensus has yet to appear on the most effective architectures and training algorithms.

III. METHODOLOGY

A Neural Networks for Coastal Water Level Modelling and Prediction was developed in this work. The modelling work covers creation of a sizeable Neural Networks Architecture with the aid of sensitivity test on number of neuron that would be devoid of outrageous result. A feed- forward method with a back-propagation algorithm and associated network training optimization technique known as Levenberg-Marquart optimization technique was deployed. The application was limited to some select water gauge stations for testing and validation of the model. Nonetheless, the model is built for regional application.

The following were carried out in the development of theNeural Networks for Coastal Water Level Modelling and Prediction

- Selection of Neural Networks Architecture
- Creation of the of the Neural Networks Model Using a chosen algorithm
- Preparation of data for training
- Training of the networks model
- Validation of the model
- Testing of the model
- Determination of the performance of the model in terms of preferred
accuracy check (in terms of Mean Square Error(MSE) and Correlation Coefficient (R)
- Development of a Graphical User Interface (GUI) for ease of data entry and subsequent application of the model

3.1 Data Collection Preparation

The water level data that were used in this work were collected basically from two sources:

- Water level data acquired in 2008 by University of Lagos (UNILAG)
- Water level data from two Project sites at IkotAbasi, AkwaIbom, Nigeria, andobtainedfrom Professor O. C. Ojinaka of the University of Nigeria. The observation was done on May, 2008.

Data preparation for this thesis covered visual inspection and selection of data from the array of sample of data available.

Issues involved in the data collection are:

- Difficulty in identifying an underlying function in the presence of very high variability.
- Partitioning of the data into their functional parts and perspectives due to some of the data being acquired during hourly and half an hour interval.

The geographic coordinates of the water level gauges used for this study are in Table 1.

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Water Level Gauge Station	**Latitude**	**Longitude**	**Relative Distance Apart**
Harbour (Opobo)	4^0 33’N	7^0 32’E	
Lagos Harbour	4^0 28’N	7^0 35’E	Harbour –Lagos Harbour -12.376km
Oreta Lagoon (Lagos)	$6^0$30N	3^0 30’E	
Unilag Lagoon	$6^0$30’N	3^0 24’E	Oreta –Unilag -12.344km
Porto-Novo	$6^0$24’N	3^0 20’E	Oreta-Porto-Novo-23.650km

Other data processing stages were handled during the Script- coding phase. They included

- Processing of unknown input
- Representing the unknown target

Every data presented to the network passes through a set processing rules

[tn,ts] = mapminmax(t);

net = train(net,pn,tn);

The original network inputs and targets are given in the matrices p and t. The normalized inputs and targets pn and tn that are returned will all fall in the interval [-1,1]. The structures ps and ts contain the settings, in this case the minimum and maximum values of the original inputs and targets.

3.1.1 Processing Unknown Inputs

Input data with unknown values in the network are represented with NaN values. Where this becomes too much in the data cluster, the program would not run rather error report with attention directed to NaN and rank of the matrices would be generated.

3.1.2 Representing Unknown Targets

The Unknown targets were also represented with NaN values. A method of representing unknown targets would be used to represent those unknown targets with NaN values. All the performance functions used in the programming were set to ignore those unknown targets for purposes of calculating performance and derivatives of performance. A typical example of this is observed when an input/target with location description on the top of the column is read in for training. The description names are ignored as they will pose challenge to the training process.

3.2 Network Building

Network building phase in ANNs modeling involves specification of the following:

- Number of hidden layers
- neurons in each layer,
- Transfer function in each layer
- Training function, weight/bias learning function, and performance function.

Through this sensitivity study, a standard feed forward back propagation network with a nonlinear differentiable log-sigmoid transfer function in the hidden layer was adopted for this work.

3.3 Mathematical Explanation of the ANN Model

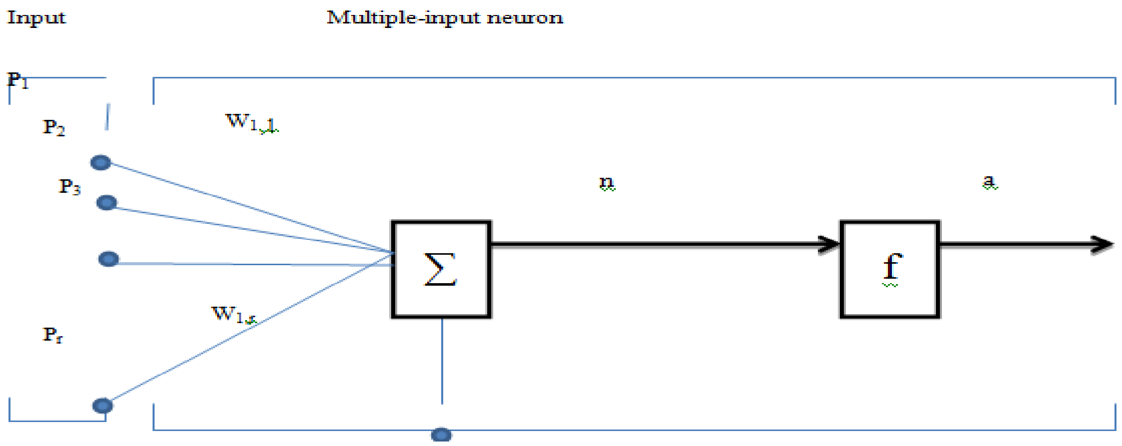


Figure 1:

From figure 1,

a = output, a = f (w_p+b)

f = Transfer function (activation/transfer function),

W = weight, b = bias,

P = inputs and n = neuron

The neuron has a bias b, which is summed with the weighted inputs to form the net- input n

$$n = W_{1,1}P_1 + W_{1,2}P_2 + \ldots\ldots\ldots + W_{1,r}P_r + b \qquad (3.1)$$

The expression in (3.1) can be written in matrix form:

$n = Wp + b,$ (3.2)

where the matrix **W** for the single neuron case has only one row.

Now the neuron output can be written as: $a = f(W_p + b)$ (3.3)

3.4 The Concept of Transfer Function

With respect to the Artificial Neural Network sense, the transfer function is a mathematical function that takes a number of inputs and transforms them into a single output. Each transfer function has a number of adjustable parameters that correspond to the input weights of the neuron. Special attention was paid to the Log Sigmoid and linear transfer functions. These two functions are the transfer function used in this work.

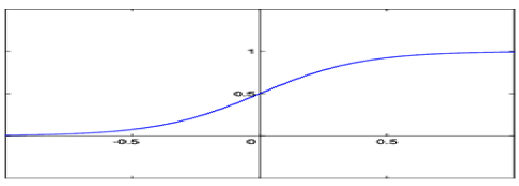
3.4.1 Log Sigmoid Function

When a detailed description is lacking, a **sigmoid function** is often used.A log-sigmoid function, also known as a logistic function is one of the members of sigmoid function, it is given by the relationship:

$$S(t) = \frac{1}{1 + e^{-t}}. \tag{3.4}$$

In general, a sigmoid is real-valued and differentiable function, having either a non-negative or non-positive first derivative which is bellshaped. There are also a pair of horizontal asymptotes as $t \to \pm\infty$. The logistic functions are sigmoidal and are characterized as the solutions of the differential equation.

The sigmoid shape of this function also explains its usefulness



$$\left.\begin{aligned} S(x) &= \frac{1}{1+e^{-x}} \\ S'(x) &= -\frac{1}{(1+e^{-x})^2}\cdot(1+e^{-x})' \\ &= -\frac{1}{(1+e^{-x})^2}\cdot(-e^{-x}) \\ &= \frac{1}{1+e^{-x}}\cdot\frac{e^{-x}}{1+e^{-x}} \\ &= S(x)(1-S(x)) \end{aligned}\right\} \tag{3.5}$$

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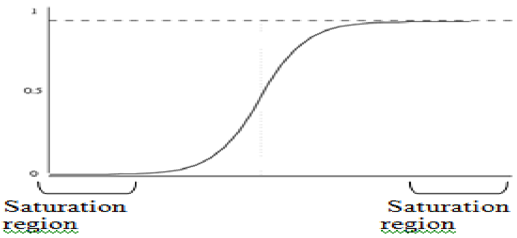

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The sigmoid shape of this function also explains its usefulness. During the calculation of the weight updates in training algorithm, sufficiently large network is moved into one of the two saturation regions as shown in the figure above. By this illustration, a sigmoid function behaves like a threshold or ramp function.

3.5 Mathematical Explanation of Levenberg-Marquardt (LM) Optimization Method

Levenberg-Marquardt(m) was used as training optimization function in the Back Propagation algorithm in this work.

$$F(x) = \frac{1}{2}\sum_{i=1}^{m}[f_i(x)]^2 \tag{3.6}$$

Let the Jacobian of $f_{1(x)}$ be denoted by $j_1(x)$, then the Levenberg-Marquardt method searches in the direction given by the solution p to the equation (3.5)

$$\left(\mathrm{J}_k{}^{\mathrm{T}}\,\mathrm{J}_k + \lambda_k\,\mathrm{I}\right) p_k = -\mathrm{J}_k{}^{\mathrm{T}} f_k\,, \tag{3.7}$$

Where λ_k are nonnegative scalars and **I** is the identity matrix(Gill *et al*,1981).
The application of LM method artificial neural network is explained by (Fitch, et al., 1991; Hagan 1995) thus: the iteration process during the training of a neural network takes the following steps,

1. Initialize weight vector, w , by using uniform random numbers from the interval (-1, 1).
Calculate error gradient, 0 g , at this point. Select initial search direction
$d0 = -g\ 0$ (3.8)

2. For each iteration k, determine constant αk, which minimizes the error function $f(w+\ \alpha k\ d\ k)$by line search where $d\ k$ is the search direction at iteration k. Update the weight vector $wk$to$wk+1$ using: w k+1 = wk +αkdk (2)

3. If error at this iteration, $k+1$, is acceptable, or if specified number of computations of the function and gradients is reached, terminate the algorithm.

4. Otherwise obtain new direction vector, d k+1: d k+1= **-** g k+1 (3.9)
If k + 1 is an integral multiple of N, where N is the dimension of w . Otherwise,
dk+1 = − g k+1+βk d k (3.10)

If the algorithm is not converged, continue from step (2) for next iteration

3.6 Relating ANN Model to the PhenomenonUnder Investigation

From Equation (3.3), **a = f(Wp + b)**
a = output (the water level to be predicted)
f = transfer /activation function: where Log-Sigmoid and linear transfer functions were chosen for hidden and output layers respectively.Thelogsimoid function is differentiable
W = weight defined by the chosen training rule (Levenberg-Marquardt Method as applied in Backpropagation algorithm)
P = Input ≡ (the water level data used as output)
b = Bias usually given a constant value as one (1). The bias is an optional factor as the model can still give a reasonable result without the bias.
The generalized form of the ANN Model Equation can be represented as:
Output **a**(t) = f $[w_1 * P_1(t), w_2 * P(t) \ldots. w_n * P_n(t)]$ (3.11)
where $w_i(i= 1, \ldots, n)$ are the weights of the ANN network, $p_i(i= 1, \ldots, n)$ are water level input signals, and **a**is the water level output signal (Hauanget al, 2003**).**

3.7 Network Modeling Steps

3.7.1 Step one: Network Creation

A callback function was developed to call a function which created a feed forward Backpropagation network in a Matlab environment.

3.7.2 Data division for Training, Validation and Testing

The water level dataset presented to the model was randomly divided into 3 sets in the ratio of ‘60:20:20’, for training, Validation, and testing respectively.

3.7.3 Step 2: Network Training

The training process requires a set of examples of proper network behavior--network inputs p (water level data designated as input) and target outputs t (water level input designated as input). During training the weights and biases of the network are iteratively adjusted to minimize the network performance function and this was done using the Lavernberg-Marquardt training process. The training subroutine for reading the water level data into training module via the created network was developed. This subroutine reads prepared water level data from microsoft excel into the model for training.

3.7.4 Step 3: Performance Evaluation of the Trained Network

This was achieved by using:

- Regression Analysis (R)
- Mean Square Error (MSE)

Regression Analysis: This gives the measure of how well the variation in the output is explained by the targets. The GUI designed in this work is done in such a way that the user is allowed to check for this error with great ease before adopting the network. The subroutine which handled the regression analysis is expressed as:
[m,b,r] = postreg(Y,T)
POSTREG postprocesses the network training set by performing a linear regression between one element of the network response and the corresponding target.
Mean square error function: Mean Square Error (MSE) function used in the model is mathematically expressed as:

$$F = 1/n = \sum_{i=1}^{n} (e_i)^2 \qquad (3.12)$$

where F = performance function, *n* = the total number of samples, *i*= counter or iterative term, e = error (difference between the target and output).
For each training instant, the threshold values which give good predictions are 0.8 and 0.05 for Regression and MSE respectively.

3.7.5 Adoption of Training Instant Using Regression and Mean Square Margin

The GUI developed during this study plots the results of regression, and mean square error at the prompt of performance button.

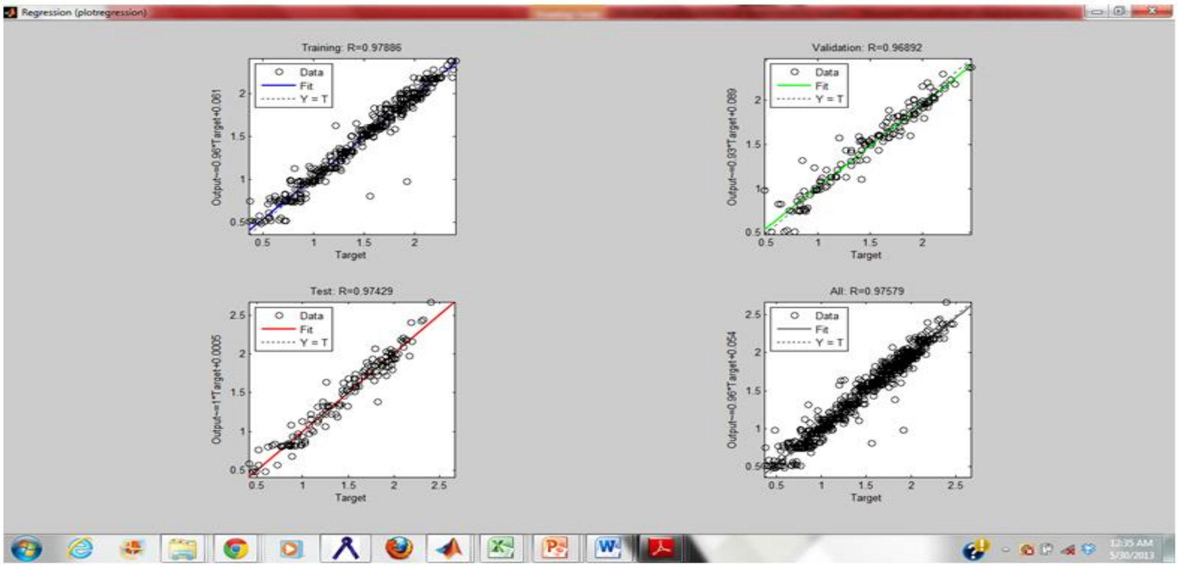


Figure 3: GUI showing the Results of the Regression

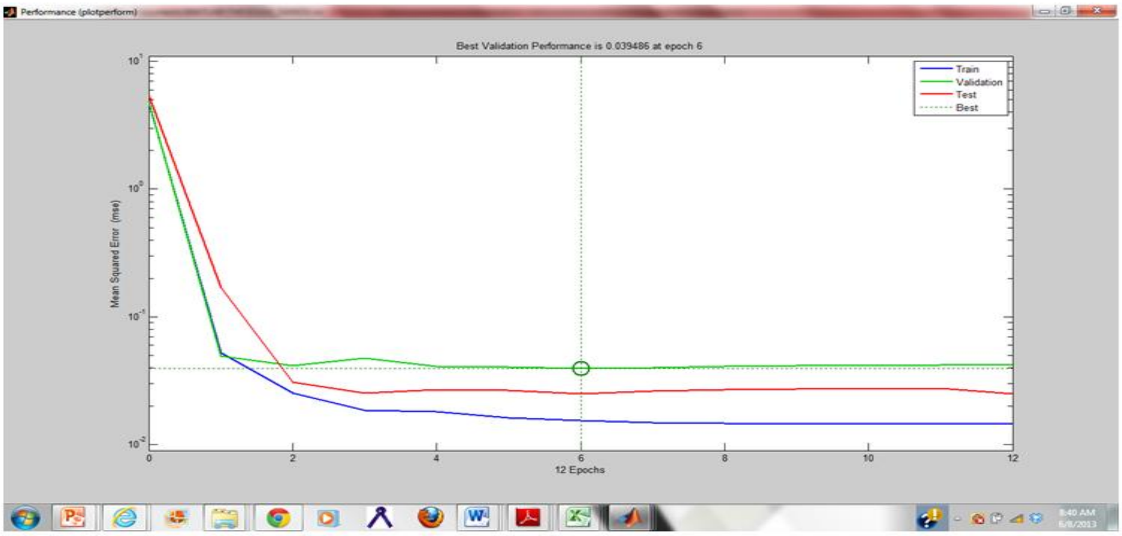


Figure 4: GUI showing the Mean Square Error

3.7.6 Step 4: Simulation and Prediction

Once the error analysis with the mean square error and regression analysis are satisfactory, the trained network is engaged for simulation by means of a call_back function via the GUI. This procedure enables a model simulation function known as 'sim' to be used for simulating the train datasets.
All these steps (1-4) were developed and compiled into application with a functional user interface.

3.8 Development of the Model Graphical User Interface

For ease of data entry into the model, a GUI was developed. The GUI was mentally abstracted to cover the various components needed to interface the user and the model.

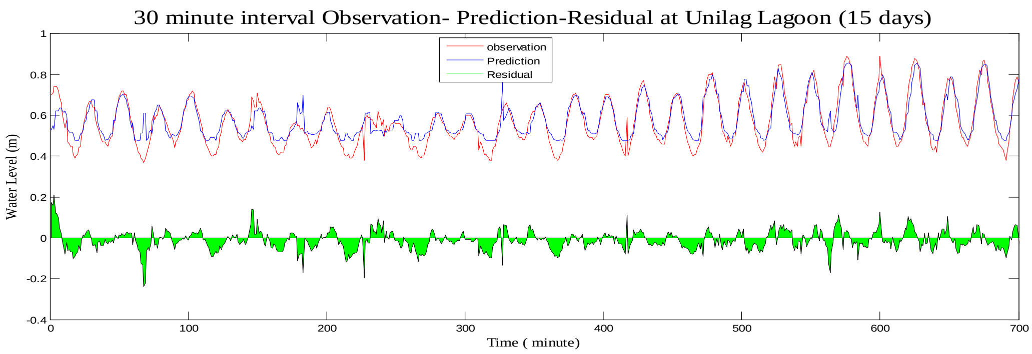
IV. RESULTS AND ANALYSIS OF RESULTS

This section focuses on the results of predictions done using the model. Each prediction result is reported with the associated satistical analysis. The statistical analysis is an integral part of the model. It was directly linked to the model Graphical User Interface(GUI) during the programming of the model. The prediction results are reported in two parts. The first part is termed by many as the 'Regional Neural Network Prediction' in which the water level of two stations are used for trainining and thereafter , one station data (designated as the 'input') is used to predict for the other (designated as the 'target'). While the second part is a prediction where water level data for one station is used to train ANN model and afterward a prediction is made to cover time or days beyond the observation period. The result for these two types of prediction are shown below.

4.1 Water Level Prediction Using Two Stations (Regional Case)

4.1.1 Prediction for University of Lagos (Unilag) Lagoon using Oreta Lagoon Water Level

Thirty days water level data observed on August ,2008 for Unilag and Oreta Lagoons were divided into two parts for each of the tidal stations. The first 15 days data for both tidal stations were used for training (that is 15 days tidal data of Oreta lagoon wereused as inputs and 15 days of Unilag lagoon tidal data were used as target. The remaining 15 days water level data of Oreta Lagoon were used to predict water level data covering 15 days at Unilag lagoon.



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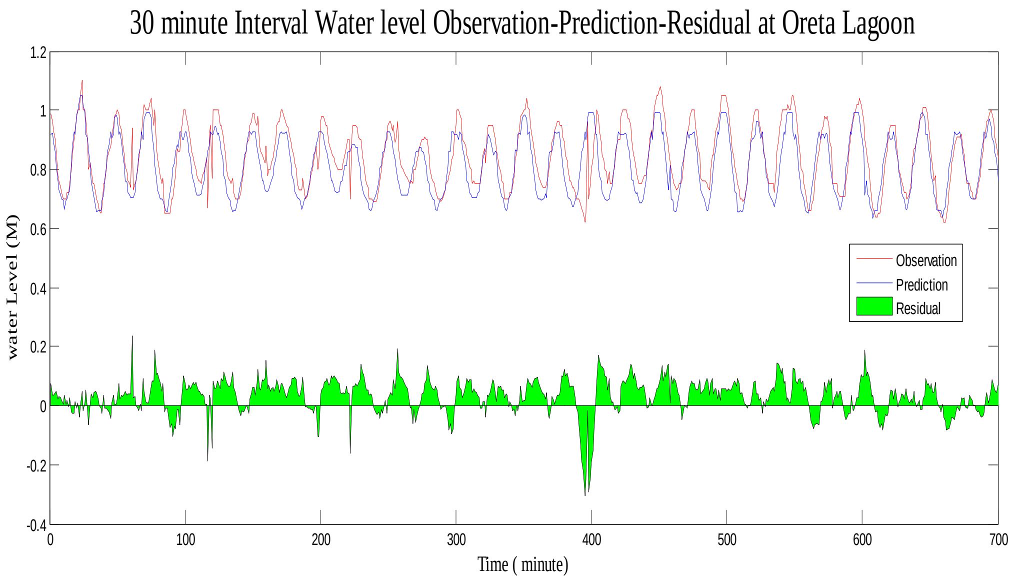
EPOCH (No of iteration)	TIME (secs)	PERFORMANCE (MSE)	GRADIENT	VALIDATION CHECK
20	2	0.00375	0.000353	6
REGRESSION				

Training	Validation	Test
0.834	0.869	0.868

4.1.2 Prediction of Water level at Oreta Lagoon using Porto-Novo Creek

30 days water Level data for Porto-Novo creek and Oreta Lagoon were used in a similar case as discussed in one (4.1.1) above and the result is as shown below.



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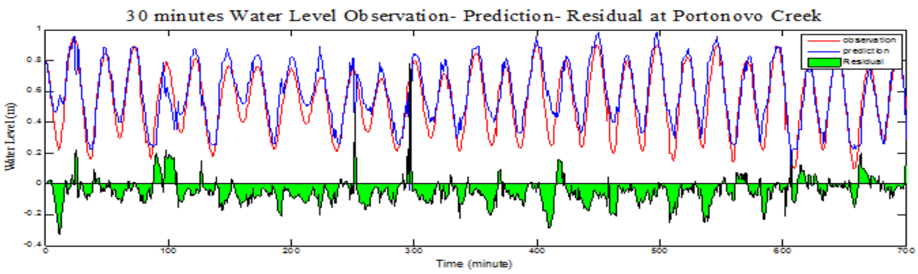
EPOCH (No of iteration)	TIME (secs)	PERFORMANCE (mse)	GRADIENT	VALIDATION CHECK
20	11	0.0012	0.000509	6
REGRESSION				

Training	Validation	Test
0.9337	0.91283	0.9087

4.1.3 Prediction of Water Level for Porto-Novo Creek

Thirty days water level for Unilag lagoon and Porto-Novo creek were subjected to the same procedure as discussed in (4.1.1.) above, prediction was made for Porto-Novo creek covering a period of 15 days. The result of the prediction is as shown below.



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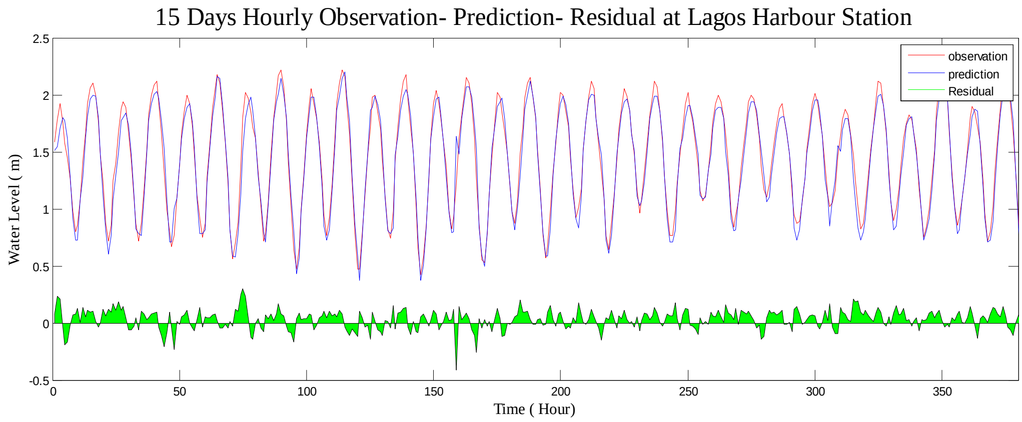
EPOCH (No of iteration)	TIME (secs)	PERFORMANCE (MSE)	GRADIENT	VALIDATION CHECK
11	11	0.007	0.000509	6
REGRESSION				

Training	Validation	Test
0.9337	0.91283	0.9487



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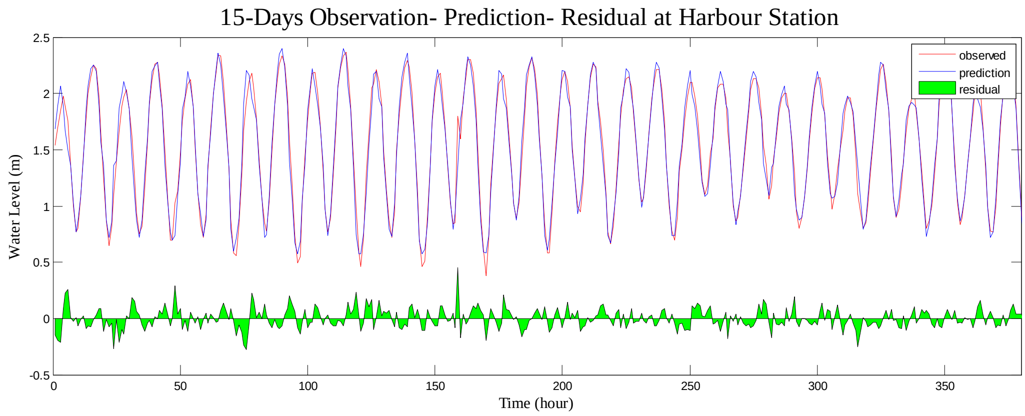
EPOCH (No of iteration)	TIME (secs)	PERFORMANCE (mse)	GRADIENT	VALIDATION CHECK
7	5	0.018	0.00065	6
REGRESSION				

Training	Validation	Test
0.9666	0.9631	0.9668



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EPOCH (No of iteration)	TIME (secs)	PERFORMANCE (mse)	GRADIENT	VALIDATION CHECK
12	3	0.0285	0.00065	6
REGRESSION				

Training	Validation	Test
0.8646	0.9238	0.9014

4.3 Statistical Test Analysis Between the Observed and the Predicted Water Level At Opobo Harbour Station

The objective of the statistical test is to compare the two populations of observed tide and predicted tides (Keller and Warrack, 2003). The parameter is the difference between the two means/standard deviations, $\bar{x}_1/s_1$and $\bar{x}_2/s_2$ in all the water level gauge locations (where $\bar{x}_{1/}$ s_1= mean/standard deviation of observed water level and $\bar{x}_2/s_2$ = mean/standard deviation of the predicted water level).

Two hypotheses, the null (H_o) and the alternative (H_a) hypotheses were investigated using the t-distribution and the F-distribution . t- distribution is used to compare difference in mean between population and the F-distribution compares the variance between the population. In either case, the null Hypothesis is rejected when the calculated value is greater than the tabulated value.

The Hypothesis questions are:

- Null Hypothesis: Is the difference between the mean/variance of water level observation and water level prediction equals zero
- Alternative Hypothesis: Is the difference between the mean/variance of water levelobservation and water level prediction greater than zero

H_0: $(\bar{x} - \bar{x})$ = 0
H_a: $(\bar{x} - \bar{x})$ > 0 for mean

H_0: $(s_1 – s_2)$ = 0
H_a: $(s_1 – s_2)$ > 0 for variance

t-test distribution is given by t the expression,

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}} \tag{4.1}$$

Where S_1 =standard deviation for population 1
S_2 ==standard deviation for population 2
n_1 = population1 size
n_1 = population2 size
v = $n_1 + n_2 – 2$ (degree of freedom)
Standard Deviation is expressed as

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}, \tag{4.2}$$

Equation (4.1) , (4.2) were used for computing t- test value for all the tidal gauge stations tested with the model. The analysis for one of the stations – OpoboHarbour Station is shown below

$\bar{x}_1$ = 1.54231771 (Observed) mean of observed data
$\bar{x}_2$ = 1.497030556 (Predicted) mean of predicted data
s_1 =0.517422089 (Observed) standard deviation of observed data
s_2 =0.5141760 (Predicted) standard deviation of predicted data

$n_1 = 384$
$n_2 = 384$
$v = n_1 + n_2 - 2 \quad = 702 + 702 - 2 = 1402$

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1{}^2}{n_1} + \frac{s_2{}^2}{n_2}}}$$

t = {(0.045287154} √0.000697202 + 0.0006884816)}

t = 1.2165

The rejection region for a 5% significance level is $t > t_{\alpha,y} = t_{0.05,383} = -1.646$

The rejection region for a 95% significance level is $t < t_{\alpha,y} = t_{0.95,383} = 1.646$
Since $t < t_{\alpha,y}$ we therefore accept the null hypothesis that mean of the observed tide is equal to the mean of the predicted tide.

F –test for Opobo Harbor Location:
Since $s_1 > s_2$, $F_{calc} = s_1{}^2/s_2{}^2 = 0.517422089^2/0.5141760^2 = 1.011878727$. The tabulated value for. $v = 383$ in each case, and a 95% confidence level is $F_{383,383} = 1.1887$. In this case,$F_{calc} < F_{383,383}$, so we accept the null hypothesis that the two standard deviations are equal. and we are 95% confident that any difference in the sample standard deviations is due to random error

The t-test and the F-test were conducted for all the stations used in this work and we are 95% confident that any difference in predicted and observed water level mean and standard deviationsis due to random error incurred during observations
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Station	**S_1**	**S_2**	**$\bar{x}_1$**	**$\bar{x}_2$**
Unilag Lagoon	0.116484012	0.093932638	0.56845934	0.582483452
Porto-Novo creek	0.107412287	0.196791059	0.54265335	0.59114693
Oreta Lagoon	0.107412287	0.1010110005	0.84510699	0.813130243
Lagos Harbour	0.456608894	0.458318126	1.452838542	1.421460677
Opobo Harbour	0.5141760	0.517422089	1.54231771	1.497030556

V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

A Neural Network for Water Level modeling and prediction has been successfully developed in this study for water level predictions at coastal zone. The Neural Networks Water Level Model (NNWLM) employs three-layer feed-forward, back propagation structure with optimized training method using Levenberg-Marquardt algorithm. The model requires the input of time series water level data with corresponding time series water level data of a coastal area whose water level is to be predicted. The two sets of data, the input and target are subjected to training with varying network parameters until a satisfactory model with some desired measure of accuracy is achieved.

The model was successfully tested in case studies using data from different coastal locations ranging from Lagos Harbour, OpoboHabour, Porto-NovoCreek, Oreta Lagoon, UnilagLagoon. Field data indicate that water levels change substantially in both amplitude and phase over the coastal zone due to the complex coastal and estuarine topography and shallow water effects. Using short-term data sets (one month), the model was trained, validated and tested using a ratio of 6: 2: 2 for training, validation and testing respectively.

The result of the model predictions indicates great performance. The predicted tidal signals matched well with observations with performance index ranging from 0.008 -0.012 in terms of Mean Square Error(MSE) and 0.83- 0.97 in terms of correlation coefficient (R-value). Given this plausible performance, The Neural Networks Water Level Model (NNWLM) developed in this study is a practical tool for coastal engineers in coastal zone management. Thus researcherscan predict long-term historic water level data at a station of interest or remote station using the regional approach.

5.2 Recommendation

We make the following recommendations based on this study:

i. More research should be done in other areas of coastal zone management using ANN.
ii. Recent innovations on combination of neural network and harmonic analysis for improved water level analysis and prediction should be explored to assess the validity of the innovation and furthercontribute to the body of knowledge on coastal study.
iii. There should be collaboration between governmental agencies, non governmental agencies and the academia to enhance coastal zone management in the country.
iv. More resources should be channeled to acquire more tidal data. Data sharing should also be encouraged among all the stakeholders in coastal zone management.

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