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Coastal Water Level Prediction Model Using Adaptive Neuro-Fuzzy Inference System

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Abstract: *This paper employs Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict water level that leads to flood in coastal areas. ANFIS combines the verbal power of fuzzy logic and numerical power of neural network for its action. Meteorological and astronomical data of Santa Monica, a coastal area in California, U. S. A., were obtained. A portion of the data was used to train the ANFIS network, while other portions were used to check and test the generalization ability of the ANFIS model. Water level predictions were made for 24 hours, 48 hours and 72 hours, in which training, checking and testing of the model were performed for each of the prediction periods. The model results from the training, checking and testing data groups show that 48 hours prediction has the least Root Mean Square Error (RMSE) of 0.05426, 0.06298 and 0.05355 for training, checking and testing data groups respectively, showing that the prediction is most accurate for 48 hours.*

Keywords: *Coastal Area, Fuzzy Logic, Neural Network, RMSE.*

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I. INTRODUCTION

Water level prediction provides an important means of environmental protection and flood hazard prevention [1]. Resulting from its closeness to the ocean, coastal area has been discovered as one of the areas that are most vulnerable to the effects of sudden rise and fall of water level resulting into flood; which has led to various degrees of damage of properties and loss of lives [2]. However, for one reason or the other, people find themselves in places closed to the ocean which put them at high risk of the effects of sudden rise and fall of water level in those areas. Remarkable loss which include lives and properties have been claimed due to lack of proper and timely awareness of these occurrences. To have proper and timely awareness of any excessive or abnormal rise in water level, accurate, efficient, low-cost, and easy-to-use prediction system is essentially paramount. Therefore, this paper focuses on using Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict water levels in coastal areas. Reliable water level forecasts enable the use of early warning systems to alert the populace to take every necessary preventive measure against dangerous effects [1].

Meanwhile, water level is a dependent phenomenon in that it depends on a set of factors (parameters) which are not linearly related. Thus, its prediction is generally tedious, inaccurate, and unreliable without employing an appropriate model or interface. Also, it is glaring that complex real-world problems can be solved with the help of intelligent systems that combine knowledge, techniques and methodologies from various sources. These intelligent systems have been discovered to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments.

So, in confronting real-world computing problems, it would be advantageous to use several computing techniques synergistically rather than exclusively, resulting in construction of complementary hybrid intelligent systems [3]. The perfect example of intelligent system of this kind is the ANFIS, which combines the strength of Artificial Neural Networks (ANN), which reliably increases its performance when more detailed information is used, and Fuzzy Logic, which performs better when the physical phenomena considered are synthesized by both a limited number of variables and IF-THEN logic statements [4], [5]. So, in this work, ANFIS-based model is chosen for its reliability, convenience, efficiency and accuracy. Using a properly trained ANFIS network, the model yields satisfactory results in predicting the water levels of different locations as may be applied.

Being a multilayer feed-forward network which uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space [6], having the ability to combine the verbal power of a fuzzy system with the numeric power of a neural system adaptive network, ANFIS has been shown to be powerful in modeling numerous processes, such as motor fault detection and diagnosis [7], power systems dynamic load, wind speed, and real time reservoir operation [6]. Another major advantage of ANFIS is that it eliminates the basic problem of defining the membership function parameters and obtaining a set of fuzzy if-then rules [8]. It possesses good capability of learning, constructing, expensing, and classifying. It has the advantage of allowing the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base. Furthermore, it can tune the complicated conversion of human intelligence to fuzzy systems.

In this study, Santa Monica, a coastal region in California, U.S.A. is used as the case study. Historical meteorological data (wind speed and barometric pressure) and the astronomical data (Tidal level) of the ocean, as well as the water level around the coast are used for model training, validation and testing. All these data were obtained online at one of the National Ocean and Atmospheric Administration (NOAA) websites, http://www.tidesandcurrents.noaa.gov, and were used only for research purpose.

II. OVERVIEW OF COASTAL AREAS

A coastline or seashore is the area where land meets the sea or ocean [9]. The term "coastal zone" is a region where interaction of the sea and land processes occurs [10]. Climate change could affect coastal areas in a variety of ways. Coasts are sensitive to sea level rise, changes in the frequency and intensity of storms, increases in precipitation, and warmer ocean temperatures. Coasts are considered as places to live, work, and play. Forty percent of the world's population lives on the coastal fringe, and that number is steadily growing [11]. Vacationers eager to lie on white sandy beaches and swim in clear waters generate tourism revenue annually. The need for humans to achieve their socio-economic objectives also causes them to perform (or locate) their activities near to the resources supporting those objectives. For example, the coastline of the United States is highly populated; of the 25 most densely populated U.S. counties, 23 are along a coast [12]. Coastal and ocean activities, such as marine transportation of goods, offshore energy drilling, resource extraction, fish cultivation, recreation, and tourism are integral to the nation's economy [13]. Meanwhile, some vulnerable cities along coastline, especially in the U.S. already experience the impacts of sea level rise to their natural resources, critical assets, and infrastructure [14]. So, there is need for efficient and easy-to-access prediction method.

III. ANFIS METHODOLOGY

The architecture of the three-inputs-six-rules prediction model employed for this work is presented in Fig. 1. The fuzzy inference system consists of three inputs, *w*, *x* and *y*; the wind speed and barometric pressure, and tidal levels of the of the ocean in a targeted location respectively and one output, *z*, which is the future water level relative to the input time. The variables are chosen because they are the meteorological and astronomical factors on which coastal water level depends. These variables *w*, *x* and *y* being natural occurrences may vary naturally and have combined effect on the output. The degree of belongingness ('low' or 'high') of the inputs are based on the numerical values obtained from the data as classified by the membership functions.

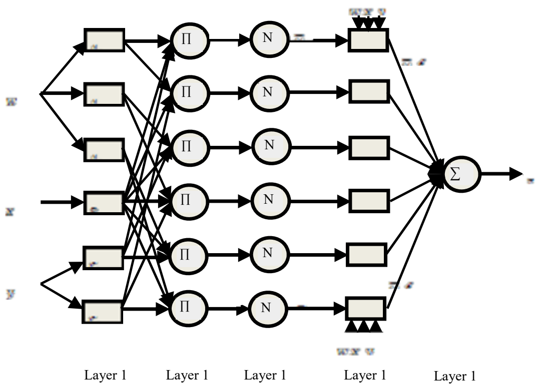

Fig. 1. Architecture of the ANFIS-Based prediction model with three inputs and six rules.

(1) Layer 1 (Input Nodes): Every node in this layer is an
adaptive node with a node function:

$$O_{1,i} = \mu A_l(w),\ \ \mu B_m(x)\ or\ \mu C_n; \qquad (1)$$

$i = 1, 2, \ldots, 6;\ l = 1, 2, 3;\ m = 1; n = 1, 2$

Where *A*, and *B*, and *C* are linguistic labels (such as "low", "moderate" or "high") associated with the nodes respectively.

(2) Layer 2 (Rule Nodes): Every node in this layer is a fixed one, whose output is the product of all the incoming signals:

$$O_{2,i} = \omega_i = \mu A_l(w)\ \mu B_m(x)\ \mu C_n \quad (2)$$

Each node output represents the **firing strength** of a rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

(3) Layer 3 (Average Nodes): Every node in this layer is a fixed node labeled N. The *ith* node calculates the ratio of the *ith* rule's firing strength to the sum of all rules' firing strenghts:

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\omega_1+\omega_2+\cdots+\omega_6}; \quad i\text{=1-6} \qquad (3)$$

(4) Layer 4 (Consequent Nodes): Every node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \overline{\omega}_i f_i = \overline{\omega}_i(p_i w + q_i x + r_i y\ +\ s_i);\ \ i\text{=1-6} \qquad (4)$$

where p_i, q_i, r_i, and s_i are the parameter sets of this node. Parameters in this layer are referred to as *consequent parameters*.

(5) Layer 5 (Output Node): The single node in this layer is a fixed node, which computes the overall output as the summation of all incoming signals:

$$O_{5,1} = \sum_{i=1}^{6} \overline{\omega}_i f_i \ = \frac{\sum_{i=1}^{6} \omega_i f_i}{\sum_{i=1}^{6} \omega_i} \qquad (5)$$

Based on a first-order Sugeno fuzzy model, the six fuzzy if-then rules for this work is expressed as:

Rule 1: If *w* is A_1 and *x* is B_1 and *y* is C_1 then $z_1 = p_1 w + q_1 x + r_1 y + s_1$

Rule 2: If *w* is A_1 and *x* is B_1 and *y* is C_2 then $z_2 = p_2 w + q_2 x + r_2 y + s_2$

Rule 3: If *w* is A_2 and *x* is B_1 and *y* is C_1 then $z_3 = p_3 w + q_3 x + r_3 y + s_3$

Rule 4: If *w* is A_2 and *x* is B_1 and *y* is C_2 then $z_4 = p_4 w + q_4 x + r_4 y + s_4$

Rule 5: If *w* is A_3 and *x* is B_1 and *y* is C_1 then $z_5 = p_5 w + q_5 x + r_5 y + s_5$

Rule 6: If *w* is A_3 and *x* is B_1 and *y* is C_2 then $z_6 = p_6 w + q_6 x + r_6 y + s_6$

where p_i, q_i, r_i and s_i (i=1-6) are linear parameters in the then-part (consequent part) of the first-order Sugeno fuzzy model.

Due to its accuracy and precision, trapezoidal membership functions were chosen as the input membership functions while constant membership functions were chosen for the output. The trapezoidal curve is a function of a vector, x, and depends on four scalar parameters a, b, c, and d, as given by (6).

$$f(x;a,b,c,d)=\begin{Bmatrix} 0, & x\le a \\ \frac{x-a}{b-a}, & a\le x\le b \\ 1, & b\le x\le c \\ \frac{d-x}{d-c}, & c\le x\le d \\ 0, & d\le x \end{Bmatrix} \quad (6)$$

or more compactly by:

$$f(x;a,b,c,d)=\max(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c},0\right)) \quad (7)$$

The parameters a and d locate the "feet" of the trapezoid and the parameters b and c locate the "shoulders."

This network was trained based on supervised learning, which aimed at training adaptive networks to be able to approximate unknown functions given by training data and then find the precise value of the above parameters. The distinguishing characteristic of the approach is that ANFIS applies a hybrid-learning algorithm, the gradient descent method and the least-squares method, to update parameters. The gradient descent method is employed to tune premise non-linear parameters (a, b, c, d) while the least-squares method is used to identify consequent linear parameters (p, q, r, s).

The task of the learning procedure has two steps: In the first step, the least square method was used to identify the consequent parameters, while the antecedent parameters (membership functions) are assumed to be fixed for the current cycle through the training set. Then, the error signals propagate backward. Gradient descent method was used, in the second step, to update the premise parameters, through minimizing the overall quadratic cost function, while the consequent parameters remain fixed.

Predictions were made for 24 hours, 48 hours and 72 hours coastal water levels at the same location (Santa Monica, California, U.S.A.) using distinctive hourly data sets. Trapezoidal membership functions were used for the input variables throughout the experiments: three for input-1, one for input-2, and two for input-3, which are wind speed, barometric pressure, and tidal level respectively. Using grid partitioning technique, hybrid learning algorithm and epoch size of 60, the model training, checking and testing were carried out and the root mean square error (RMSE) were generated by using (8)

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_i-P_i)^2} \quad (8)$$

where Q_i and P_i are the observed and predicted output values respectively; n = number of the predicted values.

IV. RESULTS AND DISCUSSION

1. Model Training, Checking and Testing for 24-Hour Prediction

Fig. 2 shows the model training with the training error indicated with plus (*) plotted against number of epochs. Checking error shown in diamond (◊) is included on the plot to determine the point of overfitting. It would be noticed that overfitting takes place towards the end of the training process: around 57th epoch when the checking error begins to rise. Hourly data for one day was used for model training and the training error observed here is 0.061289.

Fig. 3 is the plot of the fuzzy inference system (FIS) output, that is, the trained model output compared with the checking data output. The FIS output is shown in red star (*) with the checking data output in blue plus (+). The checking error produced here is 0.063137.

Yet another set of data entirely different from the training and checking data was used to check the generalization ability of the model; this data set is termed Testing data. The plot generated by testing this data output against the FIS output is shown in Fig. 4 with 0.12538 obtained as the testing error.

Fig. 5 shows the structure of the three-input-six-rules prediction model: the first three and the last one black nodes are the crisp inputs and output respectively. The two layers with six white nodes each represent the input and the output membership functions respectively. The middle layer with blue nodes represents the rules.

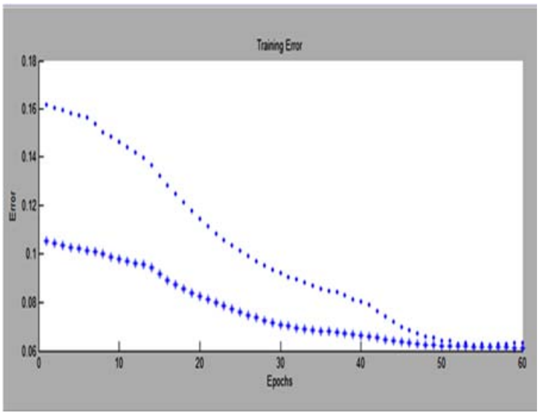

Fig. 2. Training error against epochs for the 24-hour coastal water level prediction. (*) = Training Error, (◊) = Checking error.

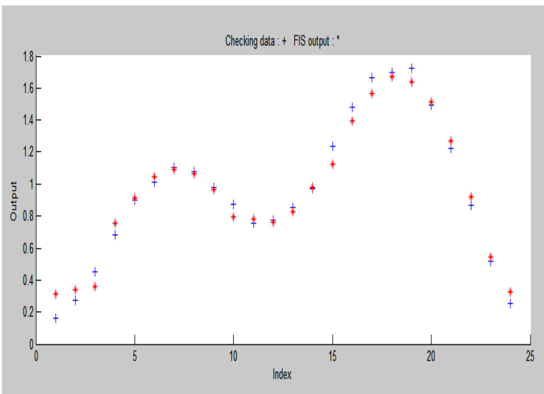

Fig. 3. FIS output against the checking data for the 24-hour coastal water level prediction. (*) = FIS output; (+) = checking data output.

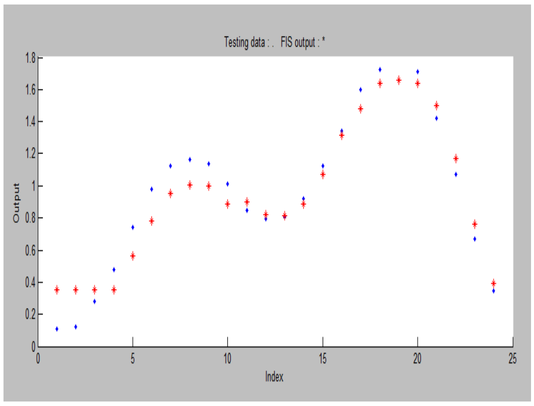

Fig. 4. FIS output against the testing data for the 24-hour coastal water level prediction. (*) = FIS output; (◊) = Testing data output.

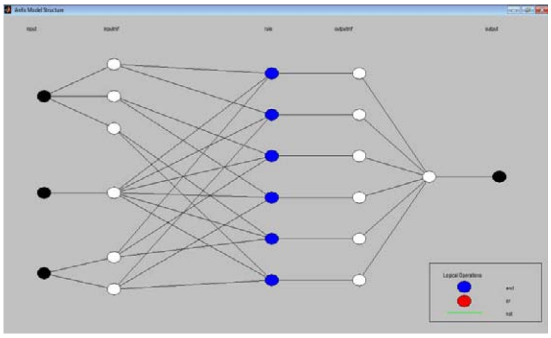

Fig. 5. Structure of the three-input-six-rule prediction model.

2. Model Training, Checking and Testing for 48-Hour Prediction

The same procedures were followed in predicting 48-hours coastal water levels relative to the input time. The results were obtained for the training, checking and testing data set as shown in Figs. 6, 7, and 8 respectively; their respective errors are 0.054264, 0.062975 and 0.053553.

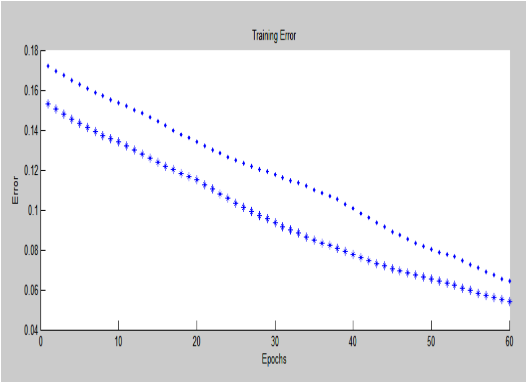

Fig. 6. Training error against epochs for the 48-hour coastal water level prediction. (*) = Training Error, (◊) = Checking error

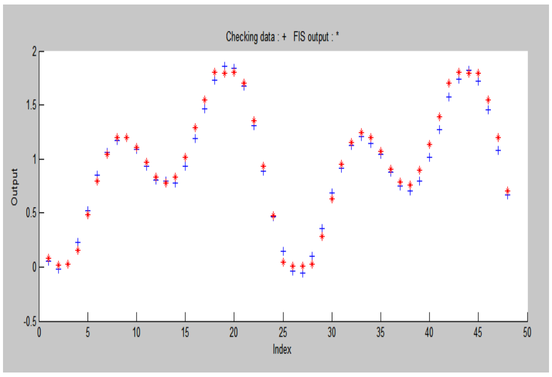

Fig. 7. FIS output against the checking data for the 48-hour coastal water level prediction. (*) = FIS output; (+) = checking data output

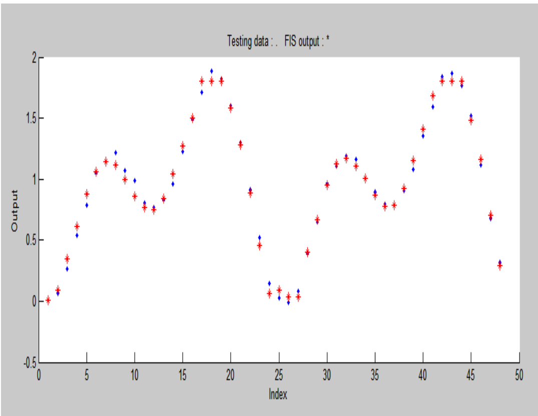

Fig. 8. FIS output against the testing data for the 48-hour coastal water level prediction. (*) = FIS output; (◊) = Testing data output.

3. Model Training, Checking and Testing for 72-Hour Prediction

The model was trained, checked and tested using another sets of data to predict 72-hour coastal water levels in the selected location. The obtained results are showed in Figs. 9, 10 and 11 for training, checking and testing data sets respectively; then the corresponding RMSE obtained are 0.096501, 0.20500 and 0.38705.

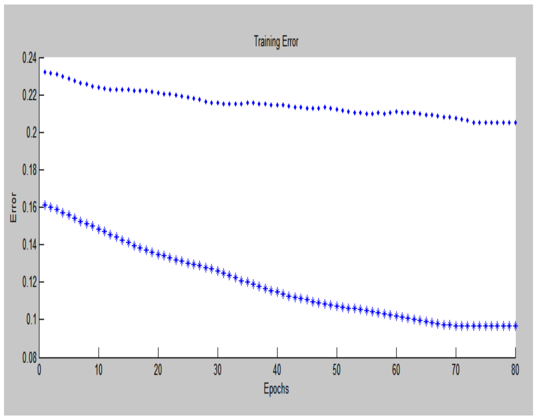

Fig. 9. Training error against epochs for the 72-hour coastal water level prediction. (+) = Training Error, (◊) = Checking error.

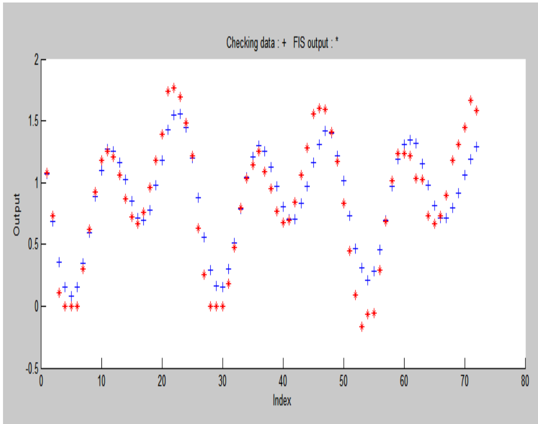

Fig. 10. FIS output against the checking data for the 72-hour coastal water level prediction. (*) = FIS output; (+) = checking data output.

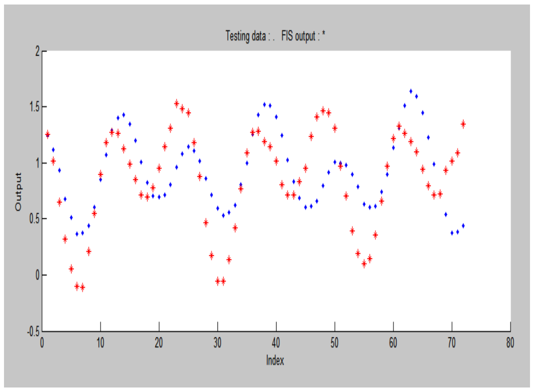

Fig. 11. FIS output against the testing data for the 72-hour coastal water level prediction. (*) = FIS output; (◊) = Testing data output.

Table I summarizes the results of the developed three-inputs-six-rules coastal water level prediction model. The lowest root mean square errors (training, checking and testing) are obtained from the 48-hours prediction model. It is inferred from here that the input variables have effects on the coastal water level at around 24-hours after their occurrences but more predominantly at about 48-hours' time. The performance of the model becomes poor as the period goes beyond two days.

V. CONCLUSION

In this paper, wind speed, barometric pressure, and tidal levels of the ocean, as well as the coastal water level data were obtained and arranged into training, checking and testing data groups. Prediction model was developed using ANFIS. The model was applied separately on each data group with 24 hours, 48 hours, and 72 hours prediction times. The output of the model showed that the 48 hours prediction time resulted in lowest RMSE for training, checking, and testing data as compared to the 24 hours and 72 hours prediction time respectively. Therefore, water level in coastal area is best predicted with ANFIS at 48 hours before time.

TABLE I

	24-HOUR PREDICTION			48-HOUR PREDICTION			72-HOUR PREDICTION		
	Data	Epoch	RMSE	Data	Epoch	RMSE	Data	Epoch	RMSE
Training	24	60	0.06129	48	60	0.05426	72	80	0.09650
Checking	24	60	0.06314	48	60	0.06298	72	80	0.20500
Testing	24	60	0.12538	48	60	0.05355	72	80	0.38705

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