



Anfis Model for Prediction of Current Velocity at Filyos Region

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Abstract

Current velocity plays a significant role in coastal engineering, especially coastal sedimentation, coastal pollution transmission, and design of coastal structures. Moreover, it is great important to determine coastal pollution propagation in time and the area affected by pollution transmission. Because of these reasons, current velocity is predicted based on observed data in this study. Current velocity data which are measured for 2 hours during 2 years in Filyos Region are utilized to develop several Adaptive Neuro-Fuzzy Inference System (ANFIS) models on Matlab to estimate future current velocity. After prediction of two hourly averages of current velocities from previous values by ANFIS model, the predicted data is compared with the actual one measured in the field. Therefore, statistical parameters in literature including root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (R) are used to test acceptability of proposed ANFIS models. The study results indicate that proposed models provide better results in comparison to widespread stochastic approaches. Consequently, this study is an alternative to other prediction methods considering the aims of current velocity prediction mentioned above.

Keywords: Current velocity forecasting; Adaptive Neuro-Fuzzy Inference System (ANFIS); Filyos Region.

1. Introduction

One of the most important issues in the design, planning and construction of coastal and offshore structures is current velocity. Even though long-term series of current velocity is needed for the coastal engineering objectives, measured data is generally for short period due to being expensive and time consuming [1]. It is obviously useful to extend time series of current velocity with the help of empirical formulas and numerical models such as JONSWAP, Shore Protection Manuel, Coastal Engineering Manuel, and Goda [2-5].

Numerically simulated wave data is used as the data bank for extracting design wave characteristics with the development of numerical wave models by virtue of the scarcity of measurements [6]. Numerical wave models which can be divided into four categories. These first, second, third and improved third generation wave models are useful in accurate wave forecasting [7]. However, numerical models are not economical for the basic design step. Empirical formulas which are based on wave characteristics and water depth, neglect the wind characteristics such as wind speed and wind direction [8]. Soft computing systems with data-driven approaches like the adaptive network-based fuzzy inference system (ANFIS) and artificial neural networks (ANN) can overcome these disadvantages of empirical formulas and numerical models [9].

Artificial intelligence techniques including ANN, genetic algorithm (GA), fuzzy logic (FL) is used as an alternative approach to the deterministic and stochastic methods. However, neuro-fuzzy model is preferred as a combination of advantages of ANN and FL models. These approaches have been

applied to many complex systems in coastal engineering. Some of these applications are given briefly as follows: Kazeminezhad et al. [10] estimated wave parameters in the fetch-limited condition by ANFIS model. Özger and Şen [11] used fuzzy logic to find relationship between wind speed and current wave characteristics in the Pacific Ocean. Günaydın [12] predicted monthly mean significant wave heights by using ANN and regression methods. ANN and ANFIS models were used by Mahjoobi et al. [13] for wave hindcasting. Bakhtyar et al. [14,15] used ANFIS model to estimate the wave run-up and longshore sediment transport in swash zone. Zanganeh et al. [16] estimated wave parameters with the help of genetic algorithm-adaptive network-based fuzzy inference system model (GA-ANFIS) at Lake Michigan for the duration-limited condition. Tür and Balas [17] used ANFIS model for prediction of the significant wave height. Aydoğan et al. [18] used the feed forward back propagation (FFBP) ANN model to forecast current velocity in straits. Shiri et al. [19] estimated the sea level fluctuations at Hillarys Boat Harbour in Perth, Western Australia by ANFIS. Akpınar et al. [20] estimated wave parameters by using fuzzy inference system and parametric models along the south coasts of Black Sea. Zanganeh et al. [9] estimated wind and wave-induced current velocities at Joetsu-Ogata coast by using both ANFIS and ANN models.

The aim of this study is to estimate future current velocity and to compare the forecasts of current velocity with actual ones. The present paper is set out in three main sections as follows: the study area, ANFIS model, and lastly results and conclusion part.

2. The Study Area

Filyos town, also known as Hisarönü, which is located in both Türkali village in Zonguldak in the western Black Sea Region of Turkey and the mouth of Filyos River that passes through Çaycuma in Zonguldak. Maritime area at Filyos region is analyzed within the scope of this paper. All data that were used in this paper had been measured at location shown in Fig. 1.



Figure 1. Location of the study area and measurement station

The instrument used in the study area is Acoustic Wave and Current Profiler (AWAC) which is designed as a coastal monitoring system and enables to measure the current speed and direction in one-meter-thick layers from the bottom to the surface.

3. ANFIS Model

ANFIS model which is originally introduced by Jang in 1993 has both advantages of neural networks including optimization, capabilities, learning capabilities and of fuzzy logic consisting the linguistic information, ‘IF-THEN’ rules [21,22].

It is needed to summarize ANFIS structure briefly. Firstly, ANFIS structure that has two inputs and one output is showed in Fig. 2:

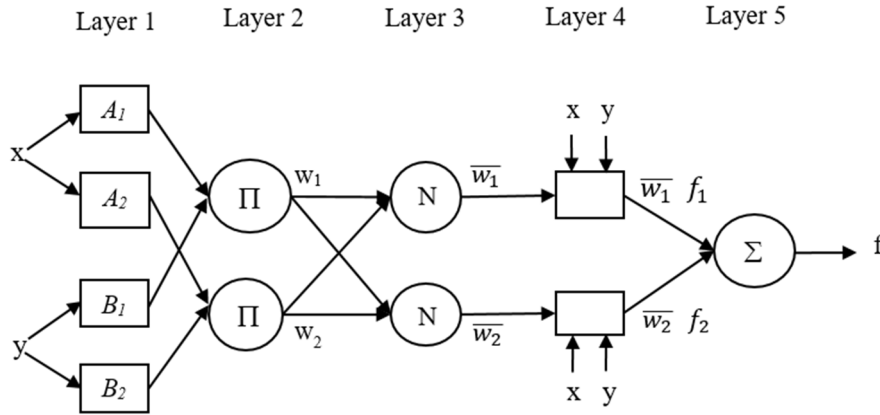


Figure 2. ANFIS architecture for two-input Sugeno fuzzy model with two rules [9,10,17,21]

It is assumed that there are two fuzzy IF-THEN rules of Takagi and Sugeno’s type:

Rule 1: IF x is A_1 and y is B_1 THEN $z_1 = p_1 x + q_1 y + r_1$,

Rule 2: IF x is A_2 and y is B_2 THEN $z_2 = p_2 x + q_2 y + r_2$,

where q_i , p_i and r_i ($i = 1, 2$) are the linear parameters, A_i and B_i are the fuzzy sets, square nodes are fixed nodes, circle nodes are adaptive ones, and f_i is the linear functions of inputs of Sugeno type first degree fuzzy model. ANFIS structure which has five layer shown in Fig. 2 can be summarized as follows [21,22]:

Layer 1: A square node shown corresponds node i with Eq. 1.

$$O_i^1 = \mu_{A_i}(x) \quad (1)$$

where O_i^1 is the membership function of linguistic label A_i and x is the input for node i . Bell-shaped membership function μ_{A_i} that is generally chosen as a typical choices shown in Eq. 2.

$$\mu_{A_i}(x) = \exp\left\{-\left(\frac{x-b_i}{a_i}\right)^2\right\} \quad (2)$$

where a_i , b_i are known as the premise parameters.

Layer 2: Every circle node that represents the firing strength of the rule, multiplies the input to get product in layer 2; such as in Eq. 3:

$$\omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i=1,2 \quad (3)$$

Layer 3: Every i th circle nodes give the normalized firing strength that means the ratio of each node's firing strength to sum of all node's ones. Eq. 4 shows the output of layer3:

$$\bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i=1,2 \quad (4)$$

Layer 4: Eq. 5 indicates the function of square nodes:

$$O'_i = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i), \quad i=1,2 \quad (5)$$

where p_i , q_i , and r_i are the consequent parameters.

Layer 5: There is a single circle node that gives the summation of outputs of the layer 4, shown in Eq. 6:

$$O_i^s = \text{overall output} = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}, \quad i=1,2 \quad (6)$$

3.1. Dataset Description

Current velocity data, approximately 8000 measured data is normalized and then used as input for ANFIS. All data is divided into two groups; 70% of total for training part and 30% for testing data. The values for these two parts that are selected randomly.

Statistical properties of all measured current velocity data are shown in Table 1.

Table 1. Statistical properties of current velocity parameters

Wave Parameter	Min (m/s)	Max (m/s)	Mean (m/s)	Skewness	Standard Deviation (m/s)
Current Velocity	0,02	71,17	12,14	1,64366	9,043203

All sub-models that are take into consideration in this study are listed in Table 2 and created according to error and efficiency in previous model.

Table 2. Sub-Model Architectures

Model	Model Architecture
Mod - 1	$V_{(t-1)}$
Mod - 2	$V_{(t-2)} V_{(t-1)}$
Mod - 3	$V_{(t-3)} V_{(t-2)} V_{(t-1)}$
Mod - 4	$V_{(t-4)} V_{(t-3)} V_{(t-1)}$
Mod - 5	$V_{(t-4)} V_{(t-2)} V_{(t-1)}$
Mod - 6	$V_{(t-4)} V_{(t-3)} V_{(t-2)} V_{(t-1)}$
Mod - 7	$V_{(t-5)} V_{(t-4)} V_{(t-3)} V_{(t-2)} V_{(t-1)}$

Seven sub-models are generated by using time-delayed current velocity data. For instance, totally three inputs, including $V_{(t-3)}$, $V_{(t-2)}$, and $V_{(t-1)}$ are taken as inputs for Mod-3 to estimate $V_{(t)}$.

3.2. Evaluation of ANFIS Models

Root mean square error (*RMSE*), mean square error (*MAE*), and correlation factor (*R*) used to show efficiency of each model are defined in Eq.7, Eq. 8, and Eq.9:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}} \quad (7)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |X_i - Y_i| \quad (8)$$

$$R = \frac{\sum_{i=1}^n (X_i - \bar{X}) - (Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (9)$$

where X_i is observed, Y_i is predicted, n is total number of data, \bar{X} is the mean of all X_i , and \bar{Y} is the mean of all Y_i .

Each generated model is tested for different type and number of membership function. Table 3 is summarized the evaluation of the proposed models and gives the results for both test and training data.

Table 3. Characteristic and result of proposed models

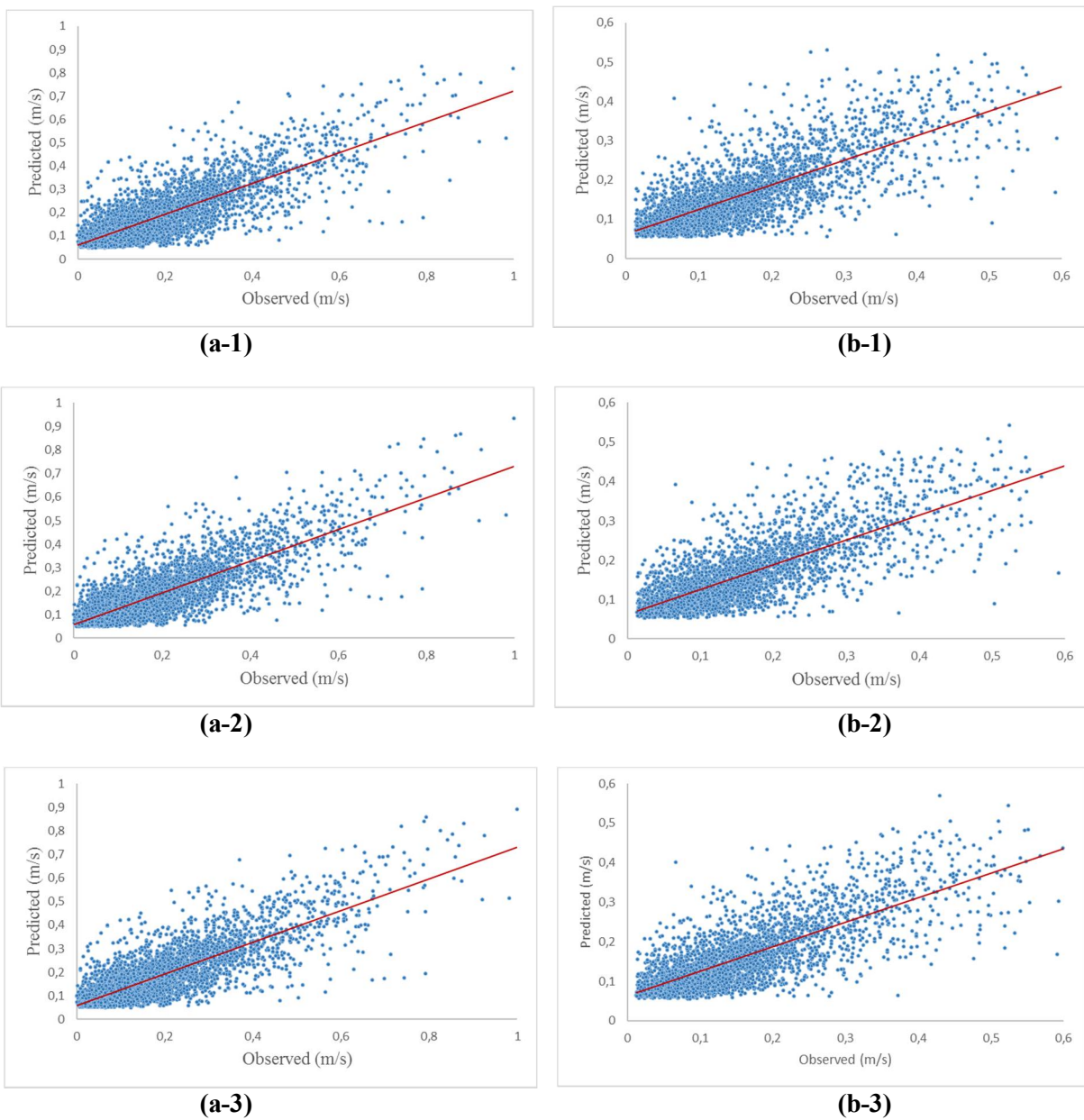
Sub-Model	Membership Function			Errors of Models				Correlations	
	Type	Algorithm	Number	RMSE of Training (%)	RMSE of Test (%)	MAE of Training (%)	MAE of Test (%)	R of Training (%)	R of Test (%)
Mod - 1	gauss	hybrid	1	8,12	6,85	5,72	4,94	81,38	75,97
Mod - 2	gauss	hybrid	2	8,00	6,74	5,65	4,90	82,02	76,63
Mod - 3	gauss	hybrid	3	8,00	6,73	5,65	4,90	82,00	76,71
Mod - 4	gbellmf	hybrid	3	8,02	6,82	5,67	4,94	81,80	76,23
Mod - 5	gauss	hybrid	3	7,79	6,77	5,49	4,93	82,95	76,59
Mod - 6	gbellmf	hybrid	4	7,81	6,81	5,54	4,94	82,83	76,26
Mod - 7	gbellmf	backp	5	8,18	6,91	5,86	5,12	80,92	76,61

4. Results and Conclusion

It can be easily concluded that gumbell and gauss provide better results by taking into consideration other membership functions, such as triangle, trapezoidal and sigmoid transfer. Moreover, hybrid algorithm provides better results in comparison to back propagation.

$RMSE$, MAE and R which are statistical performance indicators are examined to get accuracy of the proposed models quantitatively. All seven proposed models give approximately same result; R values are higher than 0,80 for training data while 0,74 for testing data. Whereas $RMSE$ is less than 0.082 for training data and 0,072 for testing data, MAE value is less than 0.059 for training data and 0,052 for testing data.

Fig. 3 is presented the scatter diagrams, including a for training and b for test data; and the numbers for sub-model; i.e. $a-1$ represents the scatter diagram for training data set of Mod-1.



-continued-

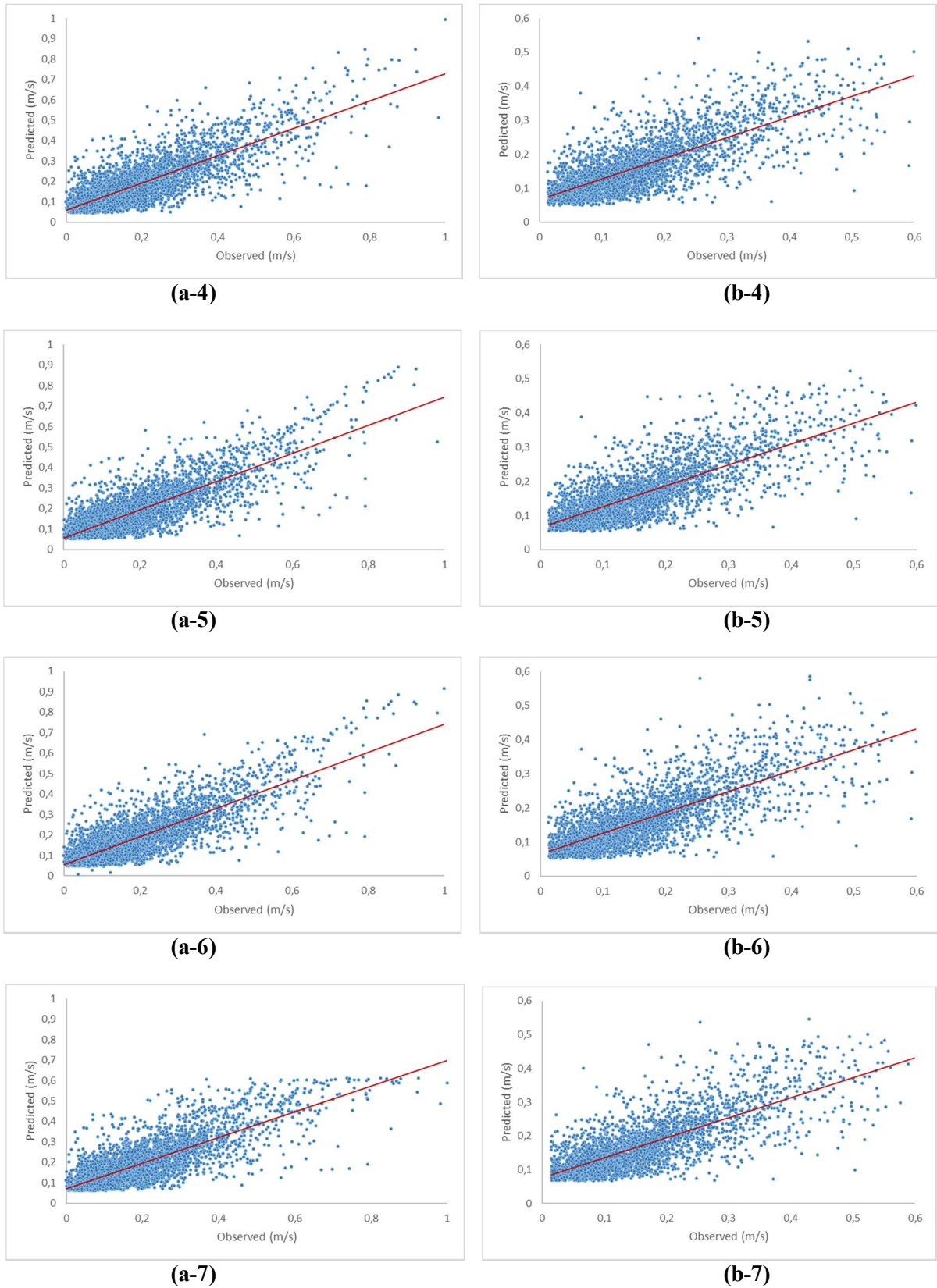


Figure 3. (a) Scatter diagram for training data set using ANFIS (a-1) Mod-1, (a-2) Mod-2, (a-3) Mod-3, (a-4) Mod-4, (a-5) Mod-5, (a-6) Mod-6, (a-7) Mod-7; **(b)** Scatter diagram for test data set using ANFIS (b-1) Mod-1, (b-2) Mod-2, (b-3) Mod-3, (b-4) Mod-4, (b-5) Mod-5, (b-6) Mod-6, (b-7) Mod-7

Mod-3 with gauss membership function and hybrid algorithm gives the best results among the proposed models according to statistical parameters, scatter diagrams, and also surface diagrams obtained from ANFIS.

Consequently, it can be concluded that ANFIS gives reasonable prediction performance for the represented current velocity. ANFIS method can be effectively utilized as a conventional deterministic or statistical model in coastal engineering by taking account the randomness and uncertainty of different predictions problems related to current velocity.

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