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Application of Artificial Neural Network and Fuzzy Inference System in Prediction of Breaking Wave Characteristics

Delavari, Ehsan; Mostafa Gharabaghi, Ahmad Reza*; Chenaghlou, Mohmmad Reza

Faculty of Civil Engineering, Sahand University of Technology, Tabriz, IR Iran

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Abstract

Wave height as well as water depth at the breaking point are two basic parameters which are necessary for studying coastal processes. In this study, the application of soft computing-based methods such as artificial neural network (ANN), fuzzy inference system (FIS), adaptive neuro fuzzy inference system (ANFIS) and semi-empirical models for prediction of these parameters are investigated. The data sets used in this study are published laboratory and field data obtained from wave breaking on plane and barred, impermeable slopes collected from 24 sources. The comparison of results reveals that, the ANN model is more accurate in predicting both breaking wave height and water depth at the breaking point compared to the other methods.

Keywords: *Wave breaking, Breaker depth and height, Artificial neural network, Fuzzy inference system, ANFIS.*

1. Introduction

As a wave train approaches to a beach, its length (L) decreases and its height (H) may increase, leading to the increased wave steepness (H/L). When the wave steepness reaches a limiting value, the wave breaks (USACE, 2008). The wave breaking is one of the most interesting phenomena of wave transformation in the nearshore region (Tsai et al., 2005). Quantitative information about the characteristics of wave breaking at a given location is necessary for studying of the coastal processes such as calculation of wave forces exerted on the coastal structures, estimation of the rate of sediment transport and prediction of wave set up produced by breaking waves. The two basic parameters required in the most design problems are the breaking wave height and the water depth at the breaking point.

In literature, there are several experimental and numerical studies about the wave breaking and different relations are developed to predict the breaking wave characteristics, i.e. the breaking wave height and the water depth at the breaking point. One of the most familiar criteria for breaker waves was presented by McCowan (1894) which determines the ratio of breaking wave height to the water depth at the breaking point to be 0.78. Similar equations are suggested by Weggel (1972), Sunamura and Horikawa (1974), Goda (1975), Komar (1998), and She and Canning (2008) based on the regular waves.

* *E-mail: mgharabaghi@sut.ac.ir*

It should be noticed that these equations are basically developed bythe regression analysis which introduces a direct relation between the variables. However, its accuracy decreases in some complicated situations where there are not any clear relations between the parameters. While the need for further research on the wave breaking phenomenon with its complexities of turbulence and wave nonlinearities, it is also necessary to develop more accurate predictive methods which can estimate the mentioned parameters.

Artificial neural networks (ANNs) are known as soft computing tools with capabilities of maintaining the experience and learning. They do not assume any fixed relationship between the input-output and therefore, they have been recently used for prediction of breaking wave characteristics. Deo and Jagdale (2003) have used ANNs for predicting the breaking wave height as well as the water depth at the breaking point.

In the recent years, fuzzy inference system (FIS) has been employed in different engineering subjects. FIS can be used to predict uncertain systems and its application does not require knowledge of the underlying physical process as a precondition (Kazeminezhad et al., 2005). However, it has some deficiencies. In order to improve the results obtained through this method, the neuro-fuzzy methods such as adaptive neuro fuzzy inference system (ANFIS), which is a combination of ANN and FIS, were defined. These methods have been used in coastal engineering problems such as wave prediction (Kazeminezhad et al., 2005; Ozger, 2009; Sylaios et al., 2009), sediment transport estimation (Bakhtyar et al., 2008; Kisi et al., 2009) and other related fields.

The purpose of this study is to investigate the application of ANN, FIS, and ANFIS methods in prediction of the breaking wave height and the water depth at the breaking point. The results obtained from three developed models are compared with the results of semi-empirical equations.

2. Materials and Methods

2.1. Artificial Neural Networks (ANNs)

An artificial neural network is an information-processing system that has certain performance characteristics in common with biological neural networks. It is one of the artificial intelligence techniques where the intelligence results from communication between different neurons (Jain and Deo, 2006). It is also a useful tool for solving different engineering problems because it can approximate a desired behavior without the need to specify a particular function. This is a big advantage of artificial neural networks compared to multivariate statistics (Wieland and Mirschel, 2008). A neural network is characterized by (1) its pattern of connections between the neurons (called its architecture), (2) its method of determining the weights on connections (learning algorithm), and (3) its activation function (Fausett, 1994). Among the applied neural networks, the feed forward neural networks (FFNN) are the most common used method in solving various engineering problems. FFNN technique consists of layer being fully connected to the preceding layer by weights (Rajaee et al., 2009). Fig. 1 illustrates the common three-layer feed forward type of an artificial neural network.

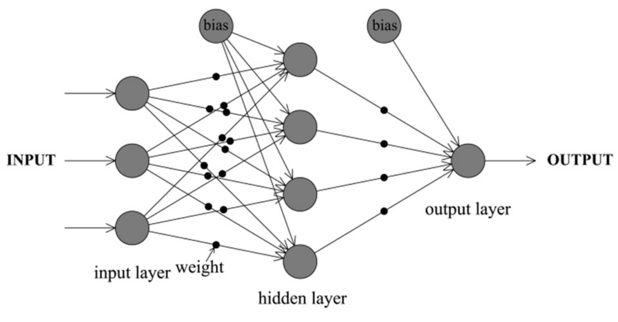

Fig. 1. Schematic representation of three-layer feed forward artificial neural network

Learning of these ANNs is performed by first or second order learning algorithms. Backpropagation, adaptive learning rate and the steepest descent are first-order methods in that they use the first derivative of error (slope) and follow the gradient descent approach. QuickProp, the Gauss-Newton method, and the Levenberg-Marquardt method are second-order methods and they rely on both first and second derivative of error (slope and curvature) in the search for the optimum weights (Samarasinghe, 2007).

In the present study, the Levenberg-Marquardt (LM) algorithm was chosen because of its high-performance and the fastest convergence. It minimizes a predetermined error function (E) of the following form:

$$E = \sum_{P} \sum_{N} (y_i - t_i)^2 \qquad (1)$$

where y_i is the ith component of ANN output vector Y, t_i is the ith component of target output vector T, N is the number of output neurons and P is the number of training patterns.

The LM algorithm uses the following formula to calculate weights (W) in subsequent iterations:

$$W_{new} = W_{old} - [J^T J + \gamma I]^{-1} J^T E(W_{old}) \qquad (2)$$

where J is the Jacobian of the error function E, I is the identity matrix, and γ is the parameter used to define the iteration step value. In this method, γ is chosen automatically until a downhill step is produced for each epoch. Starting with an initial value of γ, the algorithm attempts to decrease its value by increments of $\Delta\gamma$ in each epoch. If the E is not reduced, γ is increased repeatedly until a downhill step is produced (Samarasinghe, 2007).

Several forms of activation functions have been used in ANNs, such as linear, binary sigmoid, bipolar sigmoid, hyperbolic tangent, etc. The hyperbolic tangent function, which was used in this paper, is given by:

$$f(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \qquad (3)$$

More details on the ANN can be found in Fausett (1994) and Samarasinghe (2007).

2.2. Fuzzy Inference Systems (FISs)

The fuzzy inference system (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The basic structure of a fuzzy inference system consists of three conceptual components: (1) a rule base, which contains a selection of fuzzy rules. The general form of a fuzzy if-then rule is as follows: if X is A then Y is B. Often the first part is called the antecedent or premise, while the other part is called the consequence or conclusion; (2) a database, which defines the membership functions used in the fuzzy rules; and (3) a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion.

There are three types of fuzzy inference systems in the literature that have been widely employed in various applications: Mamdani, Sugeno, and Tsukamoto fuzzy inference systems. The differences between these three fuzzy inference systems lie in the consequents of their fuzzy rules.

Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules, it lacks the adaptability to deal with changing external environments. Thus, neural network learning concepts in fuzzy inference systems has been incorporated by various authors, resulting in neuro-fuzzy modeling (Jang et al., 1997).

An adaptive neuro-fuzzy inference system (ANFIS) is a first order Sugeno type FIS in which the premise and consequence parameters of fuzzy if-then rules are optimized by a five layers artificial neural network. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules and three inputs is as follows:

Rule 1: If x_1 is A_1 and x_2 is B_1 and x_3 is C_1, then $f_1 = p_1 x_1 + q_1 x_2 + r_1 x_3 + s_1$, Rule 2: If x_1 is A_2 and x_2 is B_2 and x_3 is C_2, then $f_2 = p_2x_1 + q_2x_2 + r_2x_3 + s_2$.

Fig. 2(a) illustrates the reasoning mechanism for this Sugeno model. The corresponding equivalent ANFIS architecture is as shown in Fig. 2(b). Every node in the first layer is an adaptive node. The output of the layer are degrees of membership of linguistic variables A_i, B_i, and C_i. In the second layer, every node is a fixed one. This layer calculates the firing strength for each rule, whose output of the layer is algebraic product of all the input signals.

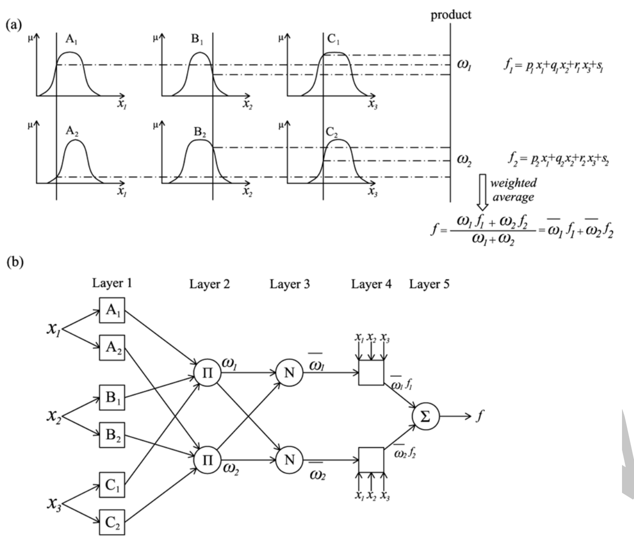

Fig. 2.(a) a first-order Sugeno fuzzy model with two rules (three inputs); (b) equivalent ANFIS architecture.

In the third layer the ith node calculates the ratio of the ith rule's firing strength to the sum of all rule's firing strengths. Every node in this layer is a fixed node. Outputs of the layer are called normalized firing strengths. In the fourth layer the output of an adaptive node obtains from multiplying the normalized firing strength by $f_i = p_ix_1 + q_ix_2 + r_ix_3 + s_i$. The fifth layer, which has a fixed node, computes the overall output as follows:

$$f = \sum_i \overline{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{4}$$

A hybrid learning algorithm is used for learning of neural network. The hybrid learning algorithm consisted of two pass. In the forward pass, node outputs go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, when the consequent parameters are fixed, the error signals propagate backward and the premise parameters (membership functions' parameters) are updated by gradient descent. More detailed information on ANFIS can be found in Jang et al. (1997). There are many various membership functions such as triangular, trapezoidal, bell, and Gaussian functions that can be applied in fuzzy modeling. In this study, since the majority of natural phenomena follow from the Gaussian probabilistic distribution, the Gaussian membership function is used as follows:

$$\mu(x) = \exp\left[-\left(\frac{x-c}{a}\right)^2\right] \tag{5}$$

where $\mu(x)$ is the membership function, a and c are the membership functions' parameters that changes the shape of the membership function. These parameters are referred to as the premise parameters. In this paper, for developing a FIS model with a minimum number of fuzzy rules, a subtractive clustering method is used. In the subtractive clustering method (Chiu, 1994), each data point is considered as a potential cluster center and is defined a measure of the potential for each data point. A data point with many neighboring data points will have high potential value. The data point with high potential value is selected as the first cluster center. Then, the potential of the data points whose distance from a selected cluster center is less than a pre-specified value (cluster radius) are subtracted and the potential values are updated. The procedure continues until holding some conditions.

2.3. Semi-Empirical Models

Semi-empirical models have been developed based on interrelationship among dimensionless parameters. Until now many attempts have been performed to predict the wave breaking characteristics using regression methods (including linear, polynomial and logistic). According to them, beach slope (m) (or seaward slope of bar in barred beach), deep water wave height (H_0), and deep water wave length (L_0) (including wave period (T)), are effective parameters in the prediction of the breaker wave height (H_b) and the water depth at the breaking point (h_b). In Table 1 some of the currently developed equations, in the order of their publication dates, are presented. These equations are used to evaluate the efficiency and exactness of newly proposed models.

3. Data Set

The data sets used in this paper are the published laboratory and field data obtained from the wave breaking on the plane and barred, impermeable slopes. These data on the breaking wave height and the water depth at the breaking point are obtained from different sources which are summarized in Table 2.

For modeling, the data set is divided into two parts: training and testing set. The training and testing data set are used for learning and evaluating the developed models, respectively.

In order to predict the breaking wave height, 662 data points of total 701 data were selected of which almost 80 percents of data points (532 data points) were used as the training set and the remaining as the testing set. Also 644 data points of total 701 data were selected for predicting the water depth at the breaking point of which 519 data points (almost 80 percents) were used as the training set and125 data points as the testing set. In Table 3, the statistical characteristics of training and testing data set used in predicting the breaking wave height are presented. Also, the statistical characteristics of the data points used in predicting the water depth at the breaking point are presented in Table 4.

4. Results and Discussion

At first, two artificial neural networks were developed, separately, using training data to predict the breaking wave height and the water depth at the breaking point. Before learning the ANNs, the training input and output values are normalized in the range of -1 to 1, using the following equation:

$$x' = 2\frac{x - x_{min}}{x_{max} - x_{min}} - 1 \quad (19)$$

where x_{min} and x_{max} denotes the minimum and maximum of data set.

After examining different topologies with tangent hyperbolic activation function, the best topology for both models was found to be $3 \times 7 \times 1$. Three input neurons are beach slope (m)(or seaward slope of bar in barred beach), wave period (T) and deep water wave height (H0), seven hidden neurons and one output neuron that is breaking wave height (Hb) and water depth at the breaking point (hb), in each model, separately. Despite semi-empirical models, in this study, we have used dimensional parameters due to some deficiencies in the published laboratory and field data. Of course, as an advantage, this eliminates the need for trial and error process for predicting the breaking wave characteristics. Number of hidden neurons was chosen according to Kolmogorov's theorem. As a result of it, the number of hidden neurons is preferably not greater than one plus twice the input neurons (Zijderveld, 2003):

$$h \leq 2n + 1 \quad (20)$$

in which h and n are number of hidden and input neurons, respectively.

After learning, the developed ANNs are evaluated using the testing data. The comparison between observed and predicted breaking wave height and water depth at the breaking point using the testing data are shown in Fig. 3 and 4, respectively.

Table 1. Currently presented equations for prediction of breaking wave characteristics.

Authors	formula	Eq. no.
Galvin (1969)	$h_b/H_b = 0.92$ if $m \geq 0.07$; $h_b/H_b = 1.40 - 6.85m$ if $m \leq 0.07$	6
Collins and Weir (1969)	$H_b/h_b = 0.72 + 5.6m$	7
Weggel(1972)	$H_b/h_b = b - a(H_b/gT^2)$; $a = 43.75[1 - \exp(-19m)], b = 1.56/[1 + \exp(-19.5m)]$	8
Komar and Gaughan(1973)	$H_b/H_0 = 0.56(H_0/L_0)^{-1/5}$	9
Goda(1975)	$H_b/L_0 = 0.17\{1 - \exp[-1.5\pi(h_b/L_0)(1 + 15m^{4/3})]\}$	10
Battjes(1974)	$H_b/h_b = 1.062 + 0.137 \log\left(m/\sqrt{H_0/L_0}\right)$	11
Sunamura and Horikawa(1974)	$H_b/H_0 = m^{0.2}(H_0/L_0)^{-0.25}$	12
Singamsetti and Wind (1980)	$H_b/h_b = 0.937\, m^{0.155}(H_0/L_0)^{-0.13}$	13
Sunamura(1981)	$H_b/h_b = 1.1\left(m/\sqrt{H_0/L_0}\right)^{1/6}$	14
Komar(1998)	$H_b = 0.39g^{0.2}(TH_0^2)^{0.4}$	15
	$h_b = H_b\{1.2[m/(H_b/L_0)^{0.5}]^{0.27}\}$	16
She and Canning (2007)	$H_b/gT^2 = \alpha \tanh[\beta(h_b/gT^2)^\gamma]$; $\alpha = 0.0277, \beta = 152m + 6.6$ if $m \geq 0.073, \beta = 17.7$ if $m < 0.073$; $\gamma = 1.92m + 0.72$ if $m \geq 0.094,\quad \gamma = 0.9$ if $m < 0.094$	17
Camenen and Larson (2007)	$H_b/h_b = \left(0.284/\sqrt{(H_0/L_0)}\right)\tanh\left[f_*(m, H_0/L_0)\pi\sqrt{H_0/L_0}\right]$; $f_*(m, H_0/L_0) = A_1 + A_2 \sin\{(\pi/2)(m/m_{max})^\alpha\}, m_{max} = 0.10 + 1.6\, H_0/L_0,$ $\alpha = 1 + 14\, H_0/L_0$ if $m \leq m_{max}$; $\alpha = -(1 + 20\, H_0/L_0)$ if $m > m_{max}$, $A_1 = 0.87, A_2 = 0.32 + 14\, H_0/L_0$	18

Table 2. Summary of collected laboratory and field data.

source	*Conditions*	*m*	*T (sec)*	H_0/L_0	Number of data
Munk (1949)+	Laboratory data/Plane beach	0.009-0.159	0.86-1.97	0.007-0.0092	53
Munk (1949)+	Field data/Plane beach	0.04	6.5-13.7	0.0042-0.0316	74
Iversen (1952)*	Laboratory data/Plane beach	0.02-0.1	0.74-2.67	0.0025-0.0907	68
Morison and Crooke (1953)+	Laboratory data/Plane beach	0.02-0.1	0.78-2.62	0.0036-0.0778	6
Horikawa and Kuo (1967)*	Laboratory data/Plane beach	0.0125-0.05	1.2-2.3	0.006-0.073	97
Komar and Simmons (1968)+	Laboratory data/Plane beach	0.036-0.105	0.81-2.37	0.0032-0.071	44
Galvin (1968)+	Laboratory data/Plane beach	0.05-0.2	1.0-8.0	0.0002-0.056	43
Galvin (1969)*	Laboratory data/Plane beach	0.05-0.2	1.0-6.0	0.0007-0.0503	22
Saeki and Sasaki (1973)*	Laboratory data/Plane beach	0.02	1.3-2.5	0.005-0.039	2
Iwagaki et al. (1974)*	Laboratory data/Plane beach	0.03-0.1	1.0-2.0	0.005-0.073	23
Walker (1974)*	Laboratory data/Plane beach	0.033	1.17-2.33	0.001-0.038	15
Singamsetti and Wind (1980)*	Laboratory data/Plane beach	0.025-0.2	1.03-1.73	0.017-0.08	95
Mizuguchi (1981)*	Laboratory data/Plane beach	0.1	1.2	0.045	1
Visser (1982)*	Laboratory data/Plane beach	0.05-0.1	0.7-2.01	0.014-0.079	7
Maruyama et al. (1983)*	Laboratory data/Plane beach	0.034	3.1	0.091	1
Stive(1984)	Laboratory data/Plane beach	0.025	1.79-3.0	0.01-0.032	2
Smith and Kraus (1990)	Laboratory data/Plane beach	0.033	1.02-2.49	0.009-0.092	5
Smith and Kraus (1990)	Laboratory data/Barred beach	0.08-0.437	1.01-2.49	0.008-0.095	77
Ting and Kirby (1995, 1996)	Laboratory data/Plane beach	0.0286	2.0-5.0	0.0023-0.02	2
Hoque(2002)	Laboratory data/Plane beach	0.1053	1.12-1.8	0.024-0.076	6
Deo and Jagdale(2003)	Laboratory data/Plane beach	0.033-0.1	0.74-1.2	0.0419-0.1272	20
Cox and Shin (2003, 2006)	Laboratory data/Plane beach	0.0286	1.5-3.0	0.0055-0.0362	4
Scott et al. (2005)	Laboratory data/Barred beach	0.054	4.0	0.0256	1
Tomasicchio(2006)	Laboratory data/Barred beach	0.033	2.5-3.5	0.0072-0.0114	3
Okamoto and Basco(2006)	Laboratory data/Plane beach	0.033	1.6-3.8	0.012-0.046	27
Mori and Kakuno(2008)	Laboratory data/Plane beach	0.033	1.6-3.8	0.012-0.046	3

+: Data from Gaughan et al. (1973)
*: Data from Smith and Kraus (1990)

Table 3. The statistical characteristics of data points used in predicting the breaking wave height.

Training data (numbers =532)					**Testing data (numbers =130)**			
	m	**T (sec)**	**H_0 (m)**	**H_b (m)**	**m**	**T (sec)**	**H_0 (m)**	**H_b (m)**
Min.	0.009	0.73	0.0104	0.0150	0.009	0.7	0.0137	0.0305
Max.	0.4366	13.7	2.46	3.05	0.3757	12.5	3.0	3.47
Avg.	0.0798	2.65	0.2604	0.3386	0.0838	2.51	0.2921	0.3663
SD*	0.0753	2.74	0.4966	0.6694	0.0767	2.73	0.5578	0.7185

*SD: Standard Deviation

Table 4. The statistical characteristics of data points used in predicting the water depth at the breaking point.

Training data (numbers =519)					**Testing data (numbers =125)**			
	m	**T (sec)**	**H_0 (m)**	**h_b (m)**	**m**	**T (sec)**	**H_0 (m)**	**h_b (m)**
Min.	0.009	0.7	0.0137	0.0335	0.009	0.74	0.0104	0.0305
Max.	0.4366	13.70	3.0	4.45	0.3757	10.5	2.36	3.87
Avg.	0.0773	2.54	0.2788	0.4478	0.0738	2.29	0.2581	0.4064
SD	0.0743	2.78	0.5222	0.9025	0.0758	2.42	0.5026	0.8618

The other prediction model developed is ANFIS model. Two ANFIS models were developed using the training data; the first one as a breaking wave height predictor and the second one as a water depth at the breaking point predictor. At first, using the subtractive clustering method and the training data including deep water wave height, wave period and beach slope (or seaward slope of bar in barred beach) as input parameters, a FIS model was developed. The developed FIS model was then used as an initial FIS for ANFIS model.

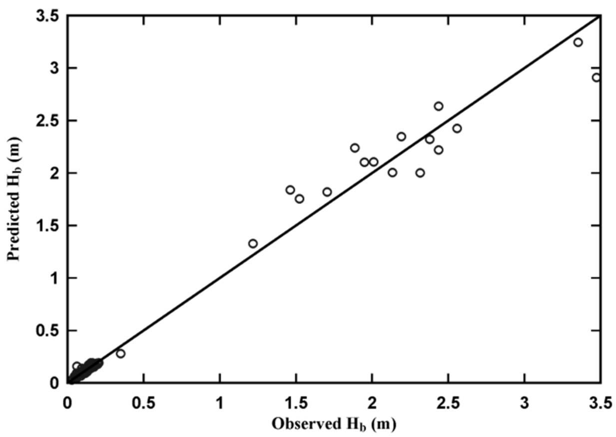

Fig. 3. Comparison between observed and predicted values obtained from ANN model for breaking wave height.

After developing FIS and ANFIS models, testing data were used to evaluate the accuracy of the developed models. Fig. 5 and 6 shows the comparison between observed and predicted breaking wave height and water depth at the breaking point using the developed FIS models, respectively. These mentioned results are for testing data.

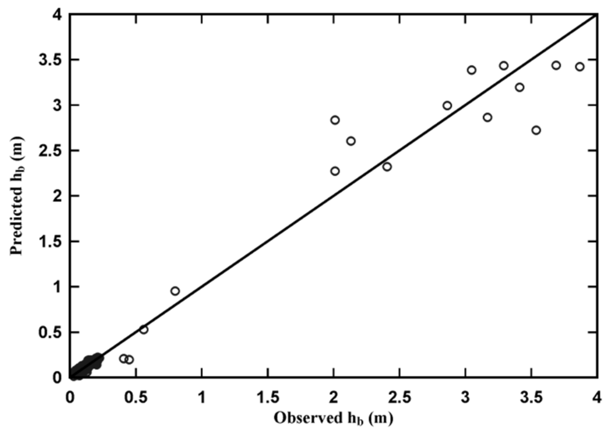

Fig. 4. Comparison between observed and predicted values obtained from ANN model for water depth at the breaking point.

Also the observed and predicted breaking wave characteristics obtained from the ANFIS models are shown in Fig .7 and 8. As it is shown the breaking wave height and the water depth at the breaking point were slightly unbiased in all of these three developed models, especially for the large scale field data. Moreover, it can be noticed that in all Figs, there are some gaps between the greater and smaller values which it is due to the difference between the large scale, field data and the small scale laboratory data.

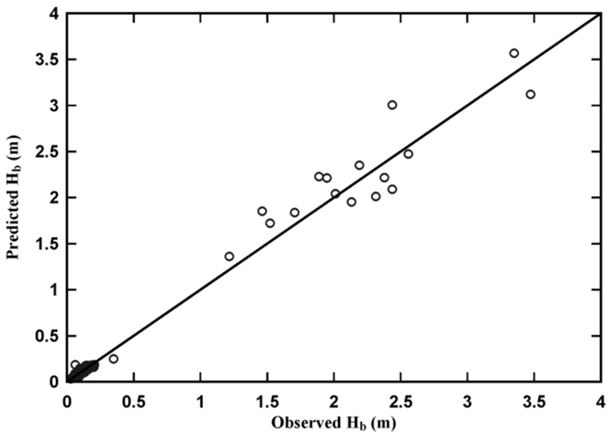

Fig. 5. Comparison between observed and predicted values obtained from FIS model for breaking wave height.

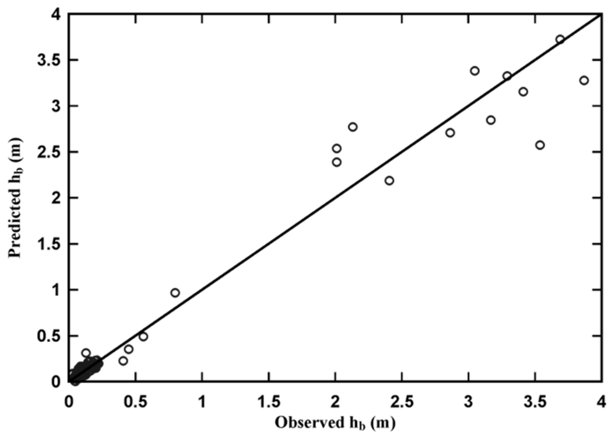

Fig. 6. Comparison between observed and predicted values obtained from FIS model for water depth at the breaking point.

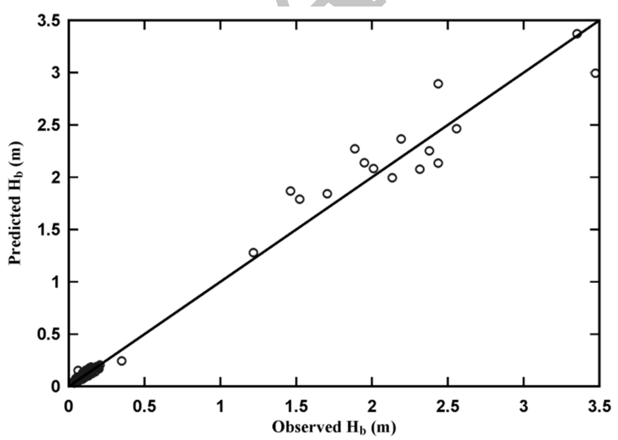

Fig. 7. Comparison between observed and predicted values obtained from ANFIS model for breaking wave height.

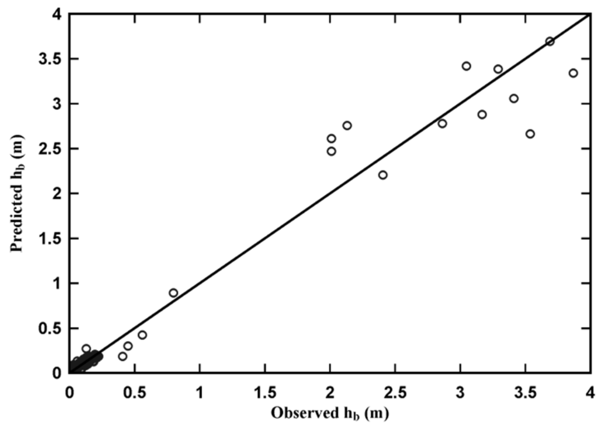

Fig. 8. Comparison between observed and predicted values obtained from ANFIS model for water depth at the breaking point.

Fig. 9 shows the initial and Fig. 10 shows the final membership functions of input variables for breaking wave height prediction.

It is seen that there is a considerable change in the shape of membership functions of beach slope after training. The change in the shape of membership function of deep water wave height is also considerable but its change is less important than the beach slope. For deep water wave heights greater than 0.5 m, the values of membership functions become almost zero. It is due to the smaller number of large scale, field data compared to small scale, experimental data which leads to the effects of field data (the deep water wave heights greater than 0.5 m) become smaller than the experimental data. The initial and final membership functions of three input variables for water depth at the breaking point prediction is shown in Fig. 11 and Fig. 12, respectively. As can be seen the maximum change in the shape of membership functions after training belongs to the beach slope. The change in the shape of membership functions of two other variables is not as significant as beach slope. As a result, the beach slope parameter is an important and sensible variable in prediction of both the breaking wave height and the water depth at the breaking point.

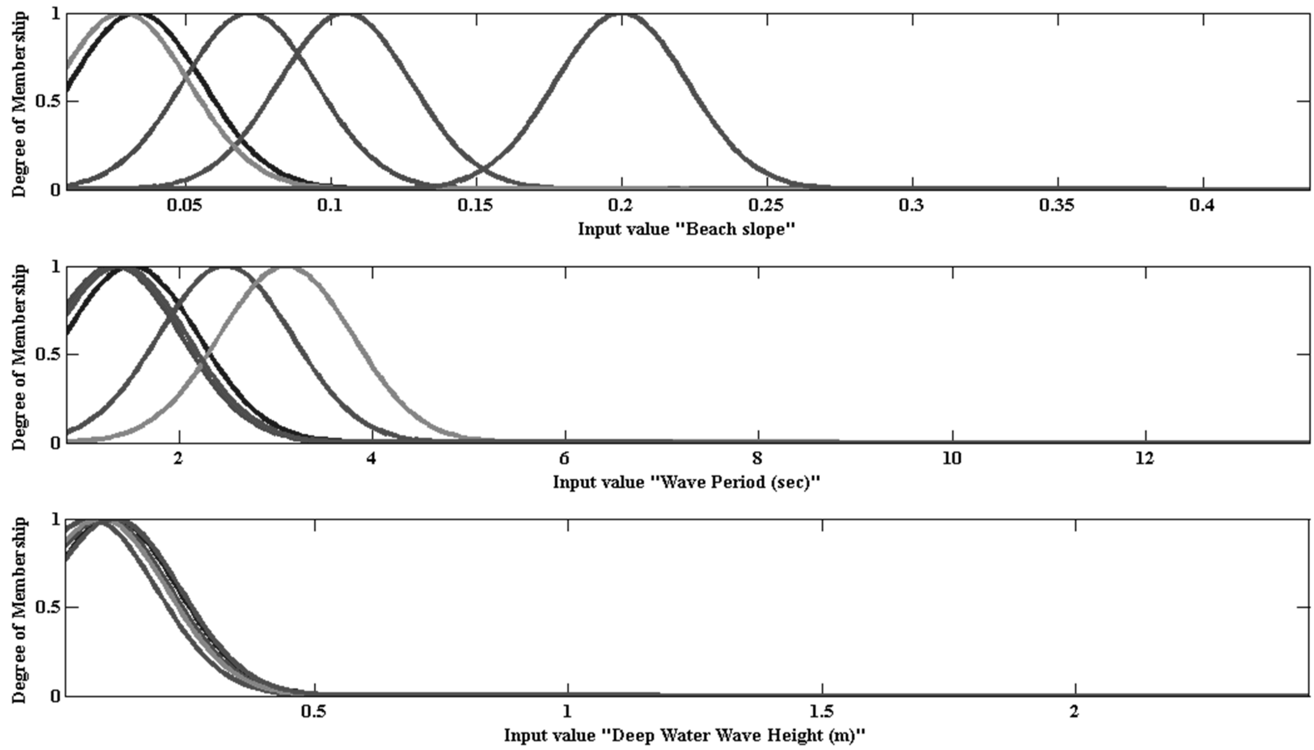

Fig. 9. Initial membership functions of input variables in predicting the breaking wave height

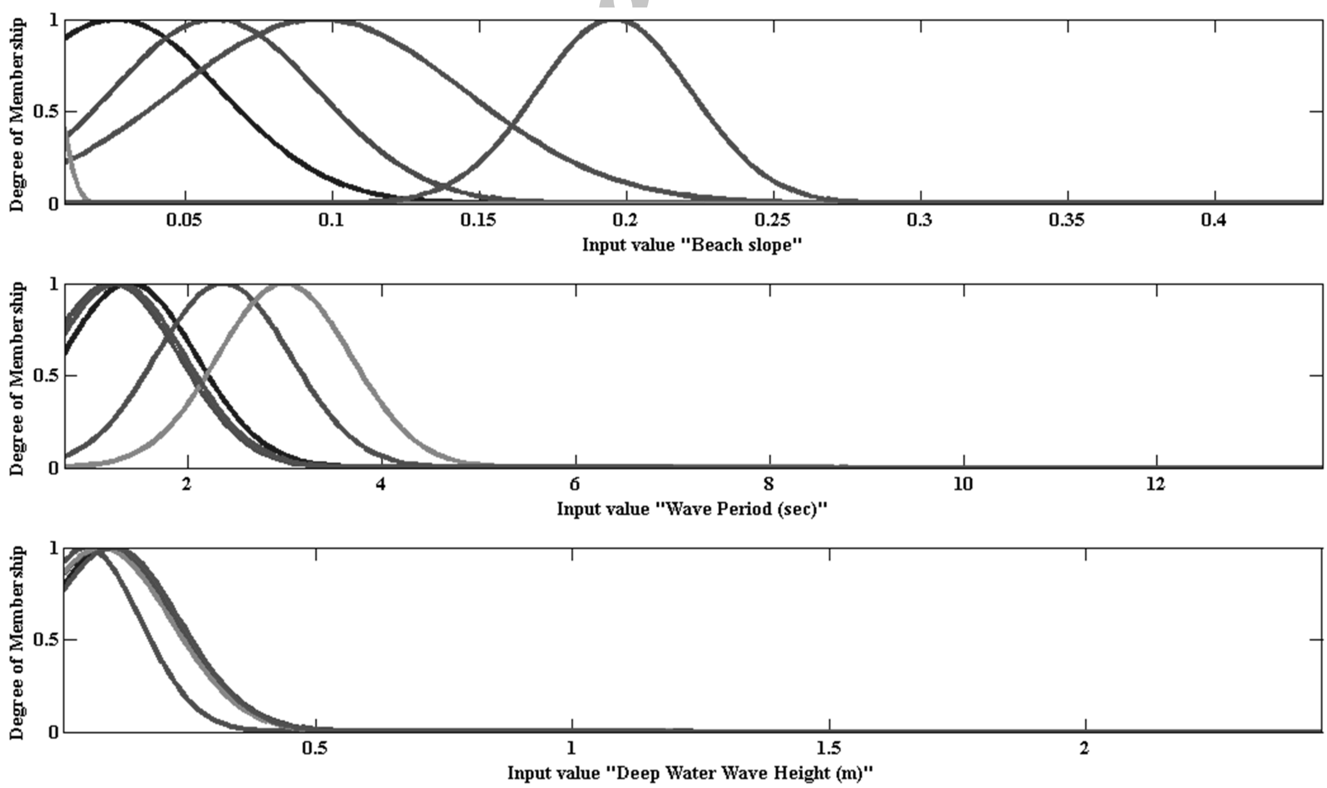

Fig. 10. Final membership functions of input variables in predicting the breaking wave height

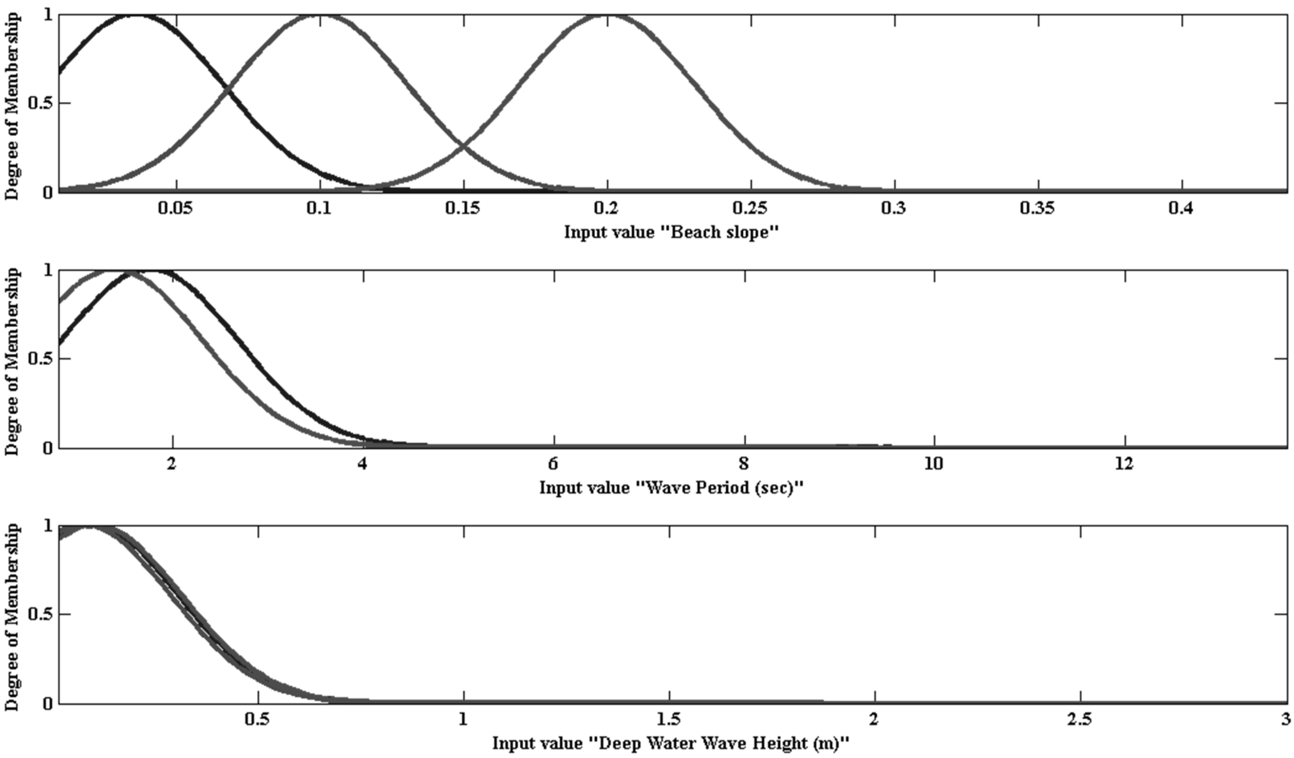

Fig. 11. Initial membership functions of input variables in predicting the water depth at the breaking point

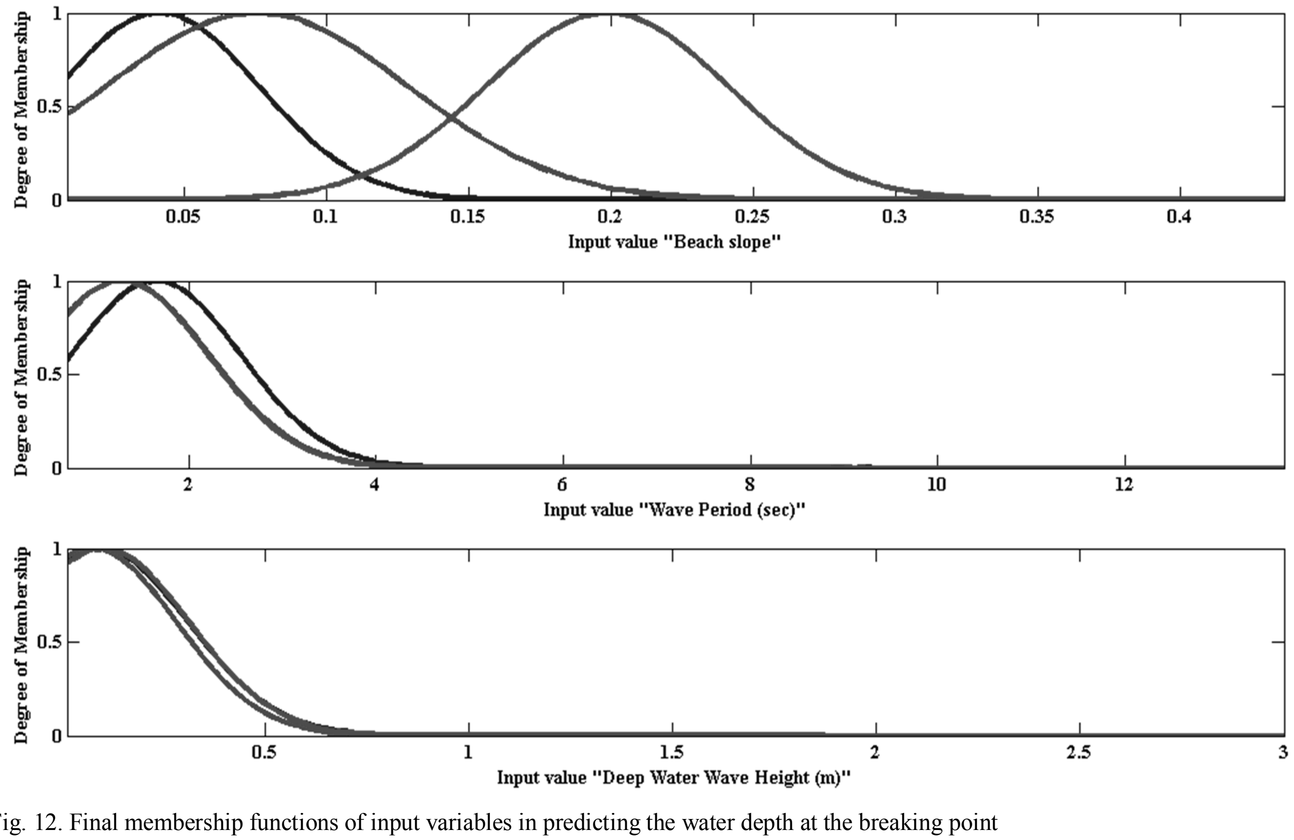

Fig. 12. Final membership functions of input variables in predicting the water depth at the breaking point

A statistical comparison between the observed and predicted parameters of wave breaking characteristics was studied to evaluate the developed soft computing models as well as the previous semi-empirical equations using bias, mean absolute error (MAE), root mean square error (RMSE), scatter index (SI) and correlation coefficient (CC) which are defined as follows:

$$\mathrm{bias} = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i) \qquad (21)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - t_i| \qquad (22)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2} \qquad (23)$$

$$\mathrm{SI} = \frac{\mathrm{RMSE}}{\text{average observed value}} \times 100 \qquad (24)$$

$$\mathrm{CC} = \frac{\sum_{i=1}^{N}(t_i - \bar{t}_m)(y_i - \bar{y}_m)}{\sqrt{\left(\sum_{i=1}^{N}(t_i - \bar{t}_m)^2\right)\left(\sum_{i=1}^{N}(y_i - \bar{y}_m)^2\right)}} \qquad (25)$$

where N is the number of observations; t_i is an observed value; y_i is a predicted value; $\bar{t}_m$ is the observed mean value; and $\bar{y}_m$ is the predicted mean value.

Table 5 shows the error statistics of the proposed ANN, FIS and ANFIS models as well as preceding equations for predicting the breaking wave height. These errors are related to the testing data. As shown, the error statistics of the FIS model is larger than those of the ANN model. Also, the bias and MAE of this model are larger than the equation of Komar and Gaughan (1973). However, after training the FIS model, the errors related to the ANFIS model has become lower than the FIS model and also above mentioned equation but it is still larger than the errors related to the ANN model. The bias of the proposed ANFIS model is 0.0072m which is still slightly larger than the bias of the equation of Komar and Gaughan (1973) that is equal to 0.0069m. As can be seen the errors of ANN model developed for predicting of breaking wave height is less than the other methods. The MAE, RMSE and SI of the ANN model are 0.0369m, 0.0872 m and 23.81%, respectively. These are lower values compared to the other methods. Furthermore, the bias of the proposed ANN model is minimum value between the others and is equal to 0.0029mwhich it means that it overestimates the breaking wave height.

The statistical comparison of the predicted values for the water depth at the breaking point is shown in Table 6. According to this table, the minimum MAE, RMSE and SI belong to the proposed ANN model with values of 0.0562m, 0.1382m and 34.00%, respectively. The bias of the proposed ANN model is 0.0002 and it overestimates the water depth at the breaking point. As shown, the minimum value of bias belongs to the proposed ANN model. It can be noticed that the error statistics of three proposed models are considerably lower than the preceding equations, for example they have decreased the RMSE between 45 to 158%. As a result, although a small number of field data has been used in this study, the results obtained from the testing data including both laboratory and field data show that the ANN and ANFIS models proposed in this study provide better predictions for the estimation of the breaking wave height and the water depth at the breaking point, compared to the other methods. Using of a larger number of the field data can even lead to more accurate results. Of course, it is obvious that the results are valid in the range of the data reported in table 2.

5. Conclusions

In this study, using soft computing tools such as ANNs, FIS and ANFIS, some models were developed to predict the breaking wave characteristics. With the purpose of developing these models, the published laboratory and field data of wave breaking on plane and barred, impermeable slopes is used.

Table 5. Statistics of the predicted breaking wave height using the testing data.

Methods	Average observed value (m)	Average predicted value (m)	bias (m)	MAE (m)	RMSE (m)	SI (%)	CC
Galvin (1969)	0.3663	0.4022	0.0359	0.0513	0.1379	37.65	0.9884
Collins and Weir (1969)	0.3663	0.4501	0.0838	0.0874	0.1925	52.54	0.9856
Weggel(1972)	0.3663	0.4468	0.0804	0.0845	0.2268	61.93	0.9870
Komar and Gaughan(1973)	0.3663	0.3732	0.0069	0.0404	0.0994	27.12	0.9908
Goda(1975)	0.3663	0.4225	0.0562	0.0663	0.1554	42.42	0.9870
Battjes(1974)	0.3663	0.4439	0.0776	0.0829	0.2229	60.85	0.9882
Sunamura and Horikawa (1974)	0.3663	0.4435	0.0772	0.0810	0.1899	51.87	0.9897
Singamsetti and Wind (1980)	0.3663	0.4432	0.0769	0.0824	0.2319	63.30	0.9850
Sunamura(1981)	0.3663	0.4123	0.0460	0.0584	0.1659	45.31	0.9869
Komar(1998), Eq. 15	0.3663	0.3754	0.0091	0.0407	0.1006	27.46	0.9908
She and Canning (2007)	0.3663	0.3750	0.0087	0.0524	0.1294	35.33	0.9870
Cammenen and Larson (2007)	0.3663	0.4028	0.0365	0.0518	0.1497	40.86	0.9880
ANN	0.3663	0.3692	0.0029	0.0369	0.0872	23.81	0.9926
FIS	0.3663	0.3745	0.0082	0.0419	0.0987	26.94	0.9909
ANFIS	0.3663	0.3735	0.0072	0.0404	0.0945	25.79	0.9914

Table 6. Statistics of the predicted water depth at the breaking point using the testing data.

Methods	Average observed value (m)	Average predicted value (m)	bias (m)	MAE (m)	RMSE (m)	SI (%)	CC
Galvin (1969)	0.4064	0.3505	-0.0559	0.0661	0.2116	52.08	0.9844
Collins and Weir (1969)	0.4064	0.3229	-0.0835	0.0877	0.2478	60.98	0.9840
Weggel(1972)	0.4064	0.3176	-0.0888	0.0947	0.2855	70.25	0.9825
Battjes(1974)	0.4064	0.3168	-0.0896	0.0932	0.2804	68.99	0.9838
Singamsetti and Wind (1980)	0.4064	0.3229	-0.0835	0.0909	0.2828	69.58	0.9816
Sunamura(1981)	0.4064	0.3451	-0.0613	0.0725	0.2359	58.04	0.9828
Komar(1998), Eq. 16	0.4064	0.2775	-0.1289	0.1386	0.3566	87.74	0.9842
Cammenen and Larson (2007)	0.4064	0.3520	-0.0544	0.0694	0.2284	56.20	0.9832
ANN	0.4064	0.4066	0.0002	0.0562	0.1382	34.00	0.9870
FIS	0.4064	0.4042	-0.0022	0.0630	0.1464	36.01	0.9855
ANFIS	0.4064	0.4068	0.0004	0.0599	0.1444	35.52	0.9858

For each method, two separate models were established with outputs of breaking wave height and water depth at the breaking point. The inputs were deep water wave height, wave period and beach slope (seaward slope of bar in barred beach). A comparison between the semi-empirical models and the proposed ANN, FIS and ANFIS models indicate that the errors of the ANN model in predicting the breaking wave height and the water depth at the breaking point are less than those of the other methods. In addition, the errors of the FIS and ANFIS models in prediction of the water depth at the breaking point were also very lower than those of the semi-empirical equations. As a general result, soft computing methods are able to considerably improve the prediction of the characteristics of uncertain, complicated wave breaking phenomenon.

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