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ORIGINAL ARTICLE

Predicting temporal rate coefficient of bar volume using hybrid artificial intelligence approaches

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Abstract To project the structures to be built in the coastal zone and to make the best use of the coastal area, the mechanism of sediment transport, including both longshore and cross-shore transport, in this region should be well known. Within this context, temporal change rate of cross-shore sediment transport is of vital importance, especially to predict the erosion quantitatively. In this study, hybrid artificial intelligence models based on physical model data were established to determine the α coefficient used to describe the temporal change of cross-shore sediment transport. Teaching–learning-based optimization (TLBO) and artificial bee colony (ABC) algorithms were used for training of artificial neural network (ANN) in the model setup. Then, these models were compared with the classical back propagation ANN (ANN-BP) model. Wave height and period, bed slope and sediment diameter were considered as input parameters in the models. In all models, the used data for training and testing sets were 42 and 10 of total 52 experimental data, respectively. In the end of the analyses, it has been determined that the ANN-TLBO and ANN-ABC models have resulted in better results than the BP models. Also, the smallest mean absolute error and root mean square error values for testing set have been obtained from the ANN-TLBO model with 0.0068 and 0.0081, respectively. Therefore, it has been concluded that the best model ANN-TLBO can be successfully applied to predict the α coefficient.

Keywords Bar volume · Neural networks · Sediment transport · Teaching–learning-based optimization · Artificial bee colony

1 Introduction

It is necessary to know the mechanism of sediment transport in coastal area to not only design the coastal structures but also understand the features and make best use of coastal zone. Coastal structures are generally built on coastal area in the nearshore zone, which has a very complex nature. In this region, especially in the sandy coast, the sediment, which forms the bottom, moves to various directions, as both longshore and cross-shore transport. Therefore, the interaction between structures and coast must be well known in all of the studies carried out on the coast.

Most of the studies in literature related to cross-shore sediment transport focused on the prediction of coastal profile geometry. Watanabe et al. [1] analyzed the cross-shore sediment transport using the laboratory test data on two-dimensional beach deformation. Larson [2] developed a numerical model to evolution beach profile and to calculate the cross-shore transport rate under random waves. Hsu [3] conducted a series of experiments to investigate the geometric characteristics of a storm profile. Rozynski [4] proposed empirical orthogonal functions to determine the characteristic evolution patterns of multiple longshore bars at a coastal segment of the Baltic coast. Günaydın and Kabdaşlı [5] carried out an experimental investigation of coastal erosion under the effect of regular and irregular waves. The results of the study suggest that the wave types, whether regular of irregular, were not effective in describing the geometric characteristics of coastal erosion. Günaydın and Kabdaşlı [6] also investigated bar geometry

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using both regular and irregular waves and proposed new empirical formulas to determine the geometric parameters. Kömürcü et al. [7] studied cross-shore sediment movement and coastal profiles using a physical model. They proposed dimensional and non-dimensional equations by regression methods through the experimental data. Kömürcü et al. [8] obtained 80 experimental data for offshore bar geometric parameters. The experimental results in the study were evaluated by the genetic algorithms. Özölçer [9] performed experimental study to determine coastal erosion geometry under the influence of the regular waves and proposed the regression equations. Demirci and Aköz [10, 11] carried out the experiments to investigate the geometrical characteristics of beach profiles under storm conditions. Demirci and Aköz [12] also developed non-dimensional equations to determine various bar geometric parameters using linear and non-linear regression methods through the experimental data. Demirci et al. [13, 14] investigated bar volumes caused by cross-shore sediment transport using experimental data with regular waves.

A few studies have been performed to evaluate the temporal variation of cross-shore sediment transport. Kankal [15] studied the temporal variation of cross-shore sediment transport using a physical model and performed regression analysis to determine temporal rate coefficient. Kankal et al. [16] conducted regression and artificial neural network (ANN) analysis to obtain empirical temporal rate coefficient and concluded that the ANN gave better results than regression analysis.

Nowadays, ANN has become one of the most effective and reliable modeling techniques in different research areas. The model with hybrid ANN approaches has increased considerably due to their power to solve different problems. The use of these models not only significantly improves the performance of models, but also resolved different types of problems with more accurately [17]. Although ANN approaches have found wide variety of application in solving problems related to coastal engineering [18], studies using hybrid ANN models in this area are few [19–21]. Artificial bee colony (ABC) and especially teaching–learning-based optimization (TLBO) are recently proposed meta-heuristic methods which are generally used to solve combinatorial optimization problems [22]. In this study, novel, simple and robust optimization algorithms called TLBO and ABC were used to find optimum coefficients in the ANN analysis.

The main purpose of the present study is to investigate the ability of ANN models including different training algorithm namely TLBO, ABC, and back propagation (BP) for predicting temporal rate coefficient (α) of bar volume. Initial bed slope (m), wave height (H_0), wave period (T) and grain size (d_{50}) obtained from experimental study were used as input variables in the models. To the best of our knowledge, this is the first study related to coastal engineering in the literature that used the TLBO and ABC algorithms in the training procedure of ANN approach.

2 Experimental design

2.1 Apparatus and measuring method

The experiments were performed at the wave flume facility of Karadeniz Technical University, Trabzon, Turkey. The wave flume featured dimensions of 30 m length, 1.4 m width, and 1.2 m depth. The wave generator is located at the beginning of the flume, which has a sandy beach model at the end (Fig. 1). The wave characteristics were measured using three wave gauges and recording units. In each case, reflection coefficients in the experiments were estimated to be less than 7.1% (actually it changes between 2.2 and 7.1%). The flume was divided into 70 longitudinal sections and each section was divided into three horizontal measuring points (i.e., three depths were measured and averaged in a section) and 210 total points were measured during an experiment (Fig. 2). A uniform measurement grid of 20 × 20 cm was surveyed within the mesh. At each point and time of interest, sand elevations above the basin floor were simply measured [7, 8, 16].

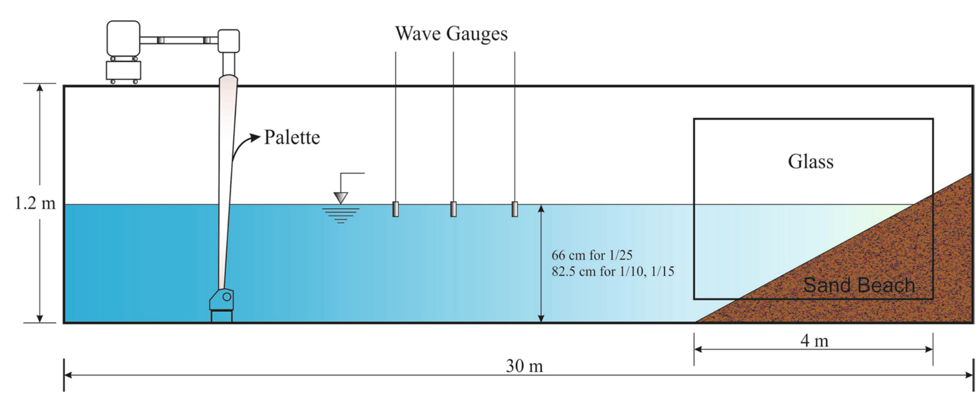

Fig. 1 Wave flume used in experiment

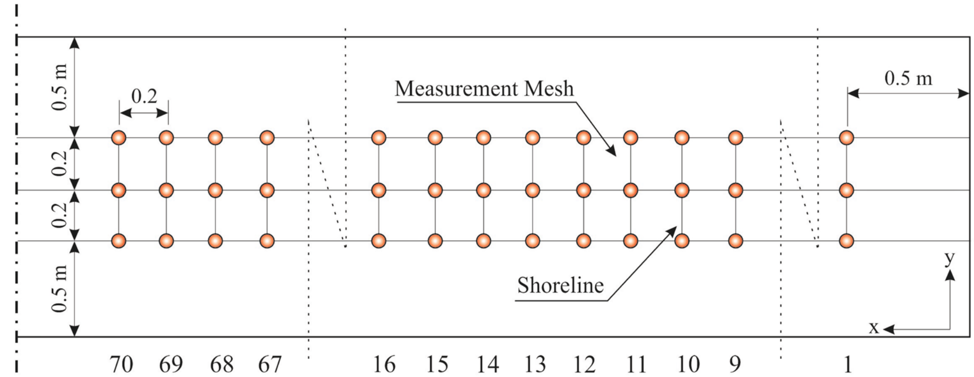

Fig. 2 Measurement mesh in wave flume

2.2 Wave conditions and experimental implementation

The experiments performed to investigate the variation in the coastal profile under different scenarios. A Froude model scale of 1:25 under undistorted conditions was designed to prepare the experimental studies. Monochromatic waves were used in all experiments. Wave conditions were chosen to be between a maximum and minimum to originate the erosion profile, as would be in nature, in order to examine the considered parameters. The seven deepwater wave heights (H_0), two wave period (T), three initial bed slopes, and four granular materials were chosen as seen in Table 1. The specific gravity of the granular materials was 2.55 t/m^3. The uniformity of materials is important aspect for sediment transport. As materials uniformly distributed around the same diameter closely move each other, the determination of diameters in these materials is, therefore, strictly considered.

Table 1 Experiment conditions

Exp. no	m	T (s)	H_0 (m)	d_{50} (m)	Exp. no	m	T (s)	H_0 (m)	d_{50} (m)
01	0.1000	1.46	0.065	0.00018	27	0.0667	2.03	0.200	0.00018
02	0.1000	1.46	0.115	0.00018	**28**	**0.0667**	**1.46**	**0.065**	**0.00026**
03	0.1000	1.46	0.200	0.00018	29	0.0667	1.46	0.115	0.00026
04	0.1000	1.46	0.230	0.00018	**30**	**0.0667**	**1.46**	**0.200**	**0.00026**
05	0.1000	1.46	0.260	0.00018	31	0.0667	1.46	0.230	0.00026
06	0.1000	1.46	0.300	0.00018	32	0.0667	1.46	0.300	0.00026
07	0.1000	2.03	0.115	0.00018	**33**	**0.0667**	**2.03**	**0.200**	**0.00026**
08	0.1000	2.03	0.160	0.00018	34	0.0667	1.46	0.115	0.00033
09	0.1000	2.03	0.200	0.00018	35	0.0667	1.46	0.200	0.00033
10	0.1000	1.46	0.160	0.00026	36	0.0667	1.46	0.300	0.00033
11	0.1000	1.46	0.230	0.00026	37	0.0667	2.03	0.115	0.00033
12	**0.1000**	**1.46**	**0.300**	**0.00026**	38	0.0667	2.03	0.160	0.00033
13	0.1000	2.03	0.115	0.00026	**39**	**0.0667**	**2.03**	**0.200**	**0.00033**
14	0.1000	2.03	0.160	0.00026	40	0.0667	1.46	0.160	0.00040
15	0.1000	1.46	0.115	0.00033	41	0.0667	1.46	0.260	0.00040
16	**0.1000**	**1.46**	**0.160**	**0.00033**	42	0.0667	1.46	0.300	0.00040
17	0.1000	1.46	0.200	0.00033	43	0.0400	1.46	0.115	0.00018
18	0.1000	1.46	0.230	0.00033	**44**	**0.0400**	**1.46**	**0.160**	**0.00018**
19	0.1000	2.03	0.115	0.00033	45	0.0400	2.03	0.115	0.00018
20	**0.1000**	**1.46**	**0.160**	**0.00040**	46	0.0400	2.03	0.160	0.00018
21	0.1000	1.46	0.230	0.00040	47	0.0400	1.46	0.115	0.00026
22	0.1000	1.46	0.300	0.00040	**48**	**0.0400**	**1.46**	**0.160**	**0.00026**
23	0.1000	2.03	0.200	0.00040	49	0.0400	2.03	0.115	0.00026
24	**0.0667**	**1.46**	**0.065**	**0.00018**	50	0.0400	1.46	0.115	0.00033
25	0.0667	1.46	0.115	0.00018	51	0.0400	1.46	0.160	0.00033
26	0.0667	1.46	0.300	0.00018	52	0.0400	2.03	0.160	0.00033

The bold experiment numbers represent 10 cases for testing set in ANN models

There is also a relationship between experimental time and erosion parameters. The experimental time was confirmed during a preliminary experiment for each slope to find the time for the erosion profile to reach equilibrium. This duration was determined by several criteria: maintain the initial erosion point, equilibrium point and final bar point, decrease the total quantity of moving material to below a certain ratio, and move materials with the same slope; the experiment time was chosen 12 h for 1/10 beach slope, while it was selected 14 h for 1/15 and 1/25 slopes [7, 8, 16].

3 Methodology

3.1 The ANN approach

Many researchers and scientists have applied neural network techniques in predicting the coastal dynamic processes like wave parameter estimation, tidal prediction, coastal structural design and storm surge. They have achieved better results as compared to that using mathematical models like statistical tools, ARMA model and regression models. It is found that the neural networks are reliable and gives accurate results [23].

The input and output data using in the training and testing process of ANN models are normalized between 0.1 and 0.9. The maximum and minimum values of the input data can be obtained from the Table 1 for the normalization process. The minimum and maximum values of the α value were 0.115 and 0.592, respectively. In this study, the architecture of ANN models were generated by using the multilayer feed forward NN and a three-layer network with one hidden layer was selected. The different number of neurons from five to 20 with an incremental of five was trialed to assign the optimum number neurons of the hidden layer. Hyperbolic tangent sigmoid (input layer → hidden layer) and linear (hidden layer → output layer) transfer functions were used within the network. The number of maximum epoch was set to 15,000 for BP and 5000 for TLBO and ABC algorithms. The mean square error (MSE) goal was selected as 8×10^{-8}.

3.2 The data used in the ANN approach

In this study, experiment data including m, d_{50}, T, and H_0 were used as independent variables to calculate α coefficient. The data used in the ANN models were divided into two parts: 42 data were reserved for network training and the remaining 10 data were used to test the network. All the independent variables were obtained from experimental studies. The dependent variable α was obtained by the experimental results with the help of some calculations given below.

As a bar moves offshore, it increases in volume to approach an equilibrium size. Since equilibrium bar volume was not entirely reached in some cases, a simple expression of exponential type was least-square fitted to the data for each case to obtain an objective method for determining equilibrium bar volume. Generally, an expression of exponential type is employed in growth problems where an equilibrium state exists [24]. In this expression, the bar volume (V) is assumed to grow toward the equilibrium volume (V_{eq}) according to

$$V = V_{eq}(1 - e^{-\alpha t}), \tag{1}$$

where t and α are time and an empirical temporal rate coefficient, respectively. α value controls the speed at which equilibrium bar volume is attained; a large α value produces a rapid response toward equilibrium. Several experimental studies have showed that equilibrium bar volume is most closely related to deep-water wave height, sand grain size (or fall speed), and initial beach slope. Various studies were also performed to relate α to some wave, sediment, and beach parameters [16, 24].

3.3 Assessment of model performance

The performance of a trained ANN model is evaluated using the average relative error (RE) and root mean square error (RMSE) and mean absolute error (MAE) as follows:

$$\text{average}\, RE = \frac{\sum_{i=1}^{n} \left| \frac{O_r - O_{\text{ANN}}}{O_r} \right|}{n} \times 100, \tag{2}$$

$$\text{RMSE} = \left[\frac{1}{n} \sum_{i=1}^{n} \left(O_r - O_{\text{ANN}} \right)^2 \right]^{1/2}, \tag{3}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| (O_r - O_{\text{ANN}}) \right|, \tag{4}$$

where O_{ANN} is the α coefficient values obtained from the ANN models and O_{r} is the real α coefficient values.

3.4 Back propagation (BP) algorithm

BP-ANN developed by Rumelhart et al. [25] is the most representative learning model for the ANN [26]. BP algorithm consists of mainly two activities: Forward pass and backward pass. In forward pass, the activities are propagated from input layer to hidden layers to output layer. In backward pass, the activity is propagated from output layer to hidden layers to input layer for updating the weights in the layers [27].

3.5 ABC algorithm

ABC algorithm is a new population-based metaheuristic approach developed by Karaboga [28]. The algorithm based on swarm intelligence has been used to solve optimization problem considering bee behavior. Honey bees living in social order know their job as instinctual. Task of each bee belonging to hive is certain. Bees must not digress from this task. Storing foods, bringing honey, communication, and searching food are bee's tasks that is given mission in social order. Bees living in colonies break down into one of three categories: the queen bee, the drones, and worker bees [29].

In the ABC algorithm, the colony of artificial honeybees comprises of three groups of bees: employed bees, onlookers, and scouts, among which the number of employed bees and onlookers are equal. There is just one employed bee for every food source. Put differently, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source has been exhausted by the bees becomes a scout. In the flow of algorithm, firstly, the amount of nectar is calculated for discovered neighbor food sources sending the employed bees to these sources. The employed bees search the food sources they serve and share information about food sources with the scout bees. The scout bees have a tendency to move more towards rich food sources in line with the information they receive from the employed bees. Finally, the scout bees are randomly sent from bee hives to explore richer sources. This process is iteratively repeated until the most optimum path is found [28].

In this study, the weights of NN model are the parameters of a solution and ABC algorithm tries to find optimum weight set of NN model. More detail information about ABC algorithm can be found in Uzlu et al. [30].

3.6 TLBO algorithm

The TLBO algorithm developed by Rao et al. in 2011 is a new metaheuristic optimization algorithm that depended on the natural phenomena of teaching and learning [31]. Advantages of the TLBO algorithm are simplicity, low computational complexity, high searching power to find the global optimum and lack of tuning parameters, except for the initial population [32]. The TLBO process is divided into a "teacher phase" and a "learning phase". TLBO is a population-based algorithm, where a group of students (i.e., learner) is considered the population and the different subjects offered to the learners are analogous with the different design variables of the optimization problem. The results of the learner are analogous to the fitness value of the optimization problem. The best solution in the entire population is considered as the teacher [33].

Teacher phase of the algorithm simulates the learning of the students (i.e., learners) through the teacher. During this phase, a teacher conveys knowledge among the learners and makes an effort to increase the mean result of the class. A student within the population consists of a number of design variables (X_i) of the problem [33].

$$X_{\text{student}i} = [X_{i,1} \quad X_{i,2} \quad \dots \quad X_{i,D_n}], \qquad i = 1, 2, \dots, P_n \tag{5}$$

where D_n is number of design variables, P_n is size of population. Teacher Phase is formulated as follows:

$$X_{\text{mean}} = [\text{mean}(X_1) \quad \text{mean}(X_2) \quad \dots \quad \text{mean}(X_{DN})], \tag{6}$$

$$X_{\text{studentnew}\_i} = X_{\text{student}i} + r * (X_{\text{teacher}} - TF * X_{\text{mean}}), \tag{7}$$

where $X_{\text{studentnew}\_i}$ and $X_{\text{student}i}$ are the new and old positions of the ith learner, X_{teacher} is the positions the current teacher, r is a random number varying [0,1] and X_{mean} is the mean parameters of each subject of the learners in the class at generation [33]. In this study, X_i is the unknown weights of a neural network. TF is a teaching factor being either 1 or 2. It is determined as follows:

$$\text{TF} = \text{round}(1 + rand * (2 - 1)) \tag{8}$$

All learners should be re-evaluated after each iteration of teacher phase. If $X_{\text{studentnew}\_i}$ is better than X_{studenti}, $X_{\text{studentnew}\_i}$ will be accepted and flowed to learner phase, otherwise X_{studenti} is not changed [33].

In learning phase, all modified students are compared with each other to increase their knowledge. Implementation of this comparison is given as follows:

for i=1:P_n

randomly select $Xstudent_j$, $i \neq j$

if $f(Xstudent_i) < f(Xstudent_j)$

difference $= Xstudent_i - Xstudent_j$

else

difference $= Xstudent_j - Xstudent_i$

end if

$Xstudent_{new\_i} = Xstudent_i + r.*difference$

end for

As noted in the teacher phase, the new student obtained from student phase is not taken into account if its objective function is not better. At the end of the last iteration, the student whose objective function is minimum is the best solution of

Table 2 The best convergence values of TLBO algorithm for ANN training

ANN Architecture	MSE*
4-5-1	0.0239
4-10-1	0.0196
4-15-1	0.0211
4-20-1	0.0191

* The error values were calculated from normalized data

optimization problem [34]. Extensive details about the TLBO algorithm and its implementation can be found in [31, 35].

3.7 The ANN Training with the TLBO and ABC Algorithm

In the current paper, the adaptations of the TLBO and ABC algorithm were presented as the learning scheme to defeat the disadvantages caused by BP in the ANN training. The reason for using the ABC and especially TLBO algorithm as the optimized tool is that it possesses the ability to find optimal solutions with relatively modest computational requirements. Thus, the ABC and TLBO algorithms are utilized to the neural networks in the training process, to obtain satisfying parameters, including weights and biases, which will minimize the error function in competitive time. The parameters are consistently updated until the convergence criterion is reached. The objective function to be minimized by the ABC and TLBO algorithms is the mean square error (MSE) function. The performance of trained ANN was calculated using the average RE, RMSE, and MAE.

The control parameters of the ABC and TLBO algorithms were selected as the same following values for all models: number of maximum iteration (NMI) = 5,000 and size of population (SP) = 50. Parameter (unknown weights of ANN) range was set [−1, 1]. The training process repeatedly applies a set of input vectors to a network, updating the network each time until certain stopping criteria are reached.

4 Result and discussion

Coastal erosion is a global problem. Already-severe coastal erosion problems witnessed in the 20th century will be exacerbated in the 21st century under plausible global warming scenarios [36]. During the coastal erosion, sediment is transported towards offshore and causes the formation of a bar. For this reason, the size of the bar and the duration of its formation are of great importance. The growth of the bar does not last forever, after a while it gets in equilibrium. α coefficient is a parameter that controls the speed at which the bar reaches the equilibrium. In this study, it was aimed to

Table 3 Various error values* for testing set of classic ANN, ANN-ABC and ANN-TLBO

ANN architecture	Average relative error (%)			Maximum relative error (%)			RMSE			MAE		
	BP Algorithm	ABC Algorithm	TLBO Algorithm	BP Algorithm	ABC Algorithm	TLBO Algorithm	BP Algorithm	ABC Algorithm	TLBO Algorithm	BP Algorithm	ABC Algorithm	TLBO Algorithm
4-5-1	5.393	4.758	**2.965**	12.184	13.009	**7.136**	0.0160	0.0133	**0.0081**	0.0129	0.0103	**0.0068**
4-10-1	6.102	4.348	3.833	15.597	9.749	8.659	0.0194	0.0133	0.0119	0.0153	0.0111	0.0097
4-15-1	5.887	3.381	4.403	16.143	8.734	12.567	0.0177	0.0116	0.0152	0.0142	0.0084	0.0114
4-20-1	6.201	5.624	3.431	11.181	14.313	13.041	0.0168	0.0185	0.0132	0.0144	0.0135	0.0086

* The error values were calculated from the real data

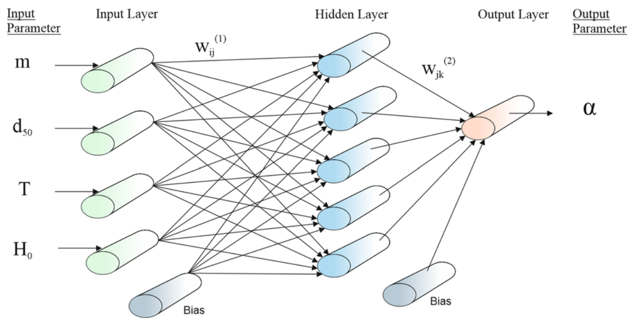

Fig. 3 The architecture of the best ANN model

estimate the α coefficient in the best way and various hybrid artificial intelligence techniques were used for this.

In the ANN models, it is first necessary to obtain a well-trained network. For this, the optimal values of weights in the selected network architecture are determined. In the present study, the training of ANN was done using three different algorithms, namely TLBO, ABC and BP. The TLBO algorithm was given the best convergence values for the training set. Table 2 shows the MSE values calculated for different network architectures of this algorithm. The smallest error value for training set was obtained in the network architecture with 20 hidden layer nodes.

The results obtained from the ANN models were compared with the experimental ones and the best model was determined. The performance of the models was evaluated using average RE, RMSE, and MAE values. Table 3 presents the error values for the testing set in the models. Taking into consideration the network architecture and models, the lowest error values were determined and given in bold in the table. As can be clearly seen from the table, the best model was obtained from the ANN-TLBO with the 4-5-1 ANN structure for all error values. Error values increased with increasing the number of elements in the hidden layer; only in the case of 20 hidden layer nodes, the error values were slightly reduced. Average RE, RMSE, and MAE values obtained from the proposed ANN-TLBO model were 2.965%, 0.0081, and 0.0068, respectively. The RMSE of the ANN-ABC and ANN-BP models was decreased by 47 and 34% using the ANN-TLBO model, respectively. The ANN-ABC and ANN-BP models gave inferior results in predicting the α coefficient.

The architecture of the best ANN model was presented in Fig. 3. Weights of the model in the figure were given as "$w_{ij}^{(1)}$" and "$w_{ij}^{(2)}$". In these expressions, i, j and k were the element of input, hidden and output layer, respectively. While (1), given as upper indices, expressed the connection between the input and hidden layer, and (2) expressed connection between hidden and output layer. The best model weights were presented in Table 4.

Table 4 The weights of the best ANN model

Weights	Value
$W_{11}^{(1)}$	− 0.3737
$W_{12}^{(1)}$	− 0.2209
$W_{13}^{(1)}$	− 0.3228
$W_{14}^{(1)}$	0.0533
$W_{15}^{(1)}$	− 0.3166
$W_{21}^{(1)}$	0.5952
$W_{22}^{(1)}$	0.9299
$W_{23}^{(1)}$	0.2875
$W_{24}^{(1)}$	0.0962
$W_{25}^{(1)}$	0.392
$W_{31}{}^{(1)}$	0.6505
$W_{32}{}^{(1)}$	0.7592
$W_{33}{}^{(1)}$	0.1649
$W_{34}{}^{(1)}$	0.775
$W_{35}{}^{(1)}$	− 0.3132
$W_{41}{}^{(1)}$	0.0346
$W_{42}{}^{(1)}$	− 0.5425
$W_{43}{}^{(1)}$	0.5225
$W_{44}{}^{(1)}$	0.0951
$W_{45}{}^{(1)}$	0.5296
$W_{51}^{(1)}$	− 0.0182
$W_{52}^{(1)}$	0.0183
$W_{53}^{(1)}$	0.4014
$W_{54}^{(1)}$	0.142
$W_{55}^{(1)}$	− 0.364
$W_{11}^{(2)}$	0.0169
$W_{21}^{(2)}$	− 0.2905
$W_{31}^{(2)}$	0.0013
$W_{41}^{(2)}$	0.5688
$W_{51}^{(2)}$	0.5455
$W_{61}^{(2)}$	0.2651

Table 5 Relative errors for testing set of the proposed model

Exp. no	Relative error (%)	Exp. no	Relative error (%)
12	1.505	30	5.980
16	4.549	33	1.669
20	0.095	39	1.186
24	1.361	44	2.746
28	7.136	48	3.446

Figure 4 shows the comparison of the results of ANN models with experimental ones for the testing set. The closest values to the experimental data were found in the ANN-TLBO model. This model was followed by ANN-ABC and ANN-BP models, respectively. Comparisons between the predicted and observed outputs of α coefficient were presented in Fig. 5. As can be seen from the figure,

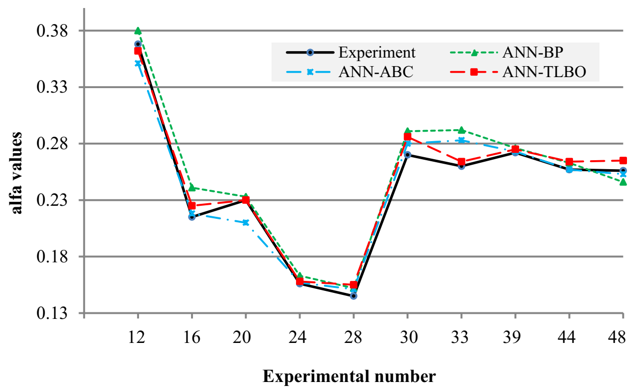

Fig. 4 The comparison of the real α values with the predicted ones by the ANN models for the testing set

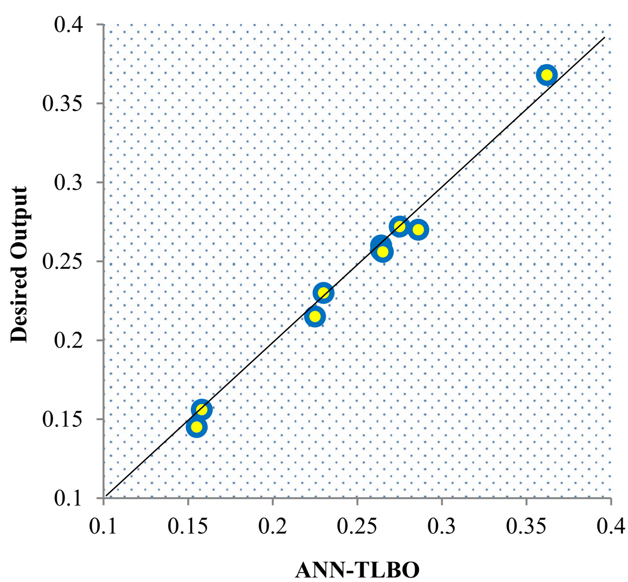

Fig. 5 α predicted by the ANN-TLBO model versus experimental values

the ANN-TLBO model provides a high correlation in the testing sets.

Individual relative errors for testing set in the best model were given in Table 5. As seen in the Table 5, predicted and observed values were very close to each other. The maximum relative errors did not exceed 7.136%. The results of proposed model show that α coefficient estimate is quite satisfactory.

5 Conclusion

In this study, the α coefficient predicting ability of hybrid artificial intelligence models, ANN-TLBO and ANN-ABC, was investigated. In the ongoing study, ANN-BP model was used to test the accuracy of these models. The independent variables in the models were designated as initial bed slope, wave height, wave period, and grain size obtained from the 52 experiments. The data set is divided into two parts; one part with 42 data for training, other part with 10 data for testing.

The accuracy of ANN-TLBO and ANN-ABC models was higher than ANN-BP for all architectures of network. The ANN-TLBO model gives lower error values than ANN-ABC in all ANN architectures except one. The MAE of the ANN-BP and ANN-ABC models for testing set was decreased by 34.0 and 47.3% using the ANN-TLBO technique, respectively.

As an outcome of current study, hybrid artificial intelligence approaches yielded quite successful results in predicting α coefficient-controlled speed of bar volume growth. It would be useful to use ANN-TLBO and ANN-ABC models, which were used for the first time in coastal engineering problems, as commonly.

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