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Prediction of wave reflection for quarter circle breakwaters using soft computing techniques

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The modified form of the semi-circular breakwater is called Quarter-Circle Breakwater (QBW). It consists of a quarter-circular surface facing incident waves, a horizontal bottom, a rear wall, and is built on a rubble mound foundation. In general, QCB may be constructed as emerged, with and without perforations that may be on one side or either side based on the coastal designer. These perforations dissipate the energy due to the formation of eddies and turbulence created inside the hollow chamber. In the present study, experimental data obtained from Binumol, 2017 are fed as input to both the models. This data is used to predict the reflection coefficient of QBW by adopting the ANN system approach. The reliability of the Artificial Neural Network (ANN) approach is done with statistical parameters, namely Model Performance Analysis (MPA) *viz*., Correlation Coefficient (CC), Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Scatter Index (SI). The results of the MPA indicate that the ANN is suited for predicting the reflection coefficient of QBW.

[**Keywords**: Artificial neural network, Quarter circle breakwater, Wave reflection]

Introduction

Inside the ports, harbor tranquility conditions must be maintained for cargo handlings and embarkation and disembarkation of travelers. To preserve suitable conditions inside the harborage, a wave energy dissipating structures like a breakwater must be constructed to dissipate the wave energy[1]. Considering the primary traveling direction of waves and winds, the size and orientation of littoral drift and the orientation of such breakwater must be carefully considered. These studies are carried out using an experimental test in a wave flume or wave basin in which many options are studied and in the end the choice is made based on the functioning and cost[2]. Physical modeling will be lengthy and expensive, while mathematical modeling of these complicated relationships will be complex. As a result, soft computing approaches are used.

Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are the computation techniques with the inbuilt artificial intelligence implemented in modeling coastal processes. Armaghani *et al*.[3] in the comparative study on ANN and ANFIS models to predict the performance indices, the developed model showed an excellent correlation. ANN outperformed the existing empirical formulae in forecasting scour depth at the top head of the wall breakwater[4]. Further, Sada *et al*.[5] investigated the machine learning process such as ANN and ANFIS. In comparison with the ANFIS technique, the ANN is considered to be relatively superior. Koc *et al*.[6] investigated the stability number (N_s) of mound breakwater using a multilayer feed-forward supervised neural networks framework with AND OR fuzzy neurons, optimizing its parameters with a gradient descent algorithm. Apart from these, Raju *et al*.[7] investigated the wave reflection coefficient (K_r) for Quarter Circular Breakwaters (QCW) beyond the experimental data ranges using ANN and ANFIS. ANFIS correlates well with the selected parameters for a wide range of input variables.

With these motives, the present study is focused to develop the ANN and ANFIS models to estimate the K_r of QCB. Further, the ANN and ANFIS prediction model results are well compared with the experimental findings.

Materials and Methods

Artificial intelligence methods

The Artificial neural network is a collection of small processing units, or neurons, that communicate by delivering analog signals. These impulses pass between neurons *via* weighted connections, and each neuron collects the information and generates solutions based on an internal activation system. This solution can be used as information for other neurons. The learning process is achieved through modification of the weights of the connections between units (Fig. 1). During the training procedure, the model forecasted results are correlated to the targets. The inaccuracy is calculated by obtaining the appropriate weight adjustments to minimize errors by back-propagation. The Neural Network (NN) models stop iterating when the inaccuracy is less than the goal error. The weights are changed to reduce the disparity between the desired and the computed outputs in response to this error signal. Adjusting weights is repeated until the appropriate level of precision between the target values and calculated results is achieved. The consequences are frozen after learning. The ANN is then supplied with a data set in order to validate its performance of the computed outputs. The experimental investigation on Quarter-Circle Break Water (QBW) with and without porosities (non-porosities) in a 2-D wave flume of wave mechanics laboratory, NITK Surathkal, India is shown in Figure 2.

The experimental data for this ANN model performance is used from the physical model work of Binumol *et al*.[8,9] and the typical section of test model is illustrated in Figure 3. ANFIS model is first established in the year 1993 by Jang[10]. ANFIS is a neuro-fuzzy technique where the ANN is fused with fuzzy logic principles, and hence it has significant performance[11]. The fuzzy system employs flexible 'if-then' rules that can be applied to modeling human knowledge and reasoning without precise quantitative measures. It is possible to model complex non-linear systems using fuzzy rule-based models with high computational speed[12].

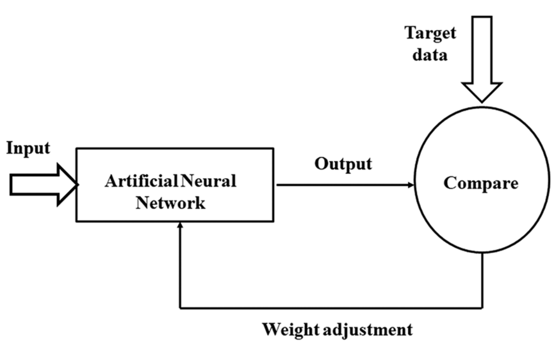

Fig. 1 — Learning process of an artificial neural network

Figure 4 illustrates the TSK-fuzzy mechanism and the ANFIS architecture. For modeling, experimental data is done with the ANFIS toolbox of the MATLAB software. The grid partition method is used to generate the optimum fuzzy rules. An ANFIS model with built-in two membership functions for each variable and 100 epoch numbers are selected. Using the experimental data, ANFIS models were developed with different membership functions. The results obtained are compared with experimental data for validation. The different membership functions considered are the triangular shaped built-in membership function (trimf), trapezoidal-shaped built-in membership function (trapmf), generalized bell-shaped built-in membership function (gbellmf) and gaussian curve built-in membership function (gaussmf). The Root Mean Square Error (RMSE), Scatter Index (SI), and Nash-Sutcliffe Efficiency (NSE) between target output and network predicted outcome is then determined. The various parameters considered for the study are given in Table 1.

Model Performance Analysis (MPA) *viz*., Correlation Coefficient (CC), RMSE, NSE, and SI were applied for checking the adequacy of ANN & ANFIS models to predict the kr values by comparing them with the observed data. The outcomes of the results were calculated as follows:

$$\mathrm{RMSE} = \sqrt[2]{\frac{1}{N}\sum_{i=0}^{N}(S_{pi} - D_{pi})^2} \qquad \ldots (1)$$

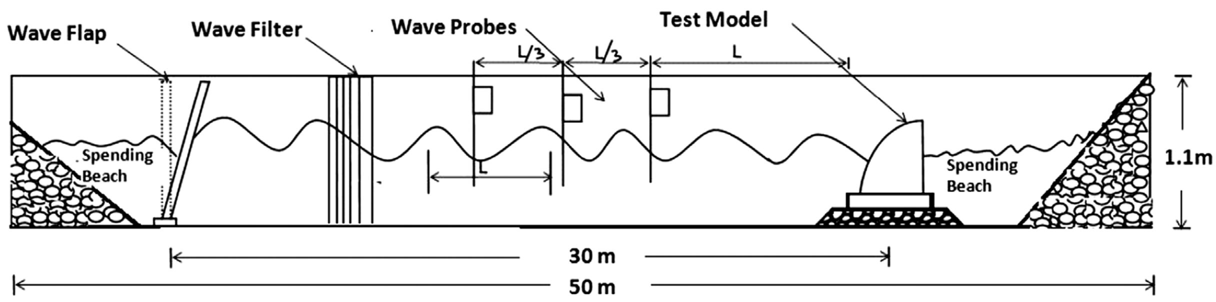

Fig. 2 — Longitudinal section of wave flume

$$NSE = 1 - \frac{\sum_{i=1}^{N}(S_{pi}-D_{pi})^2}{\sum_{i=1}^{N}(S_{pi}-\overline{D_{pi}})^2} \quad \ldots (2)$$

$$CC = \frac{\sum_{i=1}^{N}(S_{pi}-\overline{S_{pi}})\,(D_{pi}-\overline{D_{pi}})}{\sqrt{\sum_{i=1}^{N}(S_{pi}-\overline{S_{pi}})^2}\sqrt{\sum_{i=1}^{N}(D_{pi}-\overline{D_{pi}})^2}} \quad \ldots (3)$$

$$SI = \frac{\sqrt[2]{\frac{1}{N}\sum_{i=0}^{N}(S_{pi}-D_{pi})^2}}{\overline{D_{pi}}} \quad \ldots (4)$$

Where, D_{pi} D_{pi}= data collected, S_{pi} S_{pi}= simulation data and N = entire no. of data points.

Results and Discussion

ANN model results of k_r for the non-perforated QBW

The input variables like wave steepness (Hi/gT^2), the relative depth of water (d/hs), and the solution variable kr were considered. The model analysis uses Levenberg-Marquardt (LM) algorithm, 'tansig' as the activation function for the hidden layer and 'purely' for the output layer. The hidden layer is one, but the number of neurons is varied from 1 to 6, and the best ANN model is chosen. The network model is also constructed using the training data containing 176 data samples (70 %). With the testing data set of 75 data samples, the trained network predicts the intended result of 30 percentage. The solutions obtained are shown in Table 2. Table 2 illustrates that the training efficiency of the 2-3-1 model gives a good correlation with CC for training equal to 0.968 and for testing similar to 0.972. The RMSE values for training and testing are 0.05169 and 0.0630. SI values for train and test data sets are 0.1220 and 0.1486, respectively. The NSE value of the 2-3-1 model is 0.940 and 0.935 for training and testing, respectively. In comparison with statistical parameters, the 2-3-1 model can be considered the best model to predict the reflection coefficient (k_r) for quarter circle breakwater.

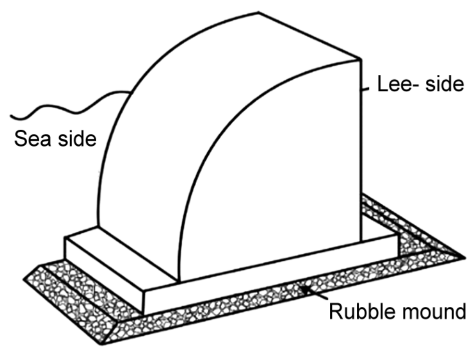

Fig. 3 — Typical section Quarter Circle Breakwater

Figure 5 represents the scatter plot of the best model (2-3-1 ANN model) for predicting the K_r of non-perforated QBW. The x-axis represents the observed k_r, an experimental result of Binumol[8], and the

Table 1 — Range of experimental variables

Variables	Laboratory range
Incident wave elevation, H_i (m)	30, 60, 90, 120, 150, 180
Depth of water, d (m)	0.35, 0.40, 0.45
Wave period, T (s)	1.4 to 2.2
% of perforations (p)	0 & 16 %

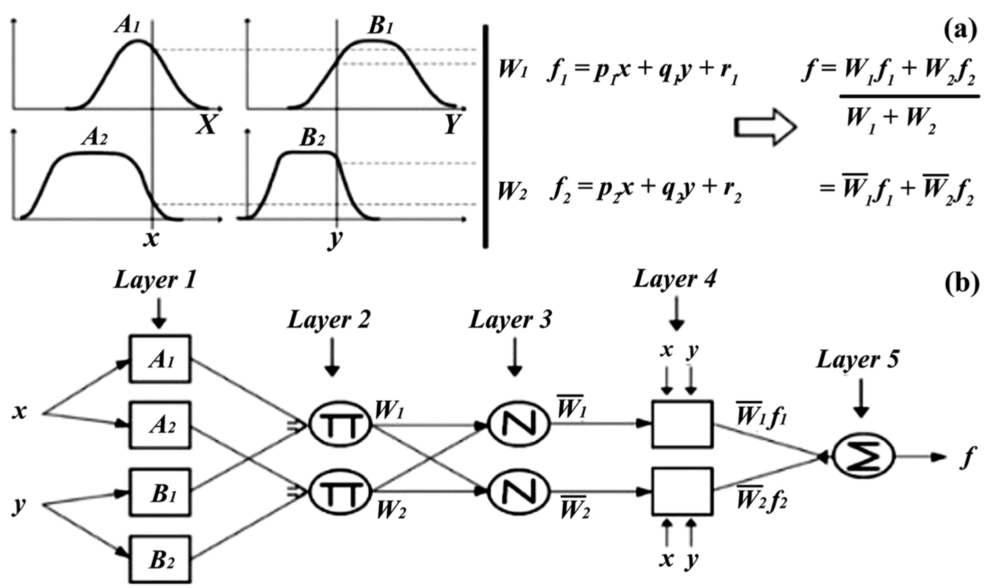

Fig. 4 — TSK fuzzy model & ANFIS architecture

y-axis gives the corresponding predicted k_r value using ANN for non-perforated QBW. The predicted and observed points are in good agreement. The comparison plot of k_r predicted using ANN modeling for three hidden neurons with observed data is illustrated in Figure 6. From the figure, the predicted values of wave reflection correlate well with the experimental findings. Hence the ANN model with three hidden neurons is considered the best model.

ANFIS model results of k_r for the non-perforated QBW

Prediction of Kr for QBW is done using ANFIS modeling. The statistical parameters obtained for different membership functions are depicted in Table 3. From Table 3, ANFIS with gaussian membership functions

Table 2 — Statistical parameters for ANN models for predicting kr for $p = 0$ %

Network	RMSE		CC		SI		NSE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
2-1-1	0.06232	0.0719	0.954	0.968	0.1471	0.1697	0.913	0.916
2-2-1	0.05880	0.0661	0.959	0.972	0.1388	0.1560	0.923	0.929
2-3-1	0.05169	0.0630	0.968	0.972	0.1220	0.1486	0.940	0.935
2-4-1	0.0511	0.0629	0.97	0.969	0.1206	0.1484	0.943	0.936
2-5-1	0.0516	0.0702	0.968	0.965	0.1219	0.1658	0.940	0.920
2-6-1	0.0502	0.0675	0.97	0.968	0.1186	0.1592	0.944	0.926

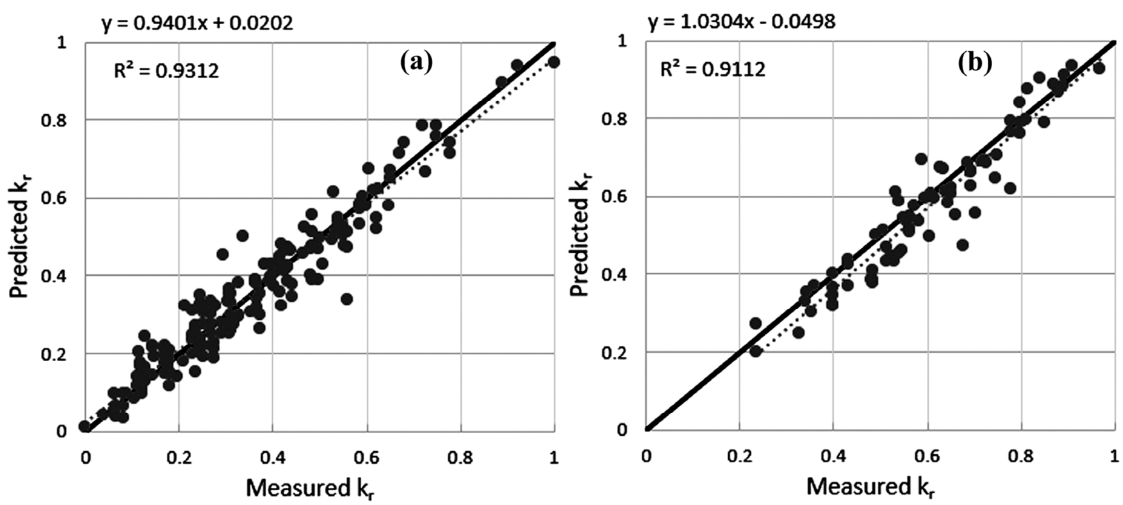

Fig. 5 — Scatter plots for (a) training and (b) testing dataset of ANN model, non-perforated QBW

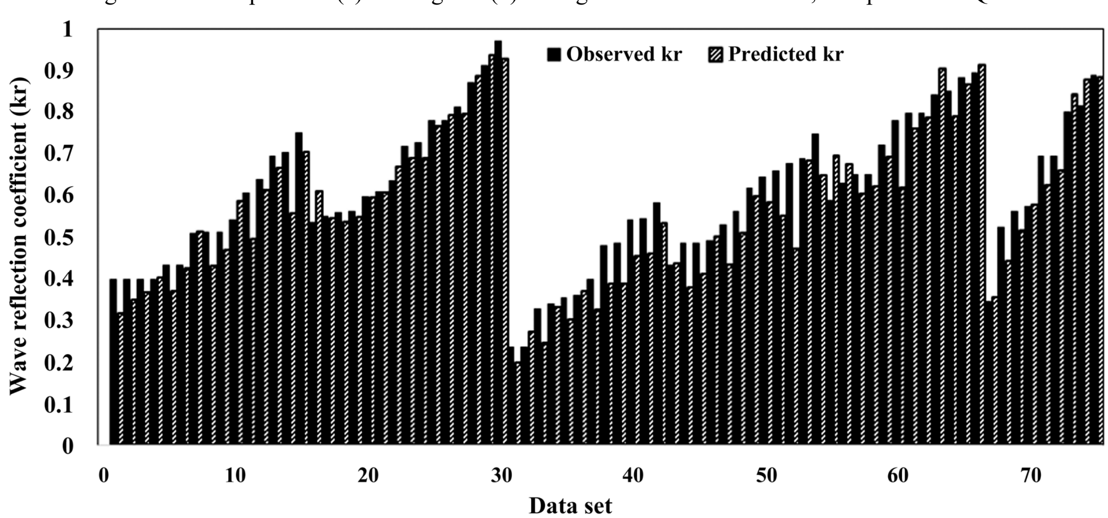

Fig. 6 — Comparison of K_r predicted by ANN for 3 hidden neurons with observed values for test data set for $p = 0$ %

performs better than a model with other functions. The statistical measures obtained for ANFIS model with gaussian membership function are RMSE = 0.0643, and NSE = 0.933. There is also a good correlation (CC = 0.971) between this model's observed and predicted wave reflection with Scatter Index = 0.1518.

Figure 7 represents the scatter plot (Gaussian membership function) of the best model (2-3-1 ANFIS model) for predicting the k_r of non-perforated QBW. The x-axis represents the observed k_r, an experimental result of Binumol[8], and the y-axis gives the corresponding predicted k_r value using ANN for non-perforated QBW. The predicted and observed points are in good agreement. The comparison plot of k_r predicted using ANFIS modeling for three hidden neurons with observed data is illustrated in Figure 8.

Table 3 — Statistical measures for ANFIS model

Statistical parameters	Triangular		Trapezoidal		Gbell		Gaussian	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
RMS	0.0574	0.0636	0.05625	0.0645	0.05151	0.0648	0.05130	0.0643
NSE	0.926	0.934	0.929	0.932	0.941	0.932	0.941	0.933
CC	0.961	0.971	0.962	0.971	0.968	0.971	0.969	0.971
SI	0.1354	0.1502	0.1328	0.1522	0.1216	0.1529	0.1211	0.1518

(Functions)

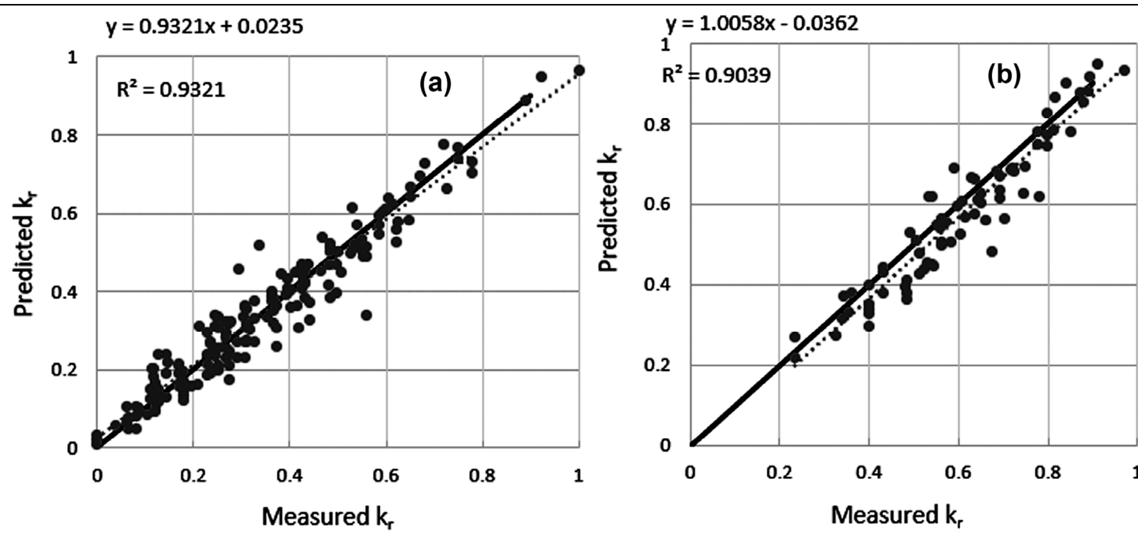

Fig. 7 — Scatter plots for (a) training and (b) testing dataset of ANFIS model, non-perforated QBW

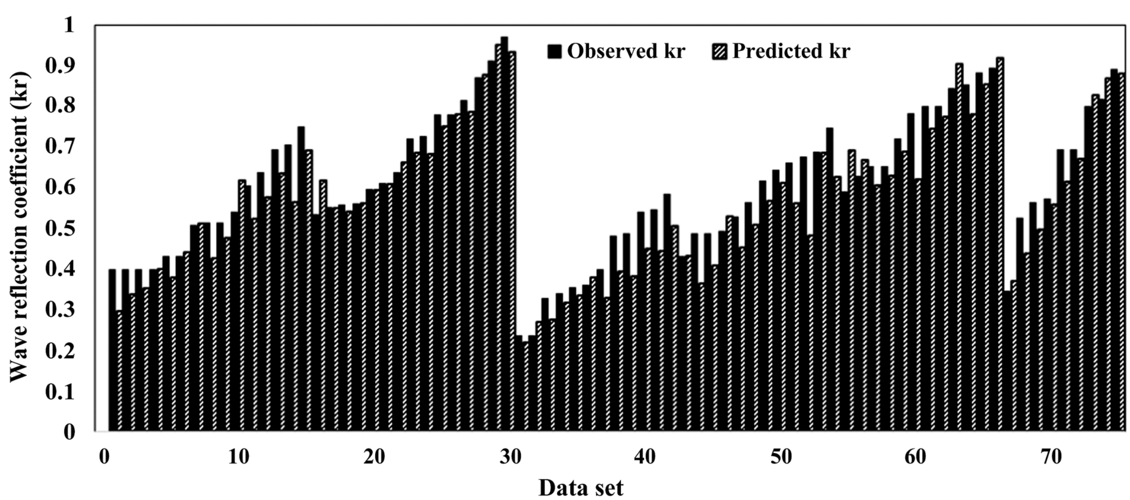

Fig. 8 — Comparison of K_r predicted ANFIS results with measured values for test data set for p = 0 %

Conclusion

The outcome of the study involves the prediction of the reflection coefficient (K_r) of QBW by adopting ANN and ANFIS approaches. From the interpretation of the data, the following solutions are drawn.

Training and testing efficiency of the 2-3-1 ANN model correlates well with CC for training equal to 0.968 and for model testing similar to 0.972. Also, the RMSE, SI & NSE values obtained were 0.0630, 0.1486 & 0.935, respectively.

The training efficiency of ANFIS model correlates well with CC for training equal to 0.969 and for testing similar to 0.971. Also, the RMSE, SI & NSE values obtained for testing sets were 0.0643, 0.1518 & 0.933, respectively.

Feeding the network with data is easy and simple which makes ANN a better option. The Time taken for the simulation of the ANN model is less compared to the simulation time of ANFIS. Considering all these factors and statistical parameters, the ANN model is recommended as an efficient and good technique to predict K_r for QBW.

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Conflict of Interest

The authors declare no competing or conflict of interest.

Author Contributions

NR & SB performed the modeling of soft computing methods, analysis and drafted the original manuscript. SR supervised and reviewed the manuscript.

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