International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252

Wave reflection coefficient prediction for emergedsemicircular breakwater usinga novel hybrid approach of GA-ANFIS

Suman Kundapura[a]

a. Associate Professor, Department of Civil Engineering, A J Institute of Engineering and Technology Karnataka, Mangaluru – 575006 India; Affiliated to Visvesvaraya Technological University

Date of Submission: 09-03-2023 Date of Acceptance: 18-03-2023

ABSTRACT

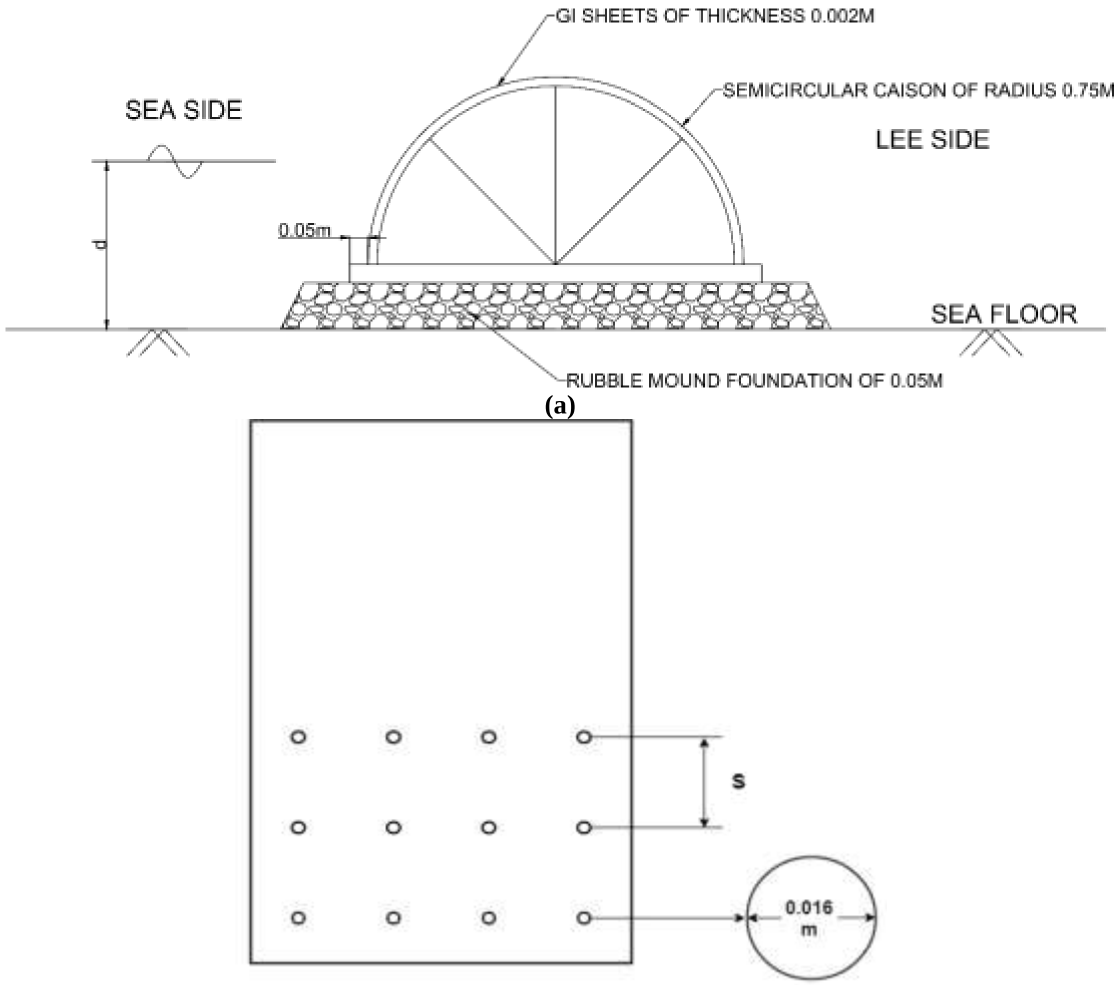
Mainitaining tranquility in the lagoon area is a priority when it comes to a better port activity management. Semicircular breakwaters with its many advantages can be an ideal option when it comes to port protection. Wave reflection coefficient (K_r) which is one of the key parameters in the hydrodynamic investigation of semicircular breakwaters has never been studied independently. This paper aims to develop a novel hybrid approach of GA-ANFIS to predict the reflection coefficient of the emerged seaside perforated semicircular breakwater by the conventional method of data segregation of 75:25. The GA-ANFIS model predicts the reflection coefficient using five input elements that are influencing the process of reflection. The dataset used here has been taken from the experiments conducted in the monochromatic wave flume laboratory of marine structures of National Institute of Technology Karnataka, Surathkal. The accuracy assessment of the GA-ANFIS model was done based on the correlation coefficient, root mean squared error, scatter index,Nash Sutcliffe Efficiencyand bias. The study shows that the prediction of K_r with reasonable accuracy is possible using GA-ANFIS model compared to other models used in the study.

Keywords: GA-ANFIS; Fuzzy C-means clustering; reflection coefficient; semicircular breakwater.

I. INTRODUCTION

The port and harbor tranquility is possible only with the planning of proper coastal protection structures. Breakwaters are one of the best coastal protection structures (Mani and Jayakumar, 1995). They are built to dissipate the enormous energy of the sea waves. The design of such structures is of great importance as their installation involves huge investment. The choice of the type of breakwater is site-specific and no single breakwater holds good under all site conditions. The semicircular breakwater is one among the several options with a precast reinforced concrete structure having a semicircular shaped hollow caisson resting on a rubble mound as shown in (Fig. 1.1a). It is made of pre-stressed concrete and cast as different elements. Since the caisson is hollow its weight and the materials to be used are significantly less. It could be either emerged or submerged type, fully perforated or partially perforated. The Fig. 1.1b shows the emerged seaside perforated SBW, by employing this kind of breakwater the wave energy dissipation is done by creating turbulence inside the chamber thus reducing the pressure and force on the caisson. The spacing between the perforations depends on the diameter of perforation and the S/D ratio. The stability against sliding for SBW is good, since, the horizontal component of the wave force is smaller compared to the vertical component. In addition, the vertical component is applied downward the curved wall. The semicircular breakwater possesses a round top and, thus, offers more stability against the action of waves. Thus it also serves well as offshore detached breakwaters adopted for the protection of the coast against erosion. The SBW enhances the scenery compared to the conventional rubble mound breakwaters. The impermeable semicircular breakwaters are effective wave reflectors and the permeable semicircular breakwaters are good energy dissipaters.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252



(b)

Fig. 1.1 (a) Semicircular breakwater (b) Typical detailing of the semicircular breakwater

Being in an era of Artificial intelligence there is a demand for alternatives to conventional methods,although the physical model usage cannot be completely ruled out. The application of several soft computing tools either individual or hybrid for the prediction of breakwater parameters has been carried out in the past (Yagci et al. 2005, Mandal et al.2009,Erdik et al. 2009, Deo 2010, Patil et al. 2012, Lee et al. 2015, Raju et al. 2015). ANFIS outperforms the ANNs and other types of Fuzzy Inference Systems, it has been widely used in prediction problems. ANFIS outperformedANNmodels in predicting wave transmission (K_t) for a horizontallyinterlaced multilayermooredfloatingpipebreakwater (Patil et al. 2011). ANFIS is easy to understand, flexible, and adaptable. However, with a large number of inputs, the number of rules increases exponentially and so does the complexity and computational cost. Thus to avoid the drawbacks of original hybrid learning algorithm of ANFIS, the ANFIS is trained using metaheuristic algorithms like GA, PSO, ABC, CSO, and their variants(Najib et al. 2016).The AI integration into coastal modeling can be seen in the review of Chau 2006. Isen and Boran 2017 created a new hybrid model combining FCM, GA and ANFIS for inventory classification such that whenever there is a new inventory item introduced the model need not be regenerated and can handle both qualitative as well as quantitative data. The ANFIS premise and the consequent parameters are optimized using Genetic Algorithm (GA) based on a population algorithm and applied to the nonlinear dynamic system identification problem. It was found that the optimization of ANFIS parameters using GA was more successful than the other methods(Haznedar and Kalinli 2016). Begic et al. 2015used nine dermatological features asinputs to classifiers of ANFIS for the first level of fuzzy model optimization and then

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252

used GA for the second level of fuzzy model optimization within GA-ANFIS system for detection of dermatological disease. AGA-ANFIShybrid model wasdeveloped by Zanaganeh et al. 2009 to predict the significant wave height and the peak spectral period in Lake Michigan was found superior to ANFIS models and SPM method. Here, GA optimized the structure and number of fuzzy if–then rules in a FIS by finding the best parameter values of subtractive clustering, whereas ANFIS is used to optimize the FIS constructed based on the clustering parameter values generated by GA.

In very large scalecoastal aquifers, the optimal management of saltwater intrusion is computationally challenging and not feasible. An ANN-GA based simulation and optimization model was developed byBhattacharjya and Datta 2010 for solving a multiple objective saltwater management problems.Fazlec et al. 2015 proposed a GA-ANFIS expert system prototype for tar detection in cigarettes during the manufacturing process. The Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA) is combined in the study. The data used from inside the cigarette factory was collected with special qualityequipment. The GA-ANFIS system performs optimization in two steps. Initially, six different ANFIS structures are generated and in the second level GA optimization of these ANFIS structures was performed. The validation of the GA-ANFIS system was carried out using a data set that was not used in the process of training and found that GA-ANFIS performs well enabling faster prediction of tar amount with a permitted deviation.Alata et al. 2013 applied subtracting clustering algorithm to find the optimal number of clusters needed by Fuzzy C-means clustering (FCM) algorithm used an iterative search approach. Further, using GA and the iterative search approach the weighting component m of FCM algorithm was optimized. GA performed better and had lesser approximation error with less time compared to iterative search approach. Li and Su 2010 developed a hybrid GA-HANFIS model that predicts a hotel's daily air conditioning consumption. The GA optimized the structure and number of fuzzy if-then rules in a hierarchical ANFIS by arriving at the best subtractive clustering parameters. The hierarchical structure used in the study helped in arranging low-dimensional rule bases and ANFIS optimizes the FIS constructed based on the clustering parameter values generated by GA. The authors found the performance of GA-HANFIS outperformed the conventional neural networks in terms of prediction accuracy. The direct measurement of soil saturated hydraulic conductivity (K_s) is tedious, exhaustive, expensive and laborious.Taraghi 2014 predicted K_s parameter from easily available metadata using Fuzzy c-mean (FCM) clustering and Genetic Algorithm (GA). The available data was clustered using FCM algorithm, a Fuzzy Inference System was generated based on these clusters by 12 rules, 6 numbers of inputs and saturated hydraulic conductivity as output. The model predicted K_s was close to the actual measured $K_{s.}$ Predicting thermal error of CNC milling machine tools were found to be more accurate using ANFIS-FCM compared to ANFIS-Grid model as the number of rules in the latter was few compared to the large rules in the grid partitioning method (Abdulshahed et al. 2015)**.**

Over the past decades, researchers have predicted the performance of various types of breakwaters using the soft computing techniques. However, there is lack of research on prediction of hydraulic responses of caissons like semicircular breakwaters. Hence, the objective of this paper is to develop a hybrid GA-ANFIS model for estimation of wave reflection coefficient of semicircular breakwaters.A conventional method of data segregation of 75:25 was applied to the entire randomized dataset. And the robustness of the model is assessed by the error metrics like the correlation coefficient, root mean squared error, mean absolute error and scatter index.

Experimental data used

The experimental data were obtained from physical model studies of emerged seaside perforated semicircular breakwater (SBW) (Nishanth 2008; Sooraj 2009; Vishal 2010; Sreejith 2015,Hegde et al. 2018)carried out in the regular wave flume of Marine Structures Laboratory in the Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal, India. Table 1presents the range of input parameters used in the experiments which are downscaled to 1:30 to represent the conditions along the Arabian Sea off Mangaluru coast.The wave climate of Mangaluru coast as given by Dattatri and KREC study team (1994) were considered for selecting the input wave parameters. The largest single wave recorded off the Mangaluru coast was found to be 5.4 m. The predominant wave period during the monsoon season is 9 to 10 s, while longer period waves are experienced in the fair weather season. In the non-monsoon months (October to May), the maximum wave heights are less than 1m in height. The tides at Mangalore are

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252

semi-diurnal type. The tidal range in the area is about 1.68 m. Hence, in the present investigations, wave heights in the range of 1.0 m to 5.4 m and wave periods in the range of 6 to 12 s are considered for modeling. Incident wave heights used in the flume varied from 3 to 20 cm, wave periods ranged from 1.4 s to 2.5 s, water depths used were 35 cm, 40 cm, 45 cm, and 50 cm and the model scale was 1:30.

The reflection coefficient (K_r) of emerged seaside perforated semicircular breakwaters has not been much explored, and there is a research gap, particularly in the application of soft computing techniques to predict K_r. In the current study, the prediction of the reflection coefficient of emerged seaside perforated semicircular breakwaters is proposed. The study involves the application of soft computing models to the data obtained from the experimental study involving emerged seaside perforated semicircular breakwaters of different radii under varying wave conditions using the Issacson three probe method. The prediction of the reflection coefficient is studied for Non-dimensional (H_i/gT^2, d/gT^2, S/D, h_s/d, R/H_i) π-terms obtained from dimensional analysis using Buckingham's π-theorem. Data segregation for prediction is done with a data division of 75:25 for a dataset of 1274 randomized data points.

Table 1 Experimental parameter ranges for K_r prediction

Input parameters	**Data Range**
Incident wave height, Hi (m)	0.06 -0.18
Wave period, T (s)	1.2– 2.6
Depth of water, d (m)	0.35, 0.40, 0.45, 0.50
Radius of the semicircular caisson, R (m)	0.45, 0.60
Perforation spacing, S (m)	0.032, 0.048, 0.064, 0.096, 0.128,
Perforation diameter, D (m)	0.012, 0.016
SBW structure height h_s (m)	0.502, 0.652, 0.730

Normalization of the data and consistency check

The wave parameters obtained from the experiments are normalized to (0, 1). The normalization is done by using Equation 3.1before feeding to the network.This is done to bring all the input variables in a common range so that the network gets trained without being hindered by the effect of very high or very low values. However, in the current study, the variation of the ranges of the input and target values are not large.

$$Z_i = \frac{\chi_i - \min(\chi_i)}{\max(\chi_i) - \min(\chi_i)} \quad (1)$$

Where,
Z_i - is the normalized data for the i^{th} variable between 0 to 1,
x_i - is the data point i^{th} variable,
x_{max} - is the maximum amongst all the data points of i^{th} variable,
x_{min} - is the minimum amongst all the data points of i^{th} variable.
The consistency of the datais as shown in the Fig. 2,

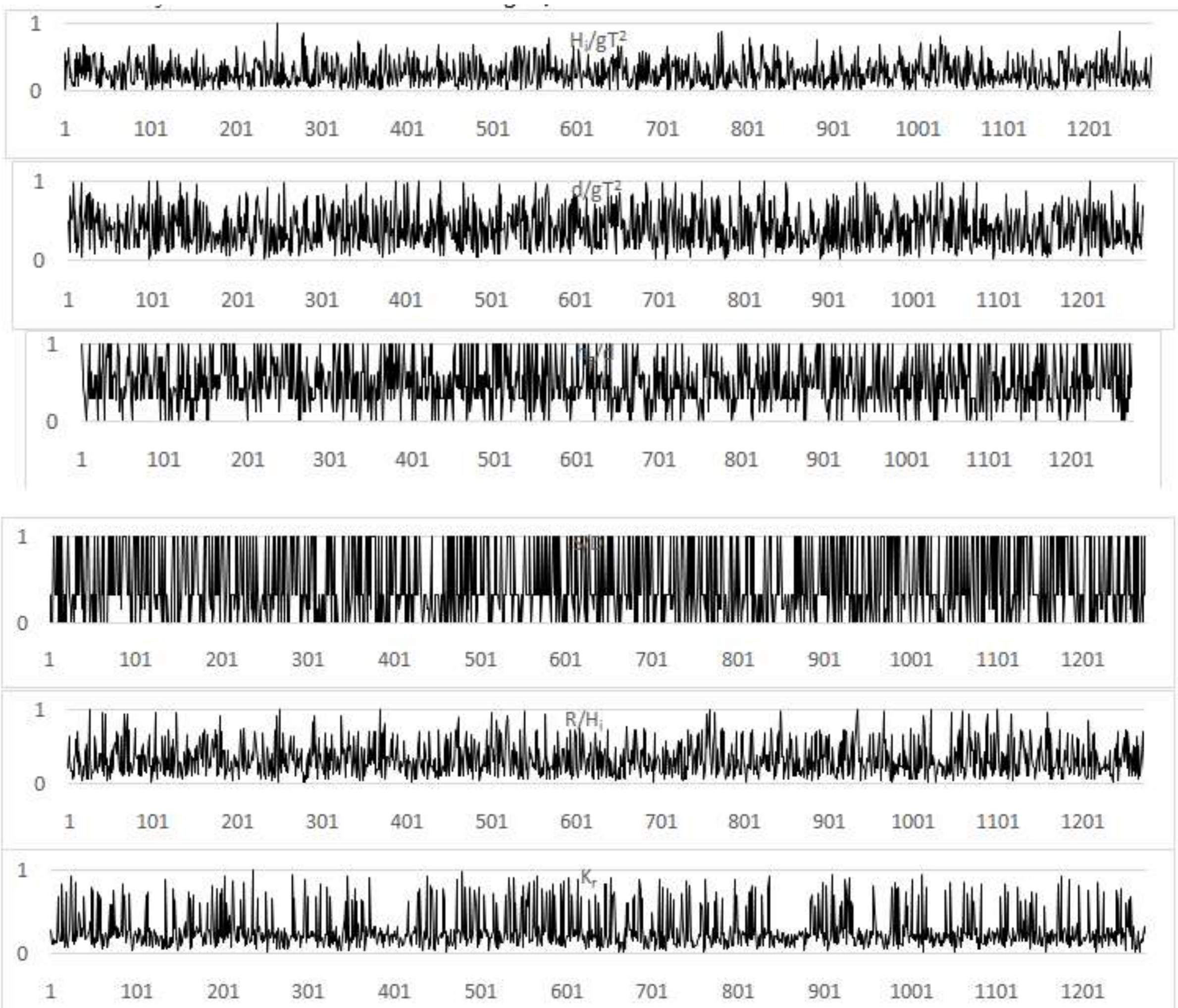


Fig. 2 Data consistency of input parameters H_i/gT^2, d/gT^2, h_s/d, S/D, R/H_i, K_r, in the case of reflection coefficient prediction

Employment of Soft computing models

Initially, the prediction of the wave reflection coefficient was done with the ANN and ANFIS models. However, the results obtained had scope for further improvement hence the optimization techniques were employed. The detailed methodology of the ANN, ANFIS, PSO-ANFIS, GA-ANFIS can be referred into in my previous publications. Here the model results of ANN, ANFIS, PSO-ANFIS are used for comparision with the GA-ANFIS.

The ANN model has been simulating exactly like the way in which the human brain will usually process the information. It gets the problem knowledge by detecting the patterns and relationships in data and does the learning which is called as data training.

Whereas the ANFIS model is a Neuro-Fuzzy technique used for the modeling of not well defined, uncertain problems. ANFIS is an intelligent model that leans based on the input/output datasets. The optimisation techniques adopted here like Genetic Algorithm and Particle swarm are both inspired by nature. GA is based on the concept of Charles Darwin's theory of natural evolution. Here the natural selection of the fittest individuals are done to reproduce offsprings of the next generation. Also in the particle swarm optimization (PSO) which is a computational method it optimizes the given problem by iteratively improving a candidate solution with regard to a given measure of quality say root mean square error.

Results and discussion ofK_r prediction of semicircular breakwater using different soft computing models for 1274 data points

The reflection coefficient prediction

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252

performance of different soft computing models for non-dimensional input parameters for 1274 data points is done by conventional data segregation method. The entire dataset was randomized, normalized and a data division of 75% for training and 25% for testing was taken up to check the prediction possibility.

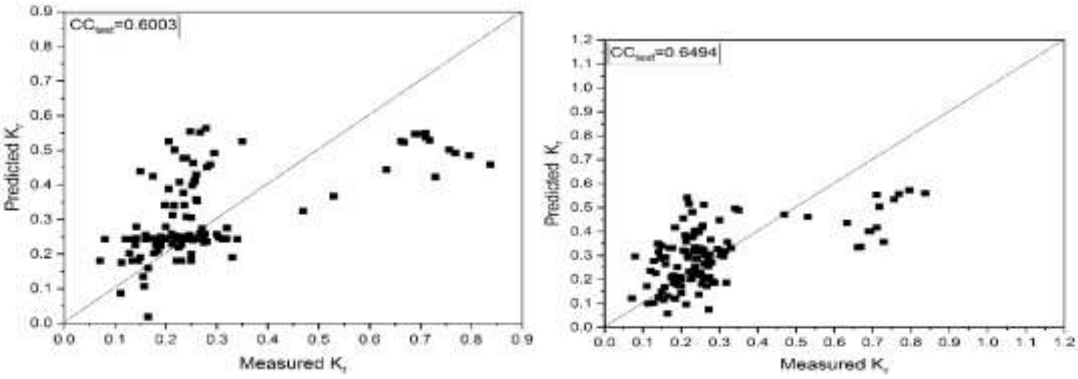
The training and testing of ANN Model for prediction of K_r for 1274 global data pointsare carried out. The best ANN architecture obtained by trial and error basis is 5-11-1 with the least testing RMSE=0.1703for epoch 133. The network is fed with 5 inputs and the prediction of single output is done by varying the number of neurons in the only set hidden layer. The values of the measure of error are presented in Table 2. The correlation coefficient for training R=0.6803 and for testing R=0.6003 is found. Fig. 3ashows the scatter plot of model predicted K_r and actual values for the case of 1274 global data points testing using ANN.

The ANFIS model with fuzzy C-means clustering is adopted with the input membership function for each input variable is 'gaussmf' and the output membership function type is 'linear' for sugeno systems. Here the number of clusters is set as 9 as the entire dataset has 9 distinct wave heights. The model prediction for m=2 with the minimum improvement factor set as of 0.001 in the objective function in between the two consecutive iterations and the maximum iterations count is set to 25 for which RMSE=0.1282 is obtained. Training and testing performance of ANFIS model for the case of 1274 global data points is validated by error measure as shown in Table 2 and the scatter plot of predict K_r and actual values of ANFIS is as in Fig. 3b. Here FCM constructs aFIS with five inputs and one output. ANFIS predicted the K_r value for non-dimensional input parameters with an improvement in the R-value of training and testing with respect to ANN prediction as seen in Table 2.

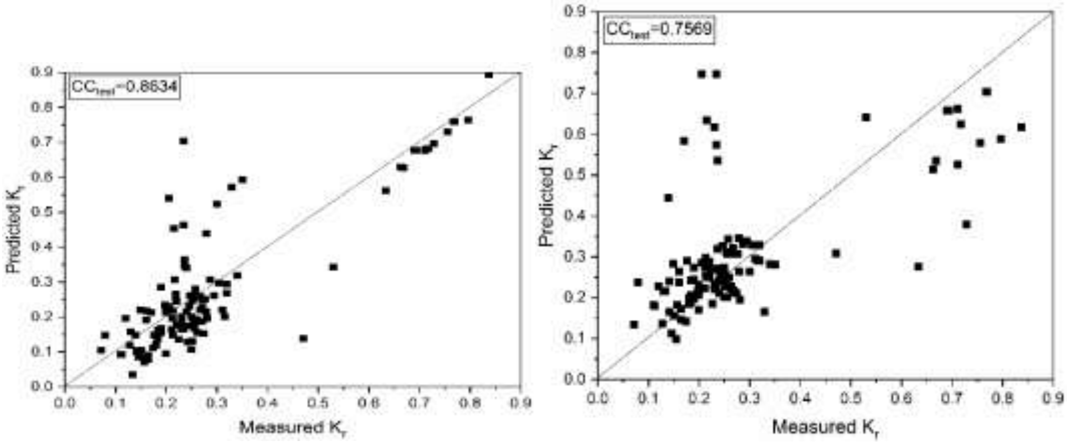
An attempt to further improve the ANFIS training was done by GA-ANFIS model whose objective function is to reduce the RMSE of the prediction of K_r of the semicircular breakwater. In the FCM the number of clusters was set as 9, with m=1.2 was optimal with least RMSE, for a maximum FCM iteration of 50 and minimum improvement of 1e-5. GA parameters population size and the maximum number of iterations ARE varied to arrive at the best R values and lower RMSE. Finally, a population size of 20 with a maximum number of iterations 8000 was found optimal. Also, the mutation rate is set to 0.15, the crossover percentage is set to 0.4, mutation percentage is set to 0.7, and the selection pressure is set to 8. GA-ANFIS model prediction is found to improve over the ANFIS model prediction and is found to be the best among the four models adopted. Table 2 shows the comparison of GA-ANFIS and ANFIS model results in case of non-dimensional input parameters and the scatter plot of prediction and actual values of GA-ANFIS is as seen in Fig. 3c. The Nash Sutcliffe efficiency of the GA-ANFIS model of testing is 66% best among all four models for this case of prediction. The scatter index for testing reduced relatively with respect to the other three models as shown in Table 2.

Further to check if PSO is better than GA in improving the ANFIS training PSO-ANFIS model is employed with an objective function to reduce the RMSE of the prediction of wave reflection (K_r) of the semicircular breakwater. In the employment of PSO-ANFIS model, an initial FIS for the dataset of non-dimensional input parameters is generated using FCM and the PSO is applied to fine-tune the ANFIS training. In the FCM the number of clusters was set as 9, as the data involved 9 different wave heights. The optimal found m=1.7 with least RMSE is set for a maximum FCM iteration of 50 and minimum improvement of 1e-5. The model is run for different values of c_1 and c_2 but the least RMSE was attained only when the acceleration coefficient c_1=2, c_2=2. The model is run for various population size and finally set for a population size of 50 and 1000 iterations which gave the best prediction with least RMSE for inertia weight of w=0.7. Table 2 shows the comparison of PSO-ANFIS and ANFIS model results in case of non-dimensional input parameters. The PSO-ANFIS model prediction for training R=0.8886 is better than ANFIS model training and for the testing R=0.7569. On further increase of iterations in PSO-ANFIS, the model results did not improve. A scatter plot of prediction and actual values of PSO-ANFIS is as seen in Fig. 3d. Among the four models considered GA-ANFIS model gave better results. Fig. 4shows the comparison of predicted K_r by ANN, ANFIS, GA-ANFIS and PSO-ANFIS models with observed K_r values.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252



(a) ANN model (b) FCM-ANFIS model



(c) GA-ANFIS model (d) PSO-ANFIS model

Fig. 3 Scatter plot of predicted versus actual values of K_r for different models in case of 1274 global data points with non-dimensional input parameters

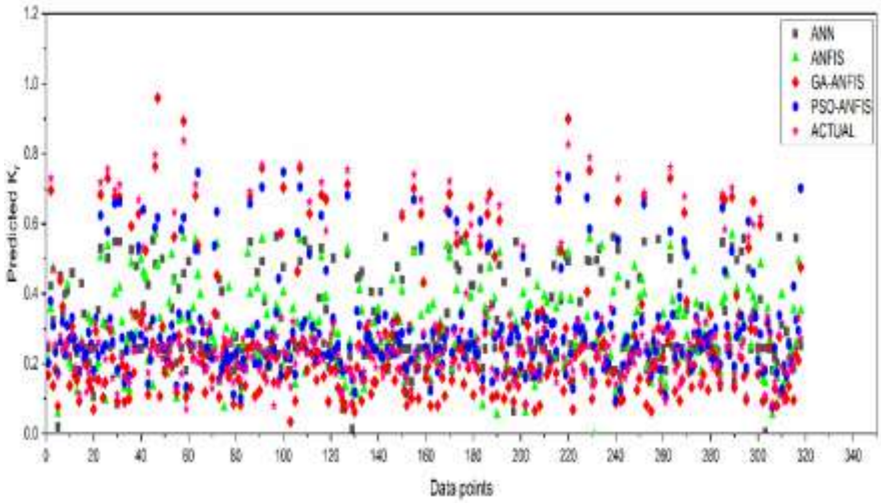


Fig. 4 Comparison ofpredicted K_r by ANN, ANFIS, GA-ANFIS, PSO-ANFIS models for the case of non-dimensional input parameters with observed K_r values

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 3 March 2023, pp: 995-1004 www.ijaem.net ISSN: 2395-5252

Table 2Error metrics for different soft computing models for non-dimensional input parameters in the case of global data of 1274 points for predicting reflection coefficient

Input form	Error metrics	Soft computing models							
		ANN		ANFIS		GA-ANFIS		PSO-ANFIS	
		Train	Test	Train	Test	Train	Test	Train	Test
Non-dimensional	R	0.6803	0.6003	0.6991	0.6494	0.9096	0.8634	0.8886	0.7569
	RMSE	0.1656	0.1703	0.1312	0.1282	0.0869	0.0974	0.0785	0.1116
	NSE	0.4621	0.3190	0.4886	0.4158	0.7757	0.6626	0.8209	0.5580
	SI	58.26	65.07	43.45	45.20	28.78	34.34	25.97	39.32
	BIAS	-0.0060	0.0258	3.129E-05	0.0074	-0.0184	-0.0151	-0.0097	0.0160

II. CONCLUSIONS:

This study verified the possibility of prediction of hydraulic response the K_r of the semicircular breakwater subjected to regular waves using soft computing models. Looking into the results the study concludes that GA has optimised the results obtained by ANFIS compared to that of PSO. The time consumed by the GA-ANFIS was less compared to that of the PSO-ANFIS model. However, there is further scope to carry out a similar study for semicircular breakwater employing other soft computing techniques like Extreme Learning Machines, Ant Colony optimization or Firefly optimization algorithm.

Acknowledgment
The authors are grateful to the Director, National Institute of Technology Karnataka, Surathkal, India, for the support and encouragement provided by them and for the permission to publish.

Appendix

H_i/gT^2	Incident wave steepness parameter
d/gT^2	Depth parameter
S/D	Ratio of spacing to diameter of perforations
R/H_i	Relative caisson radius
h_s/d	Relative structure height

REFERENCES

[1]. Abdulshahed, A. M.; Longstaff, A. P.; Fletcher, S.: The application of ANFIS prediction models for thermal error compensation on CNC machine tools. Appl. Soft Comput. J., Elsevier B.V., 27, 158–168 (2015)
[2]. Alata, M.; Molhim, M.; Ramini, A.: Using GA for optimization of the fuzzy C-means clustering algorithm. Res. J. Appl. Sci. Eng. Technol. 5, 695–701 (2013)
[3]. Allsop, N.W.H.; Hettiarachchi, S.S.L.: Reflections from coastal structures. Coast. Eng. Proc., [S.l.], 21, ISSN 2156-1028 (2011)
[4]. Arumugadevi, S.; Seenivasagam, V.: Comparison of Clustering Methods for Segmenting Color Images. 8, 670–677 (2015)
[5]. Azmathulla H.Md.; Ghani AAb.: ANFIS-Based Approach for Predicting the Scour Depth at Culvert Outlets. J. Pipeline Syst. Eng. Pract., 2011, 2(1), 35-40 (2011)
[6]. Begic, L.; Avdagic, K.; Omanovic, S.: GA-ANFIS Expert System Prototype for Prediction of Dermatological Diseases. pp. 622–626.
[7]. Bhattacharjya, R. K., and Datta, B. (2010). “ANN-GA-Based Model for Multiple Objective Management of.” 135(5), pp. 314–322.

[8]. Bryant, M. A., Hesser, T. J., and Jensen, R. E. (2016). "Evaluation Statistics Computed for the Wave Information Studies (WIS)." (July), pp. 1–10.

[9]. Castillo, O., Rubio, E., Soria, J., and Naredo, E. (2012). "Optimization of the Fuzzy C-Means Algorithm using Evolutionary Methods." (February).

[10]. Chau, K. (2006). "A review on the integration of artificial intelligence into coastal modeling." 80, pp. 47–57.

[11]. Deo, M. C. (2010). "Artificial neural networks in coastal and ocean engineering." Indian J. Geo-Marine Sci., 39(December),pp.589–596. http://nopr.niscair.res.in/bitstream/123456789/10807/1/IJMS%2039(4)%20589-596.pdf

[12]. Dhinakaran, G. (2011). "Hydrodynamic Characteristics of Semi-circular Breakwaters: Review Article." Asian J. Appl. Sci., 4(1), pp. 1–21.

[13]. Dhinakaran, G., Sundar, V., Sundaravadivelu, R., and Graw, K. U. (2009). "Effect of perforations and rubble mound height on wave transformation characteristics of surface piercing semicircular breakwaters." Ocean Eng., Elsevier, 36(15–16), pp. 1182–1198.

[14]. Engineering, S., and Boran, S. (2017). "A Novel Approach Based on Combining ANFIS , Genetic Algorithm and Fuzzy c-Means Methods for Multiple Criteria Inventory Classification."

[15]. Erdik, T., Savci, M. E., and Şen, Z. (2009). "Artificial neural networks for predicting maximum wave runup on rubble mound structures." Expert Syst. Appl., 36(3), pp. 6403–6408.

[16]. Fazlic, L. B., Avdagic, Z., and Besic, I. (2015). "GA-ANFIS Expert System Prototype for Detection of Tar Content in the Manufacturing Process." (May), pp. 25–29.

[17]. Goyal, R., Singh, K., and Hegde, A. V. (2014). "Quarter Circular Breakwater : Prediction and Arti fi cial Neural Network." Mar. Technol. Soc. J., 48(February), pp. 1–7. DOI: 10.4031/MTSJ.48.1.7.

[18]. Harish, N., Mandal, S., and Rao, S. (2012). "Adaptive neuro fuzzy inference system modeling to predict damage level of non-reshaped berm breakwater." 5(4), pp. 1–7.

[19]. Haznedar, B., and Kalinli, A. (2016). "Intelligent Systems and Applications in Engineering Training ANFIS Using Genetic Algorithm for Dynamic Systems Identification." 4(1), pp. 44–47.

[20]. Hegde, A., Mohan, S., Pinho, J. L. S., and Sharhabeel, P. S. (2018). "Physical model studies on the stability of emerged seaside perforated semicircular breakwaters." 47(March), pp. 681–685. http://nopr.niscair.res.in/handle/123456789/44113

[21]. Jabbari, E., and Talebi, O. (2011). "Using Artificial Neural Networks for estimation of scour at the head of vertical wall breakwater." J. Coast. Res., (64), pp. 521–526.

[22]. Jang, J. R. (1993). "ANFIS : Adap tive-Ne twork-Based Fuzzy Inference System." 23(3).

[23]. Jiang, X., Zou, Q., and Zhang, N. (2017). "Wave load on submerged quarter-circular and semicircular breakwaters under irregular waves." Coast. Eng., Elsevier, 121(November 2016), pp. 265–277.

[24]. Kudumula, S. R., and Mutukuru, M. R. G. (2013). "Experimental Studies on Low crested Rubble Mound , Semicircular Breakwaters and Vertical wall System." 4(3), pp. 213–226.

[25]. Kundapura, S. and Hegde, A. V. (2017). "ANFIS Vs ANN for prediction of wave reflection coefficient for a semicircular breakwater", Hydro-2017 International, L.D. College of Engineering Ahmedabad, India.

[26]. Kundapura, S., Hegde, A. V. and Wazerkar A., (2018). " Beyond the data range approach to soft compute the reflection coefficient for emerged perforated semicircular breakwater". ICOE 2018., The 4th International conference in Ocean Engineering, 18-21 February 2018, IIT Madras, Chennai, India

[27]. Lee, A., Kim, S. E., and Suh, K.-D. (2015). "Estimation of Stability Number of Rock Armor Using Artificial Neural Network Combined with Principal Component Analysis." Procedia Eng., Elsevier B.V., 116(1), pp. 149–154.

[28]. Li, K., and Su, H. (2010). "Forecasting building energy consumption with hybrid genetic algorithm-hierarchical adaptive network-based fuzzy inference system."

Energy Build., Elsevier B.V., 42(11), pp. 2070–2076.

[29]. Liu, Y., and Li, Y. (2011). “Wave interaction with a wave absorbing double curtain-wall breakwater.” Ocean Eng., Elsevier, 38(10), pp. 1237–1245.

[30]. Mani, J. S., & Jayakumar, S. (1995). Wave transmission by suspended pipe breakwater. Journal of the waterway, port, coastal, and ocean engineering, 121(6), 335-338.

[31]. Mohammady, S. (2016). “Optimization of adaptive neuro fuzzy inference system based urban growth model.” City, Territ. Archit., Springer Berlin Heidelberg.

[32]. Najib, M., Salleh, M., and Hussain, K. (2016). “A Review of Training Methods of ANFIS for Applications in Business and Economics.” 9(7), pp. 165–172.

[33]. Nishanth N. (2008) Sliding stability and hydrodynamic performance of emerged semicircular breakwater M. Tech Thesis, NITK, Surathkal. Mangaluru. India.

[34]. Patil, S., Mandal, S., & Hegde, A.V.,“Wave transmission prediction of multilayer floating breakwater using neural network,” Proc 3rd International Conference in Ocean Engineering, ICOE-2009, IIT Madras, Chennai, 1-5 February, 2009, pp 574-585. 2009.

[35]. Patil, S. G., Mandal, S., and Hegde, A. V. (2012). “Genetic algorithm based support vector machine regression in predicting wave transmission of horizontally interlaced multi-layer moored floating pipe breakwater.” Adv. Eng. Softw., Elsevier Ltd, 45(1), pp. 203–212.

[36]. Patil, S. G., Mandal, S., Hegde, A. V., and Alavandar, S. (2011). “Neuro-fuzzy based approach for wave transmission prediction of horizontally interlaced multilayer moored floating pipe breakwater.” Ocean Eng., Elsevier, 38(1), pp. 186–196.

[37]. Raju, B., Hegde, A. V., and Chandrashekar, O. (2015). “Computational Intelligence on Hydrodynamic Performance Characteristics of Emerged Perforated Quarter Circle Breakwater.” Procedia Eng., Elsevier B.V., 116(1), pp. 118–124. doi: 10.1016/j.proeng.2015.08.272.

[38]. Ren, M., Liu, P., Wang, Z., and Yi, J. (2016). “A Self-Adaptive Fuzzy *c* -Means Algorithm for Determining the Optimal Number of Clusters.” 2016(1).

[39]. Sooraj, M. (2009) Sliding stability and hydrodynamic performance of emerged semicircular breakwater. M. Tech Thesis, NITK, Surathkal. Mangaluru. India

[40]. Sreejith, (2015) Sliding stability and hydrodynamic performance of emerged semicircular breakwater. M. Tech Thesis, NITK, Surathkal. Mangaluru. India

[41]. Taraghi, B. (2014). “Fuzzy c-mean (FCM) clustering and Genetic Algorithm capability in predicting saturated hydraulic con ductivity.” (Ictck), pp. 26–27. 16)

[42]. Vishal Kumar, (2010) Hydrodynamic performance characteristics of one side and two side perforated semicircular breakwater. M. Tech Thesis, NITK, Surathkal. Mangaluru. India

[43]. Yagci, O., Mercan, D. E., Cigizoglu, H. K., and Kabdasli, M. S. (2005). “Artificial intelligence methods in breakwater damage ratio estimation.” Ocean Eng., 32(17–18), pp. 2088–2106. doi: 10.1016/j.oceaneng.2005.03.004

[44]. Young, D. M., and Testik, F. Y. (2011). “Wave reflection by submerged vertical and semicircular breakwaters.” Ocean Eng., Elsevier, 38(10), pp. 1269–1276.

[45]. Zanaganeh, M., Mousavi, S. J., Farshad, A., and Shahidi, E. (2009). “Engineering Applications of Artificial Intelligence A hybrid genetic algorithm – adaptive network-based fuzzy inference system in prediction of wave parameters.” Eng. Appl. Artif. Intell., Elsevier, 22(8), pp. 1194–1202.

[46]. Zanuttigh, B., Mizar, S., and Briganti, R. (2013). “A neural network for the prediction of wave reflection from coastal and harbor structures.” Coast. Eng., Elsevier B.V., 80, pp. 49–67. doi: 10.1016/j.coastaleng.2013.05.004

[47]. Zhou, K., and Yang, S. (2016). “Knowledge-Based Systems Exploring the uniform effect of FCM clustering : A data distribution perspective.” 96, pp. 76–78.