

## **Adaptive neuro fuzzy inference system modeling to predict damage level of non-reshaped berm breakwater**

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**Abstract:** In this paper, the Adaptive Neuro Fuzzy Inference System (ANFIS) model is constructed using experimental data set to predict the damage level of berm breakwater. Experimental data for non-reshaped berm breakwater are collected from Marine Structures Laboratory, Department of Applied Mechanics and Hydraulics, NITK, Surathkal, India. The experimental data are used to train the ANFIS model and thereafter test outputs are obtained. The statistical measures like mean square error, root mean square error, correlation coefficient (CC) and scatter index (SI) for test data are 8.072, 2.841, 0.92 and 0.218 respectively. Comparing with the Artificial Neural Network model, ANFIS yields higher CC and lower SI. From the results it can be concluded that ANFIS can be an efficient tool in predicting the damage level of non-reshaped berm breakwater.

**Keywords:** *Berm Breakwater, Damage, ANFIS*

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### **Introduction**

A berm breakwater is a rubble mound structures constructed with the horizontal berm at or above still water level at seaward side. During the wave attack, non-reshaped berm breakwater under goes no or minor damage to the structure. The term damage is defined as the displacement of armor units. The berm breakwater is designed to utilize locally available quarry to optimum usage. Breakwaters are the structures constructed to provide protection to the port and harbor facility from dynamic forces of the ocean waves. They are used to protect beaches, cultivation land, and valuable habitats from erosion. From the past, physical models are developed and experiments are carried out to design safe breakwaters ( Brunn P. et al., 1976; Baird and Hall, 1984; Van der Meer 1988, Torum et al. 1999, 2003; Subba Rao et al. 2004 and 2008; Moghim et al., 2011)

which are time consuming and expensive in terms of cost.

Experimental cost and time in conducting the experimental work is reduced by using the soft computing tools. The soft computing tools like Artificial Neural Network (ANN), Support Vector Machine (SVM), Adaptive Neuro Fuzzy Inference System (ANFIS), etc., are being widely used to predict outcome of the experimental results. These soft computing tools have been used in coastal field for prediction of experimental results. Mase et al. (1995) applied neural network technique to predict the stability and damage level of rubble mound breakwater. The predicted damage levels are matching with the measured damage levels by Vander Meer's (1988) and Smith et al (1992). Yagci et al. (2005) used neural network technique to predict the damage ratio of breakwater. Model

estimations of damage ratios were matching with the predicted values by neural network method. The ANN application enables the consideration of wave period, wave steepness, and breakwater slope and wave height in estimating damage ratio. Kim and Park (2005) applied the artificial neural network method to design the rubble mound breakwater. According to them the neural network technique gave more accurate results than the conventional empirical model and the extent of accuracy was affected by structure of neural network. Kim et al., (2011) used Support Vector Regression to predict the stability number of armor blocks of breakwaters. The proposed method proves to be an effective tool for designers of rubble mound breakwaters to support their decision process and to improve design efficiency. Balas et al., (2010) applied hybrid model for the preliminary design of rubble mound breakwater and a better agreement between the predicted and measured was obtained when compared to stability equations of Vander Meer's (1988) and ANN. Patil et al., (2011) used ANFIS model for predicting wave transmission coefficient of horizontally interlaced multilayer moored floating pipe breakwater and showed that ANFIS model outperformed ANN model for predicting wave transmission coefficient.

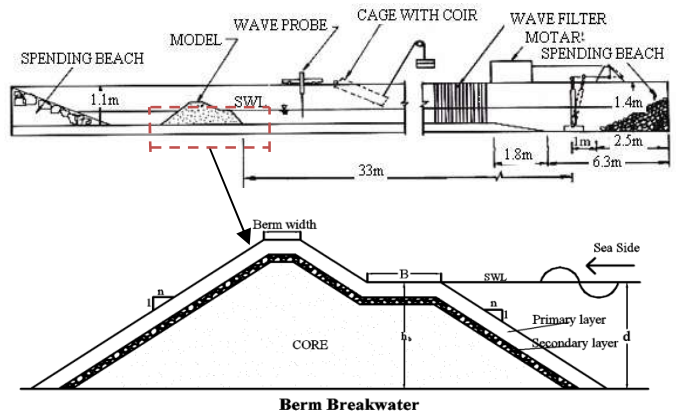
In the present paper, performances of the ANFIS for the prediction of damage level for non-reshaped berm breakwater are investigated, and the results are compared with Artificial Neural Network.

### Experimental Data

The experimental work was carried in Marine Structures Laboratory, Department of Applied Mechanics and Hydraulics, NITK, Surathkal, India. The wave flume is 50 m long, 0.71 m wide, 1.1 m deep, and has a 42 m long smooth concrete bed. Fig.1 shows a sketch of the wave flume.

Four set of experiments were carried out for 3000 waves. In the first set of experiment,

stability for different wave periods and height on conventional breakwater model with trapezoidal cross section with armor stone weight  $W_{50} = 74$  gm was tested. In the second set of experiments, statically stable non-reshaped berm breakwater models were tested with the armor stones weight  $W_{50} = 52$  gm which is about 30% less than 74 gm. They studied the influence of berm width on the stability of the breakwater, runup and rundown (Subba Rao et al., 2004).



**Fig.1** Experimental Set-Up

In the third set of experiments armor stones weight  $W_{50} = 58.6$  gm which is about 20% less than 74 gm. The influence of tidal effect and stability were studied by changing the depth of water in front of the breakwater model. In the fourth set of experiments the influence of location of the berm and stability were studied by keeping the armor stones weight  $W_{50} = 52$  gm, the weight used in conventional breakwater (Subba Rao et al., 2008). Range of experimental variables is shown in Table 1.

For the present analysis, experimental data are converted into non dimensional parameters like Wave Steepness ( $H_0/L_0$ ), Surf Similarity( $\zeta$ ), Relative berm width by water depth ( $B/d$ ), Armor Stone Weight ( $W_{50}/W_{50max}$ ), Relative berm width ( $B/L_0$ ) and Relative berm location ( $h_B/L_0$ ) and they are used for the analysis. 124 data sets are considered for the present study. From 124 data sets randomly 93 (75%) data sets are used for training the networks and 31 (25%) data sets are used for testing the models.

**Table1. Range of Experimental Variables**

Variables	Range
Wave height H (m)	0.10, 0.12, 0.14, 0.16
Wave period T (Sec)	1.6, 2.0, 2.6
Water depth above the bed level d (m)	0.25, 0.30, 0.35, 0.40
Armor stone weight W <sub>50</sub> (gm)	52 to 74
Crest height above the seabed (m)	0.70
Berm width B (m)	0.60
Berm position above seabed h <sub>B</sub> (m)	0.32

**Adaptive Neuro-Fuzzy Inference System**

In 1993 Jang suggested Adaptive Neuro Fuzzy Inference System (ANFIS). It is a simple structure with effective learning algorithm and high speed. (Vairappan et al 2009). It serves as a starting point for constructing a set of fuzzy 'if-then' rules with appropriate membership functions to generate the fixed input-output pairs. ANFIS is a combination of least-squares method and backpropagation gradient decent method used for training Takagi-Sugeno type fuzzy inference system which is used for an effective search for the optimal parameters. ANFIS training can use alternative algorithms to reduce the error. The advantage of a hybrid approach is that it converges much faster, since it reduces the search space dimensions of the backpropagation method used in neural networks.

**Architecture of ANFIS**

A simple architecture of ANFIS with I-input variables O-output variables is shown in Fig.2. It consists of five layers and each layer is explained below.

**Layer 1**

Every node in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1, \quad (1)$$

$$O_{1,i} = \mu_{B_{i-2}}(x), \text{ for } i = 3,4 \quad (2)$$

x (or y) is the input node and A<sub>i</sub> (or B<sub>i-2</sub>) is a linguistic variables associated with the membership function of a fuzzy set (A<sub>1</sub>,A<sub>2</sub>,B<sub>1</sub>,B<sub>2</sub>). Typical membership function:

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x}{a_i}\right)^{2b_i}} \quad (3)$$

where a<sub>i</sub>, b<sub>i</sub> and c<sub>i</sub> is the parameter set. Parameters are called as premise parameters.

**Layer 2**

Each node in this layer is a fixed node, indicated by Π Norm. The output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), \text{ } i = 1,2 \quad (4)$$

output signal w<sub>i</sub> represents the fire strength of a rule.

**Layer 3**

Each node in this layer is a fixed node N Norm. The ith node calculates the ratio of the firing strength to the sum of the firing strength.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \text{ } i = 1,2 \quad (5)$$

Output signal  $\bar{w}_i$  is called normalized firing strengths.

**Layer 4**

Each node in this layer is an adaptive node, indicated by square node with a node function:

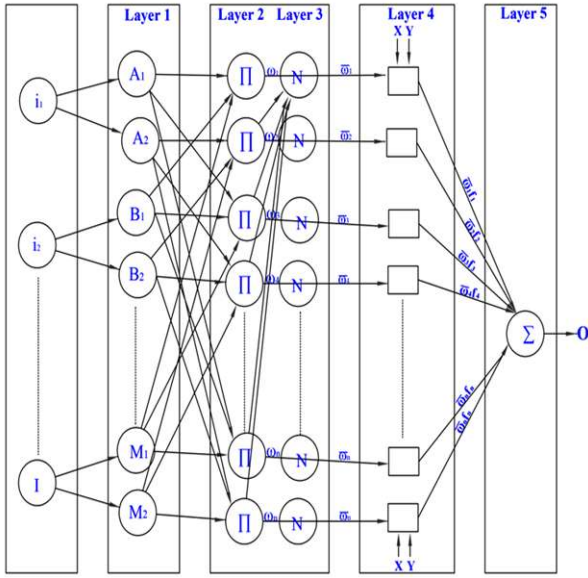
$$O_{4,i} = w_i f_i = w_i (p_i x + q_i y + r_i) \quad (6)$$

where w<sub>i</sub> is the normalized firing strength from layer 3. {p<sub>i</sub>, q<sub>i</sub>, r<sub>i</sub>} is the parameter set which are called as consequent parameters.

**Layer 5**

Each node in this layer is a fixed node, indicated by circle node which computes the overall output as the summation of all incoming signals:

$$\text{Overall output} = O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{w_i} \quad (7)$$



**Fig.2** ANFIS structure

In the present study ANFIS structure consists of 64 fuzzy rules for 6 input parameters namely  $i_1=H_o/L_o$ ,  $i_2=\zeta$ ,  $i_3=B/d$ ,  $i_4=W50$ ,  $i_5=B/Lo$  and  $i_6= hB/Lo$ . And use first order Sugeno model with 2 generalised membership functions. The different membership functions assigned for input parameters are:

Gauss membership function:

$$f(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (8)$$

where  $x$  is input parameters,  $c$  and  $\sigma$  are mean and variance respectively.

Triangular membership function:

$$f(x, a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \quad (9)$$

where,  $x$  is input parameter,  $a$  &  $c$  locate the feet of the triangle and  $b$  locate the peak.

Generalized bell-shaped membership function:

$$f(x, a, b, c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \quad (10)$$

where,  $x$  is input parameter,  $c$  locate the centre of the curve.

## Results and Discussion

In the present study, Adaptive Neuro Fuzzy Inference System (ANFIS) is used to predict the damage level of non-reshaped berm breakwater to reduce the time and cost for carrying the experimental work. The performance of the model is evaluated using

statistical measures which are defined as follows:

Mean Square Error

$$(MSE) = \frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2 \times 100\% \quad (11)$$

Root Mean Square Error

$$(RMSE) = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2} \times 100\% \quad (12)$$

Correlation Coefficient

$$(CC) = \frac{\sum_{i=1}^n (O_i - \bar{O}_i)(P_i - \bar{P}_i)}{\sqrt{\sum_{i=1}^n (O_i - \bar{O}_i)^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P}_i)^2}} \quad (13)$$

Scatter Index

$$(SI) = \frac{RMSE}{\bar{O}_i} \quad (14)$$

where,  $O_i$  and  $P_i$  are observed and predicted damage level respectively,  $n$  is the number of data set used and  $\bar{O}_i$  &  $\bar{P}_i$  are average observed and predicted damage level respectively.

In this study, the ANFIS model is used to predict the damage level of non-reshaped berm breakwater. Out of 124 experimental data set, 93 data set are used for training the model and 31 data set are used for testing the model.

The ANFIS model, with a combination of gradient descent algorithm and least squares algorithm is used for an effective search for the optimal parameters to yield good results. Based on this hybrid approach, correlations of training and testing are increased. Here, Sugeno first order with 64 fuzzy rules and 2 generalised 'gauss' membership function are used to train the model.

The results obtained during training and testing processes for input parameters are calculated by means of statistical measures like Correlation Coefficient, Mean Square Error, Root Mean Square Error and Scatter Index values are shown in Table 2. The ANN model results are also shown in Table 2 (Mandal et al 2011) where CCs in two models i.e., in ANFIS and ANN are higher than 0.94 and 0.88 for train and test data respectively.

MSE and RMSE for all models are less than 5.879, 2.424, 12.412 and 3.523 for training and testing respectively. And SI is less than 0.1004 and 0.218 for training and testing respectively for all the models. Fig.3 shows the correlation between the observed and predicted damage level for train and test of ANFIS model with gauss membership function. Fig 4 shows the test performances for ANFIS model with gauss membership function for prediction of damage level and it shows that observed and ANFIS model have similar outline which indicates better model for prediction.

The ANFIS model with 64 fuzzy rules and 2 generalized gauss membership function is used which reduces the processing time and gives better results for prediction of damage level than ANN and other ANFIS membership model for all statistical criteria. The ANFIS with gauss membership function model outperformed ANN model and other ANFIS membership model and provided the best performance, i.e., the lowest RMSE and highest CC for test output. Results of the study also indicate that the predictive capability of the ANFIS with gauss membership function model used in this study is better when compared with ANN in damage level prediction.

### **Summary and Conclusion**

In the present study, the ANFIS model is applied to predict the damage level of non-reshaped berm breakwater. The experimental data generated by wave flume at Marine Structure laboratory, NITK, Surathkal, India is used in this study. From 124 data sets randomly 93(75%) data sets are used for training the network and 31(25%) data sets are used for testing the network.

Two models show good results in terms of statistical measures like mean square error, root mean square error, correlation coefficient and scatter index for observed and predicted damage level. Among these two models, ANFIS structure which uses first order Sugeno containing 64 rules and 2 generalized gauss

membership functions yields better results compared to ANN model.

From the present study we can conclude that ANFIS model is an effective tool in predicting the damage level of non-reshaped berm breakwater and fast in predicting the damage values. Therefore it can be used as an alternative tool to determine the damage level of non-reshaped berm breakwater.

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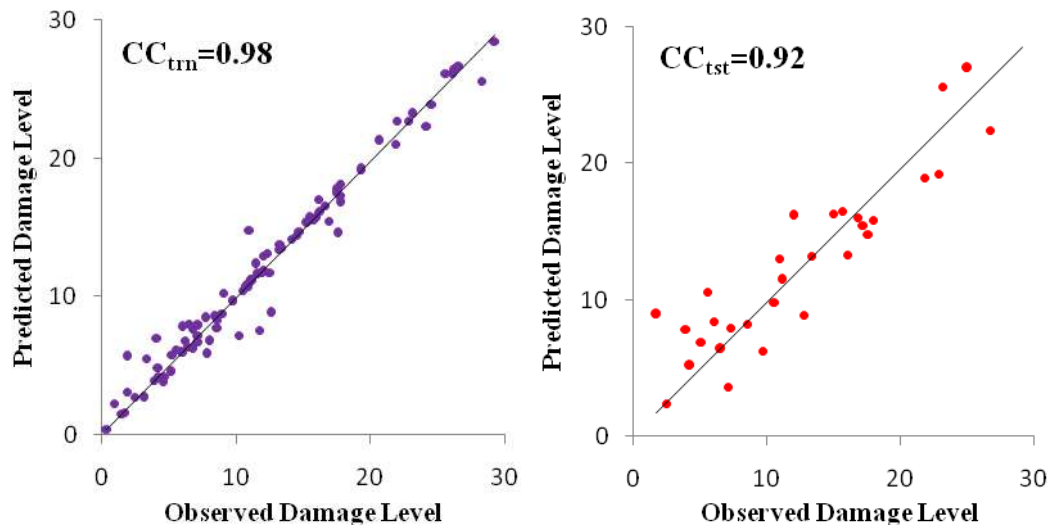
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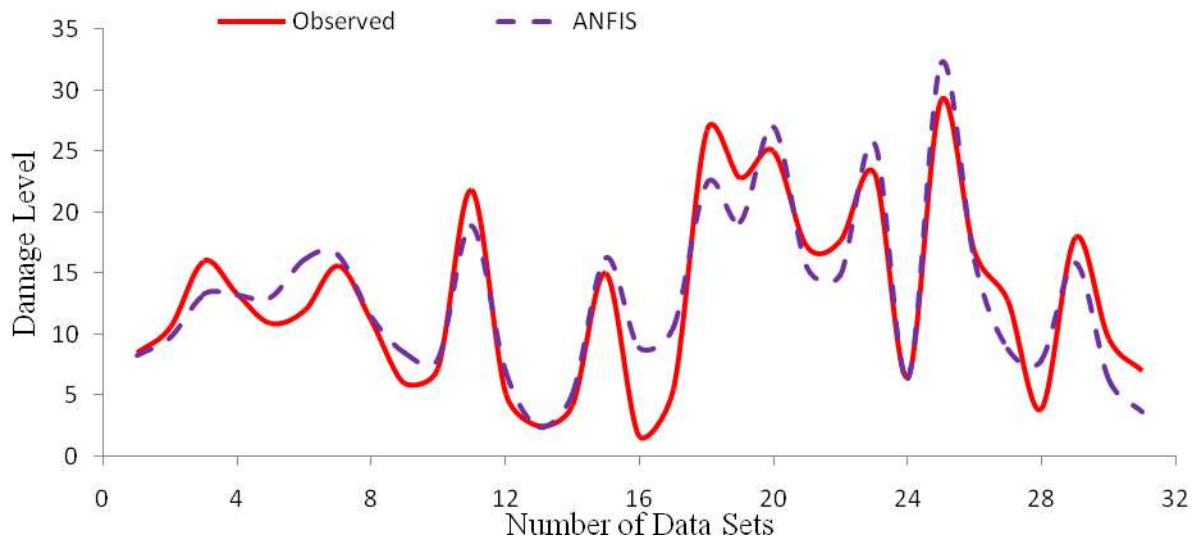
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**Table2. Statistical measures for different model**

Model		Membership Function	MSE	RMSE	CC	SI
ANN	Train	-	5.879	2.424	0.94	0.2028
	Test		12.412	3.523	0.88	0.2646
ANFIS	Train	Gauss	1.468	1.212	0.98	0.1004
	Test		8.072	2.841	0.92	0.218
	Train	Triangular	1.749	1.323	0.98	0.1096
	Test		19.298	4.393	0.84	0.3373
	Train	Gbell	1.554	1.246	0.98	0.1033
	Test		47.034	6.858	0.77	0.5265



**Fig. 3** Observed and predicted damage level by ANFIS using gauss membership function for train and test data.



**Fig. 4** ANFIS performances using gauss membership function for damage level prediction of test data.