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Application of Soft Computing techniques in Breakwater-A Review

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Abstract— The environmental stress on the coastal zone is rapidly growing and there is a need to protect the coastal environment. The constant challenge to coastal engineers is the development of structures like seawalls, groins, offshore breakwaters, artificial nourishments etc. to provide protection against the destructive forces of the sea waves and to withstand the action of waves. Breakwaters are used to protect beaches, cultivation land and valuable habitats from erosion. They are widely used throughout the world for protection from the wave action and to provide shelter to harbor and port. Breakwaters are also used for dual purposes like dissipating wave energy and providing loading facilities for cargo and passengers. Physical model studies can be simplified by effective machine learning techniques which are cost effective and less time consuming. Various design aspects of breakwater such as stability number, wave height, scour depth, design armour weight etc. can be predicted using soft computing techniques. The machine learning techniques like ANN, ANFIS, SVM, Fuzzy Logic, Model tree etc. are having a vast area of application in different fields of science. This paper reviews various works of soft computing done in the field of breakwater for prediction of various design aspects.

Index Terms— Breakwater, shoreline protection, soft computing techniques.

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1 Introduction

Breakwaters facilities for cargo loading and unloading and protect the harbor from wave attack. The main function of breakwater is to dissipate the wave energy thereby maintaining tranquility conditions inside the harbor. The various types of breakwaters have been developed over the years. There is a constant urge for innovation in breakwater systems, to reduce cost, time of construction, to improve efficiency and to satisfy some site specific conditions. The applicability of a specific type of breakwater mainly depends on the site conditions and availability of materials.

Structural shore protection methods or hard structures such as breakwaters, groins and jetties can reduce the energy of waves, but can also redirect it so that the erosion problem may simply move to another area. A steep beach or retaining wall allows waves to crash into the shore, thereby increasing erosion drastically; whereas, a gradual gentle slope of the shoreline can absorb the energy of waves to a large extent. The deep roots of mangroves which grow on estuarine regions and other beach vegetation like casuarinas help in binding the earth together. In marshes, swamps and creeks, the canopy of trees provides a rich cover which shields the soil surface from the impact of falling rain and thus reduces runoff. Hard methods of coastal protection including massive constructions was prevalent during 19th and 20th centuries, but alternative approaches harnessed from nature or natural resources have gained acceptance in the recent past. From the past, many physical models were developed and experiments were carried out to design safe breakwaters which are time consuming and expensive in terms of cost.

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To minimize the cost and time in conducting the experimental work, 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. . In order to reduce the cost and time in conducting the experimental work, soft computing techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Adaptive Neuro Fuzzy Inference System (ANFIS) and hybrid of these models are being applied to solve a variety of coastal engineering problems. In practical soft computing techniques are widely used in different fields and accepted as an alternative way to tackle complex problems. Soft computing techniques have an ability to learn from examples and have a capacity to handle noisy and incomplete data. Once the model learns from the examples then predictions of the outcome can be done at higher speed.

2 Soft Computing Techniques in Coastal Engineering

Soft computing is a collection of methodologies that provide effective results for real case scenario problems within minimum time available. Soft computing provides results for problems which are hard to answer analytically. Soft computing techniques finds application in the field of breakwater studies for the prediction of damage level, scour depth, transmitted wave height prediction and so on.

Many of the works on application of soft computing techniques such as Artificial neural networks(ANNs),Fuzzy systems (FS) , Generic algorithm (GA) ,support vector machines (SVM) describes the alternative way to tackle the coastal engineering problems.The ANN approach was used to estimate the wave parameters from cyclone generated wind fields (Subba Rao and Mandal S.2005).Estimation of Hs and periods was carried out using back propagation neural network with three updated algorithms, namely Rprop, Quick prop and

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super SAB[2]. Mandal et al.,(2007) used neural network technique to predict the stability number and damage levels of rubble mound breakwater.It is observed that a good correlation is obtained between network predicted stability numbers and estimated ones with less computational time compared to Mase et al.(1995) and Kim and Park(2005).Browne et al.,(2007) developed two data driven approaches to estimate waves near shore(linear and ANN),and to contrast these with a more traditional spectral wave simulation model(SWAN).They found that ANN outperformed SWAN, and the nonlinear architecture consistently outperformed the linear model. Mandal et al., (2008) applied neural network technique in predicting the stability number and compared it with the estimated stability number by Hudson and Vander Meer. The neural network is modelled with parameters, which affects the stability namely permeability of breakwater ,number of attacking waves ,significant wave height ,mean wave period, damage level, slope angle, berm width and reduced armor weight ratio. It is found that the network predicts lesser armor units compared to empirical formulae which makes the design more economical and safe. The coefficient correlation between the estimated stability number by empirical formulae and predicted stability number by neural networks are close to one.Gunaydin (2008) used ANN and regression method to predict monthly mean significant height from meteorological data. He used seven different ANN models comprising of various input combinations of monthly mean wind speeds, sea level pressures and air temperature ratios based on hourly observations. He found that ANN model having all parameters in the input layer gave the best prediction performance.

Balas et al., (2010) applied hybrid model for the preliminary design of rubble mound breakwater and better agreement between the predicted and measured was obtained when compared to stability equations of Vander Meer's(1988) and ANN. Heesung Yoon et al.,(2011) built two nonlinear time-series models for predicting groundwater level fluctuations using artificial neural networks (ANNs) and support vector machines(SVMS).The models were applied to GWL prediction of two wells at a coastal aquifer in Korea. The result of the model performance show that root mean squared error(RMSE) values of ANN models are lower than those of SVM in model training and testing stages. However, the overall model performance criteria of the SVM are similar to or even better than those of the ANN in model prediction stage. Patil et al., (2011) used ANFIS model for predicting wave transmission coefficient of horizontally interlaced multilayer moored floating pipe breakwater (HIMFPB) and showed that ANFIS model outperformed ANN model for predicting wave transmission coefficient.

Aydogan et al. (2010) studied to predict vertical current profiles of a given point in a narrow Strait of Istanbul, using the feed forward back propagation (FFBP) artificial neural network (ANN) technique. The model predicted 12 outputs of East and North velocity components at different depths in a given location. Predictions from proposed ANN model were in accordance with good overall agreement with observations and FFBP ANN can be used as a reliable tool for forecasting current profiles in straits.Hashemi et al. (2010) used an artificial neural network (ANN) to predict seasonal beach profile evolution at various locations along the Tremadoc Bay, eastern Irish Sea. The geometric properties of beach, wind data, local wave climate and the corresponding beach level changes were fed to a feed forward back propagation (FFBP) ANN.The trained ANN model results had very good agreement with beach profile surveys for the test data.

Dookie Kim et al., (2011) used Support Vector regression to predict the stability number of armour blocks of breakwaters. The proposed methods proves to be an effective tool for designers of rubble mound breakwaters to support their decision process and to improve design efficiency. Bharat et al (2016) used ANN for the prediction of transmitted wave height for submerged reef of a tandem breakwater.According to them ANN using Levenburg-Marquadart updated algorithm yields accurate values, with correlation coefficient (CC) values in the range of 0.97 to 0.98 for different model configurations. Ali et al (2017) used GP and ANN in predicting the scour depth at trunk section of breakwater for non-breaking waves. Models used non-breaking wave steepness, relative water depth at toe, and reflection coefficient and shield parameter as input parameters and predicted scour depth. Based on the value of the statistical parameters obtained, GP model outperformed ANN model in scour depth prediction.Geeta Kuntoji et al., (2017) constructed Adaptive Neuro Fuzzy Inference system (ANFIS) model to predict the effect of structure and wave characteristics on the hydraulic performance of the reef. The experimental data were used to train ANFIS models and results are determined in terms of statistical measures such as mean square error, root mean square error, correlation coefficient. The result showed that ANFIS can be efficient tools in predicting the performance of wave and structural parameters.

3 Artificial Neural Network

Artificial Neural networks (ANN) are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connecting weights between the elements. Commonly, neural networks are adjusted or trained to establish a required path so that a particular input leads to a specific target output. Such a situation is shown in Figure 1.Here, the network is adjusted, based on a computation of the output, and the target, until the network matches the target. Typically, many such input or target output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector.

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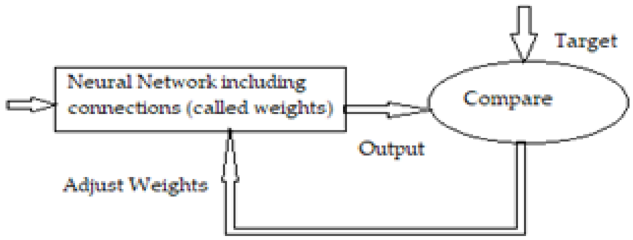

Fig 1. Basic principle of Artificial Neural Networks

4 Support vector machine

The Support Vector Machine (SVM) is a concept in computer science for supervised learning technique that is used for classification and regression analysis. The model produced by SVM only depends on a subset of the training data, because the cost function for building the model ignores any training data that is close (within a threshold) to the model prediction (Smola and Scholkopf, 1998; Vapnik, 1995; Burges, 1998; Karatzoglou and Meyer, 2006). The SVM constructs a separate hyperplane between the classes in the n-dimensional space and maximizes the margin between two data sets of two input classes. It attempts to fit a curve, with respect to the kernel function used on the data points such that points lie between two marginal hyperplanes to minimize the regression error.Fig. 2 shows the graphical representation of SVM.

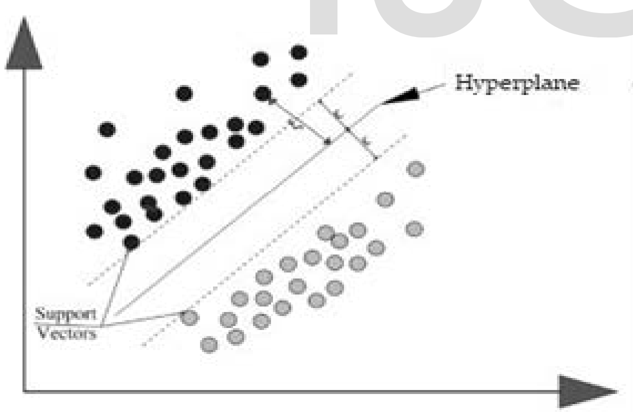

Fig 2.Graphical representation of SVM

5 Adaptive neuro-fuzzy inference system

Adaptive Neuro-Fuzzy Inference system is a combination of least-squares and backpropogation gradient decent methods used for training Takagi-Sugeno type fuzzy inference system which is used for an effective search for the optimal parameters. It can provide 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 simple structure with effective learning algorithm and high speed (Vairappan et al, 2009). 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.

6 General methodology

Predicting the data output by learning from the input provided is the main function of the soft computing technique.. Fig.1 shows the general methodology followed by soft computing techniques in prediction. The effectiveness of the model developed is evaluated from the values of statistical parameters like Root Mean Square Error (RMSE), Correlation Coefficient (CC), Scatter Index (SI), Mean Absolute Error (MAE) etc. are some of the commonly used statistical parameters. Randomness nature of the data used is also ensured by plotting data time series graph.

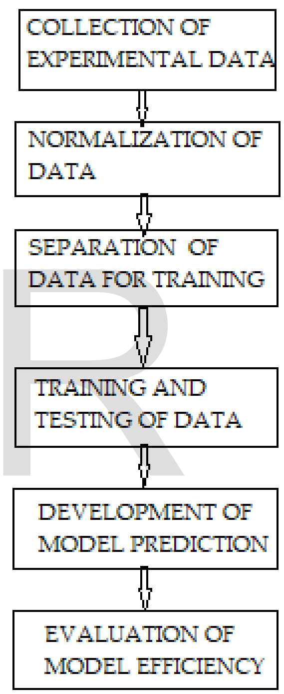

Fig 3. Methodology flowchart for prediction using soft computing techniques

7 Results

The experimental data generated by wave flume at Marine Structure laboratory, NITK, Surathkal, India is used in the study of damage level prediction of non-reshaped berm breakwater using ANN, SVM and ANFIS models. The ability of soft computing techniques is applied to predict the damage levels for non-reshaped berm breakwater.

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 as shown in table 1.

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Table 1.Statistical measures for different model

Model		MSE	RMSE	CC	SI
ANN	Train	5.879	2.425	0.940	0.203
	Test	12.412	3.523	0.884	0.267
SVM	Train	3.361	1.833	0.968	0.153
	Test	11.106	3.333	0.897	0.250
ANFIS	Train	1.445	1.202	0.985	0.099
	Test	8.463	2.909	0.919	0.223

Correlation between the observed and predicted damage levels for both training and testing:

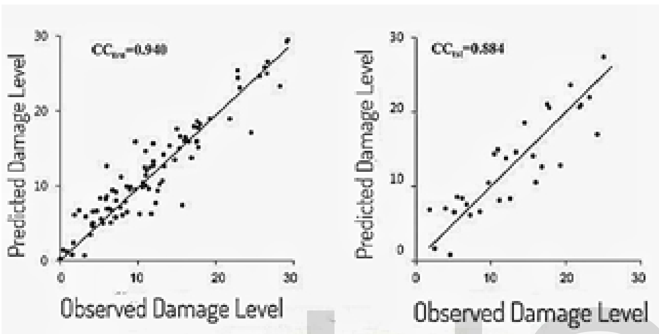

Fig.4 Observed and predicted damage level by ANN method for train and test data

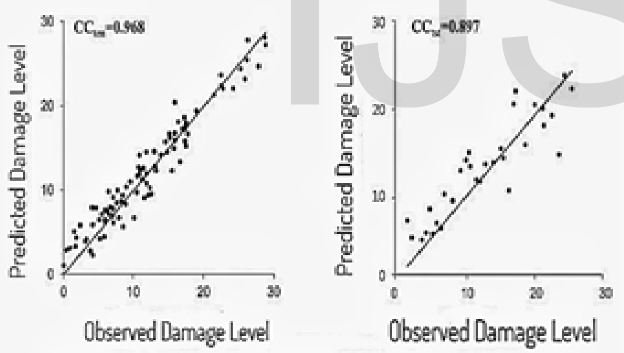

Fig 5.Observed and predicted damage level by SVM method for train and test data

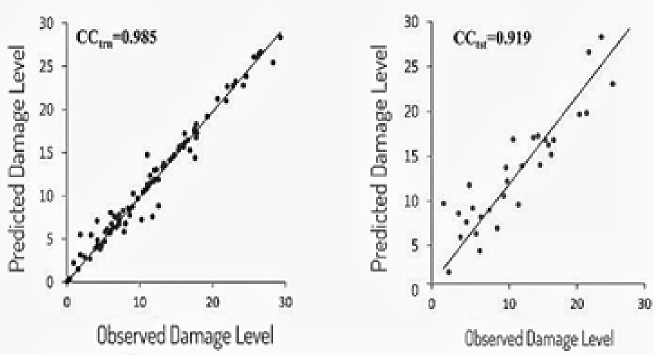

Fig 6. Observed and predicted damage level by ANFIS method for train and test data

8 Summary

Soft computing techniques have been applied widely to solve various coastal engineering problems. In the field of breakwater studies the complexity associated with mathematical modelling and the time consuming nature of physical modelling makes soft computing the better option in prediction. However only by proper physical model studies, the data input and the influential parameters can be determined Hence along with prior physical model studies application of soft computing techniques can give effective and immediate results.

Soft computing techniques have been applied by many researchers and scientists in predicting the coastal dynamic processes like wave parameter estimation, tidal prediction, coastal structural design and storm surge. It was found that the neural networks are reliable and the results obtained were better when compared to that using mathematical models and regression models.

Based on the review on various works done on soft computing in the field of breakwater studies the following conclusions are drawn:

• Predicting the design parameters of breakwater by the application of soft computing techniques.

• The predictive efficiency of a machine learning approach depends upon quality and size of the data set available.

• Soft computing techniques have a capacity to handle noisy and incomplete data and the predictions of the outcome can be done at higher speed.

• The effectiveness of the model developed depends on the selection of proper kernel and model parameters

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