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Current approaches of artificial intelligence in breakwaters – A review

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Abstract. A breakwater has always been an ideal option to prevent shoreline erosion due to wave action as well as to maintain the tranquility in the lagoon area. The effects of the impinging wave on the structure could be analyzed and evaluated by several physical and numerical methods. An alternate approach to the numerical methods in the prediction of performance of a breakwater is Artificial Intelligence (AI) tools. In the recent decade many researchers have implemented several Artificial Intelligence (AI) tools in the prediction of performance, stability number and scour of breakwaters. This paper is a comprehensive review which serves as a guide to the current state of the art knowledge in application of soft computing techniques in breakwaters. This study aims to provide a detailed review of different soft computing techniques used in the prediction of performance of different breakwaters considering various combinations of input and response variables.

Keywords: breakwaters; artificial neural networks; ANFIS; support vector machines; genetic algorithm; particle swarm optimization

1. Introduction

Coast is the interface between the land and the sea, which is subjected to a dynamic environment. Global scenario of coastal urbanization and the subsequent increase in the port volumes calls for a sustainable coastal management. Breakwater is one of the several structures available for coastal protection. The effect of breakwater installation in the field needs a comprehensive study on the performance characteristics of breakwaters. The simulation models could also be used in the laboratory to assess the same involving different parameters which affects the shape, strength, alignment and base stability. The coastal processes being complex and non-linear by nature may not be numerically modeled with accuracy. The Computational Intelligence (CI) techniques could be made use to overcome these shortcomings. Artificial Intelligence has emerged as one of the most revolutionary area. This paper gives an overview of applications of Artificial Intelligence in prediction and forecasting of different wave parameters associated with breakwaters. Application of Artificial Intelligence in the absence of adequate experimental data sets is superlative as the data sets could be efficiently interpolated. The

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computer networks can be trained to think for themselves and make intelligent decisions like the human counterparts. There have been a significant number of soft computing techniques adopted to predict the wave run-up, wave transmission, reflection coefficient, stability and damage level of breakwaters. This review paper focuses on some of the work done particularly in the area of breakwaters.

2. Concepts of soft computing techniques

The soft computing techniques like evolutionary computing, artificial neural networks, fuzzy logic and bayesian statistics could be applied independently or combined with other techniques to better solve the complex problems. Soft computing techniques can resolve the non-linear problems with the expert knowledge of cognition, recognition, understanding, learning to name a few in computing. This paper highlights some areas of soft computing techniques applied in the field of breakwaters. Hybridization of soft computing techniques has a great potential, however individual techniques are also capable of good predictions. This hybrid system of soft computing techniques is growing rapidly with its many successful applications in the area of coastal engineering.

2.1 Artificial neural networks

Warren McCulloch and Walter Pitts in 1943 introduced the first neural model. There are several such models in use since then of which ANN model with backpropogation algorithm is commonly used whose structure is as seen in Fig. 1. In a network, connection between several simple nodes is done. These nodes are artificial neurons and the network connection between several such neurons is called an Artificial Neural Network (ANN). Artificial Neural Network can learn through dataset provided. A standard ANN has three layers i.e., an input, hidden and an output layer all interconnected. Every connection is assigned with a weight (strength of the signal) chosen by experience for smaller network whereas for a larger network algorithms it is adjusted automatically based on the desired output for the given input. The process in which the weights are adjusted is called learning or training. Initially random weights are chosen and altered to keep the error minimal. The inputs are multiplied by the weights and then summed, which is passed through an activation function. Most commonly sigmoid function is used as activation function. There is no definite rule to choose the number of hidden layers and its neuron number it is done heuristically. Neural networks are very flexible, it can easily learn from training. The information flow through the connections between the nodes could be unidirectional or bidirectional i.e., feedforward ANN and feedback ANN respectively (Erdik *et al.* 2009).

2.2 ANFIS (Adaptive Neuro Fuzzy Inference System or Adaptive Network based Fuzzy Inference System)

ANFIS is a neuro fuzzy technique where the ANN is fused with fuzzy logic principles and hence it has a better potential. The fuzzy rule-based models could model the complex non-linear systems with good computational speed. The fuzzy logic accounts for the uncertainties of the system being modeled and the neural network gives it a sense of adaptability. Initially a fuzzy model along with its input variables are derived by the rules extracted from the input output variables of the system that is being modeled followed by the fine tuning of rules of the initial fuzzy model by ANN to produce the final ANFIS model of the system (Yagci *et al.* 2005). In ANFIS firstly the inputs are converted into fuzzy membership functions later combined together, followed by an averaging process and the output membership functions are obtained, to get the required output. The Fig. 2 shows the architecture of the ANFIS (Azamathulla *et al*. 2011).

2.3 Genetic algorithm

Genetic algorithm (GA) a popular evolutionary algorithm that repetitively modifies a population of individual solutions. At every step, GA randomly selects individuals from the existing population and using them as parents to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

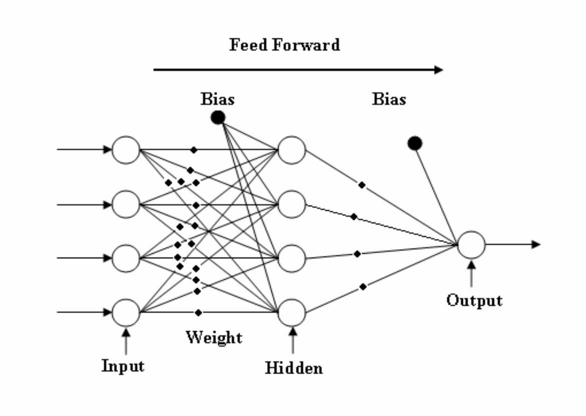

Fig. 1 Feed forward backpropagation (Jain and Deo 2008)

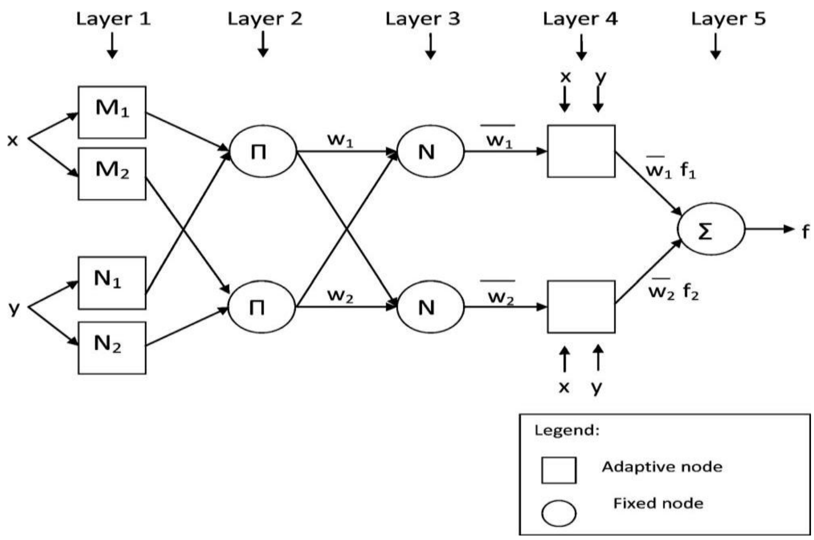

Fig. 2 ANFIS structure (Azamathulla *et al*. 2011)

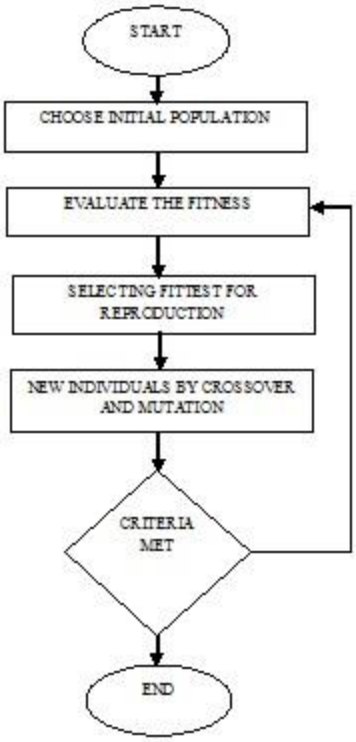

Fig. 3 Typical flowchart of Genetic Algorithm

The basic difference between a classical algorithm and a genetic algorithm is the former generates a population of points at each iteration and the best point in the population approaches an optimal solution. It selects the next population by computation which uses random number generators. Whereas in the case of latter it generates a single point at each iteration and a sequence of points approaches an optimal solution. It selects the next point in the sequence by a deterministic computation. GA solves problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly nonlinear (Patil *et al*. 2012). The typical flowchart of Genetic Algorithm is shown in Fig. 3.

2.3.1 Genetic programming

Genetic programming (GP) is an application of genetic algorithm (GA). GP automatically creates computer program to solve the problems. A random initial population of the problem is chosen, with a pre-specified maximum size. GP is based on the Darwinian natural selection and the genetic operations, where the genetic operators (reproduction, crossover and mutation) choose the best fitness population from the current population. Continuing these iterations for several generations the process is terminated when the criteria is met. The chosen individual program is copied to the new population in the process of reproduction whereas a crossover operation creates a new offspring program for the new population by recombining randomly chosen parts from two selected programs. The mutation operator creates one new offspring program for the new population by exchanging a randomly chosen part of one selected program. The given problem is solved by taking the best offspring program appearing in any generation (Koc *et al*. 2016).

2.4 Model trees

Model trees represent understandable mathematical rules which are an advantage. M5 model tree are binary decision trees that have linear regression equations at the leaves. It can handle large data sets more accurately than the regression trees. A regression tree is constructed by splitting i.e., by dividing a node into two or more sub-nodes by the model trees algorithm. This splitting condition is used to reduce the intra-subset variability in the values down from the root all the way through the branch to the node. The standard deviation is used as a measure to check variability of the values that reach that node from the root through the branches with calculating the expected error reduction as a result of testing each attribute at that node. The attribute capable of significantly reducing the error is chosen. Splitting is terminated when there is no significant variation in output values that reach the node (Etemad-Shahidi and Bonakdar 2009).

2.5 Genetic algorithm based support vector machine regression

Support vector machine regression (SVMR) is a supervised machine learning algorithm solving classification as well as regression challenges. Here every data item is plotted as a point in n-dimensional space (n number of features in the problem) with the value of each feature being the value of a particular coordinate which is support vectors. Here classification is done by finding the hyper-plane to differentiate the classes. SVMs are good at linear as well as non-linear separable problems as they make use of kernel functions. The Kernel function converts the non-separable problem to separable problem by using extremely complex data transformations and segregates the data based on the defined labels/outputs. To improve generalization of SVMR model and for accurate predictions we may need to optimize the SVMs and kernel parameters. Genetic Algorithms could be used to search for better combinations of the parameters to make the most of generalization of GA-SVMR model (Patil *et al.* 2012). A detailed review on SVM applications could be found in a review paper (N and Deka 2014).

2.6 Particle swarm optimization based support vector machine regression

For simultaneous optimization of the SVMs and kernel parameters and for improved generalising of the PSO–SVM model the support vector machine (SVM) tool is combined with Particle Swarm Optimization (PSO). Particle Swarm Optimization is one among the several stochastic optimization technique which is population based and inspired by the social behavior of the birds flocking and fish schooling. In the particle swarm algorithm the first step is to initialize PSO parameters particle position and velocities that are likely to be used to find optimal factors of kernel functions and SVMs. It evaluates the objective function at each particle position and finds the best function value and the best location. Using the fitness function updates the optimum particle positions (pbest) and global optimum particle position (gbest) is found. Position of every particle is updated using its preceding position and updates the velocity vector. Iterations continue until the algorithm reaches stopping criteria (Harish *et al*. 2015).

2.7 Fuzzy neural networks

Fuzzy neural network is amalgamation of the logic driven method and neural networks, in a single framework. The fuzzy logic approach is used when the mathematical model of the system to be controlled is unavailable, and the system is nonlinear and time varying. In the fuzzy approach the problem has to be linguistically described from which the fuzzy sets, fuzzy logic operations, and fuzzy rules are derived. Whereas NNs are trainable systems, which learns from the training. Learning of a NN typically implies to the connection weights and bias adjustments to minimize the square error between observed and predicted values (Koc and Balas 2012).

2.8 Hybrid Genetic Algorithm based Fuzzy neural networks

To improve the computational performance of FNNs (logic driven network) a hybrid learning scheme should be introduced. Genetic algorithms (GAs) can be integrated with FNNs preferably to solve a structural optimization problem and not parametric optimization. Parametric optimization is normally subjected to gradient-based algorithms. Hence the network structures are evolved without any connection weights. This problem could be alleviated by improving on the GAs. This can be done by hybridization of GAs with local search methods. Hybrid GAs with local search method can simultaneously optimize both the structures and the weight parameters more efficiently (Koç *et al.* 2016).

3. Applications of soft computing techniques

The design of armor layer units of breakwater is based on the anticipated damage ratio. Prediction of damage ratio of breakwater is possible using ANN model. Artificial Intelligence simulations can efficiently interpolate the experimental data sets for a variety of combinations of wave height, wave period, wave steepness and slope angle. Damage ratio estimation for breakwater design using the inputs like mean wave period, wave steepness, significant wave height and the breakwater slope can be done. Though ANN models can efficiently model the non-linear relationships between inputs and outputs, fuzzy logic better estimated the damage ratio as it closely mimics the environment. The damage ratio was modeled as function of wave height, wave period, wave steepness and breakwater slope instead of generating a typical regression equation (Yagci *et al*. 2005).

The stability number forecasting of the conventional rubble mound structures by fuzzy logic approach was found accurate, as it deals with the uncertainties not accounted for by empirical formulae. The input parameters to the developed FL model are permeability of structure, slope angle of breakwater, number of waves, surf similarity parameter, and damage level are used together to predict the stability number. Along with these parameters in Van der Meer’s equations the non-dimensional parameter i.e., depth to significant height ratio (d/H_s), at the structure toe is also used so as to take into account the effect of foreshore breaking waves. The spectral shape parameter is not considered in the study. Fuzzy logic model developed is the most superior model in stability number prediction of conventional rubble mound breakwater design, followed by Van der Meer’s approach and Mase *et al*.’s ANN model, respectively. The Van der Meer has tested for a wide range of conditions, under these circumstances the current algorithm can be used anywhere in the world (Erdik 2009).

Stability number of armor block is vital issue while designing rubble mound breakwaters. The prediction of Stability number of armor block can be accurately done using model trees. Model trees are easier to use and they represent understandable mathematical rules. Here the conventional governing parameters were used as input variables and the predicted stability numbers of breakwater armor outperformed the previous empirical and soft computing methods. Model trees produce easy and significant formulas (Etemad-Shahidi and Bonakdar 2009).

The maximum wave runup on breakwaters for determining crest level of breakwaters through traditional regression based empirical model approaches involves several assumptions such as linearity, normality, variance constancy etc. Whereas, ANN predicts the maximum wave runup accurately overcoming the drawback of the conventional empirical model and suffice as a modern approach towards $R_{u2\%}/H_s$ prediction in order to determine the crest level of coastal structures accurately. Here many three layer feed-forward type of ANN are used and the model with four inputs, five neurons in hidden layer with only one output, yields the best result out of all developed models. The accuracy of the developed model is evaluated with the empirical model based on RM of Van der Meer and Stam (1992) and found that the ANN outperformed RM in $R_{u2\%}/H_s$ prediction (Erdik *et al*. 2009).

Artificial Intelligence (AI) models can be developed for the preliminary design of rubble mound breakwaters however, the final design necessitates examining of other failure modes because the coastal structure safety is highly variable. The fuzzy systems and fuzzy neural networks are found more advantages in the prediction of stability number of rubble mound breakwaters as it incorporates fuzzy logic as expert systems relative to hybrid neural networks. (Balas *et al*. 2010).

Adaptive Neuro-Fuzzy Inference System (ANFIS) was used in the prediction of wave transmission coefficient of horizontally interlaced multilayer moored floating pipe breakwater (HIMMFPB). In this work the input variables that influence the K_t of HIMMFPB such as S/D, W/L, H_i/d and H_i/L are considered and six ANFIS models are constructed. The four ANFIS models were developed with W/L, H_i/d, H_i/L and K_t as input data with first order Sugeno model containing 27 rules and 3 generalized bell membership functions. The ANFIS5 model was developed including S/D ratio also as the input parameter with the structure using first order Sugeno model containing 81 rules and 3 generalized bell membership functions. The ANFIS6 model is similar to ANFIS5 model but does not consider H_i/L as the input parameter. With Principal Component Analysis (PCA) the most influencing parameter is found to be S/D and W/L whereas, the least influencing parameter was found to be H_i/L. The variation of the parameters is studied in ANFIS5 and ANFIS6 models. The various ANFIS model study concludes that S/D has a significant influence and H_i/L has no significant influence in the prediction of K_t of HIMMFPB. ANFIS outperformed the ANN model (Patil *et al*. 2009) in the prediction of wave transmission coefficient of HIMMFPB. The study concludes that the ANFIS can serve as another approach to study the wave-structure interactions of HIMMFPB (Patil *et al*. 2011).

Prediction of normalized scour depth at the head of the vertical wall breakwater using Artificial neural networks (ANN) outperformed the existing empirical formulae. They found that ANN predicts well for dimensional input parameters compared to the non-dimensional input parameters. For the network with dimensional parameters the inputs to the network were bed particle diameter, pile diameter, wave period, maximum current velocity and maximum shear velocity and the network output was non-dimensional scour depth. A forward perception three layers network with back propagation was adopted for prediction of scour depth around breakwaters. As the number of inputs to the network was five the number of input layer neurons was taken as five, on the trial and error based method the number of hidden layer neurons was taken as three and the output layer neuron was one. Similarly for a network with non-dimensional parameters, the network was trained with the dimensionless parameters of pile Reynolds number, Froude number, Shields number, Keulegan-Carpenter number and sediment Reynolds number. Here the number of input layer neurons and output layer neurons were four and one respectively. Based on a trial and error method the number of hidden layer neurons was taken as three. A sensitivity analysis shows that the Keulegan - Carpenter number is the most influencing parameter in the scour process (Jabbari and Talebi 2011).

An ANN model is developed to predict the reflection coefficient. The input parameters which most influences the reflection coefficient are crest freeboard R_c, crest width B, seaward angle α, the significant incident wave height Hi and peak period T_p or peak wavelength L_p. But for the current study three dimensionless parameters were selected as model inputs i.e., Iribarren number Ir, relative crest freeboard R_c/H_i and relative crest width k_pB, with k_p as wave number associated to the peak wavelength. The optimum architecture was arrived by evaluating the performance of each architecture. The results obtained from 400 different ANN model with ten different architectures were trained, tested and validated and the best architecture was chosen and also validated. They concluded that this model could be regarded as a virtual laboratory, replacing physical model tests in a conventional laboratory in determining the reflection coefficient (Castro *et al*. 2011).

To predict the wave transmission of horizontally interlaced multilayer moored floating pipe breakwater (HIMMFPB) a hybrid Genetic Algorithm Tuned Support Vector Machine Regression (GA-SVMR) is built. The MATLAB SVM toolbox is interfaced with genetic algorithm and for better generalization of GA-SVMR model the SVMs and kernel parameters are optimized simultaneously. Six GA-SVMR models were developed using different kernel functions (with linear, polynomial, rbf, erbf, spline and b-spline kernels) for training. The first step is for GA to generate the initial population to identify optimum factors of kernel functions and SVMs. Next step is to perform SVM process using assigned value of the factors in the chromosomes, and calculate the individual chromosome performance using fitness function for GAs. Optimal parameters are selected if the calculated fitness value satisfies the terminal condition in GAs, if not apply the genetic operators to produce new generation of the population. After which again perform the training process with calculation of the fitness value. Repeat the process until stopping condition is satisfied. With the completion in genetic search, chromosomes that show the best performance in the last population is selected as optimal SVMs and kernel parameters. These optimized parameters are tested with the test data. Finally based on the statistical measures the best model out of the six is chosen. The GA-SVMR model with b-spline kernel function performs better than other kernel functions for the given set of data. The performance of GA-SVMR model with b-spline kernel function, also outperformed his earlier developed ANN and ANFIS models. Thus GA-SVMR could be taken as another approach to study the prediction performance of HIMMFPB (Patil *et al*. 2012).

Balas predicted the stability number of rubble mound breakwaters using FNN in the framework of multilayer feed-forward supervised neural networks with AND and OR fuzzy neurons optimizing its parameters with gradient descent algorithm. As the accuracy of the prediction was not appreciable there was a need for improvement. Improvement over Balas fuzzy neural networks in the prediction of stability number of rubble mound breakwaters by structural and parametric optimisation using HGA-FNN (hybrid genetic algorithm-based fuzzy neural network) is established for better stability assessments. Here two models where developed one the standard GA-FNN (genetic algorithm-based fuzzy neural network) and the other is HGA-FNN (hybrid genetic algorithm-based fuzzy neural network). The HGA-FNN is having an advantage over GA-FNN as it involves a local search method, in the current study hill climbing method was used. In the case of both the models the training, validation and testing was done for the same data involving five inputs they are the permeability coefficient (P), the damage level (S), the number of waves (N), the slope of the breakwater (cot θ), and the surf similarity parameter (ε_m), to predict the only output the stability number (N_s). The results show that the predictive performance of the HGA-FNN model is better than that of the GA-FNN model, since it effectively combines local and global optimisation. HGA-FNN has better prediction potential as it combines local and global search methods for stability assessments of rubble mound breakwaters by simultaneously optimising structures and weights (Koc and Balas 2012).

Wave reflection coefficient prediction by using ANN for a wide database with structures of straight and non-straight slopes, seawalls, caissons and circular caissons, Acquareefs and structures under wave attacks. The developed ANN model is trained by 13 non-dimensional input elements chosen based on a sensitivity test of ANN performance considering the extended input dataset (including wave and structure characteristics) and 40 hidden neurons. Uncertainty of predictions through the technique of bootstrap sampling is found to have same error distributions as the ones obtained from the non-bootstrap sampling. The results show that the model has a good stability. Prediction of wave reflection coefficient from coastal and harbor structures for a wide variety of wave conditions, structure geometry and structure type is possible using Artificial Neural Networks (Zanuttigh *et al.* 2013).

The estimation of damage of breakwater armor blocks can be better by considering tidal level variation. The comparative study with tidal level being constant as well as varying was performed. The study reveals that the expected damage increased with the increase in the tidal level. Here a shallow water wave height prediction artificial neural network (ANN) model was developed using offshore wave height and estimated the breakwater damage incorporating tidal level variation near shore. This reduced the total analysis time in estimating the breakwater damage of armor blocks and also allows it to apply a random simulation method such as Monte Carlo simulation (MCS) to estimate the damage using deep sea wave distribution. The ANN predicted waves were compared with that from a wave transform analysis. The study shows that by assuming tidal level constant at HWL, the damage of breakwater armor blocks is overestimated hence the tidal level variation should be incorporated (Kim *et al.* 2014).

MATLAB-based regression is used to determine the wave transmission coefficient of a quarter-circular breakwater (QBW). Here the wave transmission coefficient (K_t) is established as a dependent variable on the independent non-dimensional parameters H_i/d (relative wave height), H_i/gT^2 (incident wave steepness parameter), and h_c/H_i (relative freeboard). The relation established between the two using a MATLAB-based regression is checked for accuracy using some statistical parameters. The noise in the experimental data was removed using the method suggested by MATLAB, where the data with more than ±15% in MSE and relative error was removed. The refined set of data is further subjected to regression in MATLAB and a new model is obtained for wave transmission coefficient (K_t) whose accuracy improved significantly. The author further applied ANN for the same problem. The predominant input variables influencing the performance and stability of quarter-circular breakwaters (QBW) are H_i/d (relative wave height), H_i/gT^2 (incident wave steepness parameter), and h_c/H_i (relative freeboard), while the transmission coefficient K_t is considered as the output variable to train the ANN. The ANN is trained after the noise in the collected experimental data is removed to get accurate model prediction. Using the Levenberg–Marquardt method of backpropagation, an ANN model is developed to predict the K_t

of QBW. The predicted wave transmission coefficient using ANN was found to be better than that of MATLAB-based multiple regression. Study concludes ANN was a better approach in the prediction of wave transmission (Goyal *et al.* 2014, 2015).

Experimental data of a Double-layered perforated wall (DLPW) is converted to model using ANFIS which can model the correlation between wave parameters, DLPW design variables and performance criteria considering the uncertainties in the experiments and results. This simulation model is further included in a Non-dominated sorting genetic algorithm-II which is a multi-objective optimization algorithm. A trade-off curve between wave transmission and reflection is drawn. Using two efficient multi-person decision-making models, namely unanimity fall back bargaining and condorcet social choice method the best agreed-upon design point on the trade-off curve is obtained (Nikoo *et al.* 2014).

ANN models can predict the reflection coefficient (K_r) of emerged perforated quarter circular breakwater (EPQCB) for beyond the range data of wave period (T) used for training. Here the prediction of reflection coefficient (K_r) for two modes of data was done i.e., dimensional as well as non-dimensional. The input parameters used in the case of dimensional mode are water depth (d), wave height (H), structure height (h_s), spacing (S), Diameter (D) and radius (R). The input parameters used in the case of non-dimensional input parameters are wave steepness H_i/gT^2, depth parameter d/gT^2, spacing-perforation ratio S/D, relative wave run-up R/Hi and relative water depth h_s/d. The results show that the prediction of reflection coefficient (K_r) of emerged perforated quarter circular breakwater using ANN with dimensional input parameters gave better accuracy than the non-dimensional input parameters (Raju *et al.* 2015).

Soft computing techniques are an alternate to physical and mathematical model study to determine the damage level of a non-reshaped berm breakwater which is complex and non-linear. In the damage analysis input parameters that influence the damage level (S) of non-reshaped berm breakwater are used as inputs, such as wave steepness (H/L_o), surf similarity, relative berm position by water depth (h_B/d), armor stone weight (W_{50}/W_{50max}), relative berm width (B/L_o), and relative berm location (h_B/L_o). The proposed model optimizes SVMs and kernel parameters simultaneously and predicts damage level. The PSO-SVM model with polynomial kernel function predicted better than the other SVM models (Harish *et al*. 2015).

The armor stone weight required for a particular site condition for particular wave height range is determined based on the stability number which will indicate how stable the armor stone is. To estimate this stability number, it is important to know the relation between the stability number and other parameters which are related to waves and structure. Hence using Principal component analysis variable selection method the influence of variables unused in the previous studies was considered and research was carried out. Here a hybrid model of ANN with PCA is developed for estimating the stability number of rock armor using the experimental datasets of Van der Meer (1988). The experimental data had 11 input parameters of which 6 were grouped as one Group1 with well distributed values and the remaining 5 as another group i.e., Group 2 which varies amongst only a few values. The Group 1 parameters are transformed into six PC's using PCA and then all the parameters are fed into ANN. The sixth PC obtained here had zero percent of the total variance. But the results obtained by including all PC's were better compared to that by excluding the sixth PC. Finally six PC's of Group 1 and five parameters directly from Group 2 were used as the input variables of the ANN model. This hybrid ANN with PCA model outperformed the previous empirical and ANN models (Lee *et al.* 2015).

The construction of a berm breakwater and further allowing it to reshape subjecting to storms to achieve a stable profile rather than constructing a reshaped berm breakwater directly is found more economical as it requires smaller size armor stones. However, the study of the stability of such breakwaters is important. The input variables are wave height, wave period, water depth, berm width, berm position from sea bed, slope of breakwater, nominal dimension of armor unit and storm duration. Whereas, the output variable was failure of the breakwater in terms of berm recession. The dimensionless parameters obtained by performing a dimensional analysis on these variables are stability Number $H/\Delta D$, wave steepness H/gT^2, storm duration N, relative berm position hb/d, relative berm width B/d, number of primary layers N, breakwater slope $\cot\alpha$ and relative berm recession R_{ec}/D_{n50}. A Principal Component Regression (PCR) was performed using Xlstat® software with all the seven input parameters of which stability Number $H/\Delta D$, wave steepness H/gT^2, relative berm position h_b/d and relative berm width B/d had high factor loadings above 0.6. These four parameters are further subjected to a PCR analysis and the loadings of all the four parameters were found to be greater than 0.70 and found to be important. Even with the reduction of three parameters the decrease in R^2 and RMSE was insignificant. The reason for the elimination of these parameters is due to the fact that the variation of storm duration and number of primary layers was not high and breakwater slope was a constant which did not vary the output significantly. Principal Component Regression (PCR) analysis is a very effective tool in reducing the number of input parameters. The damage level of Reshaped berm breakwater can be well estimated by knowing the most influencing input variables on the output (Janardhan *et al.* 2015).

Stability assessment of a rubble-mound breakwater has been attempted here by applying Genetic programming (GP) models to explore explicit relationship between the stability number of armor blocks and influencing variables. He developed four GP models called GPM1, GPM2, GPM3 and GPM4 using the training subsets Type 1 and Type 2. The total available data sets of Van Der Meer experiments were divided into Type 1 and Type 2 categories. The Type 1 included data samples of small-scale tests on the static stability of rock slopes and large-scale tests on scale effects. Type 2 data set contained data sets of a low-crested structure. For GPM1 and GPM2 models the function set used was $F1 = \{\times, /, \exp, \log, \sqrt{}, \sqrt[3]{}\}$ and for the GPM3 and GPM4 models the function set used was $F2 = \{+, -, \times, /, \exp, \log, \sqrt{}, \sqrt[3]{}\}$. The prediction performance of GPM1 and GPM2 models were compared with the measured stability numbers of Van der Meer (1988). Similarly, the prediction performance of GPM3 and GPM4 models were compared with the measured stability numbers of Van der Meer (1988). The measured stability numbers of Van der Meer (1988) are compared with the stability numbers predicted by the stability equations of VdM. The GPM3 and GPM4 models produced lower values of SI, MAPE and RMSE with respect to GPM1 and GPM2 models. Which concludes that more functions means better solutions with larger search space. The experimentally measured data of Van der Meer (1988) are in better agreement with the Genetic programming (GP) model predicted values than the empirical model values of VdM (Van der Meer 1988). Genetic programming (GP), a data driven method found to have better prediction performance compared to the Van der Meer’s stability equations of rubble-mound breakwaters. Genetic programming can capture complex real-world relationships effectively with a limit on the parse tree size to control the bloating of GP (Koc *et al.* 2016).

4. Conclusions

This is a gentle review on the soft computing techniques and its successful applications in breakwaters. The paper aims to account the quantum of research happening to integrate different soft computing techniques and utilisation of advanced tools. The spectrum of research carried out in the application of Artificial intelligence in breakwaters to predict the stability number, damage level, wave-runup, and evaluation of performance characteristics is found to be very limited and has scope for further works in this area. Artificial Intelligence in the performance prediction of breakwaters can be regarded as an alternate method to the existing complex and time consuming methods. This review is about the concepts of various soft computing techniques both individual and hybrid, and it also explains their significance in application to the field of breakwaters. The conclusion of the review is there is no significant research carried out using soft computing techniques to accurately predict the performance of various composite type of breakwaters, semicircular breakwater in particular. The lacuna of the existing works is no single study attempts to predict beyond and below the data ranges used for training. In this regard there is a need to develop prediction models which are more flexible, accurate and efficient. To the knowledge of the author it is found that the use of Artificial intelligence in the field of coastal structures is an effective alternate approach to the complex mathematical modelling.

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