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Particle Swarm Optimization based support vector machine for damage level prediction of non-reshaped berm breakwater

Narayana Harish [a,*], Sukomal Mandal [b], Subba Rao [c], S.G. Patil [d]

[a] Centre for Emerging Technology, Jain University, Jakksandra Post, Ramanagara 562112, Karnataka, India
[b] Ocean Engineering Division, National Institute of Oceanography, Dona Paula 403004, Goa, India
[c] Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal 575025, India
[d] Department of Built and Natural Environment, Caledonian College of Engineering, P.O. Box: 2322, CPO Seeb, PC 111, Oman

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ABSTRACT

The damage analysis of coastal structure is very much essential for better and safe design of the structure. In the past, several researchers have carried out physical model studies on non-reshaped berm breakwaters, but failed to give a simple mathematical model to predict damage level for non-reshaped berm breakwaters by considering all the boundary conditions. This is due to the complexity and non-linearity associated with design parameters and damage level determination of non-reshaped berm breakwater. Soft computing tools like Artificial Neural Network, Fuzzy Logic, Support Vector Machine (SVM), etc, are successfully used to solve complex problems. In the present study, SVM and hybrid of Particle Swarm Optimization (PSO) with SVM (PSO–SVM) are developed to predict damage level of non-reshaped berm breakwaters. Optimal kernel parameters of PSO–SVM are determined by PSO algorithm. Both the models are trained on the data set obtained from experiments carried out in Marine Structures Laboratory, Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal, India. Results of both models are compared in terms of statistical measures, such as correlation coefficient, root mean square error and scatter index. The PSO–SVM model with polynomial kernel function outperformed other SVM models.

1. Introduction

The breakwaters are constructed parallel to the shore in order to protect the coast and harbors against wave action. They are also used for other purposes like dissipating wave energy and providing loading and unloading facilities for cargo and passengers. A rubble mound structure with the presence of horizontal berm at or above still water level (SWL) on the sea side is called as berm breakwater. They are classified into statically and dynamically stable structures [1] depending on the behavior under design conditions. Statically stable structures are non-reshaped structures, where no or minor damage is allowed to the structure under design conditions. Whereas, dynamically stablestructures are reshaped into a stable profile, in which the individual stones may move up and down the slope. Many researchers have suggested adopting non-reshaped berm breakwater in most of the cases, since, movement of armor stones will lead to abrasion between the units and sometimes may lead to failure of armor layer [2–4]. The damage of a non-reshaped berm breakwater is measured in terms of 'damage level' expressed by Van der Meer [5]. 'Damage level' is defined as the displacement of armor units and is calculated using following formula [2]:

$$S = \frac{A}{D_{n50^2}} \tag{1}$$

where, A is the area of erosion and $D_{n50} = (M_{50}/\rho_a)^{1/3}$ is the nominal diameter of the stones.

M_{50}, median stone mass; ρ_a, density of stone.

In the past, several researchers [6–13] have experimented on berm breakwaters which are time consuming and expensive in terms of cost. Further, there is no simple mathematical model to predict the damage level considering all the boundary conditions due to the complex nature of the problem which includes wave structure interaction, angle of wave attack, movement of the armor, etc.

Soft computing technique is an alternate solution to physical model study and mathematical modeling, which can be adopted to minimize the cost, time and complexity of the problem. Soft computing tools such as Artificial Neural Network (ANN), Support

* Corresponding author. Tel.: +91 9900444123.
E-mail address: harishnnitk@gmail.com (N. Harish).

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Vector Machine (SVM), Adaptive Neuro Fuzzy Inference System (ANFIS), etc, are capable of solving these problems and are successfully used in solving different coastal problems. Neural network techniques have been adopted to predict the stability, damage level, damage ratio and design of rubble mound breakwater [14–16]. Support Vector Machines (SVM) has been used for the prediction of significant wave height [17] and also to predict the stability number of armor blocks of breakwaters [18]. Some of the hybrid soft computing models were implemented for the preliminary design of rubble mound breakwater which performed better than the traditional design using Van der Meer equations [5]. Patil et al. [19,20] have developed ANFIS and Genetic algorithm based support vector machine (GA-SVM) models for predicting wave transmission coefficient of horizontally interlaced multilayer moored floating pipe breakwater.

Further, the hybrid PSO–SVM was applied to diagnosis of arrhythmia cordis [21], to forecast dissolved gases content in power transformer oil [22], to radio frequency identification based positioning system [23] and recognizes targets obscured by foliage [24]. Their results showed that the PSO–SVM method gave higher accuracy with actual data compared with other soft computing models. In this concern, it is observed that there are hardly any applications of hybrid SVM models to study the stability of berm breakwaters. Hence, in the present paper, performance of PSO–SVM technique in predicting damage level of non-reshaped berm breakwaters is investigated. PSO is used for optimization of SVM and kernel parameters. Performance of PSO–SVM models are compared with that of SVM models.

2. Experimental data

The experimental work on non-reshaped berm breakwater was carried out by Rao et al. [12,13] in Marine Structures Laboratory, Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka (NITK), Surathkal, India. The wave flume is 50 m long, 0.71 m wide, 1.1 m deep, and has 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 for deep water wave length (L_0). 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 g was tested. In the second set of experiments, statically stable non-reshaped berm breakwater model was tested with the armor stones weight W_{50} = 52 g which is about 30% less than 74 g. They studied the influence of berm width on the stability of the breakwater, run-up and rundown. In the third set of experiments armor stones weight W_{50} = 58.6 g was tested which is about 20% less than 74 g. 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 g, the weight used in conventional breakwater. Damage level (S) was computed using Eq. (1). The area of erosion in Eq. (1) was measured using profiler system which consisted of nine brass rod placed equidistance along the width of the flume. The profiler was moved along the length of breakwater section to know the initial and final profile. Range of experimental variables is shown in Table 1.

Many problems involving fluid motions are quite complex in nature. In the present case the complex flow phenomenon responsible for energy dissipation cannot be easily represented by mathematical equations and one has to rely on experimental investigations. The results of such investigations are more useful when expressed in the form of dimensionless relations. To arrive at such dimensionless relations of different variables, dimensional analysis was carried out by Rao et al. [12,13]. After conducting the dimensional analysis using Buckingham's-Π theorem the dimensionless parameters, such as wave steepness (H/L_0), surf similarity (ζ), relative berm position by water depth (h_B/d), armor stone weight ($W_{50}/W_{50\max}$), relative berm width (B/L_0) and relative berm location (h_B/L_0) are obtained.

Table 1
Range of experimental variables.

Variable	Range
Wave height H (m)	0.10, 0.12, 0.14, 0.16
Wave period T (s)	1.6, 2.0, 2.6
Water depth above the bed level d (m)	0.25, 0.30, 0.35, 0.40
Water depth above or below the berm d_B (m)	+0.08, +0.03, −0.02, −0.07
Armor stone weight W_{50} (gm)	52–4
Crest height above the seabed (m)	0.7
Berm width B (m)	0.6
Berm position above seabed h_B (m)	0.32

For the present damage analysis, experimental data are divided into two sets, one for training about 80% data set and another remaining data set for testing. Input parameters (Fig. 2) that influence the damage level (S) of non-reshaped berm breakwater are H/L_0, ζ, h_B/d, $W_{50}/W_{50\max}$, B/L_0 and h_B/L_0 which are used to train SVM and PSO–SVM models.

3. Particle Swarm Optimization tuned support vector machine (PSO–SVM)

3.1. Support vector machines

The foundation of SVM has been developed by Vapnik [25] and is gaining popularity due to many attractive features and promising empirical performance. The formulation represents the Structural Risk Minimization (SRM) principle [26] which has been shown to be superior to traditional Empirical Risk Minimization (ERM) principle as adopted by conventional neural networks. SRM principle minimizes an upper bound on the expected risk, as opposed to ERM principle that minimizes the error on the training data. This difference outfits SVM with a greater ability to generalize, which is the goal in statistical learning. SVMs were developed to solve the classification problem, but recently they have been extended to the domain of regression problems [27].

3.1.1. Mathematics behind SVM algorithm for regression

Consider a training data set $g = \{(x_1, y_1), (x_2, y_2), \ldots (x_p, y_p)\}$, such that $x_i \in \nu^N$ is a vector of input variables and $x_i \in \nu$ is the corresponding scalar output (target) value. Here, the modeling objective is to find a regression function, $y = f(x)$, such that it accurately predicts the outputs $\{y\}$ corresponding to a new set of input–output examples, $\{(x, y)\}$, which are drawn from the same underlying joint probability distribution as the training set. To fulfill the stated goal, support vector regression (SVR) considers the following linear estimation function Eq. (2):

$$f(x) = (w \cdot x) + b \tag{2}$$

where, w denotes the weight vector; b refers to a constant known as 'bias'; $f(x)$ denotes a function termed feature, and $(w \cdot x)$ represents the dot product in the feature space, l, such that $\phi : x \to l$, $w \in l$. The basic concept of support vector regression is to map nonlinearly the original data x into a higher dimensional feature space and solve a linear regression problem in this feature space.