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PREDICTION OF TRANSMITTED WAVE HEIGHT OF TANDEM BREAKWATER USING PSO-SVM

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Abstract

Economic development of a country is directly dependent on the functioning of the ports and transportation facilities available. It is of vital importance to protect the ports and harbors and thereby providing safe and effective loading and unloading facilities. Proper protective measures like breakwaters have to be constructed to protect and maintain tranquility conditions inside the harbor. Apart from conventional rubble mound breakwater, newly developed hybrid type breakwaters are also used as protective structures. Final layout of the structure is determined only after prior physical model studies. Soft computing techniques, widely used in the field of prediction, are recently used in the field of breakwater studies for the prediction of transmitted wave height, damage analysis etc. Present work deals with the transmitted wave height prediction of a tandem breakwater using hybrid PSO-SVM model. Effectiveness of the models developed were measured using various statistical parameters such as RMSE, MAE, CC and SI. Results showed that, from among various kernels used, model developed with polynomial kernel showed better correlation.

Keywords:

Tandem Breakwater, PSO-SVM, Polynomial Kernel, Soft Computing

1. INTRODUCTION

Breakwaters are structures constructed to protect the harbor against the action of waves and thereby maintaining tranquility conditions inside the harbor. Apart from dissipating the wave energy, the breakwaters are also used for loading and unloading of cargo. Breakwaters have application in various other fields such as coastal rehabilitation of mangroves [15] and energy production from overtopping waves [14]. Apart from conventional rubble mound breakwater, new hybrid type breakwaters have also been developed.

A rubble mound breakwater with a submerged reef in front is called a tandem breakwater. A rubble mound breakwater upon the action of waves transforms into a berm breakwater and finally forms tandem breakwater [3]. The rubble mound breakwater stabilizes by forming an *S* shaped profile with a toe extension, which is later separated or shifted to the front as a submerged reef resulting in a tandem breakwater (Fig.1).

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. ANFIS, ANN, GP, SVM etc. are some of the widely used soft computing tools. Soft computing being time effective is also used in the field of coastal engineering. Various works have been done using soft computing techniques in breakwater studies.

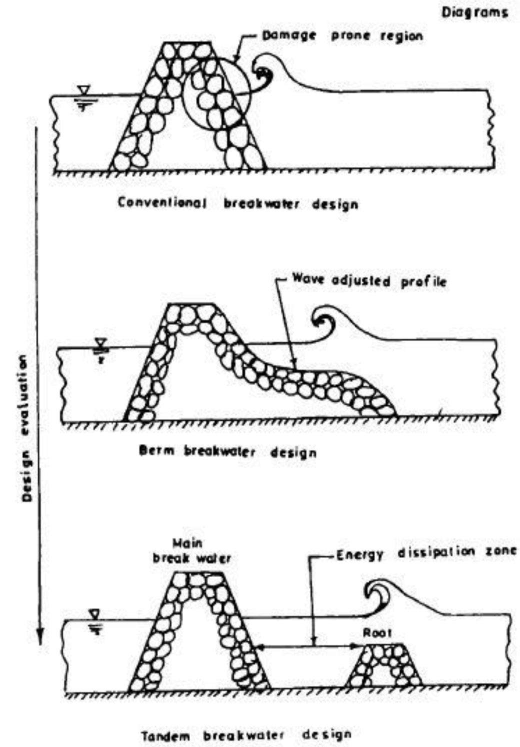


Fig.1. Evolution of tandem breakwater (Source: ISH Journal of Hydraulic Engineering)

Kim et al. [16] devised support vector regression for predicting the stability number of armor blocks [16]. Balas et al. [17] used SVM for rubble mound breakwater design and the result was compared with Van der Meer stability equations and ANN [17]. According to them SVM had better prediction ability compared to ANN and the stability equation. Mandal et al. [4] used SVM to predict the damage level of non-reshaped berm breakwater and the results were compared with ANN and ANFIS models [4]. The model was compared using various kernel functions and accurate results were obtained using polynomial kernel function. Patil et al. [12] developed GA-SVM regression model for predicting the transmitted wave for a horizontally interlaced multi-layer moored floating pipe breakwater [12]. GA was used as a tool for parameter optimization. Jithin et al. [9] predicted the transmitted wave height of submerged reef of a tandem breakwater using support vector regression [9].

In the present paper, performance of particle swarm optimization based SVM for prediction of transmitted wave height of tandem breakwater is investigated. PSO is adopted as the optimization technique for the present study. The effectiveness of the model developed is evaluated using statistical parameters such as RMSE, MAE, SI and CC.

The main objective of the present study is shown below:

- To study the applicability of soft computing technique in prediction of transmitted wave height of submerged reef of tandem breakwater.
- To develop a PSO-SVM model to predict the transmitted wave height of submerged reef of tandem breakwater.
- Compare the various kernel models using statistical parameter values and select the best model.

The paper organization is as follows: The proposed study is presented in section 2. The results and discussion are presented in the section 3. The conclusion is discussed in the last section.

1.1 SUPPORT VECTOR MACHINE

SVM was developed by Vapnik in 1995 [1]. The working principle of an SVM is structural risk minimization, which has higher generalization ability compared to the conventional empirical risk minimization principle followed in neural networks. The effectiveness of the model in prediction is estimated using various statistical parameters, such as Root Mean Square Error (RMSE), Correlation Coefficient (CC), Mean absolute Error (MAE) and so on. SVM was used initially used for classification problems, later extended its application to regression problems also.

Consider the training set $\{(x_i,y_i),\ i = 1,2,\ldots,n\}$, where x_i and y_i corresponds to i^{th} input training pattern and corresponding target output and n corresponds to the total number of data sets . Non-linear Support Vector Regression takes the form:

$$f(x,\alpha) = (w\cdot\varphi(x)) + b \tag{1}$$

where, b and w are the bias and weight vector respectively. $\varphi(x)$ is a mapping function to a higher dimensional feature space from input features. The regression problem is similar to minimizing the regularized risk function.

Minimize,

$$R(f) = \frac{1}{n}\sum_{i=1}^{n} L\left(y_i f\left(x_i, w\right)\right) \tag{2}$$

where,

$$L\left(y_i f\left(x_i,w\right)\right) = \begin{cases} \varepsilon & if\ \left|y_i - f\left(x_i,w\right)\right| \le \varepsilon \\ \left|y_i - f\left(x_i,w\right)\right| & otherwise \end{cases} \tag{3}$$

The Eq.(3) is called ε-insensitive loss function. Substituting Eq.(3) in Eq.(2), optimization function will be:

$$\text{minimize}\frac{1}{2}\left|w\cdot w\right| + C\left(\sum_{i=1}^{n}\xi_i^* + \sum_{i=1}^{n}\xi_i^*\right) \tag{4}$$

$$subject\ \text{to}\ \begin{cases} y_i - w\cdot x_i - b \le \varepsilon + \xi_i^* \\ w\cdot x_i + b - y_i \le \varepsilon + \xi_i^*, i = 1,\ldots,n \\ \xi_i, \xi_i^* \ge 0 \end{cases}$$

where, ξ_i, ξ_i^* are slack variables and $C > 0$ indicates penalty for error exceeding ε.

Using the above conditions, for a dual problem the maximization function for a non-linear regression is obtained as:

$$f\left(x,\alpha^*,\alpha\right) = \sum_{i=1}^{n}\left(\alpha_i^* - \alpha_i\right)K\left(x_i,x\right) + b \tag{5}$$

where α_i^* and α_i are Lagrange multipliers and $K(x_i,x)$ indicates the kernel function.

In the present work, kernels used are polynomial, linear and RBF. Good setting of kernel and SVM parameters are important to have better results.

1.2 PARTICLE SWARM OPTIMIZATION

PSO is a population based stochastic optimization technique based on social behaviour. Kennedy and Eberhart proposed the concept of PSO. In PSO each particle makes use of its memory and knowledge gained from the swarm to find the optimum result. Each particle moves through the problem space by following the optimum particles. The optimum position of particle is determined by the individual fitness function. Initial swarm is created by randomly distributing the population over the search space.

After each iteration, the best positions (*gbest* and *pbest*) of the particle is determined from the fitness function. After finding the two best values, the particle updates its velocity and positions with following Eq.(7) and Eq.(8).

Velocity:

$$V_{j+1}=V_j + c_1\text{rand()}(pbest_j\text{-}present_j) + c_2\text{rand()}(gbest_j\text{-}present_j) \tag{6}$$

Position:

$$Present_{j+1} = present_{j+1} + V_{j+1} \tag{7}$$

Subscript j represents the iteration count, V_j is the particle velocity, $present_j$ is the current particle position, rand() is a random number between (0,1). c_1, c_2 are scaling parameters, usually $c_1 = c_2 = 2$.

1.3 STATISTICAL PARAMETERS

The effectiveness of various models developed are checked using statistical parameters such as Root Mean Square (RMSE), Mean Absolute Error (MAE), Correlation Coefficient (CC) and Scatter Index (SI). Satisfactory results are obtained when CC is maximum and RMSE, SI and MAE are minimum for a model.

Root Mean Square Error,

$$RMSE = \sqrt{\frac{\sum_{i}^{n}\left(ob - pr\right)^2}{n}} \tag{8}$$

Mean Absolute Error,

$$MAE = \frac{1}{n}\sum_{i}^{n}\left|pr - ob\right| \tag{9}$$

Correlation Coefficient,

$$CC = \frac{\sum_{i}^{n}\left(ob - \overline{pr}\right)\left(pr - \overline{pr}\right)}{\sqrt{\sum_{i}^{n}\left(ob - \overline{pr}\right)^2\sum_{i}^{n}\left(pr - \overline{pr}\right)^2}} \tag{10}$$

Scatter Index,

$$SI = \frac{RMSE}{\overline{ob}} \tag{11}$$

where, *pr* and *ob* are predicted and observed values respectively, n is the number of observations, $\overline{pr}$ and $\overline{ob}$ are average of predicted and observed values respectively.

2. PROPOSED STUDY

Present study mainly deals with the prediction of transmitted wave height of the submerged breakwater in front of the main breakwater for a tandem breakwater. Soft computing technique of particle swarm optimization based SVM regression is used for the prediction.

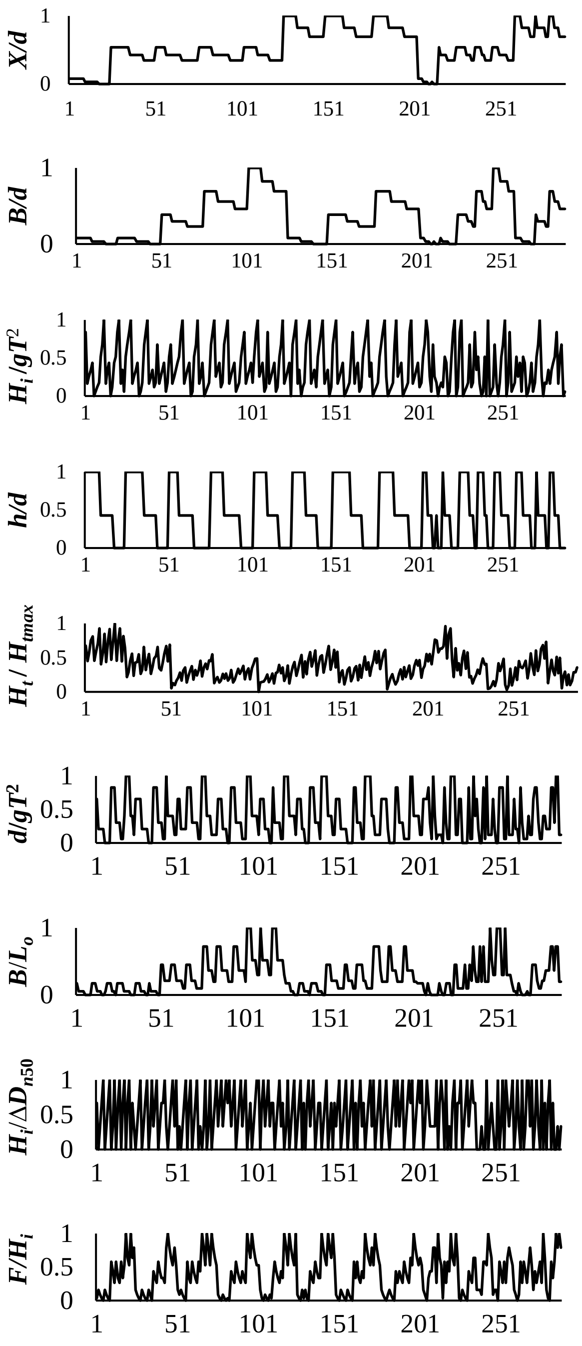


Fig.2. Data time series plot for H_t

Data is collected from the physical model studies conducted on tandem breakwater by Rao et al. [5] in Marine structures flume laboratory of Applied Mechanics and Hydraulics Department, National Institute of Technology, Karnataka, Surathkal [5]. 288 data sets are randomly chosen from the available data and divided as 70% for training and 30% for testing respectively.

The data is then normalized and time series plotted to ensure that all range values are present in both testing and training phases. Input parameters considered are wave steepness (H_i/gT^2), relative reef crest width in terms of deep water wave length (B/L_o), relative reef crest height (h/d), relative reef submergence (F/H_i), depth parameter (d/gT^2), Hudsons stability number ($H_i/\Delta D_{n50}$), relative reef spacing(X/d), relative reef crest width in terms of depth (B/d) and the output is taken as H_t / $H_{tmax.}$ Data time series plot of the inputs are drawn (Fig.2) to ensure the randomness of the data. From the output, the measured values vs. predicted values is plotted. The various statistical parameters were found out to find the correlation between the predicted and the measured values. From the results obtained, the best model is selected.

3. RESULTS AND DISCUSSION

In developing PSO-SVM model, initially parameters are randomly selected and from the statistical parameters values obtained, optimal values are identified. Initially the upper and lower bound values of kernel and SVM parameters are input randomly. Within the range given the best values are given as output by PSO searching. For the obtained parameters values corresponding statistical parameters are computed using the SVM model. From various such trials the values of parameters that give higher CC value and lower RMSE, MAE and SI value are finally chosen as the optimum values. The final optimum values of SVM and kernel parameters are shown in Table.1.

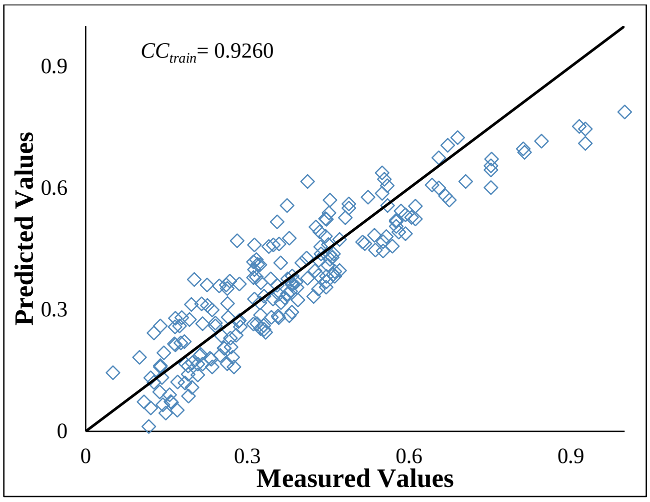
Table.1. Optimal parameters for PSO-SVM model with different kernel functions

Kernel Type	Linear	Polynomial	RBF
C	1500	183.78	18.7
ε	0.0885	0.0000538	0.0827
γ	-	-	2.6
d	-	3	-

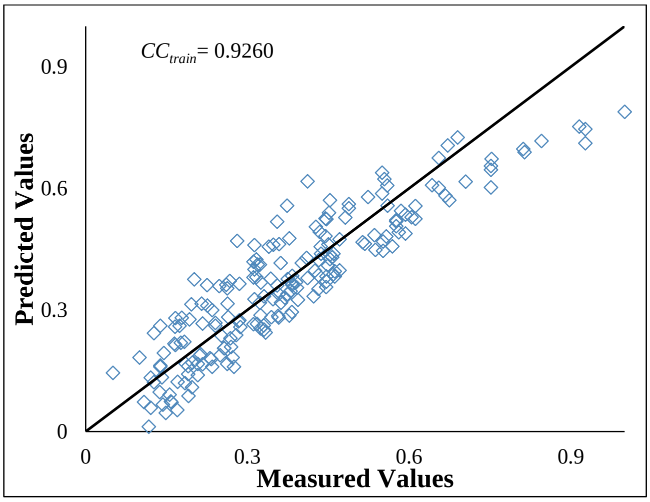
Table.2. Statistical parameters values for different kernels for PSO-SVM model

Kernel Type	Linear		Polynomial		RBF	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
CC	0.9260	0.9037	0.9910	0.9837	0.9693	0.9599
RMSE	0.0802	0.0807	0.0251	0.0376	0.0511	0.0681
MAE	0.0684	0.0694	0.0173	0.030	0.0429	0.0557
SI	0.2170	0.2172	0.0875	0.1018	0.1375	0.1842

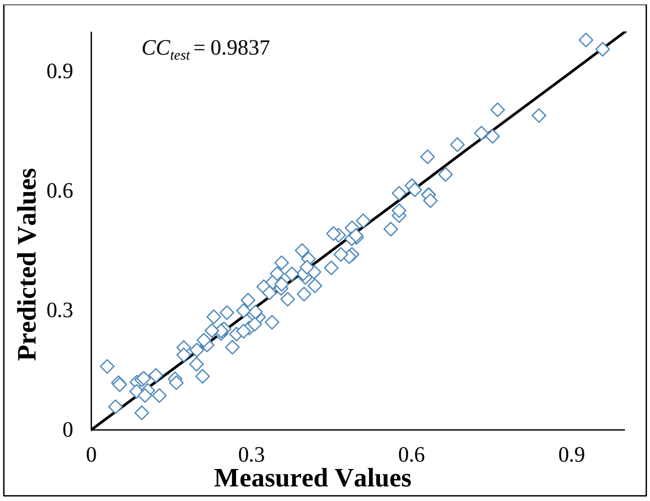
The statistical parameters computed using the predicted and observed transmitted wave height of training and testing data for the PSO-SVM models are shown in Table.2. The PSO-SVM model with linear kernel function results lower CC (Training CC = 0.9260, Testing CC = 0.9037) when compared to other kernel function in terms of statistical measures.



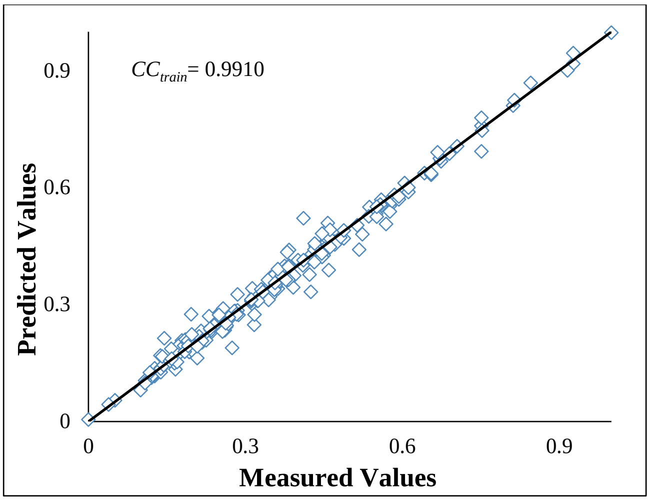
(a) Linear train



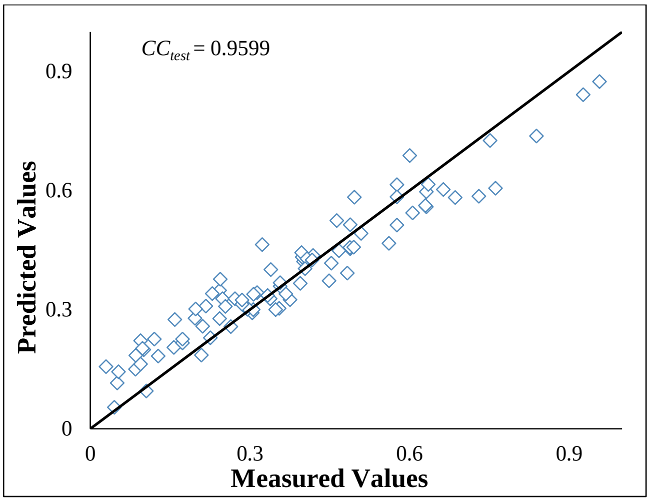
(b) Linear test



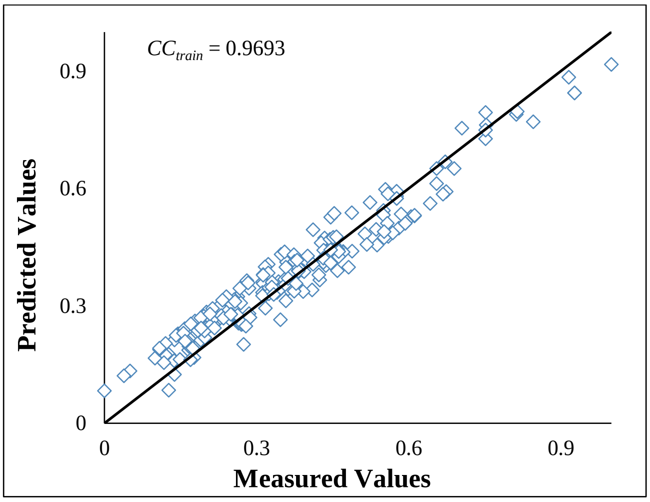
(c) Polynomial test



(d) Polynomial train



(e) RBF test



(f) RBF train

Fig.3. Training and Testing scatter plots for various kernels

The better selection of SVM and kernel parameters decides the performance of these models. The PSO-SVM model with polynomial kernel function of degree 3 shows better generalization performance with CC 0.9910 and 0.9837, RMSE 0.0251 and 0.0376, SI 0.0675 and 0.1018, MAE 0.0173 and

0.0306 for training and testing respectively when compared to all other kernel functions. The RBF kernel function also gives a comparable result as that of polynomial kernel of third degree. The scatter diagrams of PSO-SVM model for the training and testing data for various kernel models are shown in Fig.3.

4. CONCLUSION

The complexity involved in mathematical modeling and physical modeling being time consuming and expensive, makes the application of soft computing techniques a need in the field of breakwater studies. However the quantitative analysis and data provided by physical model studies are the basic input for soft computing models. So the application of physical model studies along with soft computing techniques can provide effective results. From the study, the following conclusions are drawn:

- PSO-SVM with different kernel functions were studied and among them polynomial kernel of third degree gives about 96% correlation and lower RMSE (CC = 0.9837 and RMSE = 0.0376 for test) compared to other kernel functions.
- RBF kernel model also provides comparable results with about 92% correlation. (CC = 0.9599 and RMSE = 0.0681).
- Effectiveness of model developed depends on the proper selection of SVM and Kernel parameters.
- PSO can be used as an effective technique to obtain optimized parameters of SVM models for predicting transmitted wave height.
- The developed model can be used to predict the values of transmitted wave heights for various known input parameters.

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