JOURNAL OF MARITIME RESEARCH

Vol XXI. No. III (2024) pp 219–227

ISSN: 1697-4840, www.jmr.unican.es

Assessment Of Wave Overtopping Discharge at Quarter Circle Breakwater Using Soft Computing Techniques

Vishwanatha Mane[1,*], Shankara Krishna A[1], Manu & Subba Rao[1]

ARTICLE INFO

Article history:
Received 19 Apr 2024;
in revised from 29 Apr 2024;
accepted 25 May 2024.

Keywords:
Quarter circle Breakwater, Least Square SVM (LSSVM), Support Vector Machine (SVM), Wave Overtopping (WO).

ABSTRACT

The precise prediction of wave overtopping (WO) discharge is crucial for the design of coastal protection structures, particularly in light of the challenges posed by climate change. This study focuses on a quarter-circle breakwater (QBW) comprising a vertical back wall, a horizontal base slab on a rubble mound foundation, and a quarter-circle front wall facing incident waves. Utilizing Support Vector Machine (SVM) and Least Square Support Vector Machine (LSSVM), the research aims to estimate the mean overtopping discharge at the QBW. Input parameters, including incident wave steepness (H_i/gT^2), depth parameter (d/gT^2), percentage of perforations (p), and crest height parameter (R_c/H_i), are employed, with mean overtopping discharge (q/gH_iT) as the output. Model performance is assessed using indicators such as Root Mean Square Error (RMSE), Correlation Coefficient (CC), Scatter Index (SI), and Index of Agreement (d). Results suggest that both SVM and LSSVM are effective in estimating mean overtopping discharge, with LSSVM demonstrating superior accuracy compared to SVM. The study findings contribute valuable insights for coastal engineering, particularly in designing structures resilient to wave overtopping amid ongoing climate change effects.

1. Introduction.

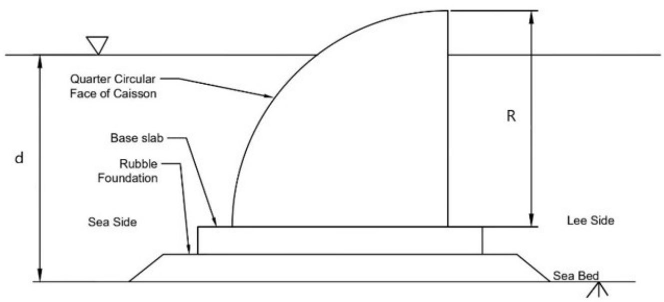
Prolonged emissions of greenhouse gases have induced significant alterations in climatic conditions, consequently affecting the ocean system. Observable changes include shifts in seawater temperature and an increase in sea levels. Given these transformations, the design and construction of coastal protection structures have become imperative. Among these structures, breakwaters play a vital role in maintaining tranquility in ports and harbors. They contribute to erosion reduction, facilitate beach growth, and aid in preventing thermal mixing.

While rubble mound-type breakwaters have historically been prevalent, evolving oceanic conditions have spurred the development of innovative breakwater designs. Breakwaters are generally classified as rubble mounds, vertical walls, and composite breakwaters. Incorporating perforations in breakwaters serves multiple purposes, enhancing wave energy dissipation and allowing sand entrapment to mitigate erosion. This study focuses on a specific breakwater model, the quarter-circular breakwater (QBW). QBWs, characterized by a hollow caisson structure resting on a rubble mound foundation, represent a modification of the traditional semicircular breakwater (shown in Figs. 1 and 2). Notably, QBWs, with their reduced width, necessitate less concrete volume and rubble mound foundation compared to SBWs. This adaptation addresses both structural and environmental considerations in contemporary coastal protection design.

In the design phase of coastal protection structures, careful consideration of wave overtopping is paramount. The primary objective is to either prevent or mitigate wave overtopping volumes. While numerical modeling and empirical equations are available to address these challenges, they often entail complexities. Physical modeling studies, though highly accurate, tend to be time-consuming. In the current scenario, soft computing techniques emerge as valuable tools, particularly in the early stages of coastal structure design. Artificial Neural

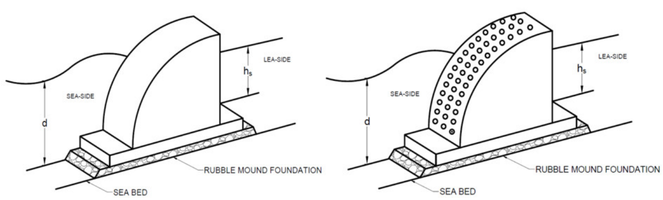
[1]Department of Water Resources and Ocean Engineering, National Institute of Technology Karnataka, Surathkal, India.
[*]Corresponding author: Vishwanatha Mane. E-mail Address: vishwanathamane@gmail.com.

Figure 1: Section of Quarter Circle Breakwater.



Source: Authors.

Figure 2: 3-D view of perforated and non-perforated QBW.



Source: Authors.

Networks (ANN), Support Vector Machines (SVM), and other hybrid models are increasingly employed to tackle the intricacies of coastal problems effectively. These soft computing approaches provide a more efficient and accessible means of addressing complex issues associated with wave overtopping, facilitating a streamlined design process for coastal protection structures.

In recent decades, numerous researchers (Dwarakish and Nithyapriya 2016; Kundapura and Hegde 2018; Rubio et al. 2009; Yusof and Mustaffa 2016; Guo et al. 2019; Mahjoobi and Adeli Mosabbeb 2009; Zeng et al. 2019; Ramesh et al. 2022) have employed diverse soft computing techniques to predict the performance of various types of breakwaters. In 2009, Mahjoobi and Adeli Mosabbeb utilized the SVM model to forecast the significant wave height, employing data gathered from the deep waters of Lake Michigan. The SVM's predictive capabilities were compared with those of ANN's and Multi-Layer Perceptron (MP) models. The findings led to the conclusion that the SVM model demonstrated successful utility in accurately predicting significant wave height, offering a competitive alternative to the other models assessed.

Kuntoji et al. (2017) applied a SVM to estimate the damage level of a Tandem Breakwater. Various kernel functions were applied to predict the damage level, and the evaluation of their performance was based on various statistical parameters. Among the diverse kernel functions considered, the Radial Basis Kernel Function (RBF) yielded superior results. The assessment of different kernel functions underscored the effectiveness of RBF in predicting the damage level of the Tandem Breakwater according to the measured statistical parameters.

Guo et al. (2019) employed an enhanced Least Square SVM (LSSVM) model to forecast the water level on daily basis of the Yangtze River in China. The outcomes were juxtaposed with those derived from the traditional LSSVM. The improvement in the LSSVM model involved the introduction of an additional bias error control term. The findings indicated that the enhanced LSSVM model yielded more precise results than the conventional LSSVM, underscoring the efficacy of the introduced modification.

Alqahtani et al. (2023) extensively investigated and compared the effectiveness of SVM and Gradient-Boosted Tree (GB-T) methods in accurately predicting WO discharge for coastal structures featuring composite slopes, mainly focusing on "without a berm" condition. The findings indicated that the GBT technique exhibited superior accuracy in predictions compared to the SVM technique. Noteworthy outcomes highlighted the GBT model's substantial reduction in overall error, showcasing its effectiveness in accurately estimating wave overtopping discharge. This study also contributes valuable insights into improving prediction methods, particularly emphasizing the enhanced performance of the GBT model in the context of coastal structure design and management.

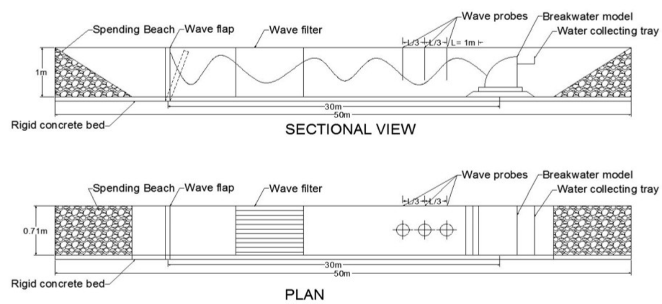
In 2023, Alshahri and Elbisy explored artificial neural network - based approaches, including the MP neural network (M-PNN), cascade correlation neural network (CCNN), general regression neural network (GRNN), and SVM with radial-bias function. Their investigation mainly focused on estimating WO discharge for coastal structures characterized by a straight slope and without a berm. Comparative analysis was conducted between the results obtained from GRNN and those from the aforementioned models. The study included a comprehensive sensitivity analysis to assess the significance of each predictive variable. The outcomes demonstrated high accuracy for both validation methods, with the leave-one-out validation method slightly surpassing the cross-validation method.

Very few studies has been focused on assessing WO discharge at a QBW utilizing soft computing techniques. Wave overtopping holds pivotal importance, particularly in the design of the emerged QBW structure. This study addresses this gap by utilizing SVM and LSSVM for predicting wave overtopping discharge across quarter-circular breakwaters featuring various radii and perforations. Performance evaluation incorporates key statistical parameters such as RMSE, CC, SI, and d, facilitating a comprehensive comparison to determine the model with superior prediction accuracy.

2. Data Collection.

The dataset utilized in this research originates from investigations conducted by Mane et al. (2023) through physical modeling at the Marine Structures Laboratory of the National Institute of Technology Surathkal in Karnataka. The experimental setup includes a wave flume with dimensions of 50 m x 0.71 m x 1.1 m (length x width x depth). Wave generation is facilitated by a bottom-hinged flap, also known as a wave paddle, positioned in a deep chamber with dimensions of 6.3 m x 1.5 m x 1.4 m (length x width x depth), located at one end of the setup, as represented in Fig 3.

Figure 3: Sectional of View of wave flume (not to scale).



Source: Authors.

In this physical model study, Quarter Circular Breakwater (QBW) models of radii 0.4m, 0.45m, and 0.5m, each with perforations ranging from 0% to 20% (0, 1.25%, 5%, 10%, 15% and 20%), were examined. Table 1 displays the range of experimental variables, while Table 2 provides a description of the parameters. The investigation involved placing a water collecting tray on the lee-side of the QBW to measure the volume of water collected after overtopping. The resulting physical model dataset comprises 870 samples, which were randomly divided into training data (75% or 653 samples) and testing data (25% or 217 samples). Buckingham's π theorem was employed for dimensional analysis in the physical model investigation, converting parameters into non-dimensional counterparts. The dataset underwent normalization using a specified equation, ensuring that values fall within the range [0,1].

$$Z_{norm} = \frac{Z - Z_{min}}{Z_{max} - Z_{min}} \tag{1}$$

Where Z is the data point; Z_{norm}: Normalized data point; Z_{max} and Z_{min} are the maximum and minimum among all the data points respectively.
The performance of the model is evaluated with the help of statistical parameters RMSE, CC, SI and d. The equation of each parameter is listed below, where Z_{pi} = predicted $\frac{q}{gTH_i}$, Z_{oi} = observed $\frac{q}{gTH_i}$, Z_{pi}= average of predicted $\frac{q}{gTH_i}$, $\overline{Z}_{oi}$ = average of observed $\frac{q}{gTH_i}$, N= number of observations.

1. Root Mean Square is calculated as,

$$\text{RMSE} = \sqrt{\frac{\sum_{i=0}^{N} (Z_{pi} - Z_{oi})^2}{N}} \tag{2}$$

2. Correlation Coefficient is calculated as,

$$\text{CC} = \frac{\sum_{i=1}^{N} (Z_{pi} - Z_{oi})(Z_{oi} - \overline{Z}_{oi})}{\sqrt{\sum_{i=0}^{N} (Z_{pi} - \overline{Z}_{pi})^2}\sqrt{\sum_{i=0}^{N} (Z - \overline{Z}_{oi})^2}} \tag{3}$$

3. The Scatter Index is calculated as,

$$\text{SI} = \frac{\sqrt{\frac{\sum_{i=0}^{N} (Z_{pi} - Z_{oi})^2}{N}}}{\overline{Z}_{oi}} \tag{4}$$

4. The index of agreement is calculated as,

$$d = 1 - \frac{\sum_{i=0}^{N} (Z_{oi} - Z_{pi})^2}{\sum_{i=0}^{N} \left(\left|Z_{pi} - \overline{Z}_{oi}\right| + \left|Z_{oi} - \overline{Z}_{oi}\right|\right)^2} \tag{5}$$

Table 1: Range of Experimental Variables.

Wave-Specific Parameters	Experimental Range		
Incident Wave Height, H_i (m)	0.08, 0.10, 0.12, 0.14, 0.16		
Wave Period, T (sec)	1.4, 1.6, 1.8, 2.0, 2.2		
Depth of Water, d (m)	0.4,0.375,0 .35	0.40, 0.425, 0.45	0.45,0.475, 0.5
Structure Radius (m)	0.4	0.45	0.5
Percentage of Perforation, p (%)	0,1.25, 5, 10, 15 and 20		

Source: Authors.

Table 2: Parameter Description.

Parameter	Description of the parameter
H_i/gT^2	Non-dimensional wave steepness
d/gT^2	Non-dimensional depth
R_c/H_i	Non-dimensional crest height
q/gH_iT	Non-dimensional mean WO discharge

Source: Authors.

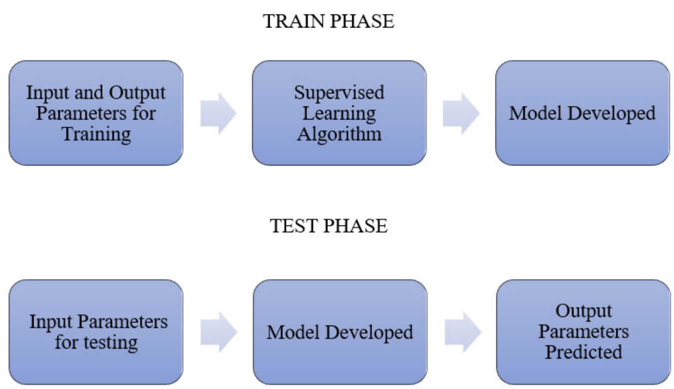
3. Support Vector Machine.

3.1. General.

Based on the type of problems to be solved, the techniques in Machine Learning are mainly classified into three categories: supervised, semi-supervised, and unsupervised learning. Skouras et al. (2013) came up with the idea of the SVM, which is based on the Structural Risk Minimization (SRM) Principle and the Statistical Learning Theory. SVM is a type of supervised learning technique used to solve classification (pattern recognition) and regression (function approximation) problems. There are two phases involved in this technique, the training phase and the testing phase. The flow chart (Fig 4) below illustrates a Supervised Learning Algorithm's training and test phases.

Support Vector Machine, with the aid of kernel functions, transforms input data into some high-dimensional feature space. According to the type of kernel functions an optimal separating hyperplane is created in this high-dimensional space. The most commonly used kernel functions are linear, polynomial, gaussian, etc. Hyperparameters for each kernel should be carefully tuned as the performance of the model depends on this. Support Vector Regression uses Vapnik's ?-insensitive approach to form a symmetrical flexible tube around the hyperplane. The distance between the hyperplane and the decision boundary is of this threshold value ?, and the points outside this threshold

Figure 4: Two Phases of Supervised Learning Algorithm.



Source: Authors.

value is ignored. The regularization parameter γ gives a penalty to the points outside the threshold value. If γ is small, it results in a larger margin decision boundary and if the value of γ is large then it results in a decision boundary with a smaller margin. The kernel bandwidth (σ) represents the influence of the training points in the given model. They are inverse to the radius of influence of training points. Large values of σ may lead to overfitting of the model.

A SVM model is developed for the prediction of WO discharge over QBW with the help ofscikit–learn in Python. In this study, kernel functions linear, polynomial, and RBF are examined, and their details are outlined in Table 3. The parameters that need to be optimized in SVM include the regularization parameter (γ), which is common for all kernel functions and the kernel bandwidth (σ) for the RBF kernel. The hyperparameters are tuned using Random Search in Python. The model is trained using these hyperparameters and the trained model is simulated on the test dataset. The model's performance during the training and testing phases is assessed using the metrics such as RMSE, CC, SI, and d.

Table 3: Different Kernel Functions.

Kernel Name	Kernel Function
Linear (dot product)	$G(x_j,x_k) = x_j'x_k$
Gaussian	$G(x_j,x_k) = \exp(-\lVert x_j - x_k \rVert^2)$
Polynomial	$G(x_j,x_k) = (1+x_j'x_k)^q$, where q is in the set {2,3,...}.

Source: Authors.

3.2. Results and Discussion.

The optimized hyperparameters obtained are listed in Table 4. To validate the model, a k-cross validation technique with a chosen value of k as 10 is applied to the training dataset. The subsequent analysis, detailed in Table 5, reveals that the RMSE and scatter index for the RBF kernel are lower than those obtained for the linear polynomial kernels. Moreover, the CC and Index of Agreement values for the RBF kernel are closer to one compared to the other kernel functions. The statistical parameters collectively signify that the RBF kernel yields more accurate predictions for the mean WO discharge in comparison to the linear and polynomial kernel functions. Visual interpretation through scatterplots further reinforces these findings.

Table 4: Optimized Hyperparameters.

Kernel \ Parameter	Linear	Polynomial	RBF
γ	80	188	95
degree	-	4	-
σ	-	-	4.1

Source: Authors.

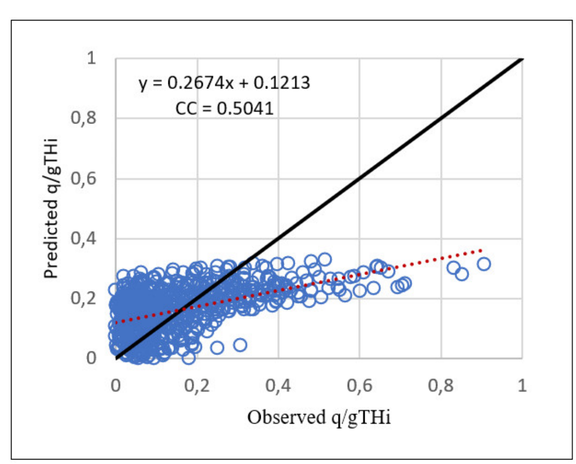
Table 5: Performance metrics for SVM Model for Prediction of Mean Overtopping Discharge.

Metrics	Linear Kernel		Poly. Kernel		RBF Kernel	
	Train	Test	Train	Test	Train	Test
RMSE	0.1264	0.1219	0.1222	0.1127	**0.0835**	**0.09235**
CC	0.5041	0.4758	0.5519	0.5576	**0.821**	**0.7519**
SI	0.7826	0.8157	0.756	0.7541	**0.5169**	**0.6179**
d	0.631	0.6282	0.6531	0.6853	**0.8964**	**0.8618**

Source: Authors.

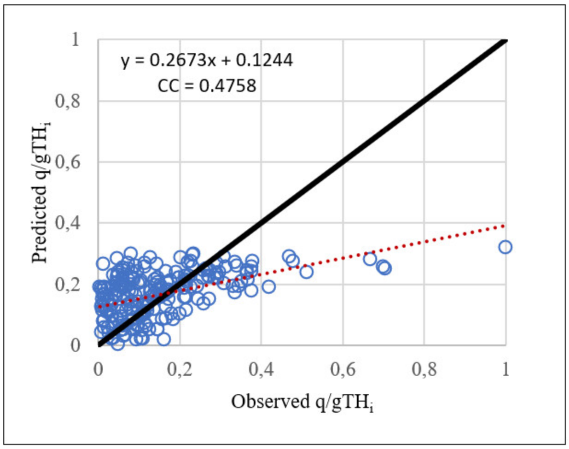
Scatter plots (Figs 5 to 10) are drawn with observed and predicted mean overtopping discharge on the x-axis and y-axis respectively, for train and test data of each kernel. The best-fit line obtained for the observed and predicted q/gTH$_i$ for each kernel is plotted. A 45° line is also drawn to compare with the results obtained. Notably, for both the training and testing data, the RBF kernel outperforms the other kernels, affirming its superior predictive capability in estimating mean overtopping discharges.

Figure 5: Scatter Plot for Train of SVM Model (Linear Kernel).



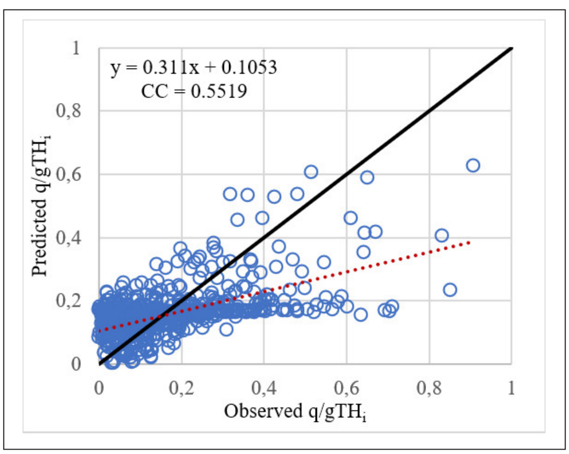
Source: Authors.

Figure 6: Scatter Plot for Test of SVM Model (Linear Kernel).



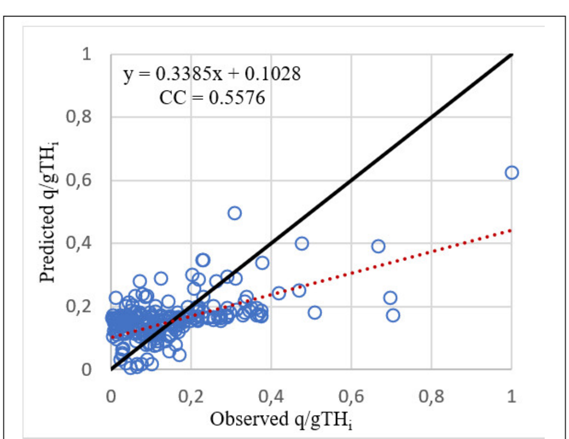
Source: Authors.

Figure 7: Scatter Plot for Train of SVM Model (Polynomial Kernel).



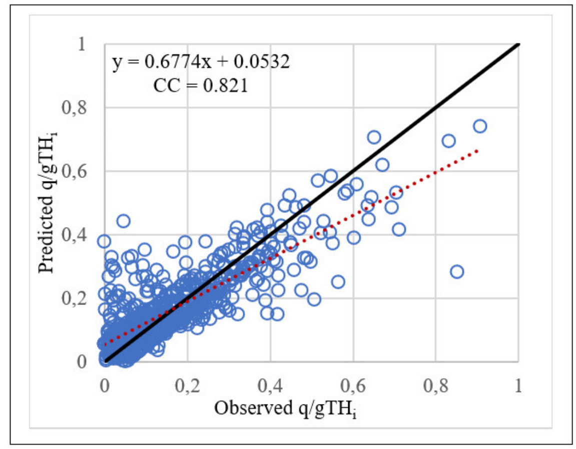
Source: Authors.

Figure 8: Scatter Plot for Test of SVM Model (Polynomial Kernel).



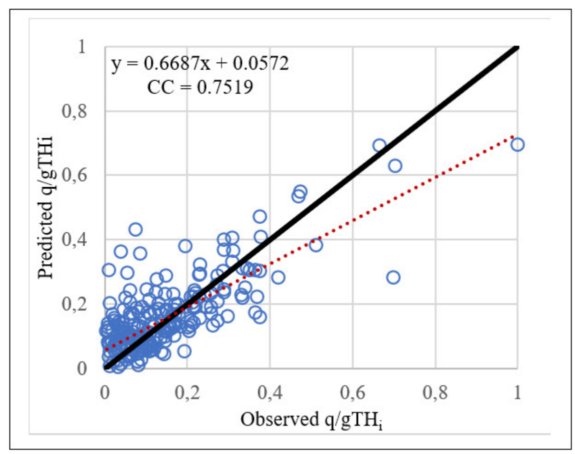
Source: Authors.

Figure 9: Scatter Plot for Train of SVM Model (RBF Kernel).



Source: Authors.

Figure 10: Scatter Plot for Test of SVM Model (RBF Kernel).



Source: Authors.

4. Least Square Support Vector Machine.

4.1. General.

LSSVM is a formulation of a SVM where instead of quadratic programming a set of linear equations is solved. They are related to regularization networks. The MATLAB LSSVMlab toolbox provides simple code for solving classification and regression problems. It is possible to train and test LSSVM models using various kernel functions. Linear, Polynomial and Radial Basis Functions are different kernel functions considered here.

The Least Square Support Vector Machine can be explained below (Samui 2011).

Consider a given set of N training data points, $\{x_k, y_k\}_{k=1}^{N}$, with input data $x_k \in R^N$, and output $y_k \in$ r, where R^N and r are the N-dimensional and one-dimensional vector spaces respectively. In feature space, LSSVM models take the form:

$$y(x) = \omega^T \varphi(x) + b \tag{6}$$

where the feature map $\varphi()$ maps the input data into a higher dimensional feature space.

$$\omega \in R^N;\ \mathrm{b} \in \mathrm{r};$$

w = an adjustable weight vector; and b = the scalar threshold.

In LSSVM, for function estimation, the following optimization problem is formulated:

$$\text{Minimize: } \frac{1}{2}\omega^T\ \omega + \ \frac{1}{2}\ \sum_{k=1}^{N} e_k^2$$

Subject to:

$$y(x) = \omega^T \varphi(x) + b + e_k, \quad k = 1.\ldots.N \tag{7}$$

The linear kernel function is given by,

$$k(x_k,\ x_l) = \ x_k^T x_l \tag{8}$$

The polynomial kernel function is given by,

$$k(x_k,\ x_l) = (x_k^T x_l + t)^d, t \geq 0 \tag{9}$$

(t - intercept and d -polynomial degree)

The radial basis function employed in this analysis is expressed as:

$$k(x_k,\ x_l) = \exp\left\{-\frac{(x_k -\ x_l)^T (x_k - x_l)}{2\sigma^2}\right\},\ k, l = 1, \ldots N \tag{10}$$

(σ^2 - squared kernel bandwidth)

Using LSSVMlab in MATLAB, an LSSVM model is created to forecast mean overtopping discharge over a quarter-circle breakwater. The data are normalized in the range [0,1]. The train data consists of 653 samples and the test data consists of 217 samples. K-cross validation optimization technique is performed on the training dataset. The value of k is chosen as 10. The kernel parameters degree is tuned for the polynomial kernel and σ^2 is tuned for the RBF kernel. The accuracy of the developed model depends upon the optimization of hyperparameters. The trade-off between smoothness and fitting error minimization is determined by the regularization parameter. A smaller γ would ensure a good fitting of the model. The capacity of the kernel to fit the function would decline as bandwidth increases because the hyperplane would get flatter. There are different optimization techniques available for efficient tuning of the hyperparameters. The hyperparameters are tuned using simplex.

The sequence of commands to be followed to obtain an LSSVM model are:

Step 1. The command initlssvm is carried out using an object-oriented interface.

Step 2. The parameters are tuned using tunelssvm.

Step 3. The tuned parameters are used to train the model using trainlssvm.

Step 4. The performance of the model on test data can be simulated using simlssvm.

4.2. Results and Discussion.

The models are trained for different kernels using the tuned parameters listed in Table 6. To assess the efficiency of the models, a comprehensive evaluation is conducted considering key metrics such as RMSE, CC, SI and d. The statistical parameters obtained for the different kernels are listed in Table 7. Notably, the values of RMSE and SI of the linear and polynomial kernel surpass those of the RBF kernels. The correlation coefficient and index of agreement (d) are closer to 1 for the RBF kernel when compared to linear and polynomial kernel. The results showed that the model with RBF kernel performs better for training and testing data in comparison to other kernels. The RBF kernel notably shows a higher correlation of 0.9573 and 0.8155 for training and testing datasets, respectively. Additionally, the RMSE values for the RBF kernel stand at 0.0413 and 0.08041 is obtained for the training and testing datasets. The scatter plots for LSSVM models of different kernels are given in Figs 11 to 16.

Table 6: Optimized Hyperparameters.

Kernel	Linear	Polynomial	RBF
γ	0.7652	230	105
degree	-	4	-
σ^2	-	-	0.055

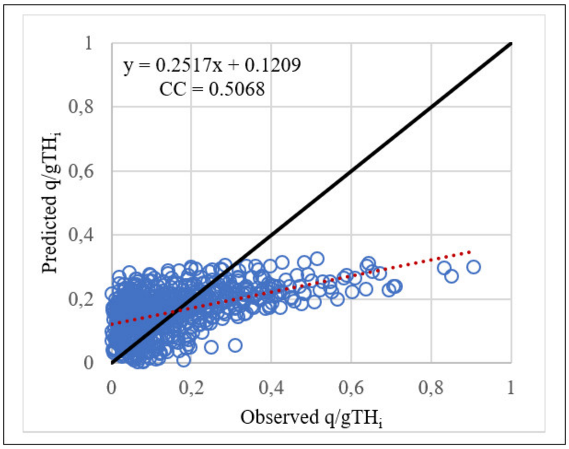
Source: Authors.

Table 7: Performance metrics for LSSVM Model for Prediction of Mean WO Discharge.

Metrics	Linear Kernel		Polynomial Kernel		RBF Kernel	
	Train	Test	Train	Test	Train	Test
RMSE	0.1261	0.1203	0.0942	0.0939	**0.0413**	**0.08041**
CC	0.5068	0.4851	0.765	0.734	**0.9573**	**0.8155**
SI	0.7806	0.8051	0.58	0.628	**0.266**	**0.538**
d	0.6151	0.6158	0.8544	0.843	**0.9756**	**0.8998**

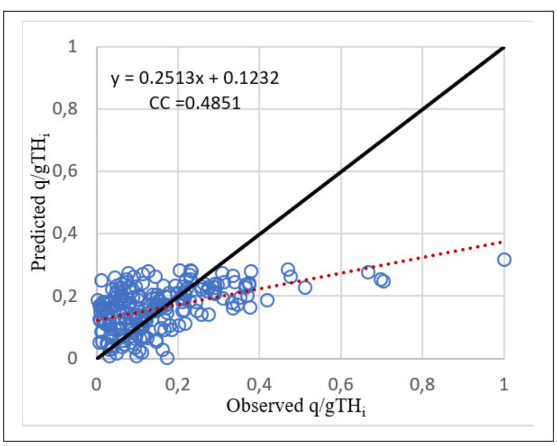
Source: Authors.

Figure 11: Scatter Plot for Train of LSSVM Model (Linear Kernel).



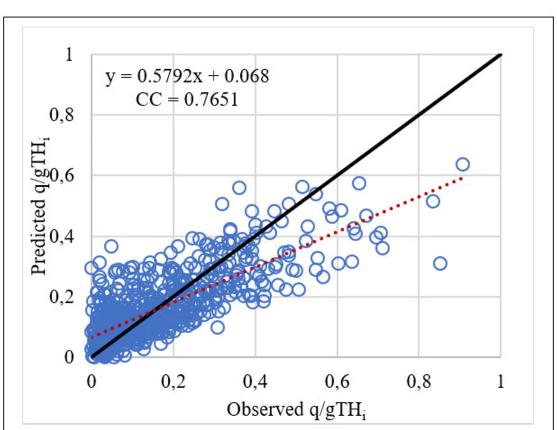
Source: Authors.

Figure 12: Scatter Plot for Test of LSSVM Model (Linear Kernel).



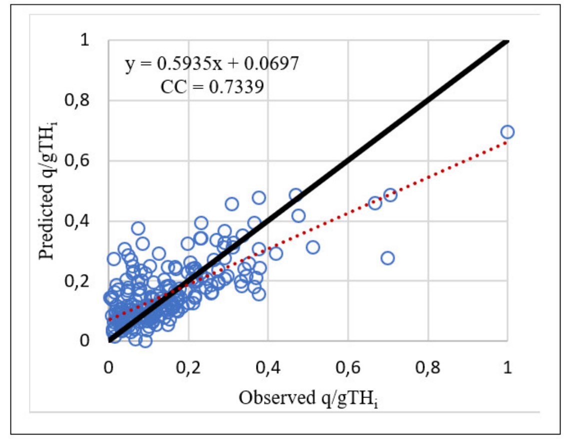
Source: Authors.

Figure 13: Scatter Plot for Train of LSSVM Model (Polynomial Kernel).



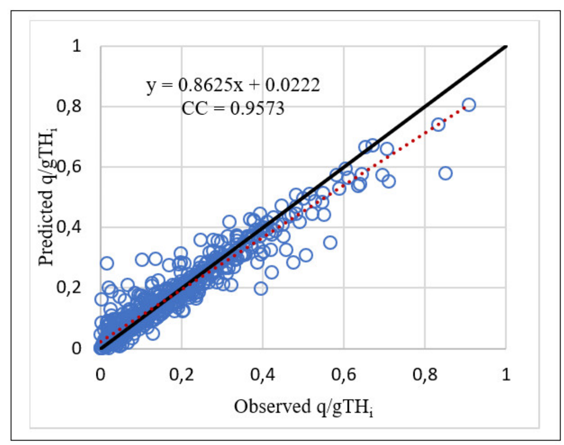
Source: Authors.

Figure 14: Scatter Plot for Train of LSSVM Model (Polynomial Kernel).



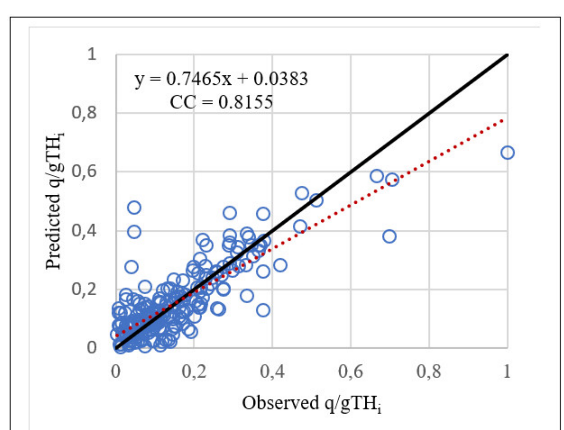
Source: Authors.

Figure 15: Scatter Plot for Train of LSSVM Model (RBF Kernel).



Source: Authors.

Figure 16: Scatter Plot for Test of LSSVM Model (RBF Kernel).



Source: Authors.

5. Comparison of performance of SVM and LSSVM models.

SVM and LSSVM models were developed with the aim of predicting the mean WO discharge over a QBW for varying radii and perforations. A comprehensive comparison of these models was conducted using performance metrics such as RMSE, CC, SI and d. For SVM and LSSVM models, the Radial Basis Function performed better in comparison to linear and polynomial kernels. The assessment incorporating statistical parameters and visual representations such as scatterplots, revealed that LSSVM consistently outperformed SVM for both training and testing datasets. Notably, the SVM model with RBF kernel exhibited RMSE, CC, SI and d of 0.09235, 0.7519, 0.6179 and 0.8618 respectively, for the test dataset. In comparison, the LSSVM model with the RBF kernel yielded improved performance with RMSE, CC, SI and d of 0.08041, 0.8155, 0.538 and 0.8998 respectively for the test dataset. Collectively, these results indicate that the LSSVM model utilizing the RBF kernel stands out as the most precise and efficient model for forecasting mean overtopping discharge across quarter-circular breakwaters.

Summary and Conclusions.

Summary.

In this study, the prediction of mean WO discharge at a QBW under varying conditions of radii and perforations employing SVM and LSSVM. The dataset utilized is collected from the experimental studies conducted by Mane et al. (2023) at NITK Wave Mechanics Laboratory. The SVM model is developed using scikit-learn in Python while the LSSVM model is developed using the LSSVMlab toolbox in MATLAB. The models are developed with different kernel functions including linear, polynomial and RBF. To assess the efficacy of these models, the performance metrics RMSE, CC, SI and d are utilized. Comparisons among the models are facilitated by evaluating the metrics, enabling the selection of the superior model for predicting mean overtopping discharge. This approach ensures a rigorous examination of the model performance, leading to the identification of the most effective model based on the considered statistical criteria.

Conclusions.

Based on the present study, the following conclusions are drawn:

1. For the SVM model, when comparing the RBF kernel to linear and polynomial kernel functions, the RBF kernel produced better results. For the RBF kernel, the optimum values of γ and σ are obtained as 95 and 4.1, respectively. The predicted mean overtopping discharge values exhibit a good correlation value of 0.821 and 0.7519 for the training and testing dataset. Additionally, the RMSE and SI values are minimized, and the obtained values of ‘d’ is closed to1.
2. For the LSSVM model, superior outcomes are achieved with the RBF kernel compared to alternative kernels. For RBF kernel γ and σ^2 are obtained as 105 and 0.055, respectively. The predicted values exhibit a good correlation of 0.9573 for the training dataset and 0.8155 for testing data. Moreover, the RMSE and SI obtained are close to zero, and the value of ‘d’ is close to 1.
3. Utilizing Soft Computing Techniques such as SVM and LSSVM allows for the prediction of mean WO discharge at a quarter-circle breakwater. In comparison to the SVM, LSSVM demonstrates a higher accuracy in predicting q / gTH_i) Therefore, LSSVM stands out as a viable alternative tool for estimating mean WO discharge at QBW.

Acknowledgements.

The authors are grateful to the Director, NITK Surathkal and Head, Department of Water Resources and Ocean Engineering, NITK Surathkal, India for the support and encouragement provided to them and for permission to publish.

References.

Alqahtani, Ammar M, Moussa S Elbisy, and Faisal A Osra. 2023. “Comparing Between Support Vector Machine and Gradient Boosted Trees Models for Prediction of Wave Overtopping at Coastal Structures with Composite Slope.” Indian Journal Of Science And Technology 16(33): 2580–88.

Alshahri, Abdullah H., and Moussa S. Elbisy. 2023. “Assessment of Using Artificial Neural Network and Support Vector Machine Techniques for Predicting Wave-Overtopping Discharges at Coastal Structures.” Journal of Marine Science and Engineering 11(3).

Dwarakish, G. S., and B. Nithyapriya. 2016. “Application of Soft Computing Techniques in Coastal Study – A Review.” Journal of Ocean Engineering and Science 1(4): 247–55. http://dx.doi.org/10.1016/j.joes.2016.06.004.

Geetha Kuntoji, Subba Rao, Manu and S Mandal (2017) “Application of Support Vector Machine Technique for Damage Level Prediction of Tandem Breakwater”, International Journal of Earth Sciences and Engineering, 10(03), 633-638. DOI:10.2-1276/ijee.2017.10.0322.

Guo, Tao et al. 2019. “An Improved LSSVM Model for Intelligent Prediction of the Daily Water Level.” Energies 12(1): 1–11.

Kundapura, Suman, and Arkal Vittal Hegde. 2018. “PSO-ANFIS Hybrid Approach for Prediction of Wave Reflection Coefficient for Semicircular Breakwater.” ISH Journal of Hydraulic Engineering 00(00): 1–9. https://doi.org/10.1080/09715010.-2018.1525688.

Mahjoobi, J., and Ehsan Adeli Mosabbeb. 2009. “Prediction of Significant Wave Height Using Regressive Support Vector Machines.” Ocean Engineering 36(5): 339–47.

Mane, V., S. Rao, Lokesha, and A.V. Hegde. 2023. “Wave Overtopping Characteristics Of Non-Perforated And Seaside

Perforated Emerged Quarter-Circle Breakwater." Journal of Naval Architecture and Marine Engineering 20(1).

Ramesh, N., S. Bhaskaran, and Subba Rao. 2022. "Prediction of Wave Reflection for Quarter Circle Breakwaters Using Soft Computing Techniques." Indian Journal of Geo-Marine Sciences 51(6): 511–16.

Rubio, Ginés et al. 2009. "Efficient Optimization of the Parameters of LS-SVM for Regression versus Cross-Validation Error." Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 5769 LNCS(PART 2): 406–15.

Samui, Pijush. 2011. "Application of Least Square Support Vector Machine (LSSVM) for Determination of Evaporation Losses in Reservoirs." Engineering 03(04): 431–34.

Skouras, Emmanouil, Stoyan Pavlov, Habib Bendella, and Doychin N. Angelov. 2013. "Conclusion." Advances in Anatomy Embryology and Cell Biology 213: 91.

Yusof, Yuhanis, and Zuriani Mustaffa. 2016. "A Review on Optimization of Least Squares Support Vector Machine for Time Series Forecasting." International Journal of Artificial Intelligence & Applications 7(2): 35–49.

Zeng, Jiye, Zheng Hong Tan, Tsuneo Matsunaga, and Tomoko Shirai. 2019. "Generalization of Parameter Selection of SVM and LS-SVM for Regression." Machine Learning and Knowledge Extraction 1(2): 745–55.