

## Estimating transmitted waves of floating breakwater using support vector regression model

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Planning and design of coastal protection works like floating breakwaters requires information about the performance characteristics of the structure in reducing the wave energy. They can be used as a temporary protection for offshore activities in hostile environment during construction, drilling works, salvage operation etc. The design involves hydraulic as well as structural aspects. The hydraulic design consists of suitable type, cross section and dimension of the breakwater to achieve the desired degree of wave attenuation. The structural design involves the design of various elements of the breakwater and checking the stability of the structure against possible modes of failure. The prime factor in the construction of floating breakwater is to obtain the optimum width of the breakwater (relative breakwater width) along the direction of wave propagation.

In this present work the performance of *support vector regression model* (SVRM) for predicting the wave transmission coefficient of floating pipe breakwater is investigated. The data used in the model are the experimental parameters obtained from the work conducted in the wave flume at Marine Structure laboratory, National Institute of Technology Karnataka, Surathkal, Mangalore, India. The goal of SVRM is to identify a function  $f(x)$  that for all training patterns  $x$  has a maximum deviation  $\epsilon$  from the target (experimental) values  $y$  and has a maximum margin. Using the training patterns, SVRM generates a model representing a tube with radius  $\epsilon$  fitted to the data. For the hard margin SVRM, the error for patterns inside the tube is zero, whereas no patterns are allowed outside the tube. For real-case datasets, this condition cannot account for outliers, an incomplete set of input variables  $x$  or experimental errors in measuring  $y$ . A soft margin in SVRM is introduced by using slack variables. In SVRM, the input  $x$  is first mapped onto an  $m$ -dimensional feature space using some fixed (nonlinear) mapping, and then a linear model is constructed in this feature space (Ivanciuc Ovidiu 2007).

Using mathematical notation, the linear model in the feature space  $f(x, w)$  is given by

$$f(x, w) = \sum_{j=1}^n w_j g_j(x) + b \dots\dots\dots (1)$$

Where  $g_j(x)$ ,  $j = 1 \dots, n$  are a set of non linear transformations,  $w$  and  $b$  are the weight vector and bias terms. The quality of estimation is measured by the loss function  $L(y, f(x, w))$  which is described as

$$L_g(y, f(x, w)) = \begin{cases} 0 & \text{if } |y - f(x, w)| \leq \epsilon \\ |y - f(x, w)| - \epsilon & \text{otherwise} \end{cases} \dots\dots\dots (2)$$

The empirical risk is

$$R_{emp}(w) = \frac{1}{m} \sum_{i=1}^m L_g(y_i, f(x_i, w)) \dots\dots\dots (3)$$

SVRM performs linear regression in the high-dimension feature space using  $\epsilon$ -insensitive loss and, at the same time, tries to reduce model complexity by minimizing  $\|w\|^2$ . This can be described by introducing non-negative slack variables  $\xi_i, \xi_i^*$ ,  $i = 1 \dots, m$  to measure the deviation of training samples outside  $\epsilon$ -insensitive zone. Thus SVRM is formulated as minimization of the following function

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi_i + \xi_i^*)$$

$$\text{Such that } \begin{cases} y_i - f(x_i, w) \leq \varepsilon + \xi_i^* \\ f(x_i, w) - y_i \leq \varepsilon + \xi_i \\ \xi_i, \xi_i^* \geq 0, i = 1, \dots, m \end{cases} \dots\dots\dots (4)$$

This optimization problem can be transformed into the dual problem and its solution is given by

$$f(x) = \sum_{i=1}^{n_{sv}} (\alpha_i - \alpha_i^*) k(x_i, x) \dots\dots\dots (5)$$

Subject to  $0 \leq \alpha_i^* \leq C, 0 \leq \alpha_i \leq C$ , where  $n_{sv}$  is the number of support vectors and the kernel function is

$$k(x, x_i) = \sum_{j=1}^n g_j(x) g_j(x_i).$$

The input non-dimensional parameters that significantly influence the wave transmission of the floating breakwater are considered as wave steepness ( $H/L$ ,  $H_i$ - wave height,  $L$ -wave length), relative wave height ( $H/d$ ,  $d$ - water depth), relative width of the breakwater ( $W/L$ ,  $W$ - breakwater width) and ratio of spacing to diameter of pipes ( $S/D$ ). Two types of kernel functions, namely radial basis function (RBF) and polynomial functions (PF) are adopted for analysis. The support vector regression model gives the correlation coefficients of 0.968 for training (Fig-1) and 0.961 for testing (Fig-2) for the radial basis kernel function.

It is concluded from the present study that the radial basis function performed better than the polynomial kernel function. The wave steepness and the wave length are important variables for the correlation results.

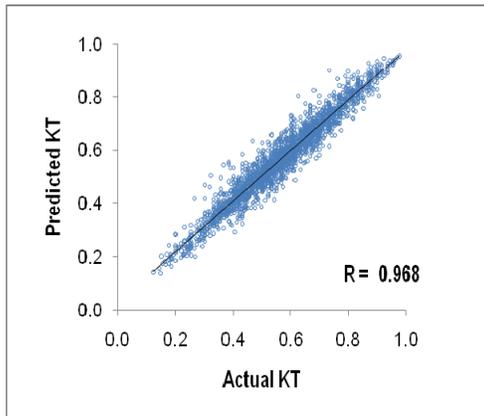


Fig. 1: correlation b/w the training actual and predicted data using SVR (RBF).

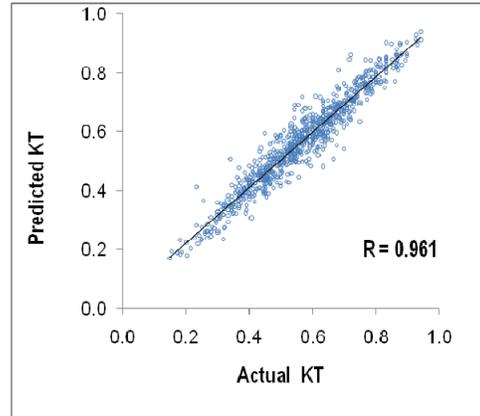


Fig. 2: correlation b/w the testing actual and predicted data using SVR (RBF)

References

1. Burges Christopher J. C, A Tutorial on support vector machine for pattern recognition, pp 1 – 43, Eds Kluwer Academic Publisher, 2004.
2. Mahjoobi J and Mosabbeh Adeli Ehsan, Prediction of significant wave height using regressive vector machines, Ocean Engineering Journal, Vol – 36, pp 339 – 347, 2009.
3. Ivanciuc Ovidiu, Applications of support vector machines in chemistry, Review in Computational Chemistry, Eds K. B. Lipkowitz and T. R. Cundari, Vol – 23, pp 291 – 400, 2007.
4. Smola alex J and Scholkopf Bernhard, A tutorial on support vector Regression, Statistics and Computing vol 14, pp 199-222, Kluwer Academic Publisher, 2004.