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PREDICTION OF RIVER PIPELINE SCOUR DEPTH USING MACHINE LEARNING APPROACHES

KAUSHIK V.[1], KULKARNI K. H.[2], TRIPATHI R. P.[3], RAMDEEN R. J.[4], Ryan Rampair[5], ALI A.[6], MOHDYUSOFF MA.[7] , ***CHABOKPOUR J.[8], Sheo P S[9], and Pandey S[10] ,***

[1] Academic Researcher of Department of Civil Engineering, Delhi Technological University, Delhi, India.
[2]Associate Professor of School of Civil Engineering, MIT-World Peace University, Pune, India
[3] Assistant Professor, Civil Engineering Department, Madan Mohan Malaviya University of Technology, Gorakhpur, 273010, India.
[4] Academic Researcher of Civil and Environmental Engineering, University of West Indies, St. Augustine, Trinidad and Tobago, (Corresponding Author: Rhowena J. Ramdeen)
[5] Academic Researcher of Civil and Environmental Engineering, University of West Indies, St. Augustine, Trinidad and Tobago
[6] Academic Researcher of Department of Civil and Environmental Engineering, University of West Indies, St. Augustine, Trinidad and Tobago.
[7] Academic Researcher of Civil Engineering, Universiti Teknologi Malaysia (UTM)., Malaysia
[8] Associate Professor of Hydraulic Structures, Civil Engineering Department, University of Maragheh, Maragheh, Iran
[9] Rajkiya Engineering College, Banda, Uttar Pradesh- 210201, India
[10] Department of Civil Engineering, Rajkiya Engineering College Bijnor, Uttar Pradesh-246725, India

ABSTRACT

The precise assessment of local scour depth under pipelines is a complicated occurrence, and the definitive method for its calculation remains unclear. This work tackles the issue by using computational models to accurately predict scour depth with great reliability. A support vector machine (SVM) was used to forecast pipeline scour depth, using an extensive dataset. The results were juxtaposed with typical datasets and other prediction methodologies, including regression equations and Radial Basis Function Neural Networks (RBFNN). The comparison study indicates that the SVM surpasses conventional regression techniques and RBFNN, attaining a superior generalization capability with $R^2 = 0.89$, RMSE = 0.046, MAE = 0.32%, and $\delta = 9.9$. Principal results indicate that the mean diameter of particles substantially affects scour depth, while flow discharge has no effect. Non-dimensional metrics, like the Shields parameter, are essential in assessing scour depth. These findings underscore the efficacy of SVM in precisely forecasting scour depth under pipelines, making it an indispensable instrument for hydraulic engineering applications. This paper introduces a unique contribution to scouring estimate approaches by using both dimensional and non-dimensional datasets, establishing a baseline for future research in this field.

Keywords: Local scour; Machine Learning approaches; Pipelines; Error analysis.

I. INTRODUCTION

Scour significantly contributes to the collapse of underwater pipelines. When pipelines encounter scour holes, they may experience self-burial, which affects their structural integrity. This phenomenon results from the intricacies of three-dimensional flow patterns and sediment movement at river or seabeds. The interaction between degraded bed surfaces and pipes intensifies scouring. Precisely determining underwater scour depth is a critical issue in hydraulic engineering. Extended free spans in pipelines may undergo resonant oscillations, resulting in settling and possible structural collapse (Chiew, 1991). Researchers, including Chao and Hennessy (1972), Kjeldsen et al. (1973), and Moncada and Aguirre (1999), have used empirical and analytical formulae to determine equilibrium scour depth. Nevertheless, these equations often inadequately represent the actual scour process. Table 1 encapsulates these empirical formulae.

Table 1: Empirical formulas for estimate pipeline scour depth

Author	Equation
Chao and Hennessy (1972) Kjeldsen et al. (1973)	$q_{bot} = U_0\left(H - \frac{R^2}{2H-R}\right), Ubot = \frac{q_{b0t}}{(H-R)} = Uo\left[\frac{2\left(\frac{H}{R}\right)^2 - \left(\frac{H}{R}\right) - 1}{2\left(\frac{H}{R}\right)^2 - 3\left(\frac{H}{R}\right) + 1}\right]$ for H≥R and H-R = maximum scour depth, R=radius of pipe, H=distance from bed to pipe centre, U_o= average flow velocity. $ds = 0.9722\left(\frac{{U_0}^2}{2g}\right)^{0.2} D^{0.8}$
Ibrahim and Nalluri (1986)	$\frac{ds}{D} = 4.706\left(\frac{U_0}{Uc}\right)^{0.89}\left(\frac{Uo}{gy}\right)^{1.48} + 0.06 clearwater$ $\frac{ds}{D} = 0.084\left(\frac{U_0}{Uc}\right)^{-0.8}\left(\frac{Uo}{\sqrt{gy}}\right)^{-0.16} + 1.33 livebed$
Dutch research group (1984)	$ds = 0.929\left(\frac{Uo}{2g}\right)^{0.26} D^{0.79} {d_{50}}^{-0.04}$
Moncada and Aguirre (1999)	$\frac{ds}{D} = 0.9\tanh(1+1.4F) + 0.55, \frac{ds}{D} = 2F\sec(1.7\frac{e}{D})$

Figure 1 illustrates the flow conditions, pipe shape, and sediment characteristics. The factors influencing the equilibrium scour depth ds under the pipeline include flow conditions, over a bed of unaltered cohesionless material, as well as spherical sedimentation, as seen in Fig. 1. The broad connection representing scour depth is shown below (Moncada and Aguirre, 1999):

$$d_s = f(\rho, \rho_s'', \nu, Q, Y, g, d_{50}, S_0, D) \qquad (1)$$

In the above equation ρ is fluid density; and ρ_s' , ν are buoyant sediment density and fluid kinematic viscosity respectively. Q is discharge, Y is flow depth & g is gravitational acceleration. d_{50} is particle mean diameter; S_0 is slope of the energy line; D is the diameter of the pipe, & d_s is equilibrium scour depth.

The six non-dimensional parameters may be derived by reducing nine variables from Equation (1) using the Buckingham theorem, selecting the fundamental variables of ρ , Q and D.

$$\frac{d_s}{D} = \Psi(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, R_p, S_0, F) \qquad (2)$$

Where τ_* is dimensionless Shields parameter relates with sediment transport; $\frac{D}{d_{50}}$ = Characteristics of dimensionless soil, $R_p = \frac{VD}{\nu}$ is Reynolds number, S_0 = energy slope and, (Froude number) F = $\frac{V}{\sqrt{gY}}$.

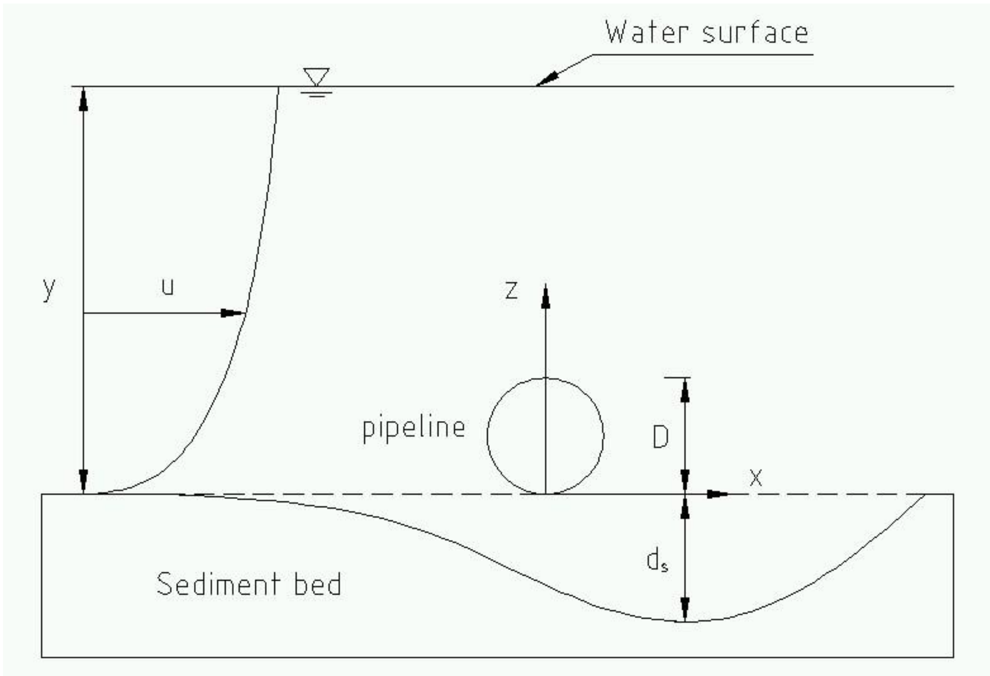

Fig 1: Local scour below pipeline in river crossing (Dey and Singh, 2008)

In fully developed turbulent flow over a rough substrate, the inaccuracy related to the Reynolds number is insignificant and may therefore be ignored (Lim and Chiew, 2001; Melville, 1992). This criterion for the Reynolds number corresponds with the results of Moncada and Aguirre (1999) and Dey and Singh (2008). The integration of soft computing techniques with field data and regulated statistical laboratory procedures produces very reliable and meaningful findings for calculating hydraulic parameters. Soft computing methodologies, including Neural Networks (NN) and Support Vector Machines (SVM), have been extensively used to tackle diverse hydraulic issues. Researchers have utilized neural network-based methodologies (Trent et al., 1993; Liriano and Day, 2001; Kambekar and Deo, 2003; Azinfar et al., 2004; Azamathulla et al., 2005, 2006, 2008; Guven and Gunal, 2008a, b; Goel, 2008) to estimate downstream flow characteristics and scour around hydraulic structures using extensive field datasets. This research employs Artificial Neural Networks and Support Vector Machines to forecast scour depth under pipelines. Advanced soft computing techniques, including Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), have shown efficacy in addressing hydraulic engineering challenges (Azamathulla et al., 2005, 2008, 2010). This work introduces a prediction model for evaluating scour depth using the SVM methodology. The outcomes from the SVM model were then compared with those generated from a Radial Basis Function Neural Network (RBFNN) and traditional regression equations.

II. METHODOLOGY

Neural Network (NN) model development

Artificial Neural Networks primarily consist of input, hidden, and output neurons, with each neuron functioning as an autonomous entity. The correlation between input and vector components provides a significant degree of strength flexibility based on its design. The neural network is trained to analyze data sets consisting of input-output pairs, yielding values for connection weights, biases, and centers. Training may need many epochs, when the whole dataset is presented to the network repeatedly until the cumulative total of squared errors attains a predetermined error threshold. The principles behind these trainings are described in the ASCE Working

Committee (2000). This research used a neural network toolbox inside the MATLAB program, using a generic feedforward architecture trained with radial basis functions (RBF). Of the 215 input-output pairings, about 75% (161 sets) were randomly selected for training, while the remaining 25% (54 sets) were used for testing. All patterns were adjusted to the range of (0.0, 1.0) using a Gaussian function prior to their application. The RBF network, including 5 inputs, 36 hidden neurons, and 1 output, was trained with varying diffusion values (α) ranging from 0 to 1. A value of 0.01 was selected since it produced optimal performance for the training data.

SVM model development

The Support Vector Machine (SVM), created by Vapnik in (1995), is increasingly favored for its appealing characteristics and potential empirical efficacy. Support Vector Machines (SVMs) were first designed for classification tasks, but they have now been adapted for regression issues (Vapnik 1998). An SVM constructs discrete hyperplanes across classes in the n-dimensional input space, maximizing the margins between the two data sets. This property enhances the applicability of SVM in comparison to ANN. The distance between two parallel hyperplanes is referred to as the margin, with one side of the separator pressed against each of the two datasets. The classifier mistake is mitigated by increasing the margins. In the event of regression development, the distinction lies in the SVR's attempt to fit a curve based on the kernel applied to the two data points of the hyperplane. This strategy may reduce the separation margins and calculation mistakes.

Initially, Support Vector Machine was used just for classification in 1996; a subsequent version of SVM was introduced by Drucker et al. in 1997. This updated version encompasses all the principal attributes of the maximum margin approach, with a non-linear function transformed via linear learning machine mapping into a high-dimensional kernel-induced feature space. The system's capacity is quantified by a parameter that is independent of surface dimensionality. SVM operates on the principles of generalization and optimization in bond regression. They depend on establishing a loss function that disregards mistakes within a certain proximity to the real value, referred to as the epsilon-intensive loss function. In SVR, the input x is transformed into an m-dimensional feature space by a nonlinear method, after which a linear model is established inside this feature space. The non-linear model represented in mathematical notation (inside the feature space) is denoted as f(x, w):

$$f(x,w)=\sum_{j=1}^{n} w_i g_i(x)+b \quad , \qquad (3)$$

In this formula *gj(x)*, $j=1,\ldots,n$ (nonlinear transformations), w= weight vector, b= bias terms. Value of loss function L (y, f (x, w)) defines the accuracy of formula. SVM regression is represented by Є (insensitive loss function) Vapnik (1998):

$$L_\varepsilon(y,f(x,w))=\begin{cases}0 & if\ \left|y-f(x,w)\right|\le\varepsilon \\ \left|y-f(x,w)\right|-\varepsilon & otherwise\end{cases} \qquad (4)$$

The empirical risk is

$$R_{emp}(w)=\frac{1}{m}\sum_{i=1}^{m} L_\varepsilon(y_i,f(x_i,w)) \qquad (5)$$

SVR shows linear regression in high-dimension feature space with ε insensitive loss and at the same time, tries to reduce model complexity by decreasing the value of $||w||^2$. This can be achieved by using positive slack variables, ξ_i, $\xi_i^*= 1,\ldots,m$ to measure the deviation of the training samples outside the ε -insensitive zone. So SVR minimize of the following function:

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

$$such\ that\begin{cases}y_i-f(x_i,w)\le\varepsilon+\xi_i^* \\ f(x_i,w)-y_i\le\varepsilon+\xi_i \\ \xi_i,\xi_i^*\ge 0, i=1,\ldots,m\end{cases} \qquad (6)$$

For optimization it is converted in dual problem and the solution of it are given below.

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

$$Subbject\ to\ \ 0 \le \alpha_i^* \le C, 0 \le \alpha_i \le C$$

In above equation n_{sv}= No. of SVs, $k(x_i, x)$ = kernel function.
The Lagrangian approach is used to resolve the aforementioned optimization, which resembles the optimization issue in the separable situation. The coefficients αi are found by solving the subsequent convex quadratic programming problem, and the kernel function is stated as follows:

$$k(x, x_i) = \sum_{j=1}^{n} g_j(x) g_j(x_i) \qquad (7)$$

The complexity of SVM models and their estimate accuracy rely on the optimal configuration of the meta-parameters C, ε, and kernel parameters (Smola & Schölkopf, 1998). Kernel functions are used to alter the dimensionality of the input space, hence enhancing the confidence in classification or regression tasks. Two prevalent kernel functions include the radial basis function (RBF):

$$k(x, x') = \exp(-\gamma \|x - x'\|^2) \qquad (8)$$

polynomial function is.

$k(x,x')-(xx'+1)^p$ (9)

Where γ > 0 represents radial parameters and p denotes kernel-specific parameters; they are assigned main values and used throughout the training phase. Additional kernel functions have been developed for certain applications (Uestuen, et al. 2006).
The Sequential Minimal Optimization (SMO) approach was introduced by Platt in 1999 to address the regression issue. It attains the maximum by repeatedly picking subsets of size 2 and optimizing the target function accordingly. The algorithm is straightforward and easy to implement; it may be resolved without using a quadratic optimizer. Shevade et al. (2000). The model development mostly comprises the SVM input and output data presented in equations 1 and 2. Seventy-five percent of the data (161 data sets) was used until optimal training performance was achieved, while the remaining twenty-five percent was exclusively employed for validating the SVM model in the MATLAB toolbox.

Error analysis
The SVM's training and testing sets were assessed using conventional statistical metrics, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute deviation (δ). All models were evaluated and compared using these four error measures. Table 2 delineates the characteristics and variances identified in the gathered data.

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |o_i - t_i| \qquad (10)$$

$$\delta = \frac{\sum |(o_i - t_i)|}{\sum o_i} * 100 \qquad (11)$$

Where t_i = target values of equilibrium scour depth (cm), while o_i = observed and $\overline{o}_i$ = averaged observed values of equilibrium scour depth (cm), N= No. of data points.

Table 2: Data variation

Parameters	Unit	Data Range	Mean	Std Dev
a)Range of different input–output parameters used for the estimation of scour depth				
Flow discharge (Q)	cm^3/s	7-94.42	35.11	21.74
Flow depth (Y)	cm	3.8-28	13.43	6.21
Particle mean diameter (d_{50})	cm	0.234-0.7	0.437	0.144
Diameter of the pipe (D)	cm	0.48-7.6	1.92	1.61
Equilibrium scour depth (d_s)	cm	0.02-11.3	4.75	2.39
b)Range of different non-dimensional input–output parameters used for the estimation of scour depth				

dimensionless Shields parameter (τ_*)	0.038-0.70	0.23	0.17
normalized flow depth (Y/D)	1.06-7	3.14	1.2
pipeline diameter cross section of sediment size (D/d_{50})	3.28-145.8	38.17	31.41
Froude number (F_r)	0.2-0.83	0.46	0.15
Reynolds number R_e	700	3250	2174
Non-dimensional equilibrium scour depth(d_s/D)	0.008-1.66	1.04	0.32

III. RESULT AND DISCUSSION

This research aims to estimate scour depth underneath pipelines using Support Vector Machine (SVM) models and to evaluate their efficacy with Artificial Neural Networks (ANN) employing Radial Basis Function Neural Networks (RBFNN). The findings are analyzed with a focus on the precision and dependability of the predicted models, together with the understanding acquired about the factors affecting scour depth. Tables 3 and 4 provide the comparative analysis of the dimensional and non-dimensional performance of the SVM and ANN-RBF models. The comparison of SVM and ANN-RBF models revealed that SVM consistently surpassed ANN-RBF in accuracy and error measures across both dimensional and non-dimensional datasets. The Support Vector Machine (SVM) attained a coefficient of determination (R^2) of 0.866 in training and 0.741 in validation, demonstrating robust predictive efficacy. The Root Mean Square Error (RMSE) for Support Vector Machine (SVM) was 0.0895 during training and 0.0957 during validation, surpassing the Artificial Neural Network with Radial Basis Function (ANN-RBF), which recorded RMSE values of 0.0978 for training and 0.0998 for validation. The Mean Absolute Error (MAE) for Support Vector Machine (SVM) was markedly lower than that of Artificial Neural Network with Radial Basis Function (ANN-RBF), exhibiting MAE values of 1.279 (training) and 1.426 (validation), in contrast to ANN-RBF's 1.933 (training) and 2.71 (validation). SVM demonstrated enhanced performance throughout training and validation. In contrast, ANN-RBF attained (training) and (validation). The RMSE values for SVM were very low (0.029 for training and 0.046 for validation), but ANN-RBF exhibited more errors (0.008 for training and 0.073 for validation). The MAE values for SVM were 0.279 (training) and 0.320 (validation), much lower than ANN-RBF's 0.083 (training) and 0.071 (validation). These findings underscore SVM's superior generalization compared to ANN-RBF, establishing it as a more dependable instrument for forecasting pipeline scour depth.

The sensitivity analysis of both dimensional and non-dimensional parameters revealed critical insights into the determinants of scour depth. The mean particle diameter was determined to be the most significant factor influencing scour depth. Flow discharge had little impact on scour depth, indicating its restricted influence on the scour process under the examined circumstances. The Shields parameter significantly influenced normalized scour depth, underscoring its essential function in sediment movement. The ratio of flow depth to pipe diameter had little impact on normalized scour depth, highlighting its relative unimportance in comparison to other factors. In comparison to conventional regression equations and ANN-RBF, SVM demonstrated enhanced performance. Although regression approaches often oversimplify the scour process, the capacity of SVM to manage nonlinear correlations guarantees enhanced accuracy. The enhanced generalization capability of SVM renders it a more favorable option compared to ANN-RBF, which demonstrated elevated error rates. The results highlight the relevance of SVM in hydraulic engineering for predicting pipeline scour depth. By precisely modeling intricate interactions among factors, SVM offers a resilient prediction framework, reducing reliance on empirical equations that may be inadequate under certain situations.

Table 3: Comparison of models for dimensional set performance of the SVM and ANN-RBF

Models for Dimensional set	R^2		RMSE		MAE		δ	
	Training	Validation	Training	Validation	Training	Validation	Training	Validation
SVM	0.866	0.741	0.0895	0.0957	1.279	1.426	5.78	10.45
ANN-RBF	0.827	0.683	0.0978	0.0998	1.933	2.71	11.49	15.67

Table 4: Comparison of models for non-dimensional set Performance of the SVM and ANN-RBF

Models for non-dimensional set	R^2		RMSE		MAE		δ	
	Training	Validation	Training	Validation	Training	Validation	Training	Validation
SVM	0.96	0.89	0.029	0.046	0.279	0.320	3.7	9.9
ANN-RBF	0.87	0.73	0.008	0.073	0.083	0.071	11.45	15.67

IV. CONCLUSION

The use of Support Vector Machines (SVM) for forecasting pipeline scour depth signifies a notable development in hydraulic engineering. This research revealed that SVM surpasses ANN-RBF and conventional regression approaches, especially in managing non-dimensional characteristics essential to scour operations. The results indicated that particle mean diameter and the Shields parameter were the most significant parameters, but flow discharge and normalized flow depth had no influence. The SVM model's exceptional generalization power, shown by its outstanding performance metrics (RMSE = 0.046 and MAE = 0.32%), highlights its resilience and dependability. This research establishes a new standard for estimating pipeline scour depth, presenting a strong alternative to traditional empirical equations and neural network models. Future research may concentrate on augmenting the model by integrating further field data, investigating alternative machine learning techniques, and tackling real-world difficulties such as sediment heterogeneity and fluctuating flow conditions. The incorporation of these elements will enhance the practical applicability of predictive models in hydraulic engineering contexts.

Declaration of competing interest

The authors declare that they have no know competing interests or personal relationships that could have appeared to influence the work reported in this paper.

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