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SUPPORT VECTOR REGRESSION BASED MODELLING OF TRAPPING EFFICIENCY OF SILT EJECTOR

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ABSTRACT

This paper investigates the potential of support vector machines based regression approach to predict the efficiency of tunnel type silt ejector using the data obtained from model study. The number of main tunnel & corresponding sub tunnels of the ejector were varied to obtain nine models. The experiments were conducted onthese models with varied concentrations for three uniform sizes of the sediment at different Froude numbers. The removal efficiency of the ejectors are predicted by support vector machine (SVM)using normalized poly kernel based function, poly kernel based function and radial based function and comparison of these results are made with observed removal efficiency. The SVM experiments were run with two types of input variables first with dimensional variablesand second with non-dimensional variablesand removal efficiency as output. The two third of random observed data was used for training andrest one third data was used forvalidation. Results of predicted efficiency of silt ejector with dimensionless data using all three algorithms suggest a better performance as compared with dimensional data. The sensitivity analysis, further, suggests the importance of silt size and concentration of silt in predicting the efficiency of silt ejector when using SVM based modelling approach.

Keywords: *Tunnel type silt ejector. Removal-efficiency models, main-tunnel, sub-tunnel, size of sediments, concentration of sediments, support vector machine (SVM)*

INTRODUCTION

The sedimentation (Sarwar et. al (2013), Mohammad et. al (2015)) in irrigation canals causes severe operational and maintenance problems. In power canals, trouble may be encountered in the turbines as silt may erode the blades and subsequently reduce the efficiency (Singh, M. et al (2013)).To tackle the menace of sedimentation in the canal, there are preventative and curative measures available. The most prevalent preventative means is provision of a Sediment Excluder in the river at head works of the canal (Kothyari et. al (1994), Sarwar et. al (2013), IS 6531 (1972)). Further, there are many available curative measures viz. vortex tube ejector, settling basins (Singh (1987)) and the vortex settling basins type of extractor have been investigated by Atkinson (1984), Raju et. al (1999), Athar et. al (2002), Ansari et. al (2014) and Niknia et. al (2011) respectively. But the most prevalent and popular curative method is tunnel type sediment ejector which is the best suited for higher discharge. Empirical and analytical methods of computation of tunnel type sediment ejector efficiency have been carried out by Tiwari (2006), Gautam and Suchitra (2005), Choudhary et. al (2004), Vittal et. al (1994),Wallingford (1993), Atkinson (1987), IPRI (1988), Atkinson and Lawrence (1984), Atkinson (1984), Dhillon et. al (1977), Garde and Pande (1976) and UPIRI (1975).The removal efficiency of the ejector has been found highly unreliable. Support vector machine (SVM) is a new tool that use input variables in the database to predict the unknown or future values of other variables of interest, often with better prediction accuracy. The advantage of modelling with the techniques is that it is capable of adapting the changes in data and is more robust to noise in the data. Several studies have also been reported on the application of SVM-based models in civil engineering (Gilardi et. al. (1999); Dibike et. al.(2001); Kanevski et. al (2002); Pal and Mather (2005); Pal (2006); Liu et. Al (2006), Singh et. al (2008), Pal et. al (2010)). However, little has been reported on the use of SVMs for the prediction of performance of silt ejectors. The present study investigates applicability of support vector method for estimation of removal efficiency on the data collected from the model test conducted in laboratory.

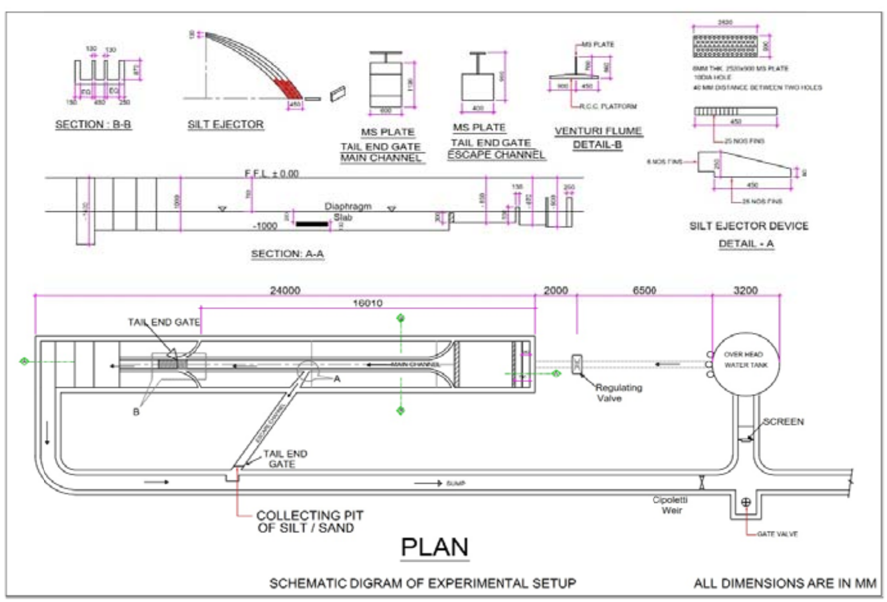

Fig. 1: Schematic diagram of experimental set up

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Experimental Set up and procedure

The experiments were conducted in rigid channel having vertical side wall 0.45m wide, 1m deep and 24.0 m long located in the hydraulic laboratory of National Institute of

Technology, Kurukshetra. A re-circulating system of water supply is established with pumping of water from a sump to an overhead tank from where water flows under gravity to the experiment channel through stilling chamber and baffle wall which is used to dampen the turbulent in the flow of water. A transition zone between stilling chamber and the channel further reduces the turbulence of flowing water, if any. At a suitable distance from the inlet of the main tunnel, the silt ejector model was fixed across the full width of the main channel from where an escape channel was taken out from which sediment laden lower portion of water was allowed to eject. An adjustable tailgate at the downstream of the main channel as well as the escape channel help to maintain uniform velocity and regulate discharge in the main channel and escape channel respectively as shown in Fig.1. Sediment of uniform sizes and varying concentrations are poured in main canal at suitable distance in upstream side of ejector and corresponding ejected from the escape channel is collected in trapping device that helps to measure the efficiency of silt ejector.

The number of main tunnel & corresponding sub tunnels of the ejector were varied to obtain nine models. The experiments were conducted on these models with varied concentrations for three uniform sizes of the sediment at different Froude numbers. The characteristics of experimental data is given in Table 1.

Table 1: Characteristics of train and test data used

Input parameter	Train data				Test data			
	Min	**Max**	**Mean**	**St. dev.**	**Min**	**Max**	**Mean**	**St. dev.**
Dimensioned data								
V	0.08	0.18	0.127	0.027	0.08	0.18	0.126	0.027
D	0.29	0.30	0.299	0.002	0.29	0.3	0.299	0.002
W	0.45	0.45	0.45	0.00	0.45	0.45	0.45	0.00
Q	0.011	0.024	0.017	0.04	0.011	0.024	0.017	0.04
Fr	0.047	0.105	0.074	0.016	0.047	0.105	0.073	0.016
r	15.385	30.25	21.591	2.886	16.6	30.25	22.348	3.058
D_n	0.15	0.425	0.293	0.111	0.15	0.425	0.293	0.112
m	3	5	3.968	0.824	3	5	3.964	0.828
s	3	5	4	0.805	3	5	4	0.805
Conc. $* 10^{-6}$	20.7	193	68.387	38.916	18.3	207	56.623	32.84
Non-dimensioned data								
V/U^*	0.828	2.124	1.404	0.394	0.736	2.124	1.381	0.385
Fr	0.052	0.105	0.074	0.016	0.047	0.099	0.073	0.015
H_1/D	0.233	0.241	0.234	0.002	0.0233	0.241	0.234	0.002
D/D_n	682.353	2000	1225.85	551.125	682.353	2000	1211.859	547.71
Q/VD^2	1.449	1.552	1.502	0.015	1.406	1.552	1.501	0.018
V/w_j	1.342	9.618	3.943	2.506	1.193	9.618	3.825	2.472
r	15.385	30.25	21.26	2.756	16.6	30.25	22.202	3.093
m	3	5	3.964	0.823	3	5	3.964	0.833
s	3	5	3.994	0.805	3	5	4.012	0.804
Conc. $* 10^{-6}$	18.3	207	77.728	38.138	19.4	71.7	36.56	11.845

Where Q=Discharge in m^3/s;V= Velocity of approaching m/s;D_n = Uniform size of sediment in mm; Conc.= Concentration (volume/volume); H_1= Diaphragm height in m;D = depth of water in m; W= Width of channel in m; s = number of sub tunnels ; m= number of main tunnels ; Fr= Froude number; r= Extraction Ratio (%); $U^* = \sqrt{g.R.S}$ in which g= acceleration due to gravity, R = hydraulic mean radius in m and S = slope of the channel

Support Vector Regression (SVR)

Support vector machines are classification and regression methods, which have been derived from statistical learning theory (Vapnik (1998)). The Support vector machines based classification methods is based on the principle of optimal separation of classes. If the classes are separable, this method selects from among the infinite number of linear classifiers, the one that minimise the generalisation error or at least an upper bound on this error, derived from structural risk minimisation. Thus, the selected hyper plane will be one that leaves the maximum margin between the two classes, where margin is defined as the sum of the distances of the hyper plane from the closest point of the two classes (Vapnik (1995)).

Vapnik (Vapnik (1995)) proposed ε-Support Vector Regression (SVR) by introducing an alternative ε- insensitive loss function. This loss function allows the concept of margin to be used for regression problems. The purpose of the SVR is to find a function having at most ε deviation from the actual target vectors for all given training data and have to be as flat as possible (Smola (1996)). For a given training data with k number of samples be represented by $\{\mathbf{x_i}, y_i\}$, i = 1, …, k, where $\boldsymbol{x}_i$ is input vector and y_i is the target value, a linear decision function can be represented by

$$f(\boldsymbol{x}) = \langle \boldsymbol{w}, \boldsymbol{x} \rangle + b \tag{1}$$

Where $\boldsymbol{w} \in \boldsymbol{R}^N$ and b $\in$ R. $\langle \mathbf{w}, \mathbf{x} \rangle$ represents the dot product in space $\mathbf{R}^N$. In Equation 1, vector **w** determine the orientation of a discriminating plane whereas scalar b determine the offset of the discriminating plane from the origin. A smaller value of **w** indicates the flatness of Equation (1), which can be achieved by minimising the Euclidean norm defined by $\|\mathbf{w}\|^2$ (Vapnik (1995)). Thus, an optimisation problem for regression can be written as (Smola, A. J., 1996):

$$\text{minimise} \frac{1}{2}\|\mathbf{w}\|^2$$

$$\text{subject to} \begin{cases} y_i - \langle \mathbf{w}, \mathbf{x}_i \rangle - b \le \varepsilon \\ \langle \mathbf{w}, \mathbf{x}_i \rangle + b - y_i \le \varepsilon \end{cases} \tag{2}$$

The optimisation problem in Equation (2) is based on the assumption that there exists a function that provides an error on all training pairs which is less than ε. In real life problems, there may be a situation like one defined for classification by Cortes, C. and Vapnik (1995). So, to allow some more error, slack variables ξ, ξ' can be introduced and the optimisation problem defined in Equation (2) can be written as below to deal with infeasible constraints of the optimization problem (2) (Smola(1996)):

$$\text{Minimise } \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{k}\left(\xi_i + \xi_i'\right)$$

$$\text{Subject to } y_i - \langle \boldsymbol{w}, \boldsymbol{x}_i \rangle - b \le \varepsilon + \xi_i$$

$$\langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b - y_i \le \varepsilon + \xi_i'$$

$$\text{and } \xi_i, \; \xi_i' \ge 0 \text{ for all } i = 1, 2, \ldots, k. \tag{3}$$

The constant C> 0 is a user-defined parameter which determines the trade-off between the flatness of the function and the amount by which the deviations to the error more than ε can be tolerated. The minimization problem in Equation (3) is called the primal objective function. It was found that t in most cases the optimization problem defined by Equation (3) can easily be solved by converting it into a dual formulation (Cortes and Vapnik (1995)). The optimisation problem in Equation (3) can be solved by replacing the inequalities with a simpler form determined by transforming the problem to a dual space representation using Lagrangian multipliers (Luenberger (1984)).

The Lagrangian of Equation (3) can be formed by introducing positive Lagrange multipliers λ_i, λ_i', η_i, η_i' i = 1,….,k and multiplying the constraint equations by these multipliers, and finally subtracting the results from the objective function. The Lagrangian for Equation (3) can now be written as:

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}\left(\xi_i + \xi_i'\right) - \sum_{i=1}^{k}\lambda_i\left(\varepsilon + \xi_i - y_i + \langle w, x_i \rangle + b\right)$$
$$- \sum_{i=1}^{k}\lambda_i'\left(\varepsilon + \xi_i' + y_i - \langle w, x_i \rangle - b\right) - \sum_{i=1}^{k}\left(\eta_i \xi_i + \eta_i' \xi_i'\right) \tag{4}$$

The dual variables in equation (4) have to satisfy λ_i, λ_i', η_i, $\eta_i' \ge 0$. The solution of the optimisation problem involved in the design of SVR can be obtained by locating the saddle point of the Lagrange function defined in the equation (4). The saddle points of equation (4) can be obtained by equating partial derivative of L with respect to **w**, b, ξ_i *and* ξ_i' to zero and getting:

$$\partial_w L = \boldsymbol{w} - \sum_{i=1}^{k}\left(\lambda_i' - \lambda_i\right) . \boldsymbol{x}_i = 0 \tag{5}$$

$$\partial_b L = \sum_{i=1}^{k}\left(\lambda_i' - \lambda_i\right) = 0 \tag{6}$$

$$\partial_{\xi_i} L = C - \lambda_i - \eta_i = 0 \tag{7}$$

$$\partial_{\xi_i'} L = C - \eta_i' - \lambda_i' = 0 \tag{8}$$

Substituting equations (5), (6), (7) and (8) in equation (4) results in the optimisation problem of maximizing:

$$-\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\left(\lambda_i' - \lambda_i\right)\left(\lambda_j' - \lambda_j\right)\left(\mathbf{x}_i . \mathbf{x}_j\right) - \varepsilon\sum_{i=1}^{k}\left(\lambda_i' + \lambda_i\right) + \sum_{i=1}^{k}y_i\left(\lambda_i' - \lambda_i\right)$$

$$\text{subject to} \sum_{i=1}^{k}\left(\lambda_i' - \lambda_i\right) = 0 \text{ and } \lambda_i, \lambda_i' \in [0, C] \tag{9}$$

Dual variables η_i, η_i' are eliminated by using conditions in equations (7) and (8) and can now be written as $\lambda_i' = C - \eta_i'$ and $\lambda_i = C - \eta_i$, whereas equation (5) can be written as $\boldsymbol{w} = \sum_{i=1}^{k}\left(\lambda_i' - \lambda_i\right) . \boldsymbol{x}_i$. Equation (9) is a quadratic programming problem and can be solved to get the values of $\lambda_i^{'}$ and λ_i. The prediction problem in equation (1) can now be written as:

$$f(\boldsymbol{x}) = \sum_{i=1}^{k} \left(\lambda_i^{'} - \lambda_i\right) \langle \boldsymbol{x}_i, \boldsymbol{x} \rangle + b \quad (10)$$

The techniques discussed above can be extended to allow for non-linear support vector regression by introducing the concept of the kernel function (Vapnik (1995)). This is achieved by mapping the data into a higher dimensional feature space. By doing this, the training data are moved into a higher-dimensional feature space where the training data may be spread further apart and a larger margin may be found by performing linear regression in feature space. The regression problem in feature space can be written by replacing $\mathbf{x_i} \cdot \mathbf{x_j}$ in equation (6) with $\mathbf{\Phi}(\mathbf{x_i}) \cdot \mathbf{\Phi}(\mathbf{x_j})$. Thus, the optimisation problem of equation (9) can be written as:

maximize

$$-\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\left(\lambda_i^{'}-\lambda_i\right)\left(\lambda_j^{'}-\lambda_j\right)K\left(\mathbf{x}_i.\mathbf{x}_j\right)-\varepsilon\sum_{i=1}^{k}\left(\lambda_i^{'}+\lambda_i\right)+\sum_{i=1}^{k}y_i\left(\lambda_i^{'}-\lambda_i\right)$$

subject to $\sum_{i=1}^{k}\left(\lambda_i^{'} - \lambda_i\right) = 0$ and $\lambda_i,\ \lambda_i^{'} \in [0, C]$. (11)

where:

$$K(\mathbf{x_i}, \mathbf{x_j}) \equiv \mathbf{\Phi}(\mathbf{x_i}) \cdot \mathbf{\Phi}(\mathbf{x_j}) \quad (12)$$

This relation is also called the kernel trick since no calculation of the mapping $\mathbf{\Phi}(\boldsymbol{x})$ is required in the feature space. Support vector regression function in equation (10) can now be written as:

$$f(\boldsymbol{x}) = \sum_{i=1}^{k} \left(\lambda_i^{'} - \lambda_i\right) K(\boldsymbol{x}_i, \boldsymbol{x}) + b \quad (13)$$

In this optimisation problem, the kernel function is computed rather than $\mathbf{\Phi}(\mathbf{x})$ so as to reduce the computational cost of dealing with the high dimension feature space. For further details about SVR, readers are referred to (Vapnik, 1995).

Details of Kernel functions

In situations with non-linear decision surfaces, SVM use a mapping to project the data in a higher dimensional feature space. To make computation simpler, the concept of the kernel function was introduced (Vapnik, V. N., 1995).A kernel function allows SVR to work in a high-dimensional feature space, without actually performing calculations in that space. Kernel functions are mathematical functions and according to Cortes and Vapnik (1995), any symmetric positive semi-definite function, which satisfies Mercer's conditions (Vapnik (1995)), can be used as a kernel function with SVR. A number of kernel functions are discussed in the literature, but it is difficult to choose one which gives the best generalisation with a given dataset. As the choice of kernel function may influence the prediction capabilities of the SVR, three most frequently used kernel functions: a polynomial kernel function ($K(\boldsymbol{x}, \boldsymbol{x}^{'}) = ((\boldsymbol{x} \cdot \boldsymbol{x}^{'}) + 1)^{d^*}$), normalized polynomial kernel function($K_{cosine}(x, x') = K(x, x')/\sqrt{K(x, x). K(x', x')}$) and radial basis kernel ($K(\boldsymbol{x}, \boldsymbol{x}^{'}) = e^{-\gamma|\mathbf{x}-\mathbf{x}^{'}|^2}$) were used in present study. Where d^* and γ are the parameters of polynomial and radial basis kernel function respectively. The use of SVR requires setting of user-defined parameters such as regularisation parameter (C), type of kernel, kernel specific parameters and error-insensitive zone ε. Variation in error-insensitive zone ε found to have no effect on the predicted shear strength in present study so a default value of 0.0010 was chosen for all experiments (Witten and Frank (2005)). The optimal value of parameters C, d^* and γ were obtained after several trials with this dataset. The correlation coefficientsand Root Mean Square Error (RMSE) were compared to reach at an optimal choice of these parameters. Training is used to generate the model with SVR on the input dataset for predicting the removal efficiency of silt ejector. The testing is used to estimate the accuracy of regression model. The correlation coefficient, R^2 and root mean square error (RMSE) were used to judge the performance of SVR in predicting the efficiency of silt ejector in present study.

RESULT AND DISCUSSION

The observed data from nine models were arranged into dimensional and non-dimensional categories as given in Table

Table 2: Coefficient of correlation, Root mean square error and R^2 for Dimensional & Non-dimensional data

Type Kernel	Training set: Correlation coefficient	Training set: Root mean square error	Training set: R^2	Testing set: Correlation coefficient	Testing set: Root mean square error	Testing set: R^2
Dimensional data						
Normalized Poly kernel	0.8704	7.726	0.743	0.8059	9.4636	0.649
Poly kernel	0.7373	9.8303	0.543	0.7178	10.8248	0.515
RBF kernel	0.7263	10.6528	0.498	0.6986	11.9999	0.488
Non Dimensional data						
Normalized Poly kernel	0.9056	5.5628	0.820	0.824	11.0495	0.659
Poly kernel	0.8174	7.4483	0.668	0.8	11.9472	0.640
RBF kernel	0.7911	8.3726	0.625	0.7381	15.666	0.544

1. These datasets are used to develop SVR models for three kernel functions, wherein two third data (169 values)are used for training whileone third (84 values)for testing. Coefficient of correlation, root mean square error (RMSE) and R^2 were estimated to compare the performance of Kernel based SVR models. Table 2 provides the value of coefficient of correlation, RMSE and $R^2$of dimensional and non- dimensional dataset.

For dimensional training data, the coefficient of correlations for normalised polykernel, polykernel and RBF kernel based SVR are found to be 0.8704, 0.7373 and 0.7063 respectively.The values of $R^2$for the three kernels were found as 0.743, 0.543 and 0.498 and that of RMSE as 7.726,9.830 and 10.952. The values of coefficient of correlation as well as$R^2$is highest and RMSE is least for the normalised polynomial kernel. Thus, the performance of normalised

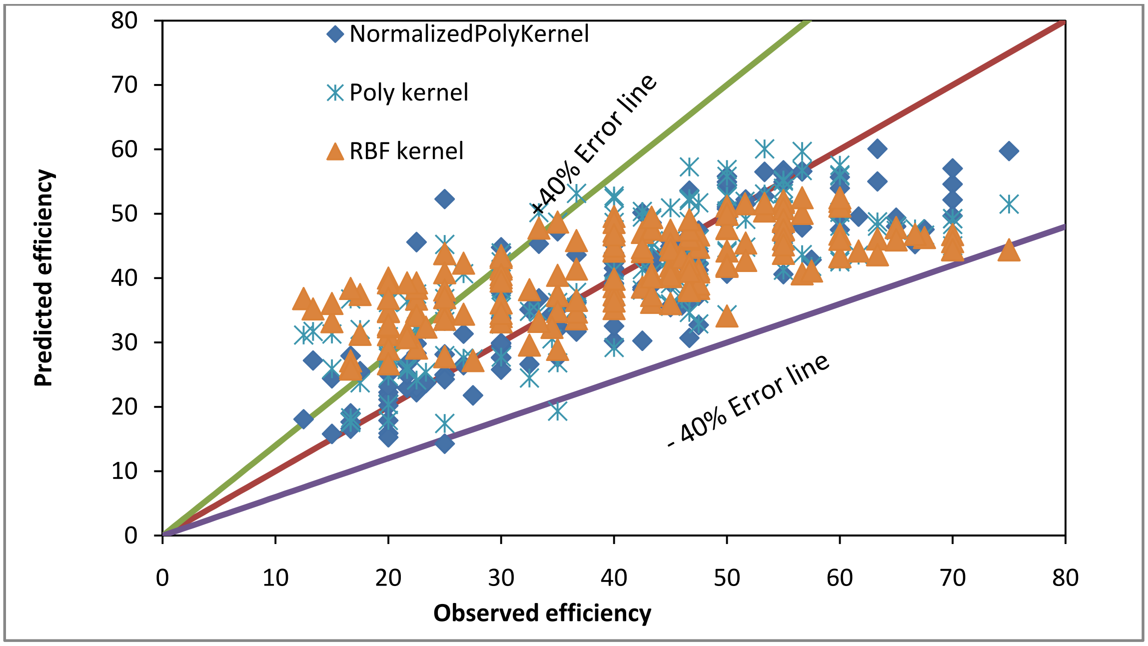

Fig.2: Predicted efficiency vs. observed efficiency of Dimensional Training Data

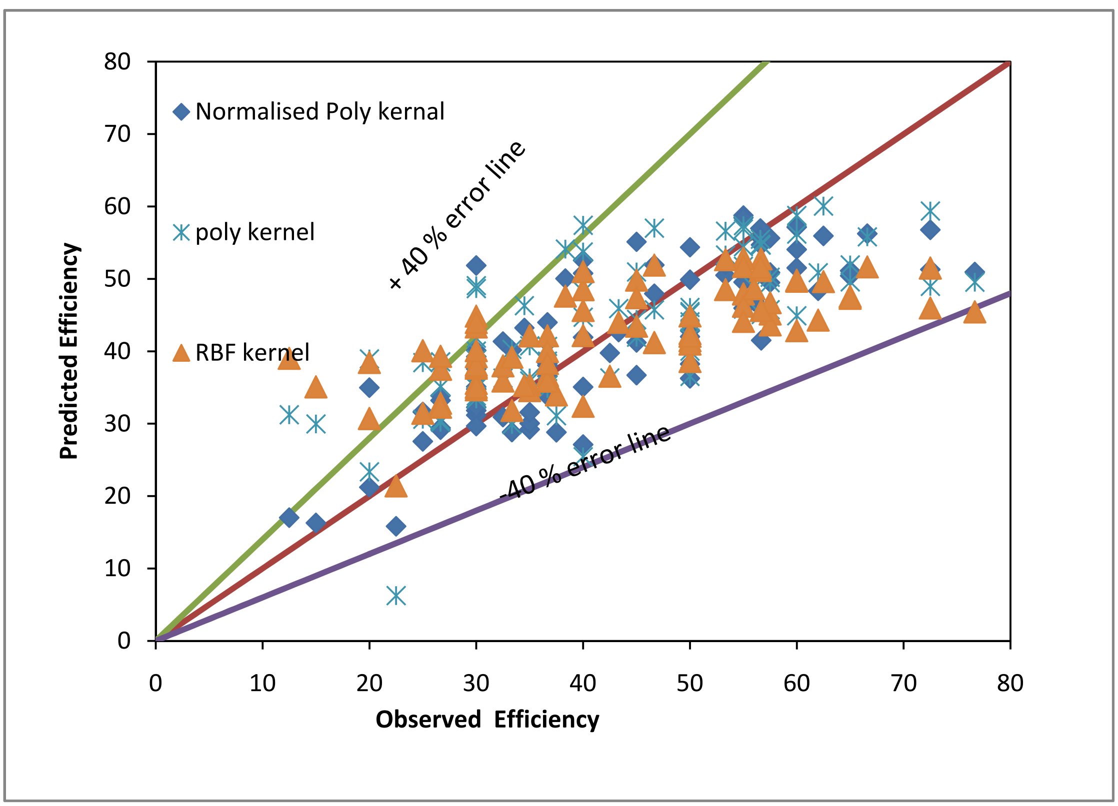

Fig. 3: Predicted efficiency vs. observed efficiency of Dimensional Test Data

polynomial kernel is betterthan other kernels in predicating the efficiency of silt ejector.

Dimensional Test Data

For test dataset, the coefficient of correlations for respective normalised polynomial kernel, polynomial kernel and RBF kernel are found as 0.8059, 0.7178 and 0.6986. The values of R^2 for the three kernels were found as 0.649, 0.515 and 0.488and that of RMSE as 9.4636,10.8248 and 11.99958. The values of coefficient of correlation as well as $R^2$are highest and RMSE is least for normalised polynomial kernel indicating better performance of normalised polynomial kernel in comparison to other kernels in predicating the efficiency of silt ejector.

Further, an agreement diagram with ± 40 % error lines of perfect agreement as shown in Fig. 2 and Fig. 3 for training and test data respectively is drawn between observed removal efficiency vs. predicted removal efficiency. It is seen that majority of the predicted efficiency by normalised polynomial kernel is close to observed efficiency.

In order to investigate the effect of non-dimensional input parameters on efficiency of silt ejector, another trial was run with training data set. To have fair comparison, same values of user defined parametersare used as in case ofdimensional data during trials. Similar trends of coefficient of correlation, R^2 and RMSE were obtained as in case of dimensional dataset. With testing dataset, the values of coefficient of correlation = 0.824,

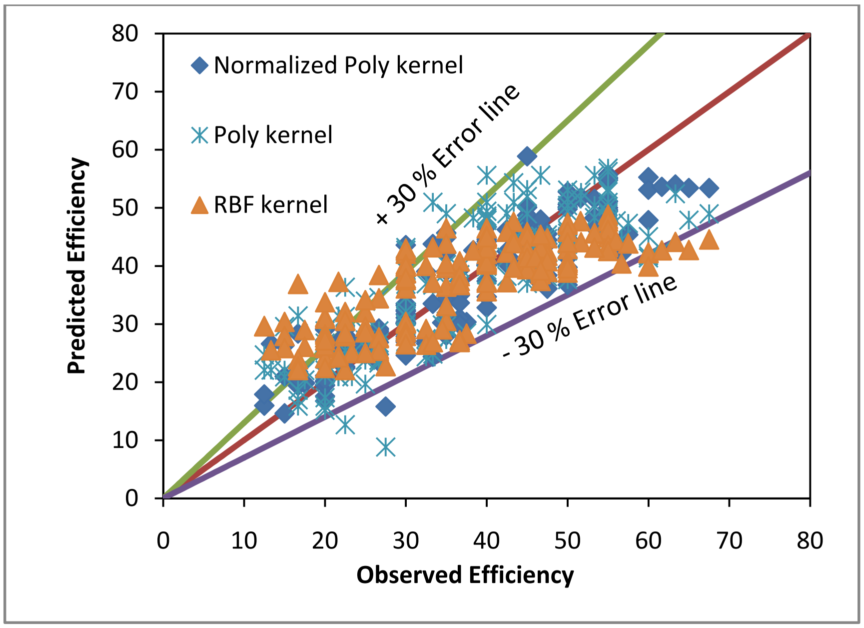

Fig.4: Predicted efficiency vs. observed efficiency of Non- Dimensional Training Data

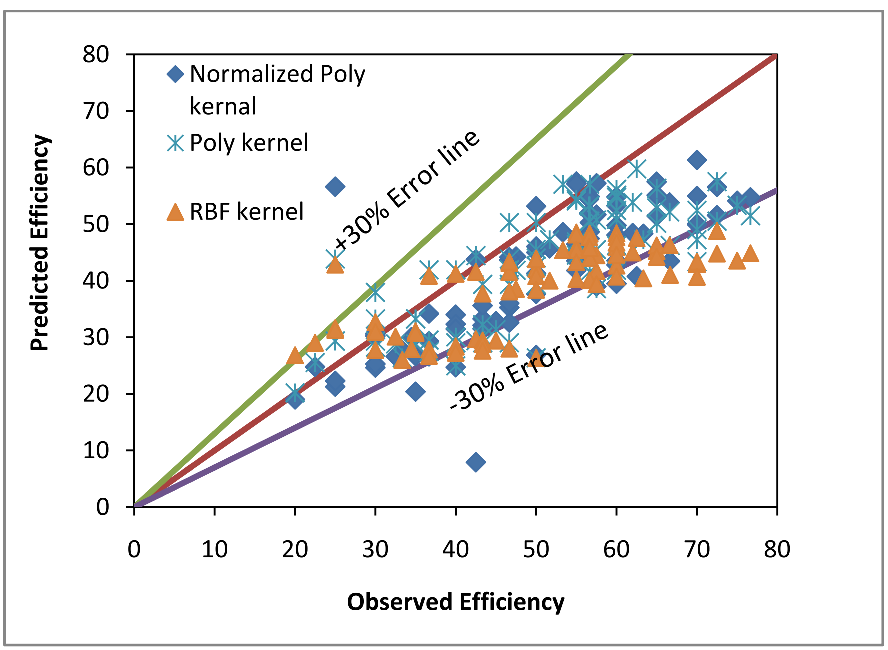

Fig.5: Predicted efficiency vs. observed efficiency of Non- Dimensional Test data

0.8, 0.7381; R^2=0.659, 0.64 and 0.544 and RMSE= 11.04, 11.94 and 15.666respectively werefoundby normalized polynomial kernel, polynomialkernel and RBF based SVR. The values of coefficient of correlation as well as R^2 is highest and RMSE is least for normalised polynomial kernel, which is similar to dimensional input parameters. Thus the performance of normalised polynomial kernel is best in comparison to other kernels in predicating the efficiency of silt ejector. Further, it is seen from Table 2 that the values of coefficient of correlation as well as $R^2$are higher and RMSE value is lower for dataset of non-dimensional input parameters, indicating better performance this data set. This is further supported by Fig.4 and 5 showing the plots between observed vs predicted removal efficiencies for normalized poly kernel, RBF based SVR with non dimensional training and testing data respectively. It is seen that the majority of predicted values are lying between $\pm$30% lines of perfect agreement that is lowering of error band is achieved from $\pm$40%.

Comparison of the values of coefficient of correlation, RMSE and R^2along with error bandsfor dimensional data and non-dimensional data suggest better performance by non-dimensional data based modelling.

SENSITIVITY ANALYSIS

Sensitivity tests were conducted using normalized polynomial kernel based SVR to determine the relative significance of each of the input parameters on the efficiency of silt ejector. Several factors affect the removal efficiency of silt ejector. These include width of channel, size of silt, concentration of silt, flow depth, approach velocity, number of main tunnel, sub tunnel and extraction ratio. Various input combinations as shown in Table 3 were considered by removing one input variable in each case and its influence on predicted efficiency was evaluated in terms of the root mean square error and coefficient of correlation as main performance criteria. Results from Table 3 suggest that the Concentration of silt and size of silt has major influence in predicting the removal efficiency of silt ejector with SVR in comparison to other input parameters and removing any other input parameter have no major influence on the predicting capability of SVR. The results suggest for normalized polynomial kernel based SVR provide best performance with data combinationof width of channel, size of silt, concentration of silt, flow depth, approach velocity, number of main tunnels, sub tunnels and extraction ratio.

Table 3: Sensitivity analysis

Input combination	Input parameter removed	SVR	
		Coefficient of correlation	RMSE
V, D, W, Q, Fr, Conc. ,r, D_n , m, s.		0.8704	7.726
D, W,Q, Fr, Conc. ,r, D_n ,m,s	V	0.8757	7.2326
V, W, Q, Fr ,Conc. ,r, D_n , m, s	D	0.8587	7.674
V, D, Q, Fr, Conc. ,r, D_n , m, s	W	0.8704	7.3726
V, D, W, Fr, Conc., r, D_n , m, s	Q	0.8701	7.3694
V, D, W, Q, Conc., r, D_n , m, s	Fr	0.8751	7.247
V, D, W, Q, Fr, r, D_n , m, s	Conc.	**0.7641**	**9.667**
V, D, W, Q, Fr, Conc., D_n , m ,s	r	0.8313	8.2828
V, D,W,Q, Fr, Conc., r, m ,s	D_n	**0.5464**	**12.737**
V, D, W, Q, Fr, Conc. ,r, D_n ,s.	m	0.8418	8.053
V, D, W, Q, Fr, Conc. ,r, D_n ,m.	s	0.8674	7.4837

CONCLUSION

This paper investigates the potential of support vector machine (SVM) using normalized polynomial kernel, polynomial kernel and radial based functions in predicting the efficiency of tunnel type silt ejector. It is concluded that the normalized polynomial kernel based SVR model works well in predicting the efficiency of silt ejector in comparison to polynomial kernel and RBF kernel based SVR. Further, non-dimensional input parameters suggest a better performance than dimensional input parameters. The finding of this study encourages the use of normalized polynomialkernel based SVR modeling in the prediction of efficiency of tunnel type silt ejector, non-dimensional input parameters offer an improved performance and also conclude that theconcentration of silt and size of silt has major influence in predicting the removal efficiency.

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