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# EVALUATION AND ANALYSIS OF TRAPPING EFFICIENCY OF VORTEX TUBE EJECTOR USING SOFT COMPUTING TECHNIQUES

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## ABSTRACT

*The problem of sedimentation is a global concern linked with the design of intake structures and hydel channels. Sedimentation decreases the water transporting capacity of canals and hydel channels. Vortex tube silt ejector comprises a cut provided on the top of the vortex tube placed across the channel, is used to extract sediments from the canalin an efficient and economical way. Experiments have been conducted withvortex tube models having variation in the size of sediment (mm), the concentration of sediment(ppm), ratio of slit thickness to tube diameter (t/d), and extraction ratio (%).To fit the observed data set and to relate trapping efficiency with the input parameters, Gaussian Process Regression (GP) and Support Vector Machine(SVM) techniques were applied to estimate the trapping efficiency given by the vortex tube silt ejector. Out of 144 observations collected from experiments, the modelsare trained with 100 observations chosen arbitrarily from the total data and tested with the remaining 44 observations. Modeling results are also compared with previous predictive relationships proposed for vortex tube silt ejection devices.Parameter sensitivity results implysediment size and the extraction ratio are the important variables influencing the trapping performance of a vortex tube device.*

**Keywords:** *Vortex tube; Extraction ratio; Gaussian Process Regression; Support Vector Machine.*

## INTRODUCTION

Sedimentation is a global issue concerned with the design of irrigation works and hydroelectric schemes. Sediment deposited causes loss of conveyance capacity in irrigation canals and water supply channels for hydropower and damage turbine blades. An off taking canal or intake structure should be designed in a way to have maximum flow capacity and minimum sediment entrance. Entry of sediment in canals and rivers is the main problem which many countries are facing frequently[19]. Several silt ejection devices are currently being utilized to avoid sediment entry in the off taking canal at diversion headwork i.e. tunnel type silt ejectors [8], vortex tube ejectors[4, 5, 13], vortex chambers [2, 3], settling basin [17,25] etc. Vortex type ejector is a cheaper method to exclude sediment content moving as bed load into the canal. Sediment particles near the bottom of the canal can be extracted by a vortex tube which usually deployed and embedded within canal bottom either normal to the flow or at some angle. The bottom water layer along with sediments enters into the tube through a slit provided at the upper portion of the ejection tube. The placement of the vortex tube is such that it allows the entry of silt water throughout the canal width parallel to the canal bed, and entering silt water produces flow with strong vortex motion, and from there on silt water make its way to the outlet of the tube and discharged to an outflow escape channel, which usually returns the sediment-loaded water (enters through slit bed)to the river. These devices show a good potential in situations where the concentration of near-bed sediments is higher. The feasibility of vortex ejector is assessed with its sediment trapping capability which is described as the amount of extraction of sediments from the flowing water by the vortex tube [4]. Various parameters viz. sediment size, ratio of slit thickness to tube diameter (t/d), sediment concentration, flow velocity (v) into the channel are affecting the efficiency of vortex tube silt ejector. Lot of researchers [4, 12, 15] has investigated the silt ejection devices related the hydraulic design and sediment removal efficiency prediction.

Trapping efficiency of the vortex tube silt ejector can be described as the ratio of sediment escaped from the canal through the vortex tube to the total sediment load carried by the canal. The maximum load of the sediments moving as bed-load can often be removed at the expense of between10 to 20% of the total discharge of canal[4].

Several studies specified in literature highlighted the influence of several geometrical parameters of vortex device in an attempt to improve the sediment extraction potential of vortex ejector. Despite some parametric study on these devices, the design of vortex tube silt ejector is still lacking specified design details as well as simple and well-defined relationships. Moreover, due to the complexity of flow behavior in vortex tubes, it is hard to fit a conventional regression model for the precise estimations of trapping efficiency [26]. Therefore, artificial intelligence-based methods can be effective in providing a good approach towards generalization and efficiency prediction due to its high learning and reasoning capabilities. In the present scenario, the soft computing based modelling has been extensively employed in many fields of research related to the subject of water and environmental engineering [1,9, 10, 14, 21, 22, 23].

Recently, some modelling techniques have been employed to relate trapping capability of the vortex tube ejector with the flow parameters along with geometrical parameters. Atkinson [4], based on the experimental study, proposed an equation to evaluate the trapping efficiency of the vortex ejection devices. Tiwari et al. [26] disused the application of

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ANFIS and ANN to the data observed with experimental study along with a comparison to some past works related to vortex tube silt ejector. Singh et al. [24] developed a predictive equation based on multilinear regression analysis for evaluating the trapping capability of the vortex tube ejector and compared it with soft computing methods viz. ANFIS, M5 tree, random forest, and GP regression. They recommended the use of random forest regression-based modelling as the method is observed to be accurate in efficiency prediction. The present study is focused on assessing the performance of support vector machines regression (SVM) and Gaussian process regression (GP) on the prediction of the trapping capability of vortex devices. Stochastic approach with Radial basis kernel function (RBF) and Pearson VII kernel function(PUK) as kernel functions is employed in both techniques for the comparative analysis. The modelling results are also compared with the existing predictive models developed by previous researchers.

### Gaussian Process Regression:

Gaussian Process regression offers a probabilistic, nonparametric supervised learning technique to solve the nonlinear and compound function mapping hidden in data sets. Rasmussen and Williams [18] presented in their theory that adjoining observation should deliver information about each other; it is a technique of specifying a prior directly over function space. The mean and covariance of Gaussian distribution are vector and matrix whereas the Gaussian process is over function. GP regression models are able to understand the predictive distribution analogous to test input. For detailed information about GP regression and different covariance functions, readers are directed to the studies of Rasmussen and Williams [18] and Kuss[11].

### Support Vector Machine (SVM):

This method is introduced by Vapnik [27] and derived from statistical learning theory. Main principle of SVM is the optimal separation of classes, from the separable classes, SVM selects the one which has minimum generalization error from the infinite number of linear classifier or set the upper limit to error which is obtained from structural risk minimization. Thus maximum margin between the two classes could be obtained from the selected hyperplane and sum of distances of the hyperplane from the closest point of two classes will set maximum margin between two classes. In support vector regression, the input is first mapped onto an m-dimensional feature space using some fixed or nonlinear mapping, and then a linear model is constructed in this feature space. A nonlinear function is used to map data from input space to feature space for making a non-linear classifier out of a linear classifier[16]. For the detailed study of SVM, readers are conferred to Vapnik[27].

### Stochastic Gradient Boosting

Friedman[6] proposed a gradient boosting based ensemble technique for the regression models. Stochastic gradient boosting works in a similar way as the other boosting methods [7].It generalizes them by optimizing an arbitrary differentiable loss function. The proposed algorithm uses a base model to obtain the eligibility of those training set sub-samples that are randomly selected in each iteration[20]. The size of the sub-sample used in each iteration is a user-defined parameter and is taken as a fraction of the size of the total training dataset. Generally, a smaller fraction of the training dataset introduces randomness into the model and helps preventing the over-fitting. The use of a smaller fraction of training dataset makes speed the algorithm because the base regression model has to fit smaller datasets at each iteration. For a training dataset $\{(x_i, y_i), I = 1, 2,\ldots n\}$, where $x_i$ is an input vector described by p features and $y_i$ is an output variable used during training with n number of training samples and a base algorithm $\varphi(y,F(x))$. The model is initialized with a constant value,

$$F_0(x) = \arg\min_{\gamma} \sum_{i=1}^{n} \varphi(y_i, \gamma) \quad (1)$$

The so-called pseudo-residuals are calculated from:

$$r_{im} = -\left[\frac{\partial\varphi(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x_i)=F_{m-1}(x)} \quad (2)$$

where, $-r_{im}$ is the path of steepest decent, $\varphi$ is the loss function, and m = 1, 2,……M, where M is the number of iterations an algorithm is run. The parameter $\gamma_m$ is then calculated as:

$$arg\ \min_{\gamma} \sum_{i=1}^{n} \varphi(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)) \quad (3)$$

The model is then updated as:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (4)$$

where, $h_m(x)$ is the base learner.

## METHODOLOGY AND DATA SET

### Experimental Program

The experimental work iscarried out in the main channel having dimensions 30 cm wide, 50 cm deep, and 149 cm long as shown in Figure 1. The maximum water supply of the main channel is 16 l/sec with re-circulating system of water. The arrangement of water for experimentation is that the water is first collected into a high head water head tank from where the water reached out at experimental channel under gravity. In the main channel, the flow discharge and velocity are controlled by a valve and regulating gate, respectively. The installation of vortex tube silt ejector models into the experimental channel is at a particular distance of 3.92 m from the channel inlet where vortex model is placed throughout full width of channel perpendicular to the flow so that problem of turbulence does not occur in the channel or around the tube otherwise sediment particles tend to hold into suspension and also have the risk of slit clogging. During experimentation, velocity is kept constant to 33 cm/s. The sediments are extracted into the trapping device from flowing water into vortex tube. The sediments which are collected from vortex tube silt ejector into the trapping device aredried and properly weighed. To maintain the reliability of experiments, the experiments areconducted three times each. From experimental work 144 observations are assembled. The summary of the experimental scheme is illustrated in Table 1.

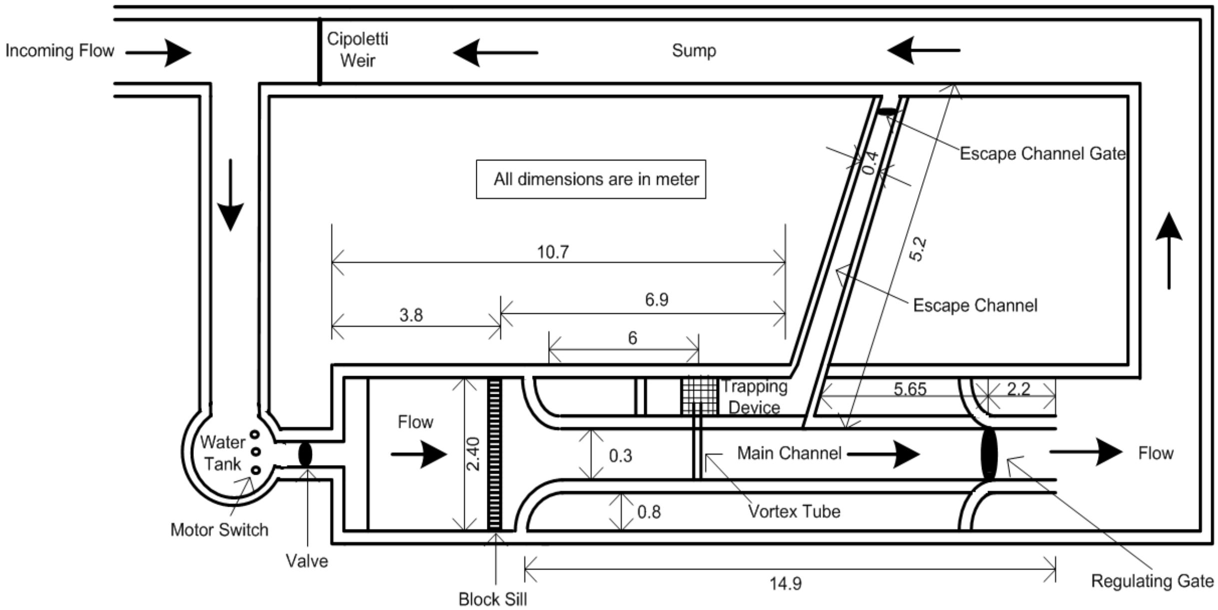



**Figure 1: A pictorial view of the experimental set-up.**

**Table 1: Summary of experimental scheme.**

| D (mm) | T (mm) | T/D | Sediment Size(mm) | Extraction Ratio (%) |
|---|---|---|---|---|
| 44.0 | 5.5 | 0.125 | 0.840, 0.504, 0.424, 0.210 | 6.250, 3.440 |
| 28.0 | 3.5 | 0.125 | 0.840, 0.504, 0.424, 0.210 | 3.125, 1.750 |
| 18.7 | 2.3 | 0.125 | 0.840, 0.504, 0.424, 0.210 | 2.500, 1.310 |
| 44.0 | 3.2 | 0.300 | 0.840, 0.504, 0.424, 0.210 | 7.500, 3.940 |
| 28.0 | 8.4 | 0.300 | 0.840, 0.504, 0.424, 0.210 | 3.750, 2.370 |
| 18.7 | 5.6 | 0.300 | 0.840, 0.504, 0.424, 0.210 | 2.940, 1.560 |

**Data Set**

From the total data set of 144 observations, 100 observations arbitrarily are chosen for training purpose, whereas the models are tested with a remaining set of 44 observations. The input variables are comprised of the size of sediments (S) in mm, the concentration of sediments (C) in ppm, slit thickness to tube diameter ratio (t/d), and extraction ratio (R) in %, whereas trapping efficiency (E) in % was taken as the output. The structure of train and test data observations are listed in Table 2.

**Table 2: The structure of train and test data observation.**

| Input Variables | Units | Train Data | | | |
|---|---|---|---|---|---|
| | | Min | Max | Mean | St. Dev. |
| **S** | mm | 0.210 | 0.840 | 0.494 | 0.228 |
| **C** | Ppm | 207.0 | 473.0 | 381 | 62.364 |
| **R** | % | 1.25 | 7.5 | 3.364 | 1.78 |
| **t/d** | - | 0.125 | 0.3 | 0.216 | 0.088 |
| **E** | % | 16.8 | 83.2 | 36.946 | 15.053 |
| | | **Test Data** | | | |
| | | **Min** | **Max** | **Mean** | **St. Dev.** |
| **S** | mm | 0.210 | 0.840 | 0.494 | 0.229 |
| **C** | ppm | 207.0 | 265.0 | 241 | 22.3 |
| **R** | % | 1.25 | 7.5 | 3.302 | 1.887 |
| **t/d** | - | 0.125 | 0.3 | 0.205 | 0.088 |
| **E** | % | 19.9 | 85.1 | 40.109 | 15.981 |

## STATISTICAL PERFORMANCE EVALUATION CRITERIA

To assess the proficiency of numerous used modelling techniques, Correlation of coefficient (CC), Coefficient of determination ($R^2$), Root mean square error (RMSE) and Mean absolute error (MAE) values are calculated with training and the testing data-set. Single factor ANOVA test has been also used to analyze the statistical difference in actual and predicted values of different techniques.

### Coefficient of Correlation (CC)

The coefficient of correlation is basically applied to determine the attainment of the numerical forecast. The coefficient of correlation (CC) is calculated as

$$CC = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n[\sum x^2 - (\sum x)^2]\, n[\sum y^2 - (\sum y)^2]}} \tag{5}$$

*x* is the actual values and *y* is the estimated values.

### Coefficient of Determination ($R^2$)

The coefficient of determination is also applied to determine the attainment of the model. Its value is calculated as:

$$R^2 = \left[\frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n[\sum x^2 - (\sum x)^2]\, n[\sum y^2 - (\sum y)^2]}}\right]^2 \tag{6}$$

### Root Mean Square Error (RMSE)

Root Mean Squared Error is the most commonly utilized method to quantify the attainment of the model. The root mean square error (RMSE) is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(x-y)^2\right)} \tag{7}$$

### Mean Absolute error (M.A.E.)

Mean Absolute error is the most frequently utilized method to measure the attainment of the model. The Mean Absolute Error (M.A.E.) is calculated as:

$$MAE = \frac{\sum_{i=1}^{n}|x-y|}{n} \tag{8}$$

## RESULTS AND DISCUSSION

Atkinson [4]suggested an equation for estimation of trapping efficiency of vortex tube ejector as:

$$\eta = \frac{a.\frac{U'_*}{U_*} + \int_a^{\alpha}[\frac{V}{U_*} + \frac{1}{k}\{\ln\left(\frac{z}{D}\right)+1\}].e^{-15\frac{\omega}{U_*}\left(\frac{z}{D}-a\right)}.d\left(\frac{z}{D}\right)}{a.\frac{U'_*}{U_*} + \int_a^{1}[\frac{V}{U_*} + \frac{1}{k}\{\ln\left(\frac{z}{D}\right)+1\}].e^{-15\frac{\omega}{U_*}\left(\frac{z}{D}-a\right)}.d\left(\frac{z}{D}\right)} \tag{9}$$

where$a$ = non-dimensional bed layer thickness ($2d_n$) relative to depth of flow, $V$= mean velocity of flow, $U_*$= shear velocity, $k$ = von Karman's constant=0.4, $U'_*$ = grain shear velocity, $\alpha$ = non-dimensional depth of diaphragm slab from bed level relative to depth of flow, $\omega$ = fall velocity of the particle and $z$ = any depth of water from the bed level.

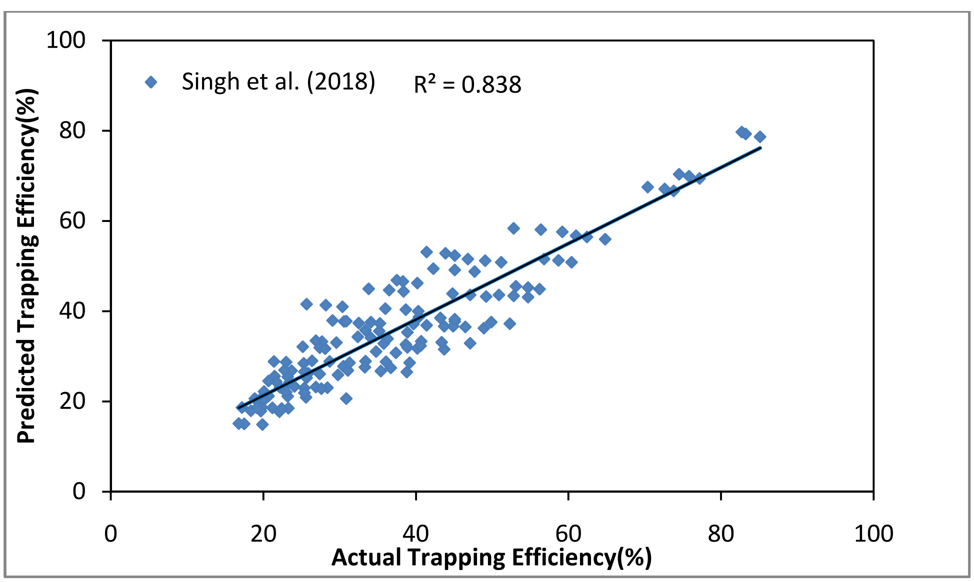
Singh et al. [24] proposed this simple predictive relationship for the trapping efficiency of vortex tube ejector based on multivariate regression analysis:

$$E = 26.91S^{0.25}C^{0.023}t/d^{0.225}R^{0.628} \tag{10}$$

where$E$ = trapping efficiency (%), $S$ = sediment size (mm),$C$ = sediment concentration (ppm), $t/d$ = ratio of slit thickness and diameter of tube, $R$ = extraction ratio (%).

Based on the current experimental study, Atkinson [4] equation proposed for vortex silt ejection devices has higher relative errors than Singh et al. [24] when estimating the trapping capacity of vortex tube silt ejector on this data.

Results of both empirical equations plotted between

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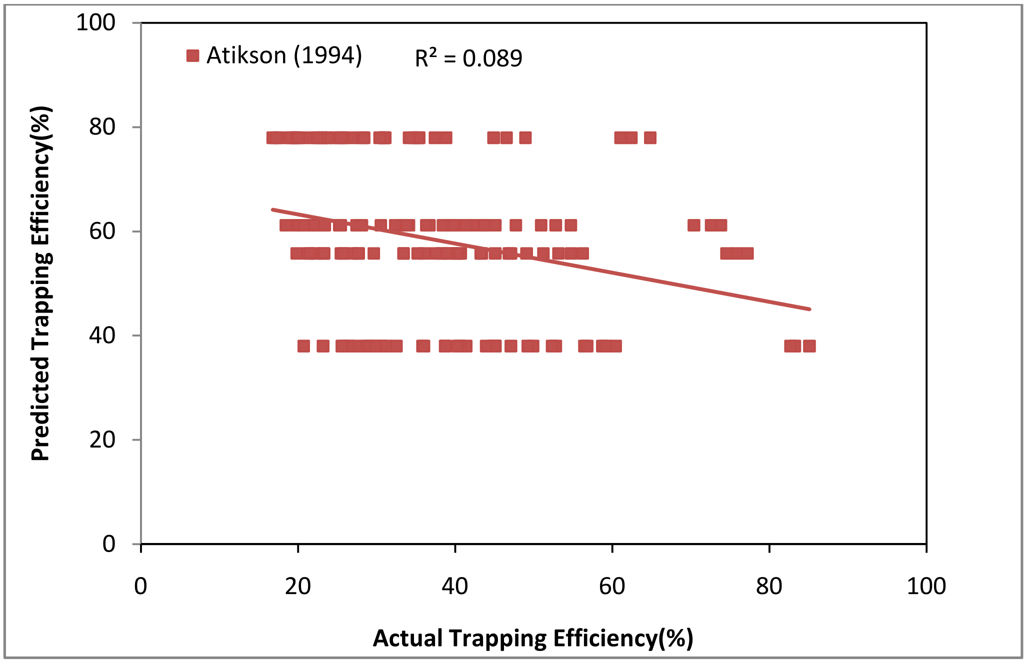



**(b)**

**Figure 2: Performance of empirical equations on the current data set**

predicted trapping efficiency versus actual trapping efficiency are shown in Figure 2. Three particular standard error indices: coefficient of correlation (CC), Root mean square error (RMSE)and mean absolute error (MAE) were chosen to examine the performance of empirical equations (Table 3). Inferred from Table 3 and Figures 2, Singh et al. [24] equation with CC= 0.9159, RMSE = 6.3242and MAE = 5.2149is observed to have relatively less error and higher accuracy than the equation proposed by Atkinson [4].

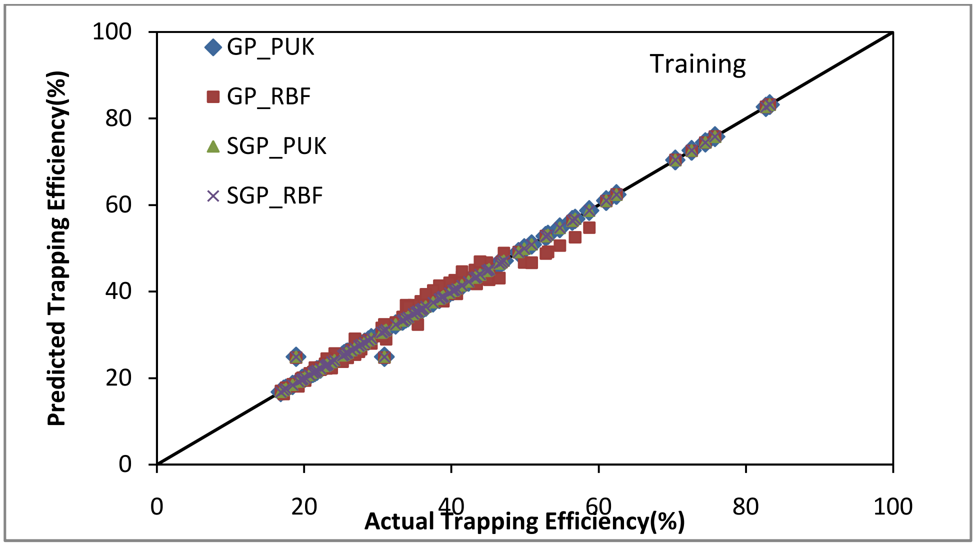
**Table 3: Performance of empirical equations**

| Equations | CC | RMSE | MAE |
|---|---|---|---|
| Singh et al. (2018) | 0.9159 | 6.3242 | 5.2149 |
| Atkinson (1994) | -0.2995 | 31.3166 | 26.2956 |

Developing the GP regression-based models (Gaussian noise, $\gamma$,$\sigma$ and ω) are a trial and error method. The models are developed with the help of two kernel functions (PUK and RBF). Both kernel functions(PUK and RBF)are compared by selecting a constant Gaussian noise function value to 0.01. The primary parameters are presented in Table 4.Meta algorithm (Stochastic) is also used with GP regression. In Stochastic GP regression (SGP)-based model the selected model parameters are same as the GP models. During the GP and SGP models development (Table 5), it is observed that the RBF kernel has a better performance as compared to PUK kernel function. To check the superiority of GP and SGP models, every phase of progress (training and testing) is presented in Figure 3. The prediction performance of the models is evaluated by the error indices (Table 5)at every stage of development and testing. Comparison of GP and SGP models suggest that stochastic approach improves the performance of GP models. SGP_RBF model works well than other GP models. The CC values of the SGP model with RBF kernel function are observed as 0.9984 and 0.9774 for training and testing, respectively. Moreover, evaluating Figure 3indicates that the SGP model with RBF kernel function isthe best fitrelative to other GP models to estimate the trapping efficiency of sediments by vortex tube ejector.

**Table 4: User-defined parameters used with GP and SGP**

| Approaches | Radial basis kernel | Pearson VII kernel |
|---|---|---|
| GP | Gaussian noise = 0.01, $\gamma$ = 5 | Gaussian noise = 0.01, $\omega$ = 0.1, $\sigma$ = 1 |
| Stochastic GP (SGP) | I= 100, Gaussian noise = 0.01, $\gamma$ = 5 | I= 100, Gaussian noise = 0.01, $\omega$ = 0.1, $\sigma$ = 1 |

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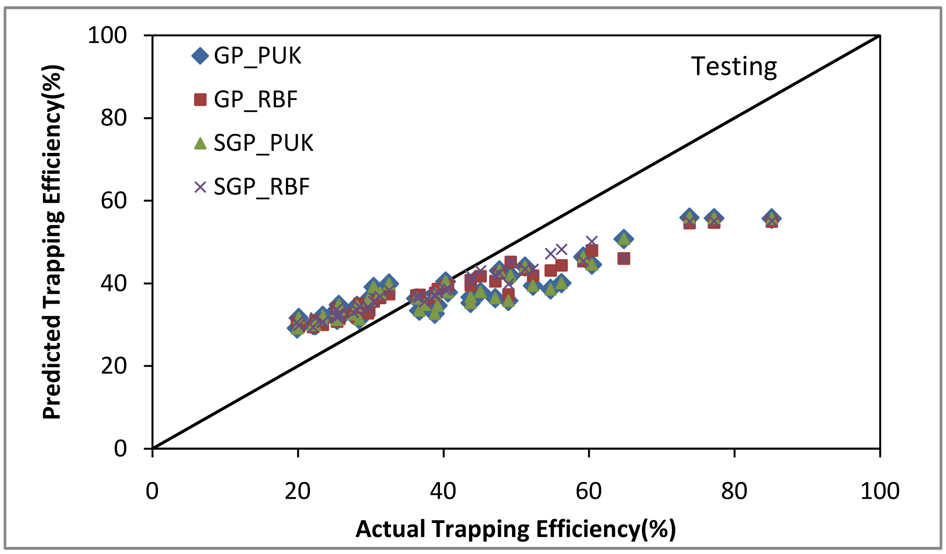



**(b)**

**Figure 3: Actual Trapping Efficiency Vs Predicted Trapping Efficiency for training (a) and testing (b) data**

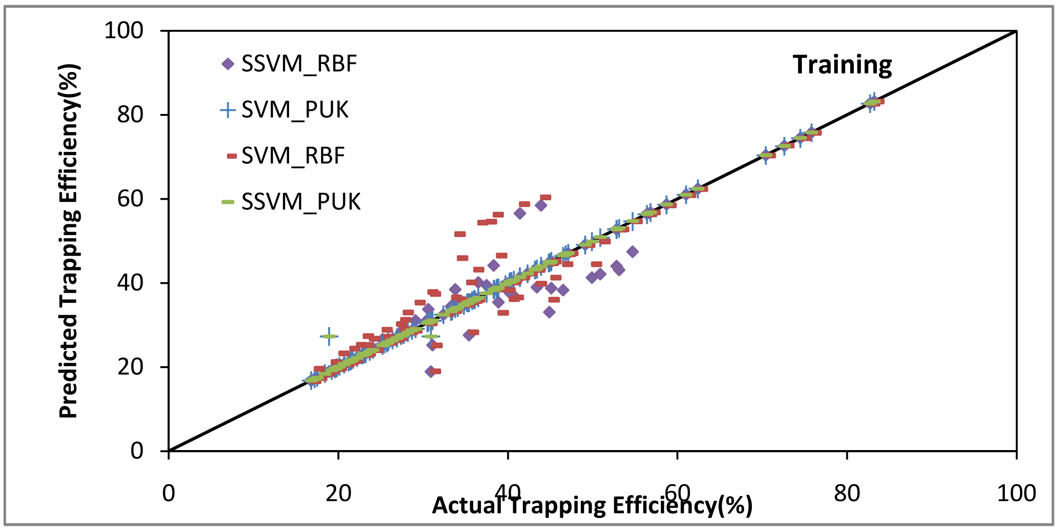
**Table 5: Performance of GP and SGP models**

| Approaches | Training data set | | | Testing data set | | |
|---|---|---|---|---|---|---|
| | C.C. | R.M.S.E. | M.A.E | C.C. | R.M.S.E. | M.A.E |
| GP_PUK | 0.9984 | 0.8485 | 0.1221 | 0.9119 | 10.3658 | 8.7386 |
| GP_RBF | 0.9920 | 1.8988 | 1.3222 | 0.9744 | 9.5877 | 7.4429 |
| SGP_PUK | 0.9984 | 0.8485 | 0.1200 | 0.9119 | 10.3656 | 8.7385 |
| SGP_RBF | 0.9984 | 0.8485 | 0.1200 | **0.9774** | **9.2487** | **7.1926** |
| SVM_PUK | 0.9981 | 0.9174 | 0.1873 | 0.9106 | 10.3500 | 8.7513 |
| SVM_RBF | 0.9428 | 5.3212 | 2.7416 | 0.8673 | 10.6227 | 8.7948 |
| SSVM_PUK | 0.9982 | 0.9118 | 0.1292 | 0.9103 | 10.3537 | 8.7501 |
| SSVM_RBF | 0.9680 | 3.8167 | 1.7091 | 0.7189 | 12.7934 | 11.2689 |

Developing the SVM regression-based models (C,$\gamma$, $\sigma$ and $\omega$) is similar to developing the GP model. The models are developed with the help of two kernel functions (PUK and RBF). The models are compared with both kernel functions (PUK and RBF) and duringcomparison, noise(C) is remained constant. The primary parameters are presented in Table 6. During the SVM and SSVM models development (Table 5), it has been observed that PUK kernel has a better workability as compared to RBF kernel function. To check the superiority of SVM and SSVM models at every phase of progress (training and testing) Figure 3 is presented. The correctness of the models is evaluated with the error indices evaluated at every stage of training and testing (Table 5). Comparison of SVM and SSVM models suggest that stochastic approach reduce the performance of SVM models. SVM_PUK model works better than the other SVM and SSVM models. The CC values of RBF kernel function based on SVM model are observedas 0.9981 and 0.9106 for training and testing, respectively. Moreover, the evaluating Figure 3 indicates that the SVM model with PUK kernel

**Table 6. User-defined parameters used with SVM and SSVM**

| Approaches | Radial basis kernel | Pearson VII kernel |
|---|---|---|
| SVM | C = 2, $\gamma$ = 5 | C = 2, $\omega$ = 0.1, $\sigma$ = 1 |
| Stochastic SVM (SSVM) | I= 100, C = 2, $\gamma$ = 5 | I= 100, C = 2, $\omega$ = 0.1, $\sigma$ = 1 |

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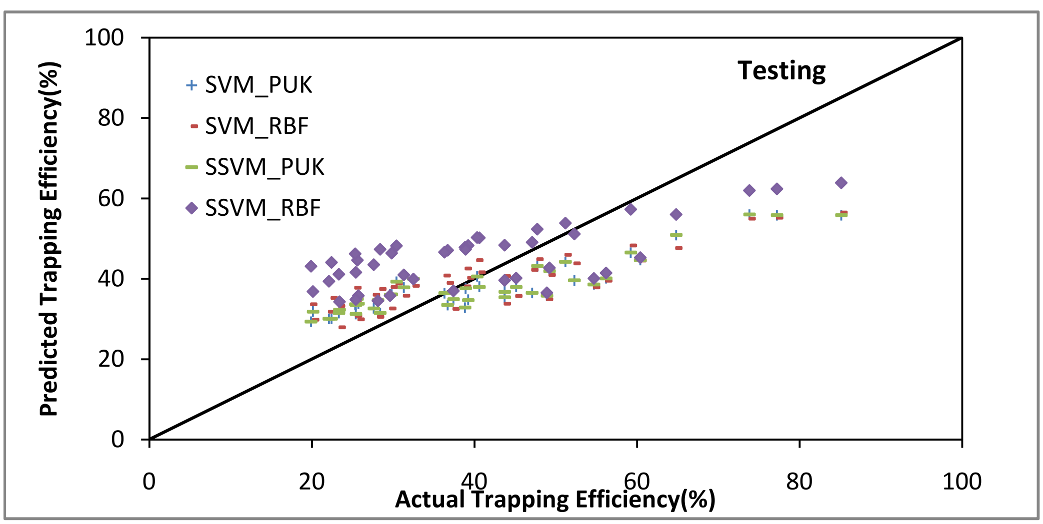


**(b)**

**Figure 4: Performance of SVM and SSVM models for training (a) and testing (b) data**

function is the best fit relative to other SVM models for the estimation of trapping efficiency of sediments by vortex tube ejector.

**Comparison of Models**

Assessing the capabilities of soft computing based models, it is analyzed that RBF kernel function based Stochastic GP model worksbetteras compared to other models. RBF kernel function works better than PUK kernel function in GP and SGP based models. In the comparison of SVM and GP models, Table 5 indicates that the GP model works better than SVM based model. Single factor ANOVA indicates by their results (Table 7) that *f*-critical has more value than *F*-values and the outcomes of *P*-values suggest that the difference in estimated values using soft computing approaches and actual values is not significant ($P$-value > 0.05). Based on the modelling results observed with the current data set, SGP_RBF is the most appropriate model to estimate the trapping capacity of the vortex tube silt ejector.

**Sensitivity Analysis:**

The most valuable parameters to estimate the trapping capability provided by vortex tube ejector SGP_RBF are found out by a simple method. This method conveys the sensitivity of every parameter on the model performance in the estimation of trapping capacityof sediments by vortex tube ejector. All the input parameters shown in Table 1 are considered as inputs of SGP_RBF based models, and then one by one each input variable is removed and the model with the same structure is developed. To test the sensitivity, the original model is implemented as described in the section of results of SGP_RBF. Dataset is separated into two parts for training and testing. The contribution of each input parameter in effecting the performance of vortex tube is examined using the performance indices: CC and RMSE. Depending on the degree of change in performance, the effect of each parameter is examined. The outcomes of the sensitivity analysis of SGP_RBF are shown in Table 8. As seen in Table8, the deficiency of the sediment size (S) and extraction ratio (R) reduced the accuracy of the estimation models, so it is detected that these two parameters are the most significant parameters for estimation of the trapping capability of vortex tube silt ejector.

## CONCLUSION

The vortex tube sediment ejection device is useful in handling sediments moving near the bottom of the canal and presents aneconomical and viable solution in controlling sediment entry into the canal. Sediments laden water enters into the vortex device through a longitudinal slit provided along its top edge normal to the flow and trapped sediments from vortex tube are evacuated through the escape channel, where the channel may be linked to the river downstream of diversion works. The trapping efficiency results yielded from the experimental study with these ejection devices are used to develop models based on machine learning approaches. To relate trapping efficiency with input parameters viz. sediment size (S), sediment concentration (C), slit to diameter ratio (t/d) and extraction ratio (R), soft computing methods: SVM regression and GP regression with RBF and PUK as kernel functions are used. Stochastic gradient boosting is also applied with both the regression techniques (SVM and GP) andan inter-comparison of the modeling results is made. The application of these techniques suggests stochastic GP regression approach with RBF kernel function works as the best modeling approach in approximating the trapping capacity of vortex tubedevice relative to other regression approaches. ANOVA results

**Table 7. Results of single factor ANOVA**

| Approaches | *F* | *P-value* | *F crit* | *Difference in actual and estimated values* |
|---|---|---|---|---|
| GP_PUK | 0.769244 | 0.382895 | 3.951882 | Insignificant |
| GP_RBF | 0.504992 | 0.479238 | 3.951882 | Insignificant |
| SGP_PUK | 0.769307 | 0.382875 | 3.951882 | Insignificant |
| SGP_RBF | 0.239447 | 0.625852 | 3.951882 | Insignificant |
| SVM_PUK | 0.671863 | 0.414669 | 3.951882 | Insignificant |
| SVM_RBF | 0.183113 | 0.669781 | 3.951882 | Insignificant |
| SSVM_PUK | 0.689 | 0.408803 | 3.951882 | Insignificant |
| SSVM_RBF | 3.890779 | 0.051765 | 3.951882 | Insignificant |

**Table 8: Sensitivity investigation using SGP_RBF**

| Input combination | Input variable eliminated | SGP_RBF | |
|---|---|---|---|
| | | **Coefficient of correlation** | **Root mean square error (%)** |
| S, C, t/d, R | | 0.9774 | 9.2487 |
| C, t/d, R | S | -0.4869 | 143.9305 |
| S, t/d, R | C | 0.9967 | 3.4198 |
| S,C, R | t/d | 0.9334 | 9.9547 |
| S,C, t/d | R | 0.4007 | 14.9663 |

with these approaches suggest the insignificant difference between all the applied regression approaches in predicting the trapping efficiency.

## REFERENCES


1. Ansari, M.A., and Athar, M. (2013). "Artificial neural networks approach for estimation of sediment removal efficiency of vortex settling basins."*ISH J. Hydraulic Eng.*, 19(1), 38–48.
2. Ansari, M.A., and Khan, M.A. (2014). "Performance assessment of vortex settling chambers." *ISH J. Hydraulic Eng.*, 20(3), 324–338.
3. Athar, M., Kothyari, U.C., and Garde, R.J. (2002). "Sediment removal efficiency of vortex chamber type sediment extractor." *J. Hydraulic Eng.*, 128(12), 1051–1059.
4. Atkinson, E. (1994). "Vortex-tube sediment extractors. I: Trapping efficiency." *J. Hydraulic Eng.*, 120(10), 1110–1125.
5. Dashtbozorgi, S., and Asareh, A. (2015). "Study of the rate of sediment trapping and water loss in the vortex tube structure at different placement angles." *J. Sci. Res. Dev.*, 2(5), 104–110.
6. Freund, Y. & Schapire, R. E. (1996). Experiments with new boosting algorithm. Machine Learning: Proceedings of the Thirteenth International Conference(edited by Lorenza Saitta) CA: Morgan Kaufmann, San Fransisco: pp. 148-156.
7. Friedman, J. H. (2002). Stochastic gradient boosting. Computational Statistics & Data Analysis, vol. 38, pp. 367-378.
8. Kothyari, U. C., Pande, P. K., & Gahlot, A. K. (1994). Design for tunnel-type sediment excluder. *journal of irrigation and drainage engineering*, *120*(1), 36-47.
9. Kumar, M., Ranjan, S., Tiwari, N.K., and Gupta, R. (2018). "Plunging hollow jet aerators oxygen transfer and modelling." *ISH J. Hydraulic Eng.*, 24(1), 61–67.
10. Kumar, M., Tiwari, N. K., and Ranjan, S. (2018). "Prediction of oxygen mass transfer of plunging hollow jets using regression models."*ISH Journal of Hydraulic Engineering*, 1-8. https://doi.org/10.1080/09715010.2018.1435311.
11. Kuss, M. (2006). *Gaussian process models for robust regression, classification, and reinforcement learning* (Doctoral dissertation, Technische Universität).
12. Mahmood, K. (1975, August). Flow through vortex tube sediment ejectors. In *Irrigation & Drainage in an Age of Competition for Resources* (pp. 421-450). ASCE.
13. Moradi, A., Hasoonizade, H., Kashkuli, H.A., Jahromi, H.M., and Sedghi, H. (2013). "Investigation of the effect of vortex tube structure with 60 and 90 degree angles on Sedimentation entrance trap efficiency to intakes at 180 degree bend location." *Int. J. Agric. Crop Sci.*, 5(23), 2885–2889.
14. Nayak, P.C., Sudheer, K.P., Rangan, D.M., and Ramasastri, K.S. (2004). "A neuro-fuzzy computing technique for modelling hydrological time series." *J. Hydrol.*, 291(1–2), 52–66.
15. Orak, S.J., and Asareh, A. (2015). "Effect of gradation on sediment extraction (trapping) efficiency in structures of vortex tube with different angles." *J. WALIA.*, 31(S4), 53–58.
16. Parsaie, A., Yonesi, H. A., & Najafian, S. (2015). Predictive modelling of discharge in compound open channel by support vector machine technique. *Modelling Earth Systems and Environment*, *1*(1-2), 1.
17. Raju, K., Kothyari, U., Shrivastava, S., and Saxena, M. (1999). "Sediment removal efficiency of settling basins." *J. Irrig. Drain Eng.*, 125(5), 308– 314.
18. Rasmussen C. E., Williams C. K. I. (2006). Gaussian Processes for Machine Learning. The MIT Press, Cambridge, MA.
19. Sarwar, M.K., Anjum, M.N., and Mahmood, S. (2013). "Impact of silt- Excluder on sediment on sediment management of irrigation canal: A case study of D. G. Khan canal, Pakistan." *Arab J. Sci. Eng.*, 38(12), 73–84.
20. Sattari, M. T., Pal, M., Mirabbasi, R., & Abraham, J. (2018). Ensemble of M5 Model Tree Based Modelling of Sodium Adsorption Ratio. *Journal of AI and Data Mining*, *6*(1), 69-78.
21. Sihag, P., Jain, P., and Kumar, M. (2018). "Modelling of impact of water quality on recharging rate of storm water filter system using various kernel function based regression." *Model. Syst. Environ.*, 1–8.
22. Sihag, P., Tiwari, N.K., and Ranjan, S. (2017a). "Modelling of infiltration of sandy soil using Gaussian process regression." *Model. Earth Syst. Environ.*, 3(3), 1091–1100.
23. Sihag, P., Tiwari, N.K., and Ranjan, S. (2017b). "Prediction of unsaturated hydraulic conductivity using adaptive neuro-fuzzy inference system (ANFIS)." *ISH J. Hydraulic Eng.*, 1–11.
24. Singh, B., Sihag, P., Singh, K., & Kumar, S. (2018). Estimation of trapping efficiency of vortex tube silt ejector. *International Journal of River Basin Management*, (just-accepted), 1-38.
25. Singh, K.K., Pal, M., Ojha, C.S.P., and Singh, V.P. (2008). "Estimation of removal efficiency for settling basins using neural networks and support vector machines." *J. Hydrologic Eng.*, 13(3), 146‑155.
26. Tiwari, N. K., Sihag, P., Kumar, S., & Ranjan, S. (2018). Prediction of trapping efficiency of vortex tube ejector. *ISH Journal of Hydraulic Engineering*, 1-9.
27. Vapnik, V.N. (1995), The Nature of Statistical Learning Theory (New York: Springer-Verlag).