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Predicting the energy dissipation of a rough sudden expansion rectangular stilling basins using the SVM algorithm

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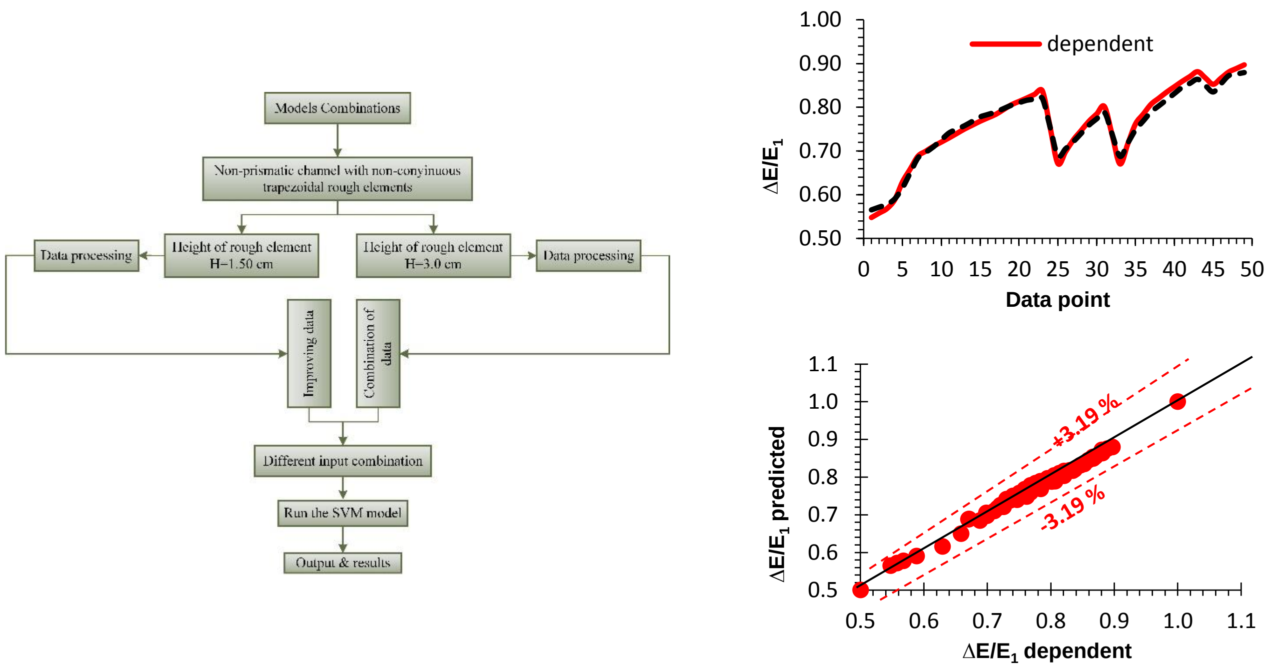
GRAPHICAL ABSTRACT



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ABSTRACT

In this research, the performance of support vector machine in predicting relative energy dissipation in non-prismatic channel and rough bed with trapezoidal elements has been investigated. To achieve the objectives of the present study, 136 series of laboratory data are analyzed under the same laboratory conditions using a support vector machine. The present study entered the support vector machine network without dimension in two different scenarios with a height of 1.50 and 3.0 cm rough elements. Two statistical criteria of Root Mean Square Error and coefficient of determination are used to evaluate the efficiency of input compounds. Hydraulically, the results show that at both heights of the rough elements, energy dissipation increased with increasing Froude number. The results of the support vector machine show that the height of the roughness element is 1.50 cm in the first scenario, combination number 6 with R^2 = 0.990 and RMSE = 0.0129 for training mode and R^2 = 0.993 and RMSE = 0.032 for testing mode and the height of the roughness element 3.0 in the second scenario, combination number 6 with R^2 = 0.989 and RMSE = 0.0112 for training mode, R^2 = 0.994 and RMSE = 0.0224 for testing mode are select as the best models. Finally, sensitivity analysis is performed on the parameters and H / y_1 parameter is selected as the most effective parameter.

1. Introduction

The kinetic energy of water flow downstream of structures such rapids, drops, spillways and sluice gates must be dissipated to prevent the riverbed erosion. Energy reduction is also necessary to ensure the stability of these structures which are prone to failure when subjected to high flowrates. Stilling basins are the most widely used energy dissipator; they dissipate the destructive kinetic energy by forming a

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hydraulic jump which is a rapid transition from supercritical to subcritical flow over a short distance. This transition is accompanied by intense turbulence which dissipates kinetic energy. The formation and stabilization of a hydraulic jump in a stilling basin depends on the downstream depth of water in the channel. In cases where the downstream depth is low, the cross section of the channel can be used to stabilize a hydraulic jump in a stilling basin. Increased energy dissipation is a more significant feature of a hydraulic jump in a non-prismatic channel compared to a prismatic channel. Given the importance of this issue, research has been conducted on rough beds and expansion stilling basins, as discussed in the following. Rajaratnam and Subramanya. (1968) is among the first to study rough bed water flow and provided an equation for expressing shear stress coefficients. Mohammad ali. (1991) studied the effect of a rough stilling basin on the length of hydraulic jump in a rectangular channel. Yasuda and Hager. (1995) investigated hydraulic jumps in a supercritical flow through a rectangular channel with a gradual contraction. The ratios of contractions are 0.3, 0.4, 0.6, and 0.8 and the lengths of 1080, 1550, and 2080 mm. The results of this experiment showed that as the upstream Froude number increases, so does the downstream flow depth. Therefore, as the flow rate increases, so does the relative flow depth. More recently, Ead and Rajaratnam. (2002) investigated hydraulic jumps on corrugated beds and showed that the shear stress coefficient for the rough bed is 10 times that of the smooth bed. Rezaul hasan and abdulmatin. (2009) studied the hydraulic jump conjugate depth ratio in a channel with sudden expansion. Abdulmatin et al. (2008) performed experiments on the hydraulic jump in a sudden expansion of a positive slope channel and showed that the hydraulic jump for such a case, the jump reduces the downstream water depth. Nikmehr and Tabebordbar. (2010) studied hydraulic jump on a reverse slope channel with a rough and a smooth bed. The results of their experiments showed that the ratio of the conjugate depth and the length of hydraulic jump for a smooth bed is greater than that for a rough bed at the same Froude number. More energy is dissipating with a rough bed compared to a smooth bed. More recently, Pgliara and Palermo. (2015) and Kumar and Lodhi. (2016), investigated hydraulic jumps on smooth and rough beds with sloped channels. Velioglu et al. (2015) used both experiments and simulation to study hydraulic jump on rough beds. Results showed that strip elements had a positive effect on the hydraulic jump and the downstream depth increased by 18-20 % compared to a classic jump. Also, energy dissipation due to roughening elements is 2-3 % higher than energy dissipation due to a classic hydraulic jump. In Daneshfaraz et al. (2017), the characteristics of a hydraulic jump in a channel with contraction and expansion are examine. The experimental results showed that energy dissipation in a contraction is greater than that in an expanding channel by 8.74 %. In Parsamehr et al. (2017), hydraulic jump characteristics are examining in a rough bed channel with rhombic geometry and an inverted slope. Experiments showed that with changing roughness and slope angle affected the depth ratio. Also, the relative length of the jump and the relative energy dissipation increased.

There has been little research on the energy dissipation of sudden expansion in supercritical flow condition. Part of the reason for the paucity of research is because of laboratory limitations and lack of facilities. Some of the limited previous work on this topic will now be discussed. Rajaratnam and Hurtig. (2000), investigated the effects of screens on energy dissipation. The results showed that screens with porosity of 40 % had a larger effect on energy dissipation is supercritical flows in small hydraulic structures. Balkiş. (2004), also examined the effect of screen slope on the efficiency of these screens with respect to energy dissipation. Their results showed that changing the slope of the screens did not have much of an effect on the energy dissipation of the flow compared to cases where the screens are place perpendicular to the flow. Sadeghfam et al. (2015), examined the behavior of hydraulic jumps that include the presence of vertical screens in the face of supercritical flow. The results showed that the flow passing through the screens has less energy than free and submerged hydraulic jumps without the presence of screens. Daneshfaraz et al. (2017), examined the effect of location of screens on energy dissipation. They found that with increasing Froude number, the relative energy dissipation increased. Also, screens with 50 % porosity, located 125 cm from the valve, performed best.

Recently, researchers have used new methods to predict hydraulic parameters, these new methods are often called data mining methods for nonlinear systems. These include Artificial Neural Networks (ANNs), Gene Expression Programming (GEP), GA, ANFIS, and Support Vector Machine (SVM). So far, relatively extensive research has been done using the above methods, including the following: Alp and Sigizoglu. (2007), used two types of artificial neural networks, FFBP and RBF, and compared the results with a multiple linear regression. They compared the results with a multiple linear regression and concluded that the neural network provides a more realistic simulation than a multiple linear regression. Goel and Pal. (2009), used both field and laboratory data to examine the potential of SVM for predicting depth of flooding and showed that changes in flow conditions, geometry, and substrate materials have an effect on the depth of flooding. Akhbari et al. (2017) Predicting the discharge coefficient of triangular plan form weirs using radian basis function and M5' methods. Noman Qasem et al. (2017) Optimizing ANFIS for sediment transport in open channels using different evolutionary algorithms. Roushangar et al. (2019) evaluated the effectiveness of SVM for predicting hydraulic jump in a sudden divergence. The results showed that the model that parameterized the Froude number led to the optimal energy dissipation and depth results. Sadeghfam et al. (2019) applied Artificial Intelligence Multiple Models (AIMM) to determine scouring caused by supercritical flow jets with upstream screens; In that study, Segeno Fuzzy Logic (SFL), Neuro-Fuzzy (NF) and Support Vector Machine (SVM) methods are used. Yarmohammadi et al. (2019) investigate the Modeling discharge coefficient of triangular plan form weirs using extreme learning machine. Majedi Asl et al. (2020) investigate the simulation of bridge pier scour depth base on geometric characteristics and field data using support vector machine algorithm. Also, Daneshfaraz et al. (2021a) used SVM method to predict the effect of screens diameter on hydraulic parameters of vertical drop. The results showed that changing the diameter of the screens had no effect on energy dissipation and the output data from SVM had the best agreement with the laboratory data.

Due to the fact that the rough stilling basins have not been studied by neural network systems, so the present study predicts energy dissipation in the non-prismatic channel by creating a rough bed with trapezoidal elements in the stilling basin with two heights and three expanding ratios and supercritical regime is performed using a support vector machine (SVM) with the main focus on the input parameters effective in energy dissipation. Therefore, this prediction has been done using dimensionless parameters. Therefore, by arranging rough elements with heights of 1.5 and 3 cm in the extended stilling basins, laboratory data are calculated and then the energy dissipation is predicting by SVM algorithm.

2. Material and methods

2.1. Experimental set-up

As noted earlier, the purpose of the present study is to utilize SVM for predicting energy dissipation in non-prismatic channels with a rough bed. In order to achieve this aim, experiments have been performed using a laboratory facility. The experiments are performed in a flume that is 0.3 m wide, 0.45 m deep, and 5 m long. The laboratory is located at the University of Maragheh in Iran. The walls are made from plexiglass to provide good visibility. Supercritical flow conditions are generated by a steel sluice gate plate with 3 mm thickness and located 0.5 m away from entrance of the flume (Fig. 1) To create a Froude range of 4 to 12, two upstream gate openings of 1.3 and 1.7 cm are used. The opening is 1.3 cm for a channel with an expansion ratio of 0.67 and 0.5 and 1.7 cm for a channel with an expansion ratio of 0.33 (Fig. 2). To create sudden expansion ratios of 0.67, 0.5 and 0.33, glass boxes with widths of 5.0, 7.5 and 10 cm, and length of 50 cm and height of 20 cm are used. Also, in order to rough the flume bed, non-continuous trapezoidal elements with heights of 1.5 and 3.0 cm, porosity of 10 %, and a zigzag arrangement are used.

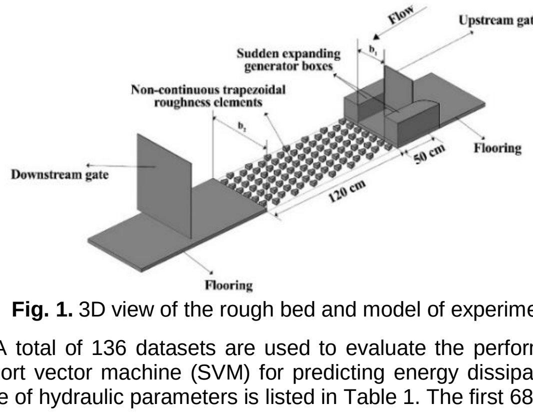
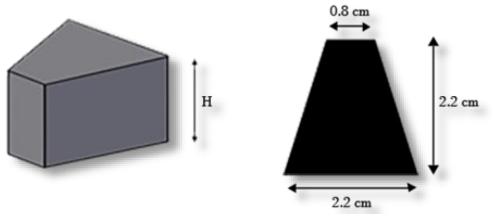


Fig. 1. 3D view of the rough bed and model of experiment.

A total of 136 datasets are used to evaluate the performance of support vector machine (SVM) for predicting energy dissipation. The range of hydraulic parameters is listed in Table 1. The first 68 datasets are from experiments performed on a rough bed with roughness heights of 1.5 cm and the remaining 68 datasets are related to a rough bed with roughness element heights of 3.0 cm. In order to determine the optimum SVM model, both sets of data, which includes three sudden expansion ratios, have been merged. For this purpose, the effective



parameters that govern energy dissipation have been analyzed and the relative energy dissipation has been estimated.

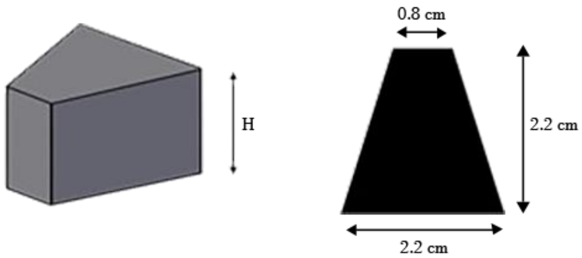


Fig. 2. Dimensions and 3D view of the roughness elements.

Table 1. Variation range of parameters in this study.

Rough bed with element height H=1.5 cm		Rough bed with element height H=3.0 cm	
Parameter	**Range**	**Parameter**	**Range**
b_1 (cm)	10 – 30	b_1 (cm)	10 – 30
Q (Lit/s)	2.50 – 9.20	Q (Lit/s)	2.50 – 9.20
Fr_0	4.5 – 11.50	Fr_0	4.50 – 11.50
y_1(cm)	0.9 – 1.250	y_1(cm)	0.9 –1.250
y_2(cm)	4 – 9.10	y_2(cm)	3.50 – 7.0
$B=b_2/b_1$	0.33 – 1.0	$B=b_2/b_1$	0.33 – 1.0
H/y_1	1.15 – 1.70	H/y_1	2.30 – 3.40
H(cm)	1.50	H(cm)	3.0

2.2. Dimensional analysis

The functional dependence of the influencing parameters can be written as shown in Eq. 1.

$$f1\left(\rho,\ Q,\ \mu,\ g,\ b_1,\ b_2,\ y_1,\ y_2,\ H,\ L_j,\ \varepsilon,\ \Delta E/E_1\right)=0 \qquad (1)$$

Here, ρ is the density, Q is the flow discharge, μ is the dynamic viscosity, g is gravitational acceleration, b_1 is the upstream width channel, b_2 is the downstream width channel, y_1 is the flow depth before the jump, y_2 is the flow depth after the jump, H is the height of rough element, L_j is the jump length, ε is the shear stress coefficient and $\Delta E/E_1$ is the relative energy dissipation. By applying the Buckingham theorem with repeating variables μ, ρ, and, y_1 and by rearranging the non-dimensional parameters, Eq. 2 is obtained.

$$f2\left(Fr_1,\ Re_1,\ \frac{b_1}{y_1},\ \frac{b_2}{y_1},\ \frac{y_2}{y_1},\ \frac{H}{y_1},\ \frac{L_j}{y_1},\ I,\ \varepsilon,\ \Delta E/E_1\right)=0 \qquad (2)$$

By dividing the two parameters $\frac{b_1}{y_1}$ and $\frac{b_2}{y_1}$, this can be rewritten as Eq. 3.

$$f3\left(Fr_1,\ Re_1,\ \frac{b_1}{b_2},\ \frac{y_2}{y_1},\ \frac{H}{y_1},\ \frac{L_j}{y_1},\ I,\ \varepsilon,\ \Delta E/E_1\right)=0 \qquad (3)$$

With the roughness and extreme turbulence of the flow, the Reynolds number is very large, so that some parameters, such as the relative jump length, shear stress, and conjugate depth effects are neglected (Daneshfaraz et al. 2020; Daneshfaraz. 2021b; Daneshfaraz. d). The parameter $\Delta E/E_1$ is a component of the dependent parameter under study. Therefore, Eq. 3 can be written as Eq. 4:

$$\frac{\Delta E}{E_1}=f4\left(Fr_1,\ B=\frac{b_1}{b_2},,\ \frac{H}{y_1}\right) \qquad (4)$$

2.3. Support vector machine (SVM)

The SVM algorithm is a type of data mining algorithm that is used in various applications such as data classification and prediction. This algorithm divides data into a training set and a testing set. The steps used in SVM analysis are schematically shown in Fig. 3.

Ⅰ: Enter a series of dependent and independent data into statistical software.

Ⅱ: Identify dependent and independent parameters.

Ⅲ: Predict the dependent hydraulic parameters based on the independent parameters.

The SVM algorithm has various parameters such as c, γ and etc. The main one for predicting the dependent parameter is γ. The correct setting of which is very effective in improving the flow conditions.

2.3.1. SVM theory

SVM is a linear classification and separation of data. The SVM model is based on the concept of optimal hyperplane that separates samples into two classes by considering the widest gap between two classes according to Fig. 4. The size of the separator screen margin is obtained from Eq. (5), which can be seen in Fig. 4 (Roshangar et al. 2019):

$$\mathrm{Margin}=\frac{2}{\|w\|}=\frac{2}{w^Tw} \qquad (5)$$

Given that the best screen separator is the one with the greatest distance between two classes, ||w|| should be minimized.

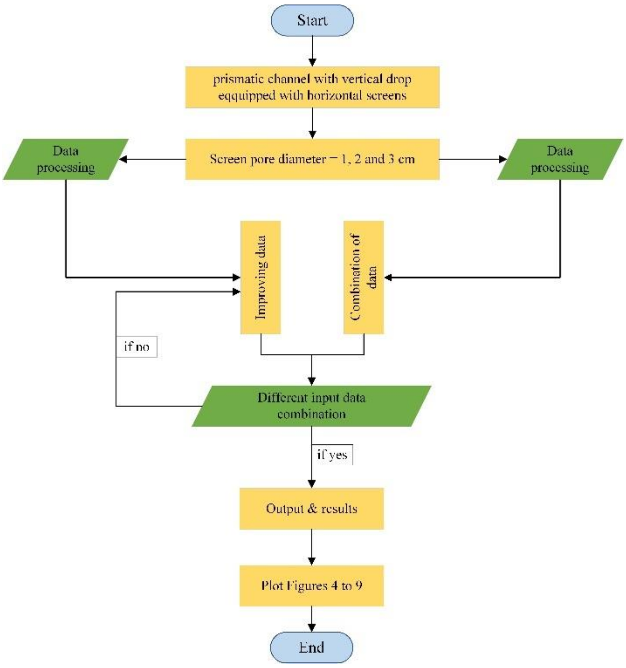


Fig. 3. Schematic representation of the study flowchart.

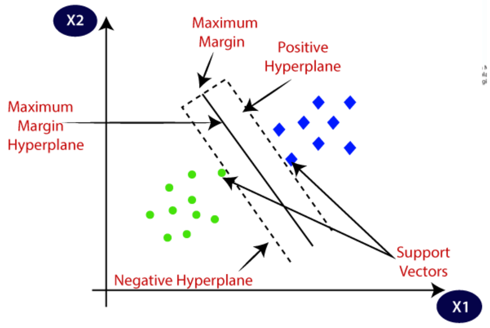


Fig. 4. Data classification and support vectors.

With nonlinear classification, where the data cannot be separated linearly, different kernels are defined that transfer the problem to the new space so that the linear separation can be achieved. A kernel function ϕ is defined that transfers x to z.

$$\emptyset{:}x \rightarrow z \qquad z=\emptyset(x)$$

As a result, the separating equation can be written as Eq. 6:

$$w^Tz+b=f(x)=0 \rightarrow w^T\emptyset(x)+b=0 \qquad (6)$$

Eq. 6 is the relationship between the dependent variable and independent variables. The term ∅(x) is the kernel, f(x) is the objective function, w is vector coefficient and b is a constant. The different types of kernels which include four kernels, are presented in Table 2.

2.4. Evaluation criteria

Two evaluation parameters are used to predict the relative energy dissipation using the SVM approach. The error metrics are described by Eqs. 7 and 8. RMSE is the root square of the mean errors and R^2 is the coefficient of determination between the measured and the predicted values. It should be noted that the best model is one in which the value is RMSE is zero and the value is R^2 is equal to one.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left[M_{Dep}-M_{Pre}\right]^2}{n}} \quad (7)$$

$$R^2=1-\frac{\sum_{i=1}^{n}(M_{pre}-M_{dep})^2}{\sum_{i=1}^{n}(M_{dep}-M)^2} \quad (8)$$

In the above relationship, the Pre index is related to the predicted values and the Dep index is related to the laboratory values and n is the numbers of data.

3. Results and discussion

In the present study, according to Table 2, using the mentioned functions, experimental data are entered into the software and the best response in all functions is presented in Table 3. According to Table 3, it is clear that the RBF function has the best response among other functions and other models are based on the RBF function.

Table 2. Different kernel function (Jia et al. 2011).

Function	Expression
Linear	$K(x_i,x_j)=(x_i,x_j)$
Polynomial	$K(x_i,x_j)=\left[\left(x_i,x_j\right)+1\right]^d$
Radial basis function	$K(x_i,x_j)=\exp\left[-\frac{\lVert x_i-x_j\rVert^2}{2\sigma^2}\right]$
Sigmoid	$K(x_i,x_j)=\tanh\left[-\alpha\left(x_i,x_j\right)+c\right]$

To estimate the relative energy dissipation on the rough bed using SVM, data is subdividing into training and testing phases. After investigating the various models, 75 % of the data is assigned to training phase and the remainder to the testing phase. Next, the results of the models are comparing. First, the effective for energy dissipation are identify and six different combinations are introduce based on the dependent and independent parameters according to Table 4.

Table 3. Comparison of the results of the four functions of SVM and optimum values.

Evaluation / Function	Training						
	H= 1.5 cm		H= 3.0 cm				
	R^2	RMSE	R^2	RMSE	γ	C	E
Linear	0.948	0.0388	0.890	0.0419	--	10	0.1
Polynomial	0.516	0.0957	0.613	0.0650	7	2	0.2
RBF	**0.990**	**0.0129**	**0.989**	**0.0112**	7	2	0.1
Sigmoid	0.138	2.054	0.221	2.183	5	10	0.1

By modifying values of the kernel parameter (γ), the best response for relative energy dissipation is found. In this case, to calculate the best gamma to achieve the best model among the various models, we selected 20 values for gamma in the range of 0 to 100, and after running the software, we have provided the best RMSE and R^2 for both modes testing and training according to Fig. 5.

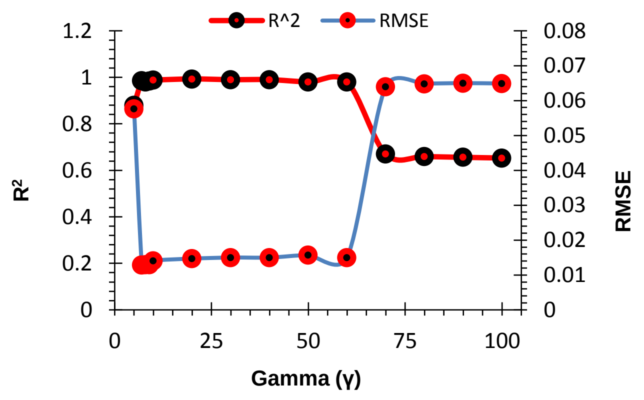
Table 4. Different input combinations applied in the present study.

Model	Input parameter	Model	Input parameter
Energy dissipation in rough bed channel with H=1.5 cm			
Model 1	Fr_1	Model 4	B, Fr_1
Model 2	H/y_1	Model 5	B, H/y_1
Model 3	$Fr_1, H/y_1$	Model 6	Fr_1, B, H/y_1
Energy dissipation in rough bed channel with H=3.0 cm			
Model 1	Fr_1	Model 4	B, Fr_1
Model 2	H/y_1	Model 5	B, H/y_1
Model 3	$Fr_1, H/y_1$	Model 6	Fr_1, B, H/y_1

First, the input combination consisting of independent dimensionless parameters are enter into the SVM network and the results are used to predict energy dissipation. This study includes two scenarios that examine roughness heights of 1.5 and 3.0 cm.

3.1. First scenario: energy depletion in a rough bed with H = 1.5 cm

In the first scenario, six different combinations have been used which include various combinations of Fr_1, B, H/y_1 dimensionless parameters. These parameters are entered into the support vector machine as listed in Table 3. The combination with the least error and the highest determination coefficient is optimal. According to Fig. 5, for the first scenario, the combination of number 6 which used input parameters Fr_1, B, H/y_1 has the lowest error with RMSE = 0.0129 and the highest coefficient of determination with R^2 = 0.990 for the training phase and RMSE = 0.032 and R^2 = 0.993 for the testing phase.



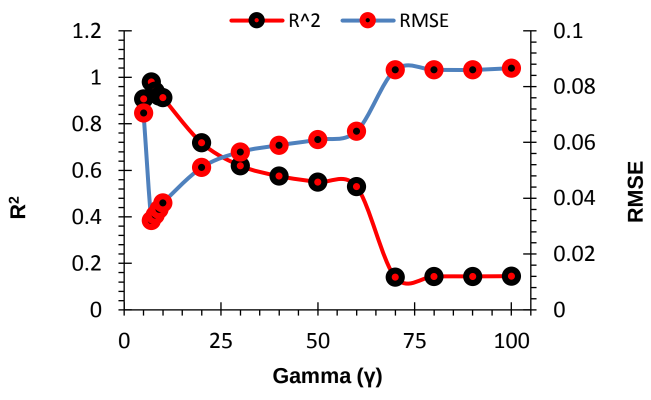


Fig. 5. Variation of RMSE and R^2 vs. Gamma values for best model in the first scenario (a) Training; (b) Testing.

Fig. 6a shows predicted laboratory data for the first scenario training phase. It is seen that laboratory data are less scattered than the predictions, which means that the output data are very well matched. Fig. 6b compares the laboratory and predicted data of the best model from the training phase and shows that there is a good correlation between laboratory and predicted data for this scenario. Figs. 6c and 6d also show the distribution and comparison curves of the laboratory data and the predicted energy dissipation of the testing phase, respectively. It is clear that the laboratory and observational data are in good agreement with each other.

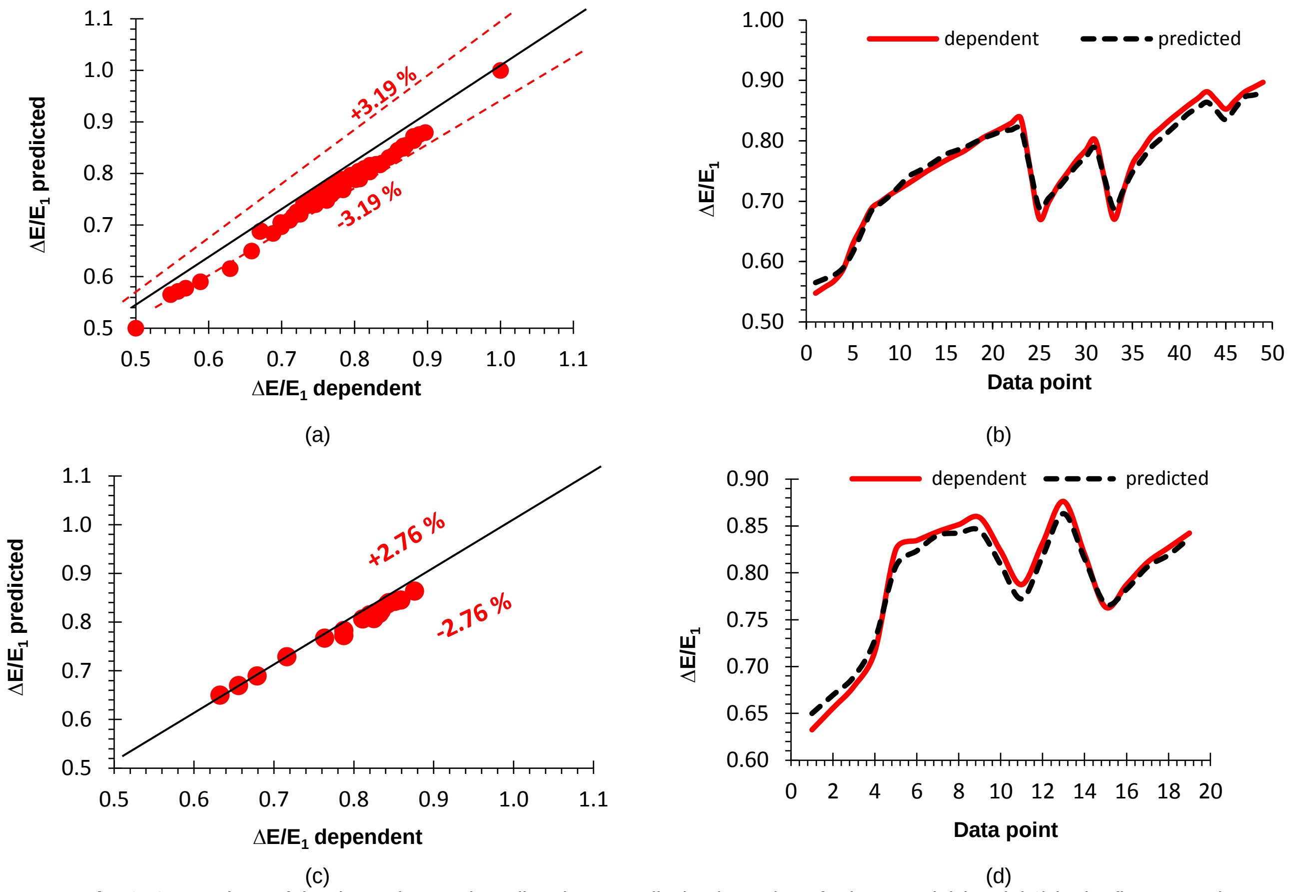


Fig. 6. Comparison of the dependent and predicted energy dissipation values for best model (model 6) in the first scenario.

Table 6. Statistical parameters for the SVM model in the second scenario.

	Training		Testing				
Model	**R^2**	**RMSE**	**R^2**	**RMSE**	**γ**	**c**	**ε**
Model 1	0.856	0.0297	0.851	0.0376	5	10	0.3
Model 2	0.414	0.0621	0.640	0.0586	30	10	0.5
Model 3	0.960	0.0157	0.961	0.0237	14	4	0.1
Model 4	0.853	0.0603	0.908	0.0657	10	2	0.1
Model 5	0.967	0.0128	0.940	0.0265	5	10	0.1
Model 6	0.989	0.0112	0.994	0.0224	4	2	0.2

The relative energy dissipation is obtained using Eq. 9, where E_1 and E_2 are the specific energy in the upstream and downstream flow, respectively.

$$\frac{\Delta E}{E_1}=\frac{E_1-E_2}{E_1} \tag{9}$$

Using Eq. 9, the relative energy dissipation is calculated based on laboratory data and diagrams of Fig. 7. The Fig. shows the relative energy dissipation versus the Froude number for different expansion ratios and for roughness heights of 1.5 cm. As can be seen in the figure, for all three expansion ratios, with increasing Froude number, the relative energy dissipation increases the reason for this is that with the entry of the flow into the expanding stilling basin with a rough bed, an S-jump is formed on the bed, which causes energy dissipation. Another factor that decreases energy is the flow collision against the roughness elements. Some of the kinetic energy is dissipated when the flow collides with the elements and some is dissipated due to the backwater profile. In other words, energy consumption in prismatic and non-prismatic channel with rough bed for all divergence ratios in both altitude ranges, compared to prismatic channel with smooth bed increases by about 10 to 29 % with a maximum value of 0.3.

3.2. Second scenario: energy depletion in a rough bed with H = 3.0 cm

In the second scenario, different parameters and a total of six different combinations have been used, which include various combinations of parameters Fr_1, B, H/y_1 . These parameters are used according to the listing provided in Table 4. The results are given in Table 6. According to Fig. 8, the results show that the second scenario Fr_1, B, H/y_1 has the lowest error with RMSE = 0.0112 and the highest coefficient of determination with R^2 = 0.989 for the training phase. This case has RMSE = 0.0224 and R^2 = 0.994 for the testing phase. It is seen to be the best combination for energy dissipation.

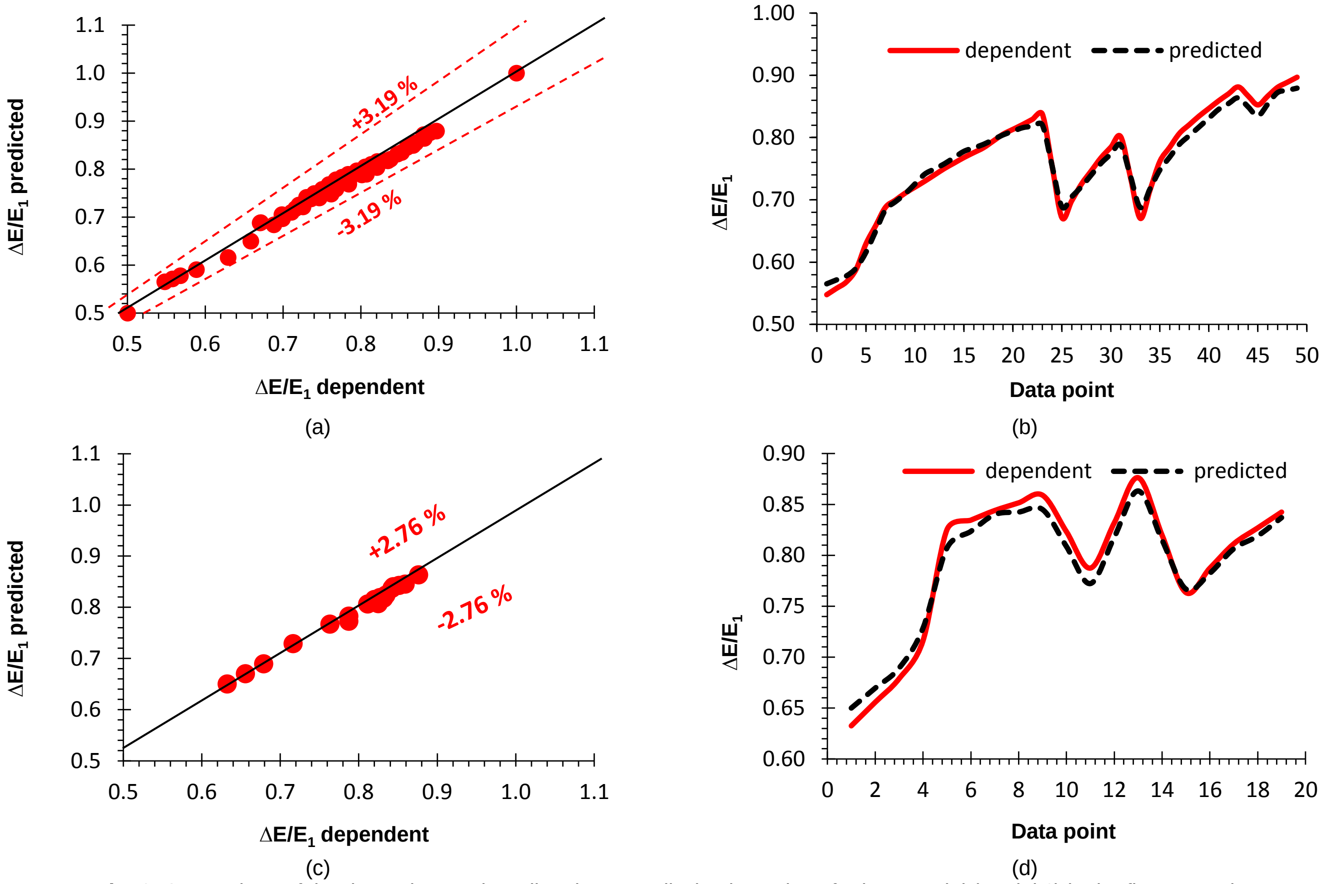


Fig. 6. Comparison of the dependent and predicted energy dissipation values for best model (model 6) in the first scenario

Fig. 9a shows the projected results for the best combination in the second scenario and from the training phase. Based on the Fig., laboratory data is found to exhibit less scattered compared with the predictions, which means that the output data is very well matched. Fig. 9b compares the laboratory and predicted data of the best model for the training phase and shows that there is a good correlation between laboratory and predicted data. Figs. 9c and 9d also show the distribution and comparison curves of the laboratory data and the predicted energy dissipation in the testing phase, respectively. It is clear that the laboratory and observational data are in good agreement with each other. Relative energy dissipation is investigate using the dimensionless parameter of relative energy loss based on the upstream Froude number. Fig. 10 shows the relative energy dissipation changes against the upstream Froude number.

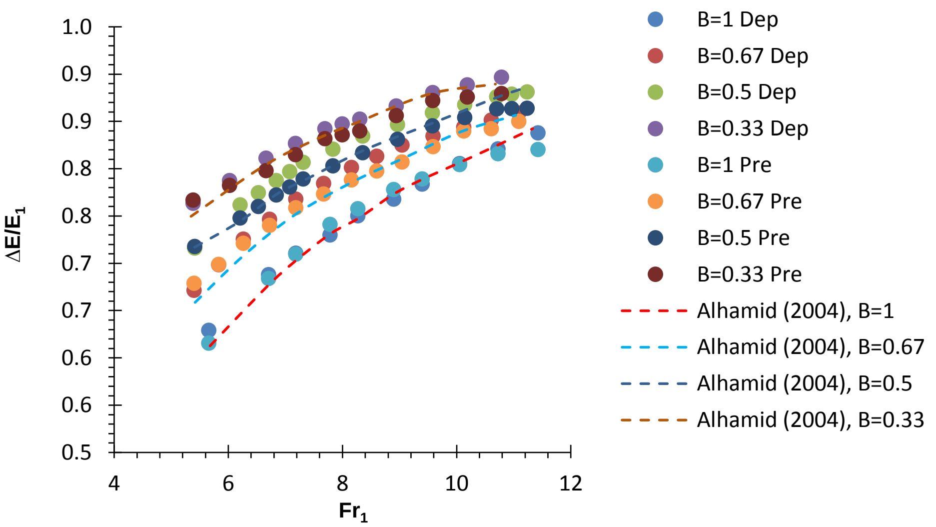


Fig. 7. Relative energy dissipation vs. Froude number values for different divergence ratios and roughness 1.5 cm for the best model (model 6) in the first scenario.

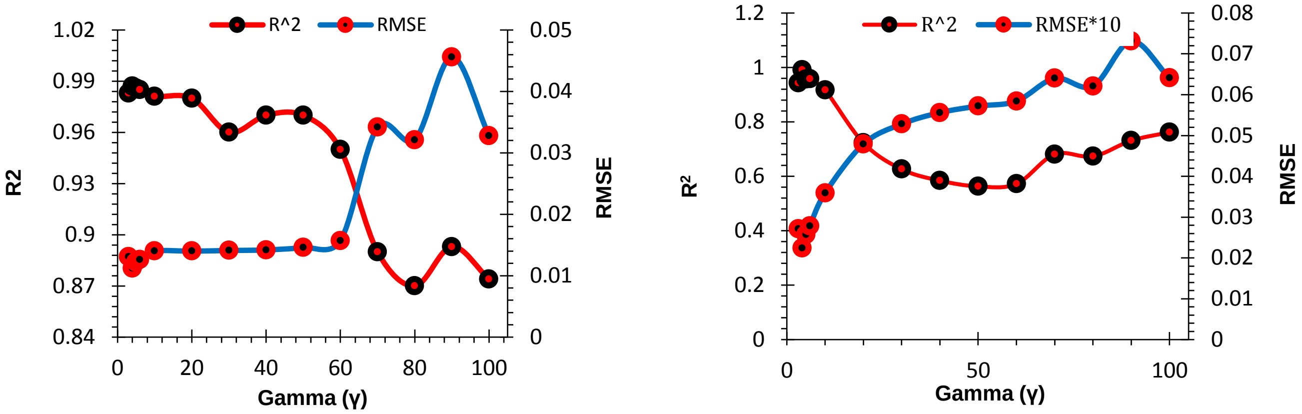


Fig. 8. Variation of RMSE and R^2 vs. Gamma values for best model in the second scenario; (a) Training; (b) Testing.

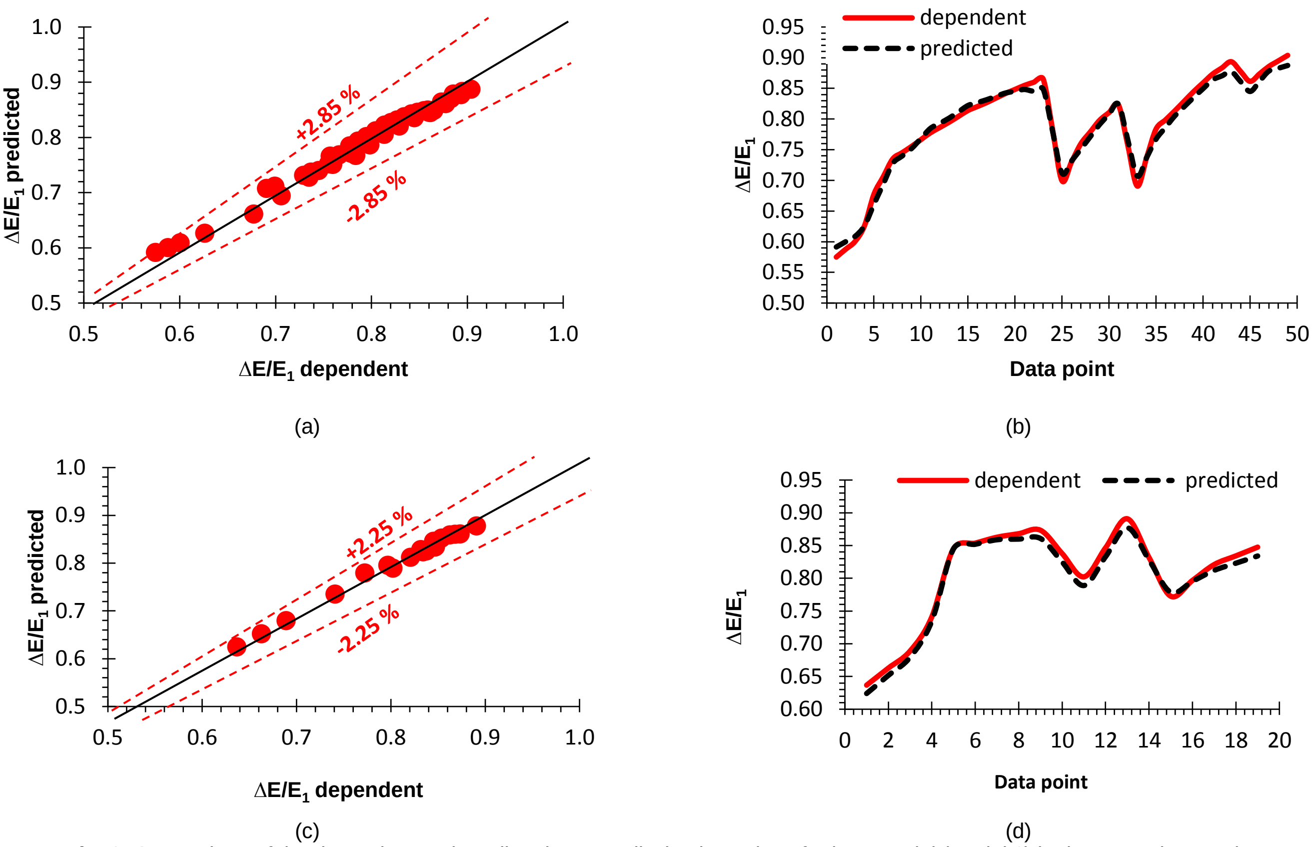


Fig. 9. Comparison of the dependent and predicted energy dissipation values for best model (model 6) in the second scenario.

Fig. 10 compares the relative energy dissipation for various Froude numbers and for different expansion ratios (roughness heights of 3 cm). As can be seen in the figure all three ratios of expansion lead to an increase in the relative energy dissipation (as the Froude number increases). The reason for this is that at the entry of the flow into the expanding stilling basin with a rough bed, an S-jump is formed on the bed which causes energy dissipation. Another factor that causes energy decrease is the collision of the flow with the roughness elements. Some of the kinetic energy is dissipated when the flow collides with the elements while some is dissipated by the backwater profile. Thus, at lower Froude numbers, the relative energy dissipation is more steep. As can be seen, in all cases of divergence, the present study and previous researchers show the trend of increasing energy dissipation by increasing the Froude number, at lower Froude values, with a greater slope. Comparing the efficiency results of the present study with Alhamid. (2004), it can be seen that the relative energy dissipation increases with increasing roughness height, so that the rough bed with a relative height range of $2.3<H/y_1<3.37$ in the present study has the highest jump efficiency compared to both researchers and in range $1.15<H/y_1<1.68$, it has the highest efficiency compared to Al-Hamid (2004).

3.3. Sensitivity analysis

Sensitivity analysis studies the variability of the statistical model. It is a formalized method to ascertain the dependence of the output variables on the input parameters. It leads to a determination of which input variables are most important for controlling the results. In the present study, the parameter that had the most impact on the prediction of relative energy dissipation is identify and its results are presented in detail in Table 7. Based on the sensitivity analysis performed in the present study, it is found that the ratio of the relative height of the roughness (H/y_1) has the greatest effect on the prediction of energy dissipation. Therefore, the SVM model has a high sensitivity to the parameter in predicting the relative energy dissipation. Fig. 11 shows the effect of the most sensitive parameter (H/y_1) on energy dissipation for both laboratory and projected data for both scenarios. According to the violin diagram in Fig. 12 and citing Table 3, it can be seen that the results of the RBF function are very consistent with the experimental results.

Table 7. Sensitivity analysis.

Input parameter	Eliminate parameter	Training R^2	Training RMSE	Testing R^2	Testing RMSE
Rough bed channel with H=1.5 cm					
Fr_1, B, H/y_1	-	0.990	0.0129	0.993	0.0320
B, H/y_1	Fr_1	0.976	0.0140	0.949	0.0240
Fr_1, H/y_1	B	0.956	0.0191	0.926	0.0312
B, Fr_1	H/y_1	**0.942**	**0.0189**	**0.899**	**0.0373**
Rough bed channel with H=3.0 cm					
Fr_1, B, H/y_1	-	0.989	0.0112	0.994	0.0224
B, H/y_1	Fr_1	0.967	0.0128	0.940	0.0265
Fr_1, H/y_1	B	0.960	0.0157	0.961	0.0237
B, Fr_1	H/y_1	**0.853**	**0.0603**	**0.908**	**0.0657**

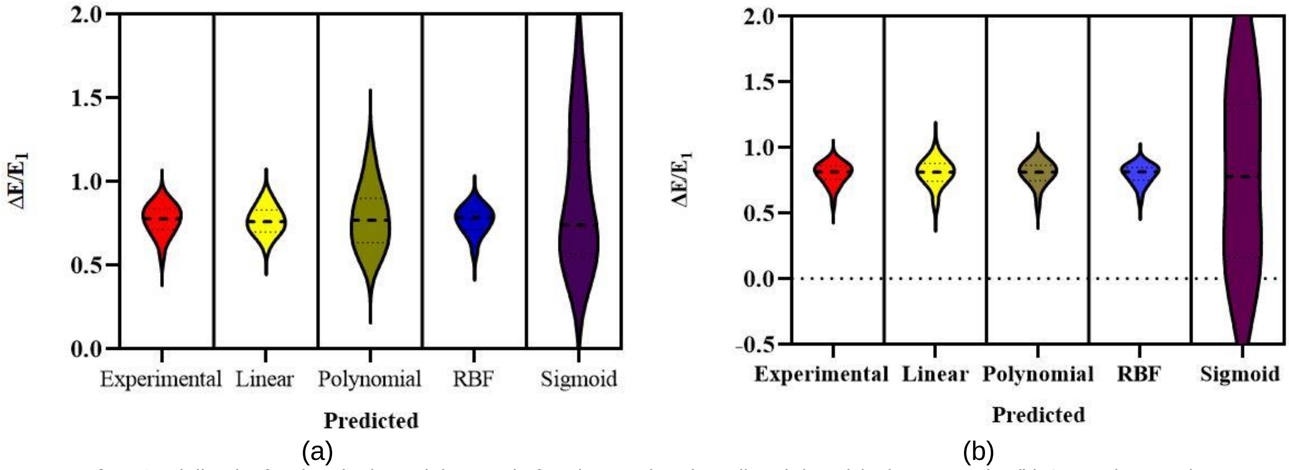


Fig. 12. Violin plot for data in the training mode for observed and predicted data (a) First scenario; (b) Second scenario.

4. Conclusions

In the present study, the relative energy dissipation in a non-prismatic channel with a rough bed with non-continuous trapezoidal elements in two states: 1- Rough bed with a rough element height of 1.5 cm 2- Rough bed with a rough element height of 3 cm It is predicted using the support vector machine. For this purpose, a total of 136 data sets with the same laboratory conditions are used and showed that the prediction of energy consumption in both cases, i.e. heights of 1.5 and 3 cm, a combination that included all independent input parameters is the best combination. In order to evaluate the efficiency of the SVM method to predict the relative energy dissipation, two parameters R^2 and RMSE are used and the results are comparing with laboratory data. Hydraulically, the results show that with increasing the downstream Froude number at both heights of the rough elements, the amount of relative energy dissipation has an increasing trend so that at lower Froude numbers, energy dissipation shows a greater slope. Also, among different divergence ratios, 0.33 ratio had the highest depreciation compared to other divergence ratios. Statistically, in the first scenario with H = 1.5 cm combination number 6 with independent input parameters (Fr_1, B, H/y_1) is recognize as the best combination, which has the results described for Training mode and for the Testing stage, and in the second scenario with H = 3.0 cm the combination results 6, which included the best combination with independent (Fr_1, B, H/y_1) parameters, is described as follows for Training mode and for Testing mode. As mentioned, the coefficients of determination and errors indicate better performance of SVM in the second scenario than in the first scenario. Also, the sensitivity analysis performed in the present study showed that the independent parameter is the most effective parameter for predicting the relative energy consumption in a non-prismatic channel with a rough bed.

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