Evaluation of the impact of channel geometry and rough elements arrangement in hydraulic jump energy dissipation via SVM

Kiyoumars Roushangar and Roghayeh Ghasempour

ABSTRACT

Rough bed channels are one of the appurtenances used to dissipate the extra energy of the flow through hydraulic jump. The aim of this paper is to assess the effects of channel geometry and rough boundary conditions (i.e., rectangular, trapezoidal, and expanding channels with different rough elements) in predicting the hydraulic jump energy dissipation using support vector machine (SVM) as a meta-model approach. Using different experimental data series, different models were developed with and without considering dimensional analysis. The results approved capability of the SVM model in predicting the relative energy dissipation. It was found that the developed models for expanding channel with central sill performed more successfully and, for this case, superior performance was obtained for the model with parameters Fr_1 and h_1/B. Considering the rectangular and trapezoidal channels, the model with parameters Fr_1, $(h_2 - h_1)/h_1$, W/Z led to better predictions. It was observed that between two types of strip and staggered rough elements, strip type led to more accurate results. The obtained results showed that the developed models for the case of simulation based on dimensional analysis yielded better predictions. The sensitivity analysis results showed that Froude number had the most significant impact on the modeling.

Key words | energy dissipation, hydraulic jump, rough element arrangement, SVM, trapezoidal channel

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INTRODUCTION

The purpose of the design of energy dissipators is to dissipate part of the kinetic energy of the inflowing flow in order to return safely the flow to the downstream channel or river and prevent scour below overflow spillways, chutes, and sluices. Based on the energy dissipating action of hydraulic jumps, stilling basins are one of the possible solutions which may be adopted. Hydraulic jump is a useful means of dissipating the excess energy of supercritical flow so that scour in the downstream is minimized. Other applications of hydraulic jumps are: increasing the efficiency of flow-measurement flumes, mixing chemicals or air into streams, desalination of sea water, sedimentation of solid particles in high velocity flows, chlorination of domestic water sustaining systems, and aeration of streams polluted by bio-degradable wastes. In order to design an optimal hydraulic structure, different devices such as sills, baffle blocks, end sills, roughness elements, and roller buckets are used in hydraulic structures. However, modeling hydraulic jump characteristics possesses great importance since it plays an important role in designing hydraulic structures. So far, various studies have been done to explain the complex phenomenon of the hydraulic jump and to estimate its characteristics. Bhutto *et al.* (1989) developed a semi-empirical equation for calculating the sequent depth and relative energy loss ratio in sloping

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and horizontal rectangular channels. Finnemore *et al.* (2002) stated that Froude number has a significant impact on characteristics of hydraulic jump. The impact of wall friction on the sequent depth's ratio was studied by Hager & Bremen (1989). Ayanlar (2004) investigated the hydraulic jump properties in channels with corrugated beds. Bilgin (2005) collected some experiments in a channel with smooth bed in order to investigate the distribution of shear stress for turbulent flow. However, due to the complexity and uncertainty of the hydraulic jump phenomenon, the results of the classical models are not universal and under variable conditions do not present the same results. Therefore, it is essential to use other methods with more accuracy in predicting the energy dissipation in channels with different shapes and rough elements. Karbasi & Azamathulla (2015) investigated the sequence depth ratio and jump length as hydraulic jump characteristics over horizontal rectangular channels with artificially roughened beds. Two types of roughness elements (a series of parallel square bars and closely packed cemented gravel particles) were used and the performances of artificial intelligence techniques compared with traditional equations. The results showed that artificial intelligence techniques outperformed the traditional equations.

The meta model approaches such as artificial neural networks (ANNs), neuro-fuzzy models (NF), genetic programming (GP), and support vector machine (SVM), have been applied in investigating the hydraulic and hydrologic complex phenomena in recent decades. Determining Chezy resistance coefficient in corrugated channels (Giustolisi 2004), evaluation of inducing equations for vegetation resistance (Baptist *et al.* 2007), velocity predictions in compound channels with vegetated floodplains (Harris *et al.* 2003), estimation of Manning's roughness coefficient for high gradient streams (Azamathulla & Jarrett 2013), and modeling flow resistance in open channels with dune bedform (Roushangar *et al.* 2018) are some examples of the meta model approach applications.

Among others, SVM technique has been used for predicting various hydraulic and hydrologic phenomena. Yu *et al.* (2004) applied EC-SVM approach for real-time hydrologic forecasting. Yu & Liong (2007) used SVM for forecasting hydrologic time series with ridge regression in feature space. Azamathulla *et al.* (2017) applied SVM for predicting side weir discharge coefficient.

In the current study, the capability of SVM as an effective kernel-based approach was assessed in modeling hydraulic jump energy dissipation in three channels with different geometry and rough elements (i.e., rectangular channel with strip and staggered elements, trapezoidal channel with strip elements, and sudden diverging channel with central sill). In order to determine the most effective combination for modeling relative energy dissipation, different input combinations were considered and the impact of hydraulic characteristics and arrangement of the rough elements was assessed. In addition, the most important parameters in predicting the relative energy dissipation are determined using sensitivity analysis.

MATERIALS AND METHODS

Used data sets

In this study, the experimental data presented by Bremen (1990), Evcimen (2005, 2012), and Simsek (2006) were employed for prediction goals. The experiments of Bremen (1990) were intended for sudden diverging basins with central sill. During experiments, the 17 m^3 upstream basin was supplied by two conduits of 0.30 m diameter (max. total discharge 375 L/s). A prismatic rectangular and horizontal channel 0.5 m wide and 10.8 m long was connected to the basin. Simsek (2006) used prismatic roughness elements with different arrangements in a rectangular channel to investigate these elements' impacts on hydraulic jump characteristics. Two types of roughness elements with stripe and staggered arrangements were used during experiments. Evcimen (2005) investigated the effects of prismatic roughness elements on hydraulic jumps using four different pitch ratios. The ranges of upstream Froude numbers were varied from 7.3 to 16.6. The experiments of Evcimen (2012) were done at the hydraulic laboratory of the Middle East Technical University, and were intended for hydraulic jump in trapezoidal channels and the impact of prismatic roughness on hydraulic jump was assessed. Figure 1 shows the side view of hydraulic jump in two types of channels (rectangular and sudden expanding channels). Also, the ranges of experimental data used in experiments are given in Table 1.

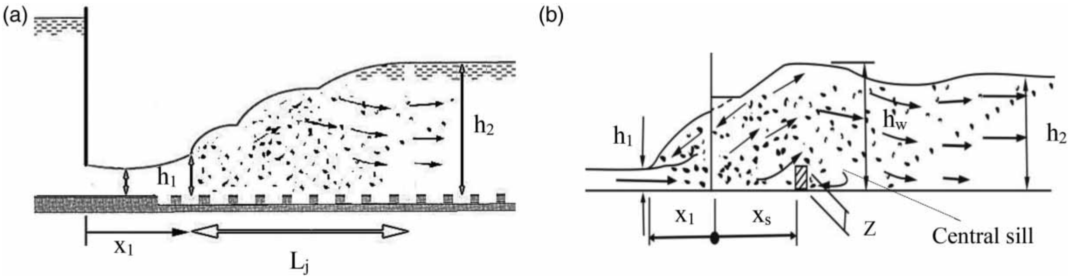

Figure 1 | Hydraulic jump in (a) rectangular channel with rough bed and (b) sudden expansion channel with central sill.

Table 1 | The range of experimental data

Researcher	Channel shape	Rough element arrangement	Fr_1 (Froude number)	*W* (cm) Space between elements	*Y* Sequence depth	*Xs* (cm) Sill position	*Z* (cm) Height of elements	No. of data
Bremen (1990)	Sudden expanding	Central sill	2.97–9.02	2–18.1	2.8–10.64	20–80	2.5–7.5	156
Evcimen (2005)	Rectangular	Strip	7.29–16.8	4–9	8.7–18.8	–	0.6–2	113
Simsek (2006)	Rectangular	Strip and staggered	2.13–11.92	3–9	2.5–14.8	–	1	92
Evcimen (2012)	Trapezoidal	Strip	3.92–13.28	2–10	4.15–14.9	–	1–3	107

Support vector machine

SVM as an intelligence approach is used in information categorization and data set classification. This approach, developed by Vapnik in 1995, is known as structural risk minimization (SRM), which minimizes an upper bound on the expected risk, as opposed to the traditional empirical risk (ERM), which minimizes the error on the training data. The SVM method is based on the concept of optimal hyper plane that separates samples of two classes by considering the widest gap between two classes (see Figure 2). Support vector regression (SVR) is an extension of SVM regression. The aim of SVR is to characterize a kind of function that has at most ε deviation from the actually obtained objectives for all training data y_i and at the same time it would be as flat as possible. SVR formulation is as follows:

$$f(x) = w\varphi(x) + b \tag{1}$$

where $\varphi(x)$ is a nonlinear function in feature of input x, b is called the bias, and the vector w is known as the weight factor and expressed as Equation (2) in which α_i is Lagrange multipliers, y_i is forecasted value, and x_i is input value:

$$w = \sum_{i=1}^{n} \alpha_i y_i x_i \tag{2}$$

The coefficients of Equation (1) are predicted by minimizing regularized risk function as expressed below:

$$R_{\min} = C\frac{1}{N}\sum_{i=1}^{n} L_\varepsilon(t_i, y_i) + \frac{1}{2}\|w\|^2 \tag{3}$$

where

$$L_\varepsilon(t_i, y_i) = \begin{cases} 0 & |t_i, y_i| \le \varepsilon \\ |t_i, y_i| - \varepsilon & \text{Otherwise} \end{cases} \tag{4}$$

The constant C is the cost factor and represents the trade-off between the weight factor and approximation

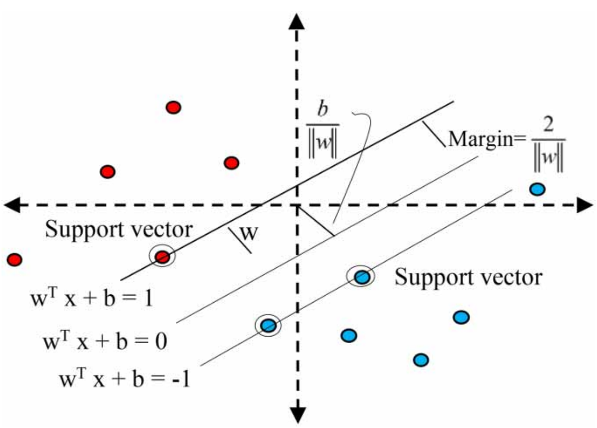

Figure 2 | Data classification and support vectors.

error. ε is the radius of the tube within which the regression function must lie. $L_\varepsilon(t_i, y_i)$ represents the loss function in which y_i is forecasted value and t_i is desired value in period i. The $||w||$ is the norm of w vector and the term $||w||^2$ can be expressed in the form $w^T.w$ in which w^T is the transpose form of w vector. According to Equation (4), if the predicted value is out of the ε-tube then the loss will be the absolute value, which is the difference between predicted value and ε. Since some data may not lie inside the ε-tube, the slack variables (ξ, ξ^*) must be used. These variables show the distance from actual values to the corresponding boundary values of the ε-tube. Therefore, it is possible to transform Equation (3) into:

$$R_{\min} = C\sum_{i=1}^{n}(\xi_i,\ \xi_i^*) + \frac{1}{2}||w||^2 \tag{5}$$

subject to: $t_i - w_i\varphi(x_i) - b \leq \varepsilon + \xi_i,\ w_i\varphi(x_i) + b - t_i \leq \xi_i^*,\ \xi_i + \xi_i^* \geq 0$

Using Lagrangian multipliers in Equation (5) thus yields the dual Lagrangian form:

$$Maxl(\alpha_i, \alpha_i^*) = -\varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) + t_i\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) - \frac{1}{2} \times \sum_{i=1}^{n} \times \sum_{j=1}^{n}(\alpha_i - \alpha_i^*) - (\alpha_j - \alpha_j^*) - K(x_i, x_j) \tag{6}$$

subject to: $\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0,\quad 0 \leq \alpha_i,\quad \alpha_i^* \leq C,\quad i = 1,\ 2,\ \ldots \mathrm{N}$

where α_i and α_i^* are Lagrange multipliers and $l(\alpha_i, \alpha_i^*)$ represents the Lagrange function. K (x_i, x_j) is a kernel function to yield the inner products in the feature space $\varphi(x_i)$ and $\varphi(x_j)$ and presented as below:

$$K(x_i,\ x_j) = \varphi(x_i) \times \varphi(x_j) \tag{7}$$

The appropriate selection of kernel type is the most important step in the SVM due to its direct impact on the training and classification precision. In general, there are several types of kernel function, namely, linear, polynomial, radial basis function (RBF), and sigmoid functions.

Performance criteria

In the current study, the model's performance was evaluated using three statistical parameters: correlation coefficient (R), determination coefficient (DC), and root mean square errors ($RMSE$), expressions for which are as follows:

$$DC = 1 - \frac{\sum_{i=1}^{N}(l_o - l_p)^2}{\sum_{i=1}^{N}(l_o - \overline{l_p})^2},\quad \mathrm{R} = \frac{\sum_{i=1}^{N}(l_o - \overline{l_o}) \times (l_p - \overline{l_p})}{\sqrt{\sum_{i=1}^{N}(l_o - \overline{l_o})^2 \times (l_p - \overline{l_p})^2}},$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N}\frac{(l_o - l_p)^2}{\mathrm{N}}} \tag{8}$$

where l_o, l_p, $\overline{l_o}$, $\overline{l_p}$, N are the observed values, predicted values, mean observed values, mean predicted values, and number of data samples, respectively.

Simulation and model development

Input variables

The crucial step during modeling process via an intelligent method is the appropriate selection of model input parameters. In Figure 3, the quantities measured for jumps in channels with different rough elements are shown. Based on Rajaratnam & Subramanya (1968), Hager (1985), and Gandhi (2014), the important variables which affect the energy dissipation are:

$$f(h_1, h_2, V_1, L_j, \Delta E, \mu, g, \rho, b_1, b_2, Z, W) = 0 \tag{9}$$

where h_1 and h_2 are sequent depth of upstream and downstream, V_1 is upstream flow velocity, μ is water dynamic viscosity, g is gravity acceleration, L_j is length of jump, ρ is density of water, b_1 and b_2 are approach channel and expanded channel width, ΔE $(=E_1 - E_2)$ in which E_1 and E_2 are energy per unit weight before and after the jump, Z is rough element or sill height, and W is space between rough elements.

From dimensional analysis and considering h_1, g, and μ as repeating variables these parameters in Equation (9) can be expressed as follows:

$$f\left(\frac{h_2}{h_1}, \frac{\Delta E}{E_1}, \frac{L_j}{h_1}, \frac{b_1}{h_1}, \frac{b_2}{h_1}, \frac{v_1^2}{gh_1}, \frac{\rho v_1 h_1}{\mu}, \frac{Z}{h_1}, \frac{W}{h_1}\right) = 0 \tag{10}$$

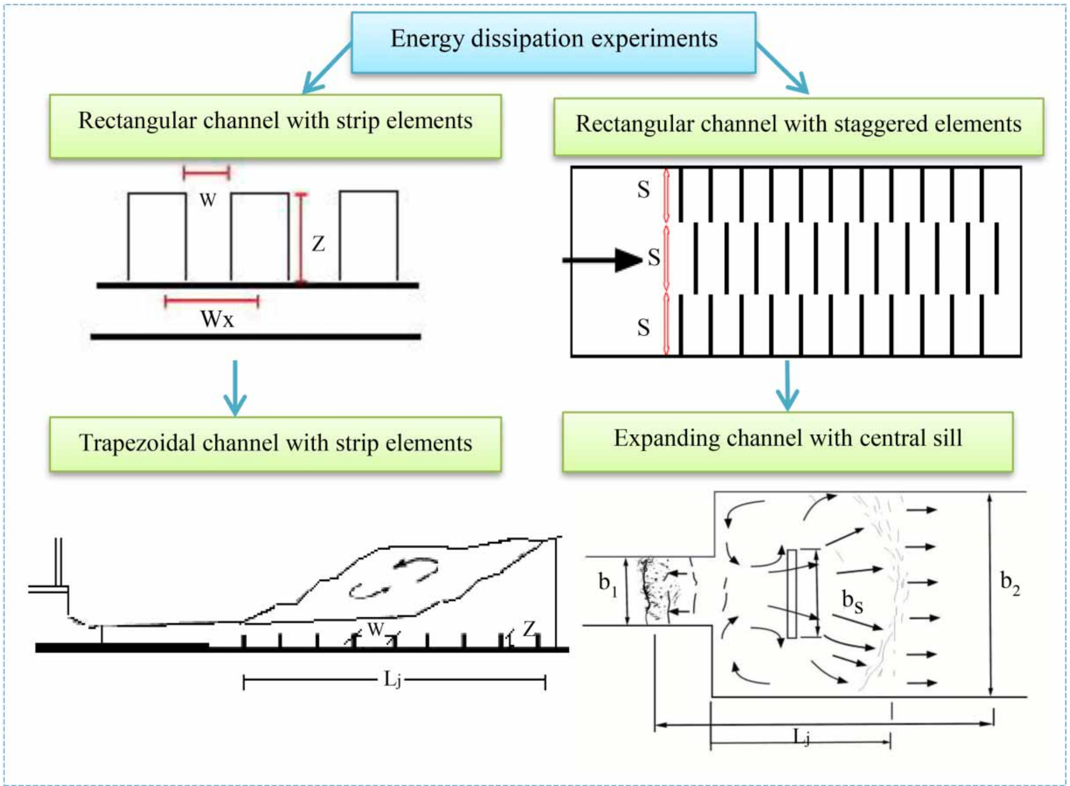

Figure 3 | The schematic view of different types of channels used in this study.

Equation (10) can be expressed as:

$$f\left(\frac{h_2}{h_1}, \frac{\Delta E}{E_1}, \frac{L_j}{h_1}, B, Fr_1, Re, \frac{Z}{h_1}, \frac{W}{h_1}\right) = 0 \tag{11}$$

where Fr_1 is flow Froude number, Re is flow Reynolds number, and $B = (b_1/b_2)$ is ratio of expansion.

Experimental studies by several researchers (i.e., Ranga Raju *et al.* 1980; Wu & Rajaratnam 1996; Elevatorski 2008) revealed that hydraulic jump characteristics only depend on Froude number and Reynolds number does not have an effective role in the predicting process. Also, Hager (1992) showed that the height of jump can affect the characteristics of hydraulic jump. In the case of expanding channel with central sill, sill position (Xs) was considered as input variable. In this study, for predicting the energy dissipation, two states were considered: simulation based on dimensional analysis and simulation based on raw data (i.e., without dimensional analysis). Therefore, according to Table 2, several models were developed based on hydraulic data and geometric data to investigate the hydraulic jump energy dissipation in different types of channels with different rough elements.

SVM models development

For determining the best performance of SVM and selecting the best kernel function, different models were predicted via SVM using various kernels. Table 3 indicates the results of statistical parameters of different kernels for model DE(VII) of channel with central sill. According to the results, using kernel function of RBF led to better prediction accuracy in comparison to the other kernels. Therefore, RBF kernel was used as the core tool of SVM which was applied for the rest of the models. Performance of the SVM method depends on the selection of three parameters of constant C, ε, and kernel parameter γ, in which γ is a constant parameter of the RBF kernel. Variable parameter used with kernel function (γ) considerably affects

Table 2 | SVM developed models

Simulation based on dimensional analysis		Simulation based on raw data	
Output variable: Relative energy dissipation ($\Delta E/E_1$)		**Output variable: Relative energy dissipation ($\Delta E/E_1$)**	
Model	**Input variable(s)**	**Model**	**Input variable(s)**
DE(I)	Fr_1	RD(I)	V_1, (h_2-h_1)
DE(II)	Fr_1, $(h_2-h_1)/h_1$	RD(II)	V_1, (h_2-h_1), W
DE(III)	Fr_1, Z/h_1	RD(III)	V_1, (h_2-h_1), Z
DE(IV)	Fr_1, W/Z	RD(IV)	V_1, (h_2-h_1), Xs
DE(V)	Fr_1, $(h_2-h_1)/h_1$, W/Z		
DE(VI)	Fr_1, Xs/h_1		
DE(VII)	Fr_1, h_1/B		

Table 3 | The statistical parameters of SVM method with different kernel functions, model DE(VII)

	Train			Test		
Kernel function	***R***	***DC***	***RMSE***	***R***	***DC***	***RMSE***
Linear	0.855	0.791	0.118	0.802	0.702	0.129
Polynomial	0.945	0.819	0.065	0.968	0.758	0.075
RBF	0.993	0.985	0.012	0.992	0.984	0.021
Sigmoid	0.577	0.111	0.202	0.346	0.102	0.241

the flexibility of function. These parameters should be selected by the user. The appropriate selection of these three parameters has been proposed by various researchers. In the current study, according to Cherkassky & Yunqian (2002), C, ε, and γ are selected by a systematic grid search of the parameters using cross-validation on the training set. First, optimized values of C and ε for a specified γ were obtained and then γ was changed. Statistical parameters were used to find optimums. The statistics parameters for optimizing γ values using the test set of model DE(VII) for channel with central sill are shown in Figure 4. The optimal parameters of the rest of the developed models were selected in the same way.

RESULTS AND DISCUSSION

Simulation based on dimensional analysis

Rectangular channels with strip and staggered rough elements

For evaluating relative energy dissipation in channels with rectangular section and with strip and staggered rough elements, several models were considered according to the flow condition and geometry of the applied rough elements. The developed models were analyzed with the SVM model to carry out the relative energy dissipation ratio prediction in these channels. Table 4 and Figure 5 show the results of SVM models. From the obtained results of statistical parameters (*RMSE*, *R* and *DC*), it can be stated that between two types of channels, developed models for the case of channel with strip rough elements in modeling of the relative energy dissipation ratio performed more successfully than the other case. For both cases, the model DE(V) with input parameters of Fr_1, $(h_2-h_1)/h_1$, W/Z led to more accurate outcome than the other models. A comparison between the results of the models DE(I), DE(III), and DE(IV) showed that for prediction the relative energy dissipation in rough

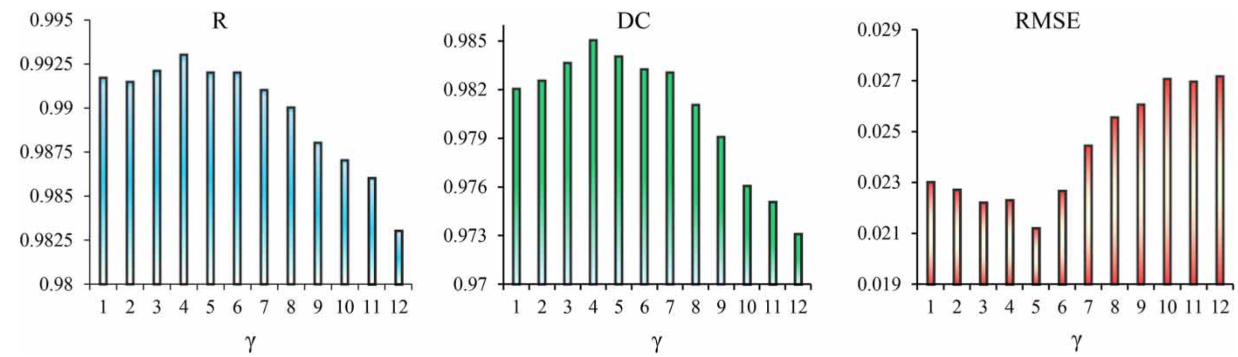

Figure 4 | Statistics parameters via γ values to find SVM optimums of the testing set for model DE(VII) of a channel with central sill.

Table 4 | Statistical parameters of the SVM models for the relative energy dissipation ratio

		Optimal parameters			Performance criteria					
					Train			Test		
Condition	SVM models	C	ε	γ	R	DC	RMSE	R	DC	RMSE
Rectangular channel with strip elements	DE(I)	5.0	0.10	5	0.959	0.914	0.038	0.934	0.892	0.067
	DE(II)	6.0	0.10	4	0.983	0.968	0.032	0.982	0.942	0.055
	DE(III)	6.0	0.10	4	0.981	0.964	0.038	0.975	0.935	0.058
	DE(IV)	6.0	0.10	3	0.978	0.963	0.039	0.973	0.922	0.062
	DE(V)	5.0	0.10	5	0.991	0.973	0.025	0.986	0.944	0.0492
Rectangular channel with staggered elements	DE(I)	8.0	0.02	4	0.863	0.859	0.043	0.841	0.818	0.075
	DE(II)	10	0.10	5	0.885	0.871	0.036	0.884	0.847	0.062
	DE(III)	10	0.10	8	0.883	0.868	0.043	0.878	0.842	0.065
	DE(IV)	8	0.10	5	0.880	0.867	0.044	0.876	0.830	0.070
	DE(V)	10	0.10	5	0.969	0.886	0.031	0.927	0.868	0.055

bed channels, using parameter Z/h_1 and W/Z as input parameters caused an increment in models' efficiency. These parameters confirm the importance of the relative height and space of applied rough elements in the relative energy dissipation estimating process. Considering the results of the models DE(III) and DE(IV), it could be inferred that the impact of parameter Z/h_1 in increasing the accuracy of the model is more than parameter W/Z. Also, the model DE(I) with only input parameter Fr_1 showed the desired accuracy. It could be stated that the applied method can successfully predict the relative energy dissipation using only the upstream flow characteristic as input data. Figure 5 indicates the scatter plots of SVM prediction and measured values for the DE(V) model in channels with strip and staggered elements.

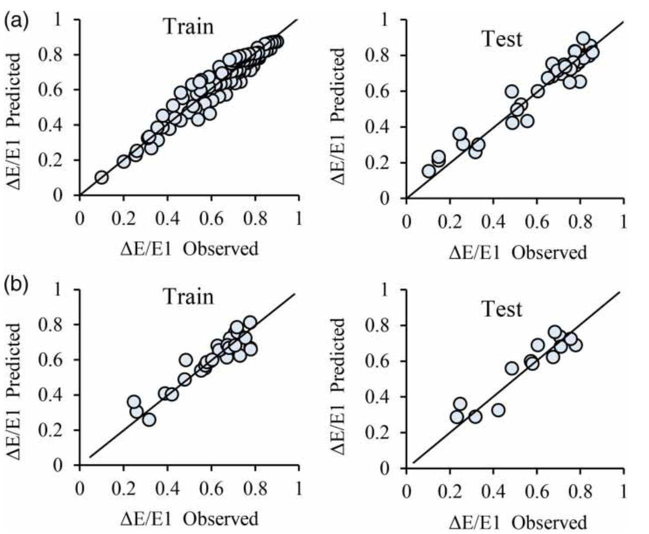

Figure 5 | Comparison of observed and predicted relative energy dissipation for superior model: (a) channel with strip elements and (b) channel with staggered elements.

Trapezoidal channel with strip rough elements

The obtained results from SVM models for predicting the hydraulic jump relative energy dissipation in trapezoidal channel with rough elements are indicated in Table 5 and Figure 6. The superior performance was obtained for the model DE(V) with input parameters of Fr_1, $(h_2 - h_1)/h_1$, W/Z. According to the obtained results from the models, it could be inferred that adding parameters $(h_2 - h_1)/h_1$, Z/h_1, W/Z as input parameters caused an increment in models' efficiency. However, for this state, the variable W/Z was more effective than variables $(h_2 - h_1)/h_1$ and Z/h_1 in improving the model accuracy. This issue shows the impact of the rough elements geometry on predicting the relative energy dissipation. From the comparison between the results of Tables 5 and 6, it can be stated that the developed models for rectangular channel with rough elements in predicting the hydraulic jump's energy dissipation performed more successfully than trapezoidal channel with rough elements.

Sudden expanding channel with central sill

The results of SVM models for relative energy dissipation ratio in sudden expanding channel with central sill are

Table 5 | Statistical parameters of the SVM models for the relative energy dissipation ratio

		Optimal parameters			Performance criteria					
					Train			Test		
Condition	SVM models	C	ε	γ	*R*	*DC*	*RMSE*	*R*	*DC*	*RMSE*
Trapezoidal channel with strip elements	DE(I)	8.0	0.10	4	0.909	0.822	0.072	0.904	0.804	0.086
	DE(II)	6.0	0.10	4	0.912	0.831	0.067	0.909	0.811	0.082
	DE(III)	8.0	0.10	4	0.910	0.825	0.069	0.906	0.809	0.084
	DE(IV)	6.0	0.10	5	0.938	0.849	0.059	0.927	0.827	0.073
	DE(V)	8.0	0.10	5	0.942	0.885	0.057	0.935	0.858	0.072

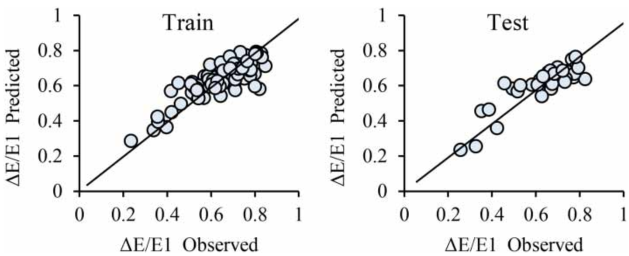

Figure 6 | Comparison of observed and predicted relative energy dissipation for superior model.

given in Table 6 and Figure 7. According to Table 6, among all developed models, the model DE(VII) with input parameters Fr_1 and h_1/B represented higher performance. Based on the results, it could be seen that the relative height of central sill (Z/h_1) and location of sill (Xs/h_1) had an impact on the prediction process and caused an increment in models' efficiency. Comparison between the obtained results from Tables 4 to 6 indicated that the developed models for channel with central sill presented higher accuracy and this type of channel in predicting the relative energy dissipation performed more successfully than the other cases. However, as Karbasi & Azamathulla (2015) stated and according to the obtained results in this study, the SVM method as an artificial intelligence approach is able to predict complex hydraulic phenomena such as hydraulic jump characteristics successfully. The comparison of observed and predicted relative energy dissipation for the superior model of expanding channel is shown in Figure 7.

Simulation based on raw data (without dimensional analysis)

For this state, several models were developed without considering the dimensional analysis using flow and rough elements geometry. The obtained results are given in Table 7 and

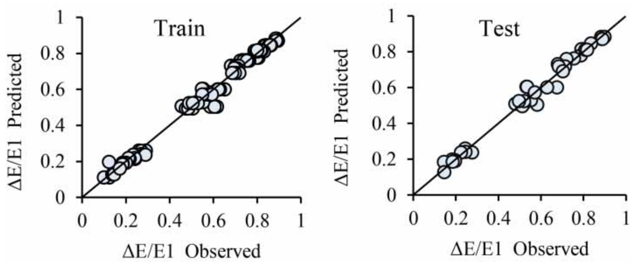

Figure 7 | Comparison of observed and predicted relative energy dissipation for superior model.

Table 6 | Statistical parameters of the SVM models for the relative energy dissipation ratio

		Optimal parameters			Performance criteria					
					Train			Test		
Condition	SVM models	C	ε	γ	*R*	*DC*	*RMSE*	*R*	*DC*	*RMSE*
Expanding channel with central sill	DE(I)	10	0.11	5	0.909	0.902	0.031	0.904	0.899	0.038
	DE(II)	10	0.10	5	0.992	0.983	0.014	0.989	0.972	0.024
	DE(III)	10	0.11	4	0.912	0.925	0.028	0.906	0.918	0.034
	DE(VI)	8.0	0.10	4	0.938	0.932	0.019	0.927	0.931	0.031
	DE(VII)	10	0.1	4	0.993	0.985	0.012	0.992	0.984	0.021

Figure 8. According to Table 8, it can be seen that for all channel types the model RD(I) with parameters of V_1 and $(h_2 - h_1)$ led to better prediction and the channel with central sill presented higher accuracy. In the case of simulation based on raw data, it can be deduced that using flow characteristics (flow velocity and depth) led to desired accuracy, while adding rough elements geometry parameters (i.e., Z, W, Xs) to input combinations decreased the models' accuracy. Comparison between the obtained results from Tables 4 to 7 indicated that simulation based on dimensional analysis in predicting the relative energy dissipation performed more successfully than the simulation based on raw data.

Sensitivity analysis

Sensitivity analysis is used to evaluate the effect of different employed variables on the hydraulic jump relative energy dissipation prediction via SVMs. For evaluating the impact

Table 7 | Statistical parameters of the SVM models for the relative energy dissipation ratio

		Optimal parameters			Performance criteria					
					Train			Test		
Condition	**SVM models**	**C**	**ε**	**γ**	***R***	***DC***	***RMSE***	***R***	***DC***	***RMSE***
Rectangular channel with strip elements	RD(I)	6.0	0.10	4	0.953	0.944	0.031	0.952	0.925	0.058
	RD(II)	6.0	0.10	3	0.946	0.942	0.034	0.948	0.916	0.063
	RD(III)	6.0	0.10	3	0.939	0.935	0.038	0.946	0.903	0.066
Rectangular channel with staggered elements	RD(I)	10	0.01	4	0.925	0.848	0.065	0.922	0.836	0.077
	RD(II)	10	0.10	6	0.915	0.841	0.068	0.911	0.828	0.079
	RD(III)	10	0.10	6	0.910	0.833	0.071	0.903	0.821	0.084
Trapezoidal channel with strip elements	RD(I)	8.0	0.10	2	0.915	0.838	0.066	0.912	0.827	0.079
	RD(II)	8.0	0.10	2	0.911	0.821	0.069	0.908	0.819	0.081
	RD(III)	6.0	0.10	2	0.909	0.814	0.074	0.905	0.811	0.085
Expanding channel with central sill	RD(I)	10	0.10	4	0.975	0.952	0.028	0.961	0.941	0.031
	RD(III)	10	0.10	4	0.968	0.942	0.031	0.942	0.936	0.035
	RD(IV)	10	0.10	4	0.966	0.944	0.030	0.939	0.934	0.037

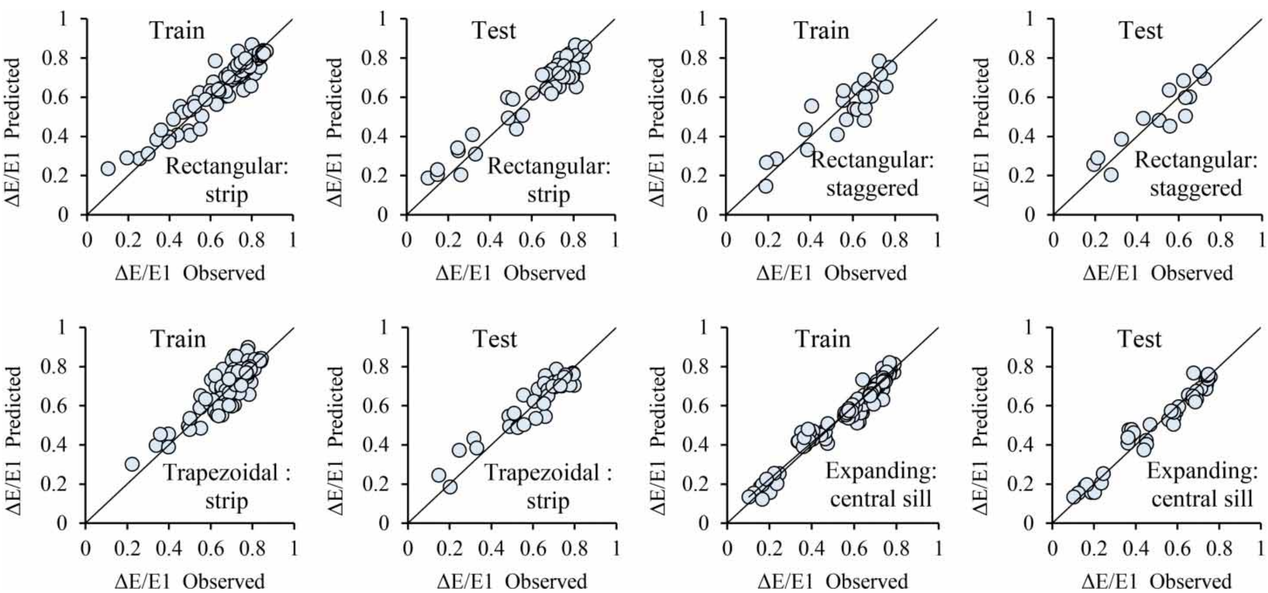

Figure 8 | Comparison of observed and predicted relative energy dissipation for superior models.

Table 8 | Relative significance of each of input parameters of the best models for each channel

		Performance criteria for test series	
Channel type	**Eliminated variable**	***RMSE***	***ΔRMSE%***
Rectangular channel with strip elements	Fr_1, $(h_2-h_1)/h_1$, W/Z	0.049	–
	Fr_1	0.106	116.327
	$(h_2-h_1)/h_1$	0.062	26.531
	W/Z	0.055	12.245
Rectangular channel with staggered elements	Fr_1, $(h_2-h_1)/h_1$, W/Z	0.055	–
	Fr_1	0.096	103.636
	$(h_2-h_1)/h_1$	0.070	27.273
	W/Z	0.062	12.727
Trapezoidal channel with strip elements	Fr_1, $(h_2-h_1)/h_1$, W/Z	0.072	–
	Fr_1	0.108	101.389
	$(h_2-h_1)/h_1$	0.073	1.389
	W/Z	0.082	13.889
Expanding channel with central sill	Fr_1, $(h_2-h_1)/h_1$	0.024	–
	Fr_1	0.081	237.500
	$(h_2-h_1)/h_1$	0.046	58.333

of each independent parameter, the best SVM model in the case of simulation based on dimensional analysis was run with all input parameters and then, one of the input parameters was eliminated and the SVM model was re-run. *RMSE* error criterion, was used as indication of the significance of each parameter. Table 8 and Figure 9 show the sensitivity analysis results. In Table 7, *ΔRMSE* represents the percentages of the added values to the error criteria for each eliminated parameter. Based on the results, it can be inferred that variable Fr_1 is the most important variable in the hydraulic jump relative energy dissipation prediction process.

Combined data

It was attempted to evaluate the performance of SVM method for a wider range of data. In other words, data sets of rectangular, trapezoidal, and expanding channels were used altogether. For estimating the dependent relative energy

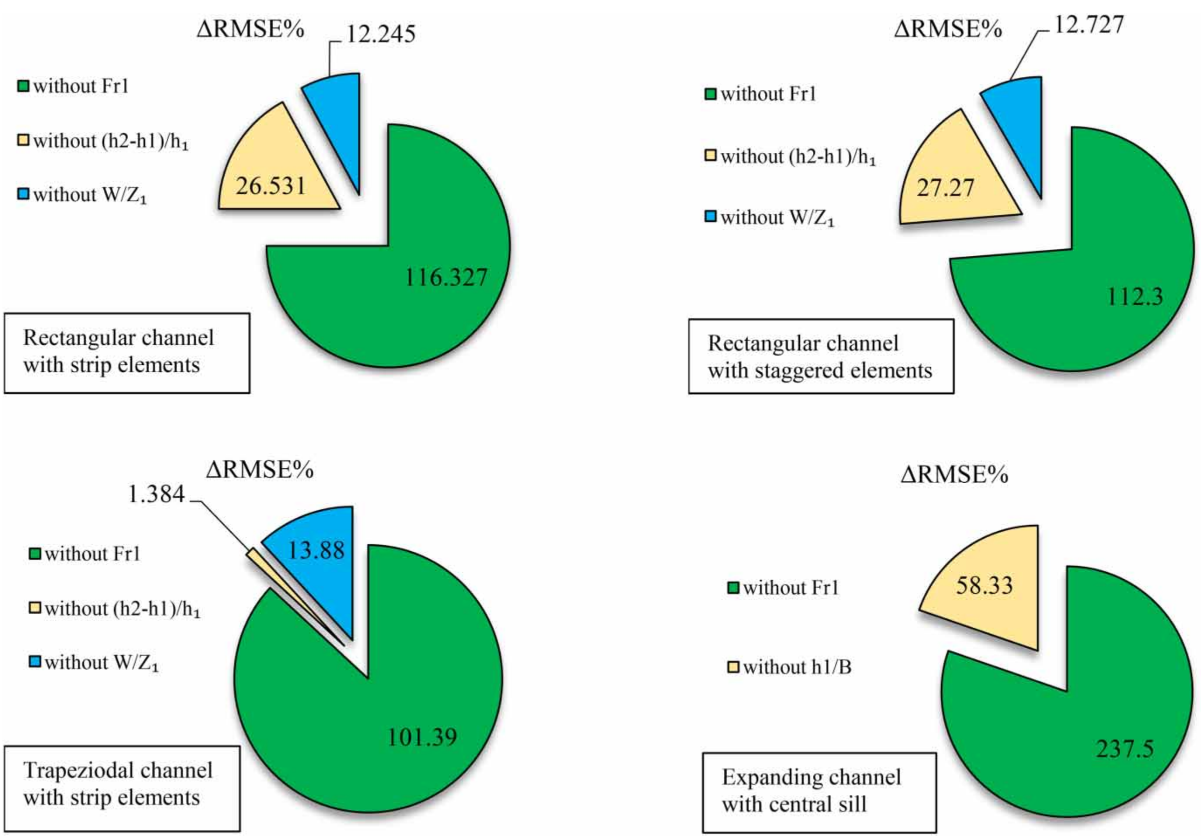

Figure 9 | Comparison of statistical parameters obtained from sensitivity analysis.

dissipation variable, three models were considered and reanalyzed for the combined data state. The results are given in Table 9 and Figure 10. According to the results of the combined data, it can be stated that adding $(h_2 - h_1)/h_1$ and Z/h_1 to input parameters caused an increment in model efficiency. However, comparison between Tables 4–6 and Table 8 indicated that SVM models for this state lead to undesired accuracy and separate data sets yield better predictions. It should be noted that for combined date state, data series with different conditions (i.e., different hydraulic data range, different shape channels, and rough appurtenances) were used altogether. Therefore, the results are not so accurate.

CONCLUSION

In this study, the SVM method was used to predict the hydraulic jump relative energy dissipation in three rectangular, trapezoidal, and sudden expanding channels with different rough elements. The SVM was applied for different models based on flow conditions and geometry of channels and rough elements. The obtained results indicated that predicting the relative energy dissipation in rectangular and trapezoidal channels the model DE(V) with input parameters of Fr_1, $(h_2 - h_1)/h_1$, W/Z as input variables performed more successfully than other models. It was found that using parameter Z/h_1 and W/Z as input parameters caused an increment in models' efficiency. This issue confirmed the importance of the relative height and space of applied rough elements in the relative energy dissipation estimating process. Between two types of rectangular channels, developed models for the case of the channel with rough elements arranged in strip form led to better predictions than elements with staggered arrangement. The superior performance for channel with central sill was the model DE(VII) with inputs parameters of Fr_1 and h_1/B. Also, it was observed that the applied method can successfully predict the relative energy dissipation using only the upstream flow characteristic as input data. Comparison between the results of three channels revealed that developed models in the case of channel with a central sill led to a more accurate outcome. Based on the obtained results

Table 9 | Statistical parameters of the SVM models for combined data

	Optimal parameters			**Performance criteria**					
				Train			**Test**		
Input variable(s)	***C***	ε	γ	***R***	***DC***	***RMSE***	***R***	***DC***	***RMSE***
DE(I): Fr_1	10	0.10	8	0.828	0.653	0.151	0.774	0.566	0.158
DE(II): Fr_1, $(h_2 - h_1)/h_1$	10	0.01	5	0.873	0.760	0.112	0.816	0.665	0.132
DE(III): Fr_1, Z/h_1	8.0	0.01	6	0.832	0.682	0.149	0.750	0.599	0.154

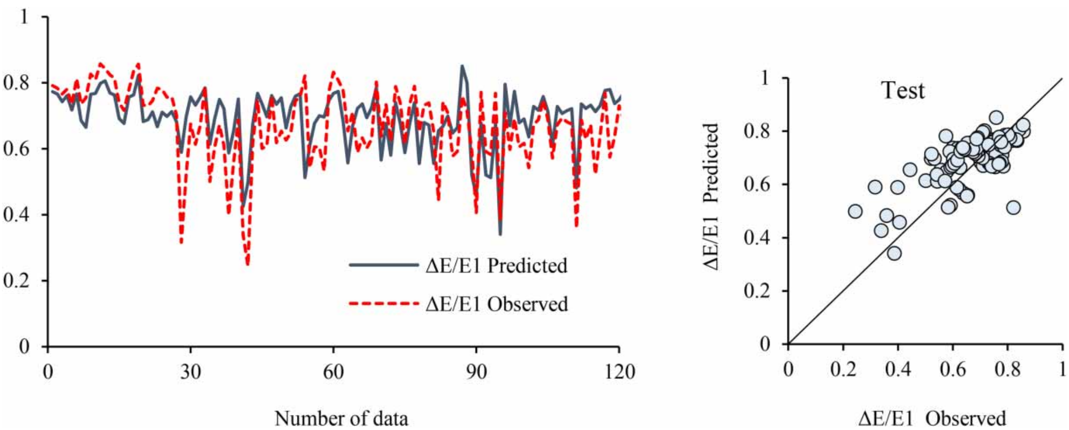

Figure 10 | Comparison of observed and predicted relative energy dissipation for model DE(II), test series.

from sensitivity analysis, it was found that Fr_1 had the most effective role in estimation of the relative energy dissipation than other variables. Comparison between the obtained results from two considered simulations (based on dimensional analysis and raw data) showed that simulation based on dimensional analysis yielded better predictions. It was observed that using flow characteristics in the case of modeling without considering dimensional analysis led to the desired accuracy; however, using rough elements geometry in the modeling process decreased the models' accuracy. It was also observed that mixed data sets led to less accurate outcome. The applied technique was found to be able to predict hydraulic jump energy dissipation in channels with rough elements successfully.

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