Numerical simulation and application of soft computing in estimating vertical drop energy dissipation with horizontal serrated edge

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ABSTRACT

In the present study, FLOW-3D software was used to simulate energy dissipation by a serrated-edge drop, downstream of this structure. For this purpose, 2, 3, and 4 serrations with 2 series of relative dimensions at the edge of the vertical drop, with a relative critical depth range of 0.2–0.35 were used for simulation. Then, using artificial neural network (ANN), support vector machine (SVM), and gene expression program (GEP) methods, the accuracy of numerical models was evaluated. Results showed that increasing dimensions of the edges increased energy dissipation, and the highest and lowest energy dissipation was related to the models with 3 and 4 serrations, respectively, Compared to the edgeless state, the 4-edge model, with relative dimension of 0.1, increased energy dissipation by an average of 20%, and the 3-edge model, with relative dimension of 0.15, by an average of 69%. Results of energy dissipation prediction using ANN, SVM, and GEP methods showed that although all three models have good accuracy for estimating energy dissipation, the accuracy of ANN method with RMSE of 0.0081 and R^2 of 0.9938 in the training phase and RMSE of 0.0125 and R^2 of 0.9805 in the testing phase, is higher than the other two methods.

Key words: artificial neural network, FLOW-3D, gene expression programming, support vector machine, vertical drop

HIGHLIGHT

- Results showed that increasing dimensions of the edges increased energy dissipation. Results of energy dissipation prediction using ANN, SVM, and GEP methods showed that all three models have good accuracy for estimating energy dissipation.

GRAPHICAL ABSTRACT
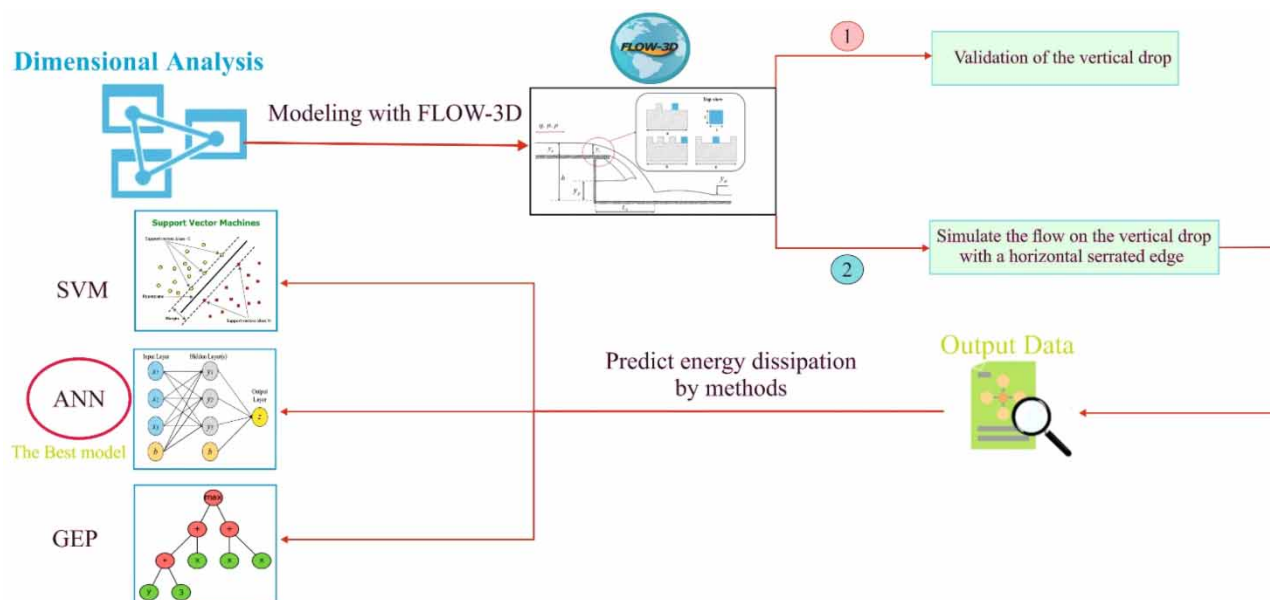
1. INTRODUCTION

Vertical drops, due to their simplicity of construction, are widely used to reduce the steep slope and the volume of earthworks in irrigation and drainage channels. The upstream flow of these structures can be subcritical or supercritical. In several studies, the hydraulic parameters of vertical drops with subcritical upstream flow are investigated. Rand (1955), by defining dimensionless number of the drop, expressed all hydraulic parameters of the vertical drop as a function of this number. Gill (1979) investigated the angle of repose of a drop jet and provided a relationship for its estimation.

Rajaratnam & Chamani (1995), using laboratory data from previous researchers and their experiments, proposed a relationship to predict energy dissipation and pool depth of vertical drop. Esen *et al.* (2004) showed that considering a square step equal to the width of the channel in the vertical drop wall increases energy dissipation compared to the model without a step. In this respect, models with a relative step height of 0.6 in comparison with the vertical drop cause a 90% increase in energy dissipation. Hong *et al.* (2010) showed that increasing the slope of downstream bed increases the fall length of the drop.

Farouk & Elgamal (2012) investigated the vertical drop using FLUENT software. They showed that as the discharge increased, the depth of the pool increased. Mansouri & Ziaei (2014) reported an increase in the energy dissipation of a vertical drop equipped with an end threshold compared to a simple vertical drop using FLUENT software. Liu *et al.* (2014) studied the effect of upstream slope of the vertical drop and stated that with increasing the slope of upstream bed, the pool depth decreases.

Chiu *et al.* (2017) by considering different dimensions of a rectangular pit at the foot of the drop (in the pool), numerically examined the flow over it. Results showed that three types of flow regimes (i.e., skimming, nappe, and periodic oscillatory) are created on this structure. Formation of such regimes depends on the geometry and flow rate.

Kabiri-Samani *et al.* (2017) investigated the flow on a vertical drop equipped with a network dissipator. They showed that the use of these plates reduces basin by about 60% to 75% compared to a simple vertical drop. Sharif & Kabiri-Samani (2018) showed that by increasing the downstream depth of vertical drop equipped with a network dissipater, air-water interference is reduced. Daneshfaraz *et al.* (2020) investigated vertical drops equipped with a double horizontal screen. Results showed that using these screens, compared to a single screen, does not affect energy dissipation.

Haghiabi *et al.* (2017) simulated the discharge coefficient of labyrinth weirs by MPL and ANFIS models. By analyzing the results, they stated that the ANFIS model is more accurate. Also, the discharge coefficient of labyrinth weirs and arch labyrinth using the support vector machine (SVM) by Roushangar *et al.* (2018) were examined. Results showed that this method has high accuracy for predicting discharge coefficient of labyrinth weirs. Majedi Asl *et al.* (2020) using the SVM, gene

expression program (GEP), and nonlinear regression models, investigated the scour of bridge piers based on the geometric characteristics. The results showed that SVM predicted results close to the actual values.

In a study by Daneshfaraz et al. (2021a), hydraulic parameters of vertical drop with double horizontal screen were predicted by using SVM model. The results stated that SVM predicted the values of hydraulic parameters with appropriate accuracy and low error. Daneshfaraz et al. (2021b) investigated the performance of SVM model in predicting the effect of horizontal screen diameter on hydraulic parameters of the vertical drop. Based on the evaluation criteria, it was found that SVM performs well in estimating the energy dissipation and the pool depth of a vertical drop.

Studies of supercritical flow producing structures such as vertical drops show that researchers and hydraulic engineers are always looking for how to increase energy dissipation downstream of these structures and minimize the cost of constructing a stilling basin. Since the effective factor in vertical drop energy dissipation is turbulence created inside the pool, so considering the horizontal serration at its edge can cause turbulence by passing flow through and between the serrations. For this purpose, in the present study, by considering the horizontal serrated edges, their effect on energy dissipation of vertical drop is numerically investigated using FLOW-3D software. Recently, the use of artificial intelligence methods to predict the parameters of hydraulic structures has become popular. Studies showed that these methods accurately estimate hydraulic parameters. Therefore, the application of artificial neural network (ANN), SVM, and GEP methods in predicting the vertical drop energy dissipation with horizontal serrated edges was evaluated.

2. MATERIALS AND METHODS

2.1. Dimensional analysis

According to Figure 1, the energy dissipation of a vertical drop with a horizontal serrated edge can be affected by discharge rate per unit width (q), flume width (B), drop height (h), surface tension (σ), gravity acceleration (g), water density (ρ), water viscosity (μ), critical depth (y_c), number of serrations (n), and length and width of serration (T):

$$\Delta E = \varphi_1(q, B, h, \sigma, \rho, \mu, g, y_c, T, n) \tag{1}$$

By choosing g, h, and ρ as iterative parameters and using Buckingham Π theorem, the dimensionless parameters become as follows:

$$\frac{\Delta E}{h} = \varphi_2\left(\frac{q}{h\sqrt{gh}}, \frac{q\rho}{\mu}, \frac{\sigma}{\rho h^2 g}, \frac{y_c}{h}, \frac{B}{h}, n, \frac{T}{h}\right) \tag{2}$$

$$\frac{\Delta E}{h} = \varphi_3\left(Fr_u, \text{Re}, We, \frac{y_c}{h}, \frac{B}{h}, n, \frac{T}{h}\right) \tag{3}$$
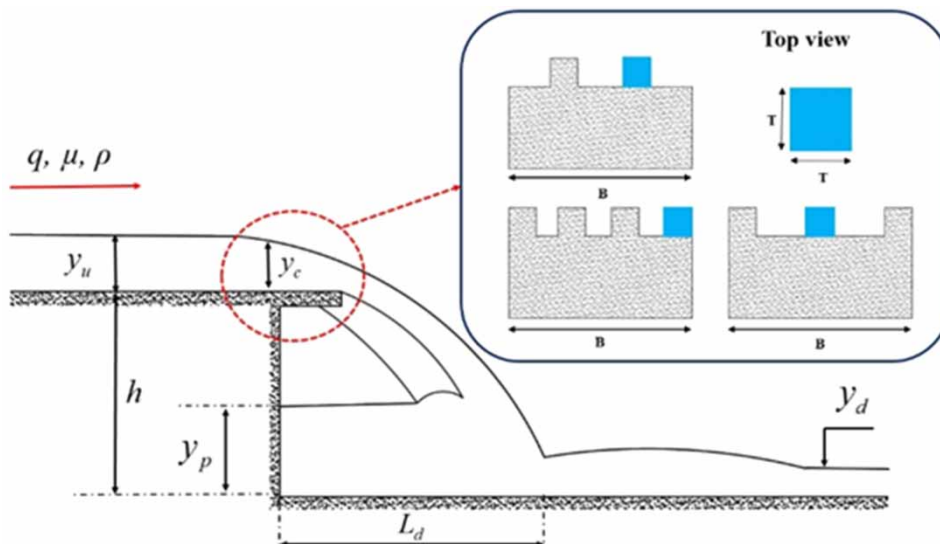

Figure 1 | Schematic of flow on a vertical drop with a horizontal serrated edge.

where Fr_u, Re, We, and y_c/h represent the Froude number upstream of the drop, Reynolds number, Weber number, and relative critical depth, respectively. The Fr_u due to the subcritical flow upstream of the drop and criticality of depth near the falling edge is omitted (Rand 1955). Also, the effect of Re and We due to the turbulence of flow along with the model (Re $\geq$ 35021) and small surface tension due to the sufficient flow depth in the model, is omitted (Bagherzadeh *et al.* 2021; Daneshfaraz *et al.* 2021c). The B/h ratio is considered constant (Chiu *et al.* 2017) and the y_c/h (drop number) is considered (Rand 1955). Therefore, by dividing the T/h to it, the relative dimensions of the serrated edges can be considered as $T/B = \alpha$. Since the relative energy dissipation of the total vertical drop is expressed as the difference between specific energy (total energy) upstream and downstream of the drop to its total upstream energy ($\Delta E/E_u$) (Rajaratnam & Chamani 1995), so instead of $\Delta E/h$ in relation (3) of $\Delta E/E_u$ is used. Therefore, relation (3) is rewritten as relation (4):

$$\frac{\Delta E}{E_u} = \varphi_4 \left(\frac{y_c}{h}, n, \frac{T}{B} = \alpha \right) \tag{4}$$

In the above relation, relative critical depth ranges from 0.2 to 0.35, number of serrations is 2, 3, and 4 and relative dimensions of the serrated edges are 0.1 and 0.15 ($T/B = (0.10 - 0.15)$).

2.2. FLOW-3D numerical model

2.2.1. Governing equations and turbulence model

In the present study, FLOW-3D software (version 11.2) was used to numerically simulate a vertical drop with horizontal serrated edge. One of the prominent features of this software is the ability to simulate free-surface flow by VOF method (Ghaderi *et al.* 2020a, 2020b). FLOW-3D software uses the Eulerian-Eulerian approach to simulate flow and solves equations explicitly and implicitly. The laws governing the continuous turbulent flow of an incompressible and viscous fluid by the continuum and momentum equations (Navier-Stokes) are expressed as follows:

$$\frac{\partial u_i}{\partial x_i} = 0 \tag{5}$$

$$u_j \frac{\partial u_i}{\partial x_j} = -\frac{1}{\rho} \frac{\partial p}{\partial x_i} + \frac{\partial}{\rho \partial x_i} \left(\mu \frac{\partial u_i}{\partial x_j} - \overline{u'_i u'_j} \right) + g_i \tag{6}$$

where u_i and u_i' are average velocity and oscillating velocity in x direction, p and g_i are kinematic pressures and weight forces, respectively. For the three perpendicular directions in Cartesian coordinates, ($x_i = x, y, z$), ($u_i = u, v, w$), ($u_i' = u', v', w'$), and ($i = 1, 2, 3$). A turbulence model is required to simulate Reynolds' stress expression ($\overline{u'_i u'_j}$) in Equation (6). FLOW-3D software uses Prandtl mixing-length models, a turbulent kinetic energy equation, model of two equations of k-ε, renormalized group (RNG), and a large eddy simulation model (LES) to simulate turbulence.

In the present study, the RNG turbulence model was used for simulation the turbulence in the water flow because of its acceptable accuracy and success in prior studies (Aydin & Emiroglu 2013; Azimi & Shabanlou 2020; Ghaderi *et al.* 2020a, 2020b).

2.2.2. Laboratory model specifications and numerical model validation

Using AutoCAD software, a 3D shape of a vertical drop geometric structure with horizontal serration was designed. Then the output was taken in STL format and entered into FLOW-3D software. The results of the Rajaratnam & Chamani (1995) laboratory model were used for validation. According to their study vertical drop with height of 25 cm, width of 46 cm and relative critical depth range of 0.2–0.35 was considered. The relative downstream depth was used to validate numerical results with the laboratory. 2, 3, and 4 serrations were used to simulate the flow on the vertical drop with a horizontal serrated edge. The serrations were square shape, with dimensions of 6.9 and 4.6 cm (0.15 and 0.1 times the flume width) and 2 cm thick. The 2, 3, and 4 serrations were placed symmetrically on the edge of the drop, so that the transverse distance between the edges was equal. The boundary conditions were: At the input, volume flow rate, at the downstream, outflow, for the walls and floor, wall condition, and at the upper boundary, symmetry. According to Dean (1978), the required length for flow development is 55 times the flow depth. Therefore, according to the present study, minimum length for flow development as well as reducing the number of grids and computational time, is 3 m. Figure 2 shows the boundary conditions of the numerical model.
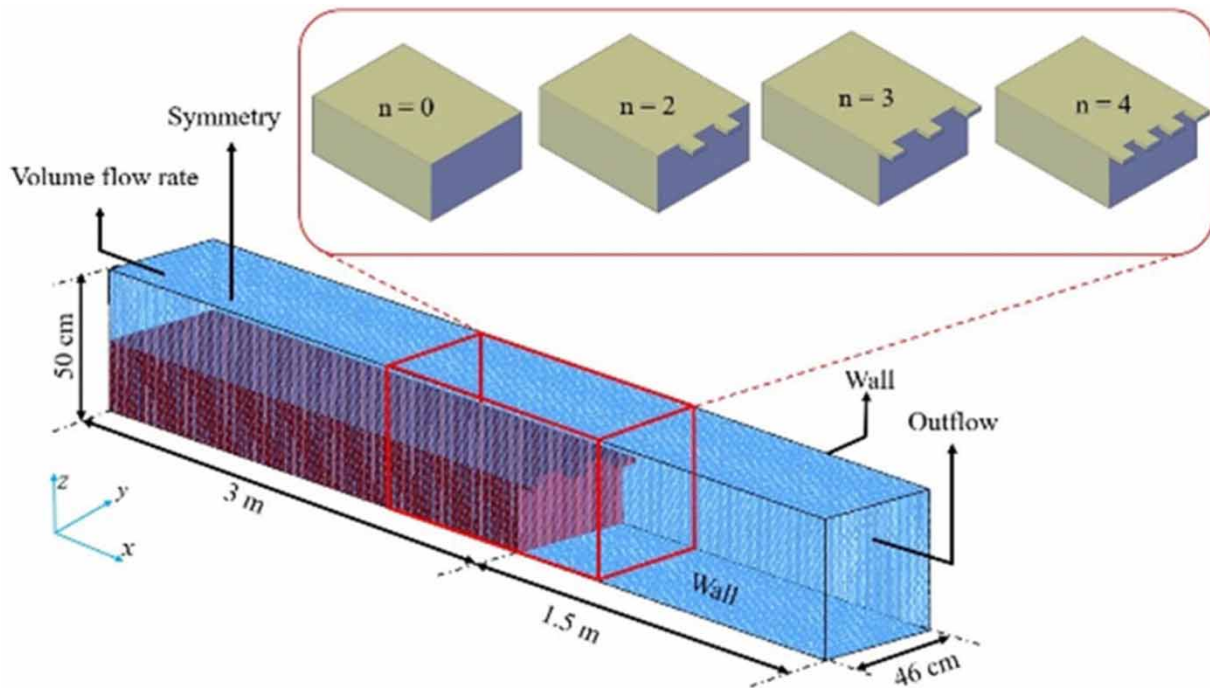
Figure 2 | Boundary conditions and meshing of the numerical model.

Several cells size were utilized to select the appropriate size. Finally, a total number of 1,237,500 cells, with largest and smallest cells size of 1.19 cm and 0.833 cm, respectively, were used. Errors and evaluation criteria for simulate and experimental data, for downstream relative depth, are shown in Figure 3.

Figure 3 shows that total number of computational grids considered for the numerical model provides acceptable results compared to the laboratory model. Therefore, to reduce the effect of computational grid on the simulation results, for all hydraulic models of the present study, this number of grid sizes was considered with the RNG turbulence model.
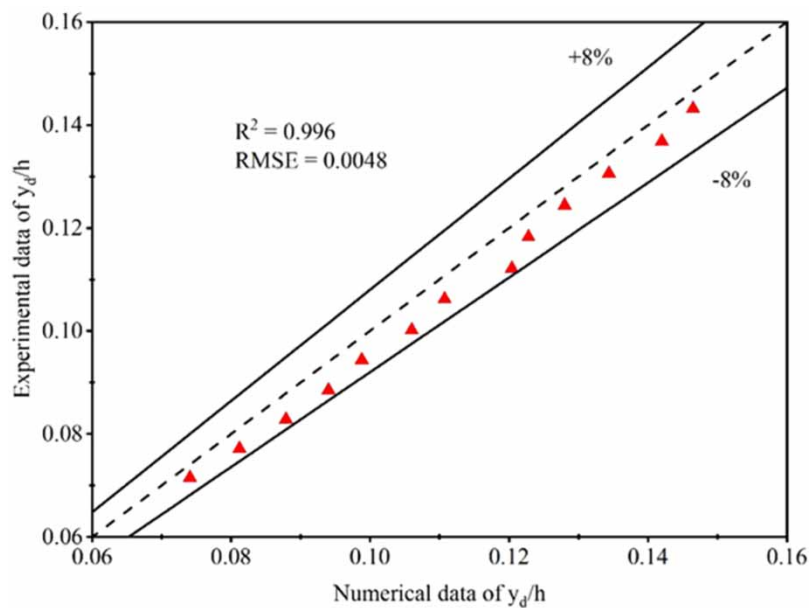

Figure 3 | Comparison of experimental and numerical data.

2.3. ANN model

ANN is a continuous nonlinear system and connecting structure that can mimic the behavior of human brain in dealing with the input information. It is based on the operation of neural networks by neurons, which is the smallest unit of information processing in the network. As the neurons come together, layers form. Each neural network consists of three input, hidden and output layers. Inputs are introduced to the network at the input layer; they are processed at the hidden or middle layer, and network responses are generated at the output layer. Neural networks have different types and structures; one of which is multilayer perceptron (MLP) neural network, and this method has been used in the present study. In the present study, Statistica software was used to predict energy dissipation by a multilayer perceptron (MLP) neural network. Quasi-Newton methods (BFGS) were used to train the multilayer perceptron and a hyperbolic tangent function to construct the output layer. The neural network had three neurons in the input layer (y_c/h, n, α) and one neuron in the output layer ($\Delta E/E_u$). Also, the minimum hidden layer of the neural network was 3 and the maximum was 10, which was the best model of in the hidden layer 9. Figure 4 shows the structure of the MLP neural network for the present study.

2.4. SVM model

SVM is a kind of data-driven algorithm similar to the ANN. This method is one of the learning methods that is used to solve classification, regression, and prediction problems. Problem solving includes two phases of training and testing. This method, unlike artificial intelligence methods that reduce computational error, targets operational risk as a target function and obtains the optimal value. In 2D space, there is an infinite number of lines for separating data into two categories, the closest training data to the support vector separator page. Also, when data separation is not possible linearly, they can be separated linearly by mapping the data to a feature space. This is done with kernel functions. Choosing the type of SVM kernel is very important in solving problems, and in problems where the type of data and their nature are not known, Gaussian (RBF) and ring kernel (ERBF) functions are used (Roushangar & Koosheh 2015; Dasineh *et al.* 2021). In the present study, the RBF function was used. Statistica software was used to predict energy dissipation by the SVM. This method, introduced the input data (y_c/h, n, α) and output $\Delta E/E_u$ data are to the software. Models based on the RBF function were trained. The optimal gamma (γ), which is the main feature of the SVM model, was determined by trial and error. The gamma range is between 0.01 and 100. Gamma 3 was selected as the optimal gamma of the best model. Figure 5 shows the schematic of the research process in the SVM model.

2.5. GEP model

The GEP method was first developed by Ferreira (2001). As the genetic algorithm, this program uses simple, linear chromosomes of constant length, and branch structures of different sizes and shapes are expressed as trees. GEP uses the popular roulette wheel method of selecting individuals, using simple elitism, keeping the best individuals of one generation for the next, and using several genetic operators to propagate modified individuals. The first step in the GEP algorithm is to generate the initial population of solutions. This can be by a random process or by using some information about the problem. The chromosomes are then represented as a tree expression (ETS), which is also evaluated according to a fitting function. The fitting function is usually evaluated by processing several target problems, also called fits. If satisfactory quality is found from one solution, or generations reach a certain number, evolution stops, and the best solution found so far is reported.
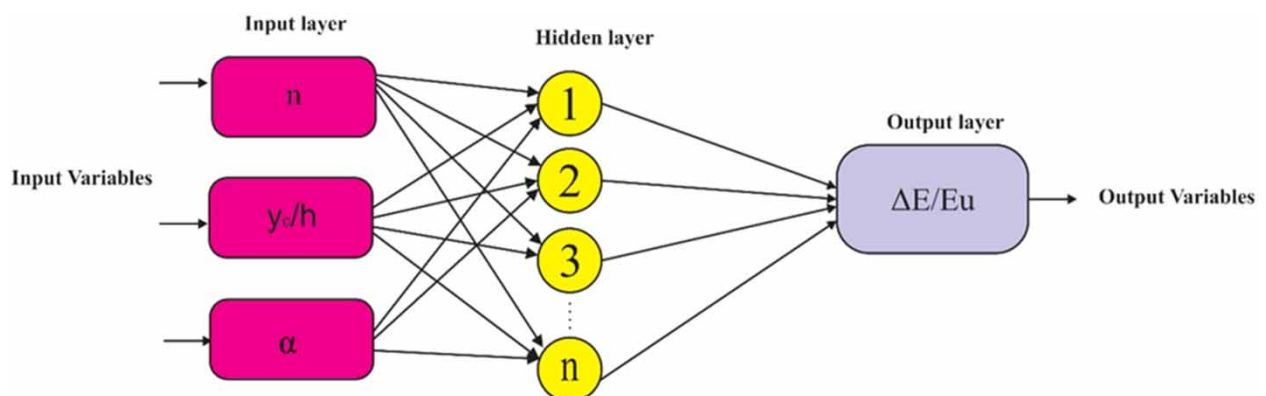

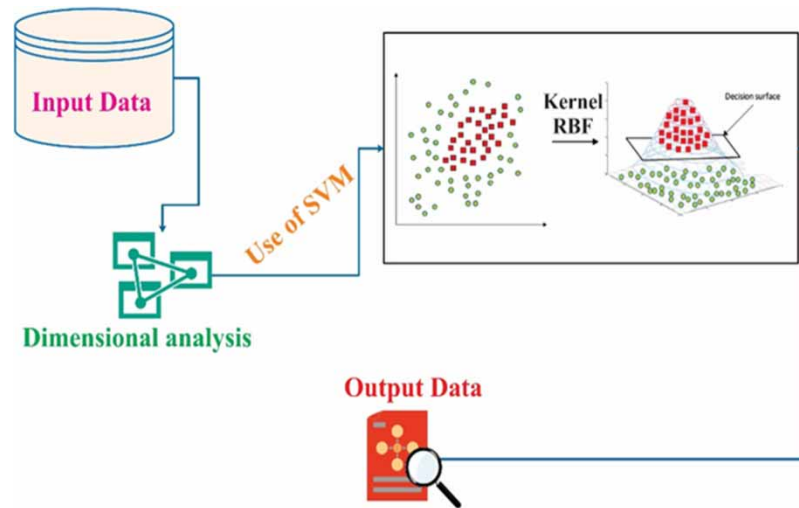**Figure 4** | Neural network structure used in the present study.

Figure 5 | Schematic of the present research process in the SVM model.

On the other hand, if the stopping conditions are not met, the best solution of the present generation is kept (i.e., elite selection) and the rest of the solutions are left to the selection process. Based on the selection of the best parents having a better chance of producing children, the whole process is repeated for several generations, and as the generations progress, population quality is expected to improve on the average (Lopes & Weinert 2004; Depnath & Chaudhuri 2010). In the present study, GeneXproTools software was used to predict the parameter energy dissipation. The combination of GEP model operators, after trial and error, finally is ($+$, $-$, $\times$, $\div$, exp, Ln, $tanh$, $power$). The parameters used to predict the energy dissipation of the present research in the GEP model are also presented in Table 1. The criterion for stopping the implementation of the GEP model was generation number, and this number was defined as 1000.

2.6. Evaluation criteria

In the present study, determination coefficient (R^2), root mean square error (RMSE), normalized root mean square of error (NRMSE), and mean absolute percentage error (MAPE) were used as evaluation criteria to compare the results of prediction

Table 1 | Parameters used in the GEP model

Parameters	value
Head size	7
Number of chromosomes	30
Number of genes	3
Mutation rate	0.044
Inversion rate	0.1
One-point recombination rate	0.3
Two-point recombination rate	0.3
Gene recombination rate	0.1
Gene transposition rate	0.1
IS transposition rate	0.1
RIS transposition rate	0.1
Fitness function error type	RMSE
Linking function	+

models of relative energy dissipation of the vertical drop (Equations (7)–(10)):

$$R^2 = \left(\frac{n \sum X_{Num} X_{Pre} - (\sum X_{Num})(\sum X_{Pre})}{\sqrt{n(\sum X_{Num}^2) - (\sum X_{Num})^2} \sqrt{n(\sum X_{Pre}^2) - (\sum X_{Pre})^2}} \right)^2 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{1}^{n} (X_{Num} - X_{Pre})^2} \tag{8}$$

$$NRMSE(\%) = \frac{RMSE}{\frac{\sum_{1}^{n} X_{Num}}{n}} \times 100 \tag{9}$$

$$MAPE(\%) = 100 \times \frac{1}{n} - \sum_{1}^{n} \frac{X_{Num} - X_{Pre}}{X_{Num}} \tag{10}$$

where X_{Pre} and X_{Num} are predicted and numerical values. It should be noted that the best model is the model in which RMSE is zero and R^2 is one, and also NRMSE and MAPE values are less than 10%.

3. RESULTS AND DISCUSSION

3.1. FLOW-3D numerical model

The ratio of the difference between upstream total energy ($E_u = h + 1.5y_c$) and downstream specific energy of the structure (ΔE) to the energy upstream of the structure (E_u) is considered to be relative energy dissipation of the vertical drop (Bakhmeteff 1932). Relative energy dissipation for all models is shown in Figure 6. It is observed that for all models, increasing the relative critical depth reduces the total relative energy dissipation and the models with a serrated edge have increased the energy dissipation compared to the model without serration. This increase in energy dissipation is higher in models with 3 serrations and the lowest value is related to the 4-serrations model. On the other hand, by comparing Figure 6(a) and 6(b), it is observed that increasing the dimensions of the edge has also led to an increase in energy dissipation.

As can be seen in Figures 7 and 8, turbulence and irregularities in the downstream streamlines of falling jet are one of the main reasons for increased energy dissipation of the serrated models. The presence of edges causes two types of nappe flow to occur on the edges and between the edges. Interaction of these two nappe flows, after colliding with the channel bed, causes turbulence in the downstream lines. The most turbulence and irregularity created in the streamlines for both relative
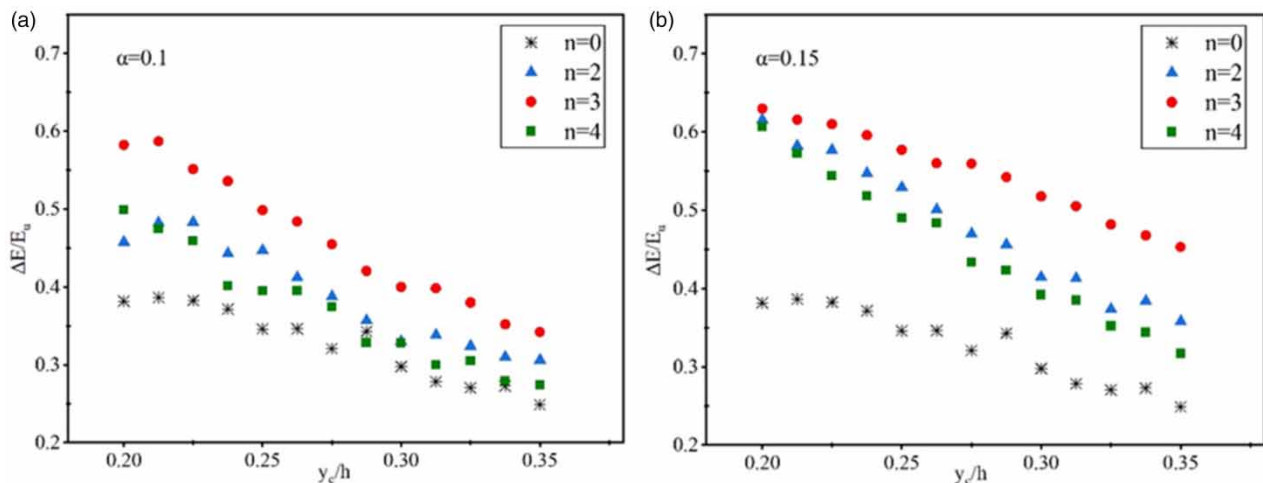

Figure 6 | Changes in relative energy dissipation versus relative critical depth.
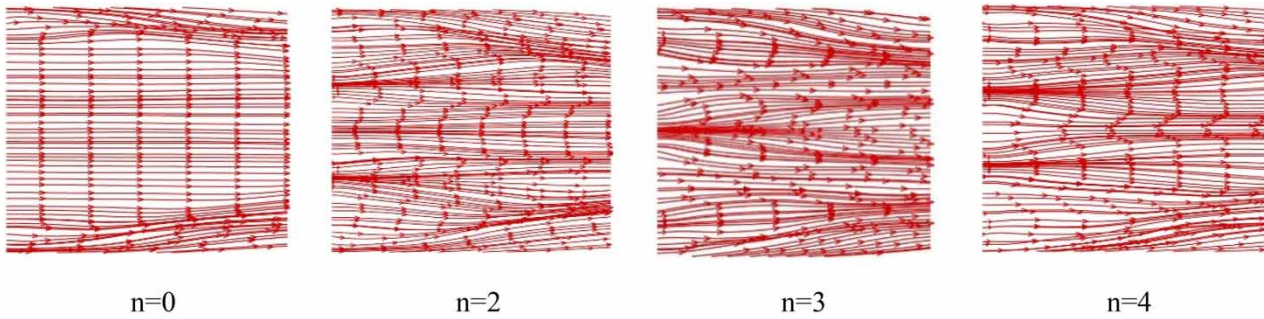
Figure 7 | Streamlines after jet fall for relative critical depth of 0.3 in relative dimensions of 0.1.
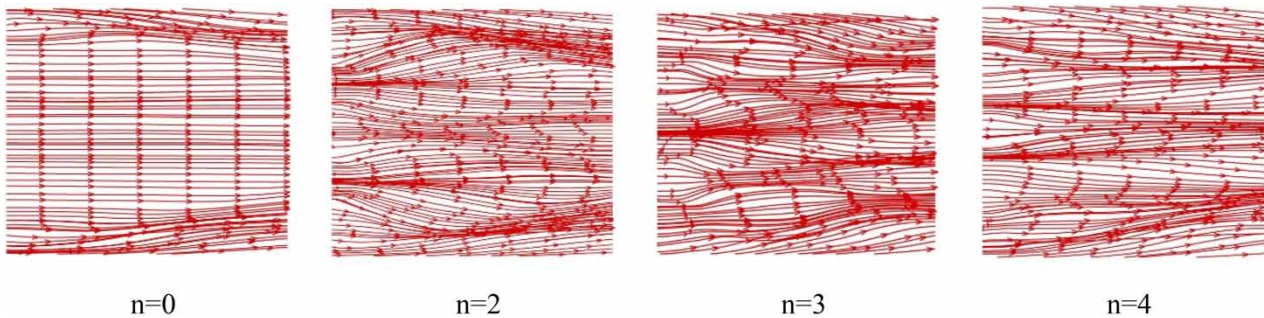

Figure 8 | Streamlines after jet fall for relative critical depth of 0.3 in relative dimensions of 0.15.

dimensions of the edges is related to the model with 3 serrations. For this reason, this model has the highest relative down-stream depth compared to the other models. Increasing the number of serrations and their dimensions, increases the falling flow intensity on the edges and decreasing it increases the intensity between the edges. Therefore, the more the amount of fall of two nappe flows is the same, the more their interference will cause turbulence after the collision. For this purpose, models with 4 serrations, in both relative dimensions, have the lowest energy dissipation.

Table 2 shows average increase in energy dissipation in a vertical drop with a serrated edge compared to the no serration model ($n = 0$).

According to Table 2, increasing the serration dimensions increases the energy dissipation and the vertical drop with 3 ser-rations, in both relative dimensions, has the highest increase in energy dissipation. Therefore, it can be said that the vertical drop with 3-serration edge and relative dimensions of 0.15 is the most optimal model among the present research models.

3.2. Results of ANN, SVM, and GEP models

To evaluate the accuracy of the FLOW-3D model, the amount of energy dissipation was predicted and compared using the ANN, SVM, and GEP methods. For this purpose, a total of 104 data were obtained from the output of FLOW-3D model, of which 75% of the data were used for training and the remaining 25% for testing. For the results to be accompanied by the least error during the prediction process, the training process was performed with several replicates. Based on dimen-sional analysis, energy dissipation is due to the relative critical depth, number of serrations, and dimensional ratio of the serration. Comparing the results of the three models presented in Table 3 shows that the ANN model with the lowest error (RMSE = 0.0081) and the highest determination coefficient ($R^2 = 0.9938$) for the training phase and

Table 2 | Increased energy dissipation of vertical drop with serrated edge compared to no serration model

n	Increase in relative dimensions of 0.1 (%)	Increase in relative dimensions of 0.15 (%)
2	20	46
3	40	69
4	13	37

Table 3 | Prediction results for relative energy dissipation of the vertical drop

model	Training				Testing			
	R²	RMSE	NRMSE (%)	MAPE (%)	R²	RMSE	NRMSE (%)	MAPE (%)
ANN	0.9938	0.0081	1.92	1.59	0.9805	0.0125	3.10	2.41
SVM	0.9814	0.0136	3.20	3.01	0.9723	0.0139	3.46	3.02
GEP	0.8049	0.0433	10.18	8.41	0.7603	0.0434	10.80	9.44
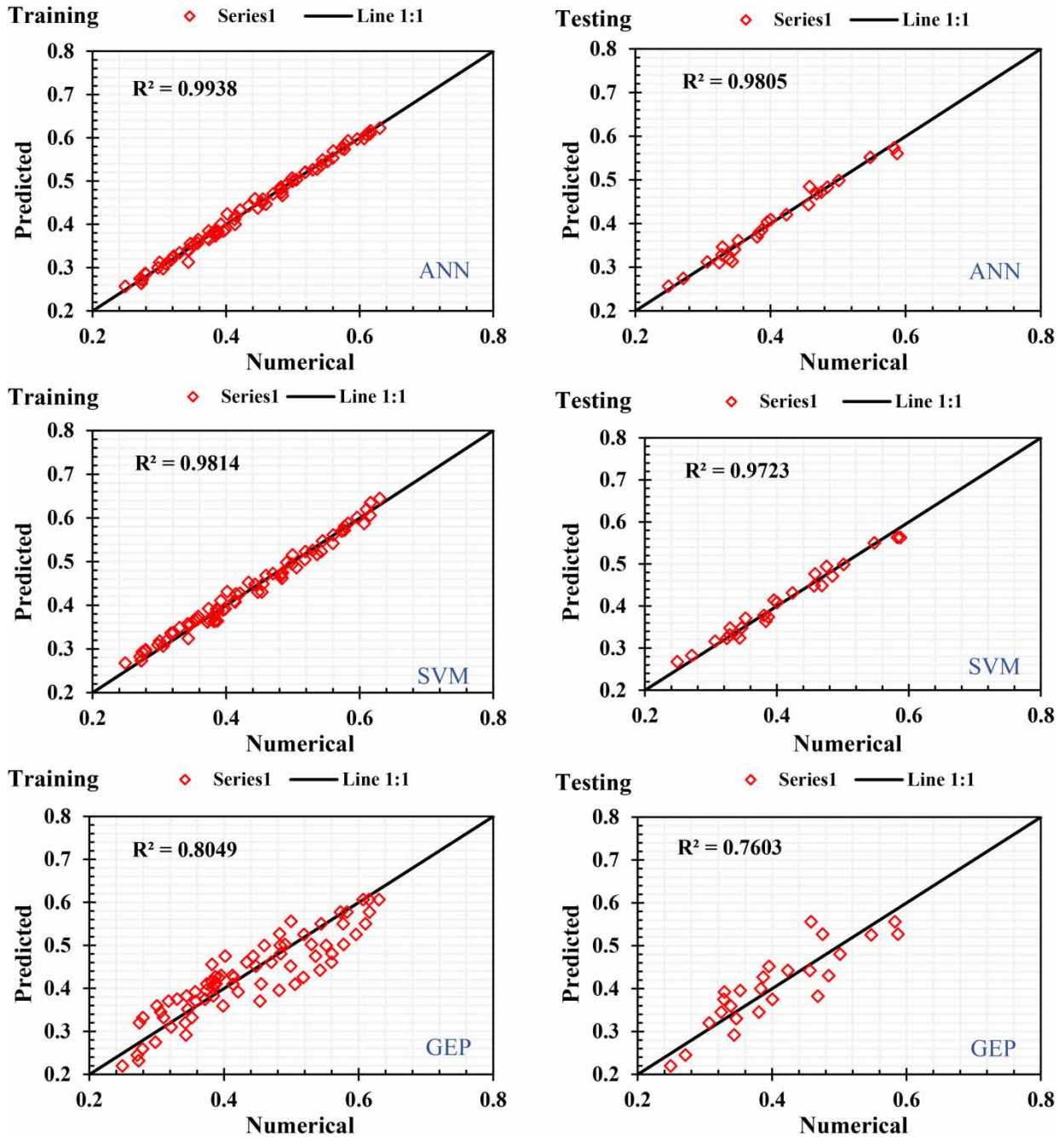
Figure 9 | Comparison of numerical and predicted model results for training and testing phases.

RMSE $= 0.0125$ and $R^2 = 0.9805$ for the testing phase was selected as the best model for prediction of downstream energy dissipation of vertical drops.

Figure 9 compares relative downstream energy dissipation values obtained by FLOW-3D model and three artificial intelligence models. It can be seen that the ANN model has results close to the numerical model and has predicted it with good accuracy. The ANN model has good determination coefficient compared to SVM and GEP methods and the error rate of this model is less than 3%, which indicates its high capability in estimating the energy dissipation of a vertical drop. It can be seen
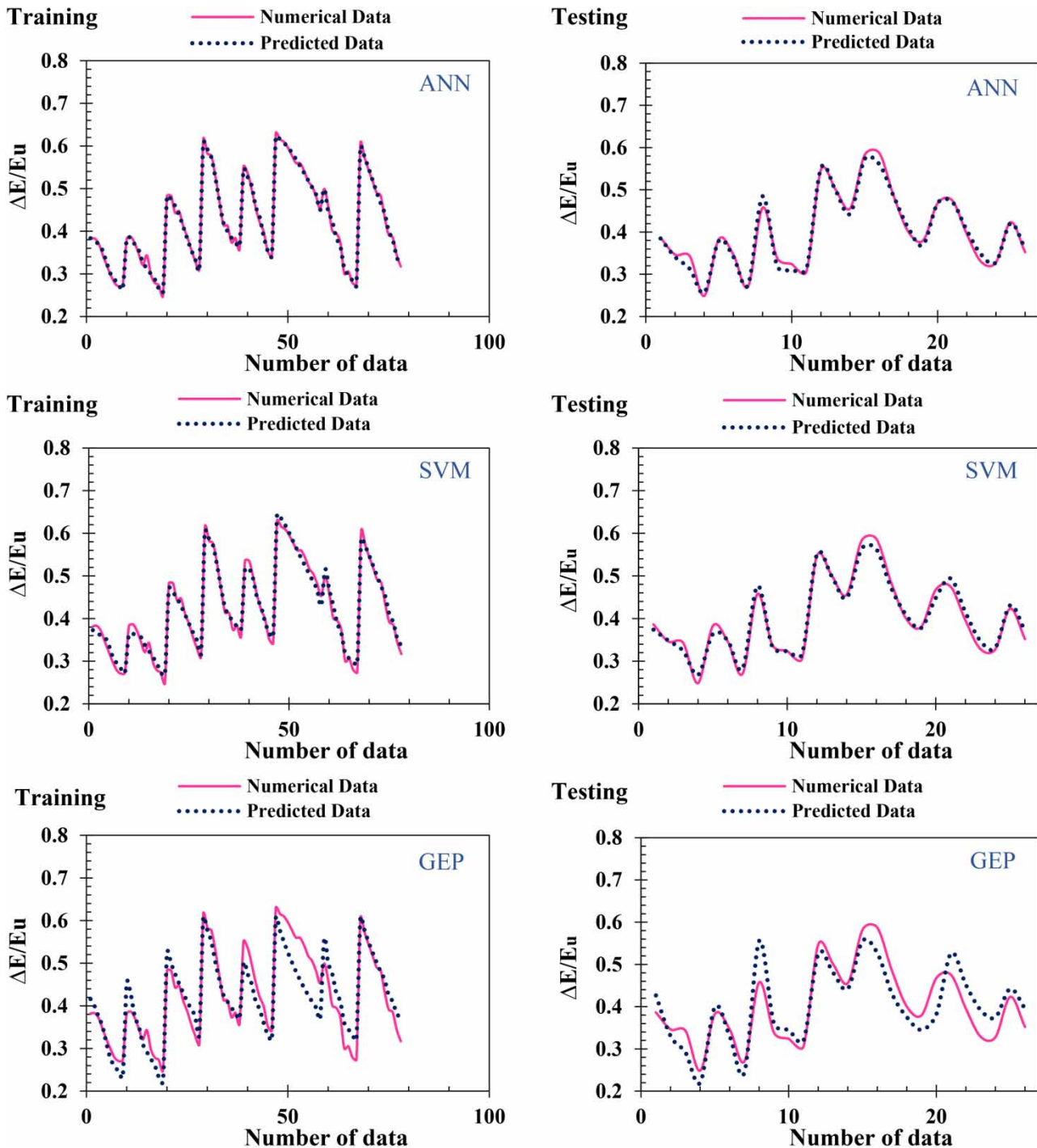

Figure 10 | Energy dissipation values of numerical and predicted models versus number of data.

that in all the models, the results of the training phase are associated with less error than the testing phase, which means that no error occurred during the network training.

Distribution curves of the numerical model and ANN, SVM, and GEP models for number of data in the training and testing phases are presented in Figure 10. According to this figure, it is clear that in comparison between the three models and the numerical model, the ANN model has the lowest error, and the output data of this model has a very good agreement with the numerical data. During the prediction process at the points of maximum and minimum energy dissipation, the outputs of the ANN model performed better than the SVM and the GEP models. After the ANN model, the results of the SVM model are also acceptable in estimating downstream energy dissipation compared to the GEP model.

For detailed review of the output results of the three prediction models and the numerical model, violin plots and Wisher boxes are presented in Figure 11. It can be seen that the model that is similar in appearance and close to the numerical model is the ANN model. Also, after the ANN model, the SVM model can be considered as the best model in predicting downstream energy dissipation, which has a much better performance than the GEP model.

3.3. Sensitivity analysis

Sensitivity analysis was performed by the ANN model to determine the effect of each of the independent variables on the prediction of downstream energy dissipation of the vertical drop. For this purpose, in each run, by removing each parameter from the series of input parameters, the model was run again and the effect of the omitted parameter on reducing the accuracy of the model was investigated using evaluation criteria. According to Table 4, it is observed that by removing the y_c/h parameter, the error values increase by a large amount, and determination coefficient decreases sharply. Therefore, it can be said that y_c/h parameter has the greatest effect on estimating downstream energy dissipation of the vertical drop. A careful look at Table 4 shows that by using all independent parameters, the best result is obtained. Also, after the relative critical depth parameter, α and n parameters had little effect on reducing the accuracy of the prediction.

4. CONCLUSIONS

Results showed that increasing the dimensions of the edges and the relative critical depth increases flow turbulence and energy dissipation and maximum and minimum irregularities in the streamlines and energy dissipation occurs in 3 and 4 serrations, respectively. Compared to the edgeless model, the serrated edge models increase energy dissipation by 20% to 69%. Next, downstream energy dissipation parameter of a vertical drop with horizontal serrated edge was predicted by ANN, SVM, and GEP methods. Results showed that all three methods were able to predict energy dissipation. The ANN model with RMSE = 0.0081 and R^2 = 0.9938 for training phase and RMSE = 0.0125 and R^2 = 0.9805 for testing phase was recognized as the best model. Comparison of the output results of the ANN model shows a very good similarity with the results of FLOW-3D numerical model. Also, based on the sensitivity analysis, it was found that y_c/h is the most effective parameter
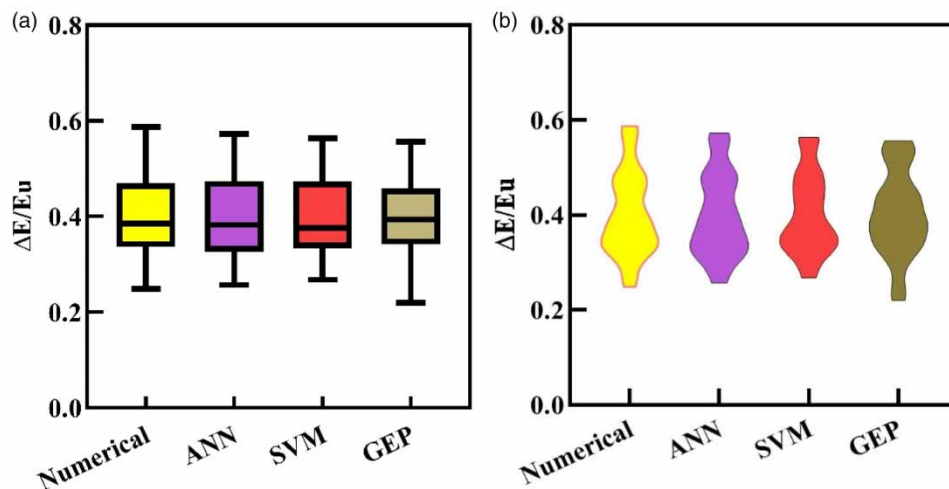

Figure 11 | Comparison of numerical model results with predictive models: (a) Violin Plot (b) Wisher Box.

Table 4 | Results of sensitivity analysis for the best model

Involved parameters	Omitted parameters	Training				Testing			
		R^2	RMSE	NRMSE (%)	MAPE (%)	R^2	RMSE	NRMSE (%)	MAPE (%)
y_c/h, n, α	__	0.9938	0.0081	1.92	1.59	0.9805	0.0125	3.10	2.41
y_c/h, n	A	0.7900	0.0422	9.96	8.30	0.7824	0.0453	11.26	9.59
y_c/h, α	N	0.8613	0.0362	8.5457	6.82	0.8048	0.0386	9.59	7.40
n, α	y_c/h	0.5494	0.0698	16.45	14.81	0.3975	0.0693	17.22	15.5

in predicting downstream energy dissipation of the vertical drops. Since downstream of the vertical drop is usually used as a stilling basin to dissipate the destructive kinetic energy of the flow and basin dimensions depending on the Froude number, using these horizontal serrations on the edge has such advantages as reducing basin dimensions, increasing energy dissipation and the need for less downstream depth to form a hydraulic jump. Therefore, considering the hydraulic and economic conditions of the design, it is possible to use serrated edges in real projects. Meanwhile, it is suggested that in the future studies, the effect of angle of these edges on energy dissipation be investigated and evaluated.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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