

Predicting Discharge Capacity in Semi-Cylindrical Side-Contracted Flumes Using MLPNN and GMDH

Abbas Parsaie^{1*}, Farid Ahmadi², Mohammad Bahrami Yarahmadi³

¹Department of Hydraulic Structures, Faculty of Water and Environmental Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran

Article Info	ABSTRACT
Article type: Research Article	Objective: The primary objective of this study is to develop and evaluate two soft-computing models (MLPNN and GMDH) for accurately predicting the discharge capacity of Semi-Cylindrical Side-Contracted Flumes (SMBF) under both free-flow and submerged regimes. The research aims to identify the optimal model structure, determine the most influential dimensionless parameters via dimensional analysis, and perform a comprehensive sensitivity analysis. A systematic comparison between the black-box MLPNN and the interpretable GMDH model is conducted to recommend the most reliable and accurate predictive tool.
Article history: Received 23 December 2025 Revised 17 June 2026 Accepted 05 September 2026 Published online 22 December 2026	Methods: The study employed two data-driven soft-computing models: a Multilayer Perceptron Neural Network (MLPNN) and the Group Method of Data Handling (GMDH). First, dimensional analysis using the Buckingham II theorem was applied to derive the key dimensionless parameters (e.g., h/w , w/B , ht/hs) as model inputs. Experimental data (450 free-flow and 170 submerged records) were collected from published sources and randomly split into training and testing sets (70-30 ratio). Model performance was evaluated using statistical indices (R^2 , RMSE), and sensitivity analysis was conducted to identify the most influential input parameters on discharge prediction. Results: The MLPNN model achieved outstanding accuracy with $R^2 = 0.987$ (free-flow) and $R^2 = 0.992$ (submerged), and $RMSE \approx 0.001$ for both regimes, significantly outperforming the GMDH model ($R^2 \approx 0.88-0.96$). Sensitivity analysis revealed that the depth-to-throat ratio (h/w) is the most influential parameter under free-flow conditions, while the contraction ratio (w/B) dominates under submerged flow. The GMDH model, though less accurate, provided superior interpretability due to its transparent, self-organizing polynomial structure. Overall, MLPNN is recommended for high-precision applications, whereas GMDH serves as a robust alternative when model transparency is prioritized.
Keywords: SMBF flume MLPNN GMDH Sensitivity Analysis	Conclusions: Both MLPNN and GMDH models demonstrated high capability in predicting SMBF flume discharge, with MLPNN showing superior accuracy ($R^2 > 0.98$) for both free and submerged flows, while GMDH offered better interpretability. Sensitivity analysis confirmed that h/w governs free-flow discharge, whereas w/B dominates under submerged conditions due to backwater effects. The study concludes that MLPNN is recommended for high-precision field applications, while GMDH serves as a transparent alternative when understanding parameter relationships is essential.

*Corresponding author, Email: Parsaie@scu.ac.ir.

Cite this article: Parsaie, A., Ahmadi, F., Bahrami Yarahmadi, M.(2026). Predicting Discharge Capacity in Semi-Cylindrical Side-Contracted Flumes Using MLPNN and GMDH. Journal of New Approaches in Water Engineering and Environment, 5(4), 1-18. <https://doi.org/10.22034/nawee.2026.574888.1194>



© The Author(s).

DOI: <https://doi.org/10.22034/nawee.2026.574888.1194>

Publisher: Gonbad Kavous University.

Introduction

Effective water resources management, particularly in agriculture and irrigation-drainage networks, necessitates accurate flow discharge measurement. Precision in flow gauging is not only crucial for equitable water allocation and reducing stakeholder conflicts but is also essential for assessing hydraulic structure performance and optimizing water use (Achour et al. 2024; Ghasemi and Vatankhah, 2024). Conventional discharge measurement methods, such as electromagnetic and ultrasonic equipment, are primarily based on direct velocity and cross-sectional area measurements. While these methods offer acceptable accuracy, they are costly, require high technical expertise, and are economically inefficient for repeated implementation in extensive irrigation networks. Furthermore, the gradual degradation of these instruments' accuracy over time necessitates periodic calibration, posing an additional challenge for the operational management of such networks (Bos, 1989). In contrast, indirect discharge measurement methods, relying on a unique relationship between discharge and flow depth at a control section, e.g., weirs (Bahrami Yarahmadi et al., 2026; Parsaie, 2025), gates (Parsaie and Haghiabi 2026; Salamati and Masoudian, 2025), and flumes (Shahinejad et al., 2022), offer an efficient and cost-effective alternative. These methods rely on creating a "hydraulic control point" in the flow path, where critical flow conditions (typically achieved through section contraction or bed-level change) establish a definitive stage-discharge relationship (Moglen 2022). Among these, flumes are widely used in irrigation and drainage networks due to their simple construction, resistance to sedimentation, and adaptability to various channel cross-sections. Based on the contraction method, flumes come in various types, including rectangular, trapezoidal, circular, and composite shapes (Achour and Amara, 2023). One efficient type is the SMBF flume, which creates a stable and controllable contraction in the flow section using two side semi-cylinders (installed on the sidewalls of a rectangular channel) (Carollo et al., 2016; Carollo and Pampalone, 2021; Majedi Asl et al., 2026; Parsaie et al., 2023; Samani, 2017; Samani and Magallanez, 1993, 2000). This flume has gained attention among designers and operators of irrigation networks because of its high accuracy, simple structure, and resistance to sediment accumulation. However, the hydraulic performance of SMBF flumes is influenced by numerous parameters, including the contraction ratio (throat width to channel width) and the flow regime—free or submerged (upstream and downstream flow depths) (Carollo et al., 2016). Under free-flow conditions, discharge is solely a function of upstream depth, and calculations are relatively simpler. However, under submerged conditions, where the downstream water level influences hydraulic conditions, the stage-discharge relationship becomes more complex, requiring simultaneous consideration of upstream and downstream depths. This complexity makes accurate modeling of flume behavior under real operational conditions (often accompanied by water level fluctuations) a significant challenge (Aminpour et al. 2020a; Vatankhah and Mohammadi, 2020). In recent decades, the emergence and expansion of soft-computing as a powerful paradigm for modeling complex, nonlinear systems has revolutionized the solution of water engineering problems. Techniques such as Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVM),

decision trees (e.g., M5P), and Group Method of Data Handling (GMDH) models have been successfully employed to predict hydraulic parameters due to their ability to learn from empirical data and capture complex nonlinear relationships ((Bijanvand et al., 2023a, 2023b, 2025). For instance, Puri et al. (2023) used a Random Forest model to predict the aeration efficiency of Parshall and Venturi flumes with very high accuracy. (Sihag et al. 2021) demonstrated that the MARS model outperformed traditional regression models in predicting the aeration efficiency of modified flumes. In the domain of SMBF flumes, Shahinejad et al. (2022) used SVM, MARS, and MLPNN models to simulate flow discharge under free and submerged conditions with remarkable accuracy. However, despite these advancements, a comprehensive study simultaneously focusing on optimizing soft-computing model structures, analyzing input parameter sensitivity, and systematically comparing the efficacy of different models in predicting SMBF flume discharge under both flow regimes is still lacking. The primary objective of this paper is to develop and evaluate soft-computing-based models for accurately predicting the discharge capacity of SMBF flumes under free and submerged flow conditions. To this end, two soft-computing models—the Multilayer Perceptron Neural Network (MLPNN) and the Group Method of Data Handling (GMDH)—will be employed. The specific objectives of this research are:

1. Determining the optimal structure for each model (including the number of hidden layers, number of neurons, and activation function type) through training and validation processes.
2. Extracting and utilizing influential dimensionless parameters (such as depth and contraction ratios) as model inputs, based on precise dimensional analysis of the phenomenon.
3. Conducting sensitivity analysis to identify input parameters that significantly affect model prediction accuracy.
4. Systematically comparing the performance of the MLPNN and GMDH models in predicting discharge under both flow regimes and proposing a highly reliable and accurate model.

Method

The objective of the present research is to develop soft-computing models for estimating the flow discharge in semi-cylindrical side-contracted flumes (rectangular flumes whose width is reduced by semi-cylindrical piers installed on the sidewalls). Figure 1 shows a schematic view of the studied flume and the flow passing through it. In this figure, the diameter of the side semi-cylinders is denoted by D , the channel width by B , the throat width (the width of the flow passage between the cylinders) by W , the upstream flow depth relative to the cylinders (under free-flow conditions) by h and, under submerged conditions, by h_s , the downstream flow depth by h_t , and the flow discharge by Q .

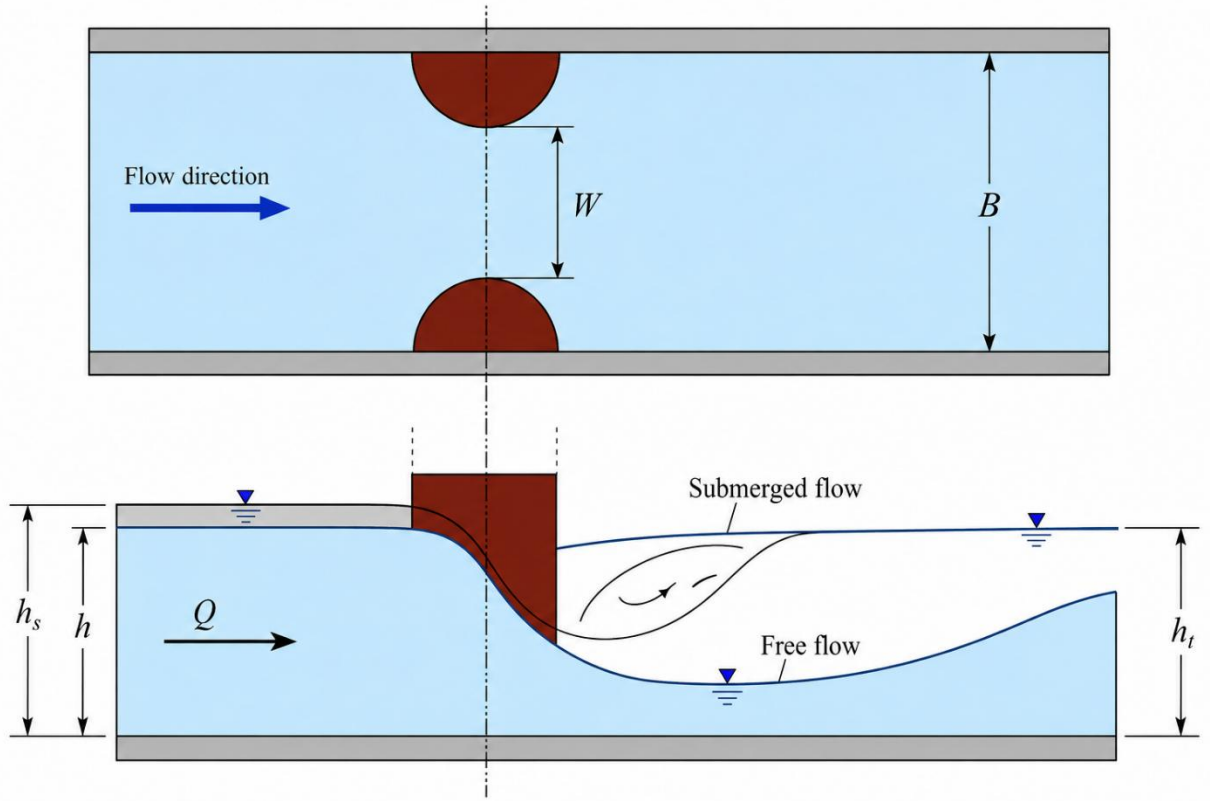


Figure 1- Plan and side view of a rectangular flume containing two side semi-cylinders (free-flow and submerged flow regimes)

To develop soft-computing models for estimating the flow discharge in this flume, it is necessary to determine the input and output variables. For this purpose, the problem must be initially analyzed. Dimensional analysis using the Buckingham Π theorem was employed to investigate the discharge capacity under both free-flow and submerged conditions. The effective parameters for the free-flow condition are presented in Equation (1). The dimensional analysis based on this relationship yields the dimensionless parameters presented in Equation (2). The raw effective parameters for the submerged condition are presented in Equation (3), and the independent dimensionless effective parameters for the submerged condition derived from the dimensional analysis are presented in Equation (4).

$$\varphi(Q, B, W, h, g, \mu, \rho) = 0 \quad (1)$$

$$\frac{Q}{W \sqrt{gh^3}} = \psi \left(r = \frac{W}{B}, \frac{h}{W} \right) \quad (2)$$

Under submerged conditions, in addition to the parameters presented in Equation (1), downstream hydraulic parameters such as the tailwater depth (h_t) are added to the set of effective parameters. Naturally, instead of h , which represented the upstream flow depth, h_s is used.

$$\varphi(Q, B, W, h_s, h_t, g, \mu, \rho) = 0 \quad (3)$$

$$\frac{Q}{W \sqrt{gh_s^3}} = \varphi \left(r, \frac{h_s}{W}, \frac{h_t}{W}, \frac{h_t}{h_s} \right) \quad (4)$$

To develop the soft-computing models, it is necessary to collect data related to flow discharge in Semi-Cylindrical Side-Contracted Flumes. For this purpose, published data from articles by Aminpour et al. (2020b), Vatankhah and Mohammadi (2020), and Baiamonte and Ferro (2007) were collected and utilized. The number of collected data points is 450 for free-flow conditions and 170 for submerged conditions. The statistical characteristics of the data used for free-flow and submerged conditions are presented in Table 1.

Table 1- Range of Geometric and Hydraulic Variables of the Collected Data: Free and submerged Flow Condition

Condition	Rang	B (m)	W (m)	h (m)	ht (m)	hs (m)	Q (cms)
e							
Submerged	Min	0.463	0.158	0.054	0.052	0.055	0.007
	Max	0.973	0.846	0.283	0.390	0.392	0.107
	Average	0.835	0.511	0.152	0.162	0.169	0.053
	STDEV	0.227	0.223	0.050	0.066	0.067	0.026
Free	Min	0.250	0.051	0.024	-	-	1.444
	Max	0.973	0.846	0.296	-	-	102.325
	Average	0.680	0.384	0.132	-	-	35.194
	STDEV	0.306	0.249	0.064	-	-	27.795

Multilayer Perceptron Artificial Neural Network

A Multilayer Perceptron (MLP) neural network is an advanced, nonlinear computational model inspired by the structure of biological neural networks. It possesses the capability to learn complex relationships between input and output variables. This network consists of processing units called neurons, organized in sequential layers (input, hidden, and output). Each neuron, upon receiving input signals, applies trainable weights and a bias (offset), and then generates its output through a non-linear activation function. Common activation functions include sigmoid, hyperbolic tangent (tanh), which grant the network the ability to model non-linear relationships (Fathi et al., 2026). The network training process is carried out using the backpropagation algorithm and gradient-based optimization methods such as Adam or L-BFGS. During this process, the weights are adjusted to minimize the prediction error between the actual values and the network's output. Due to its flexible structure, high generalizability, and ability to process multidimensional data, the MLP has become a powerful tool in the field of data-driven modeling.

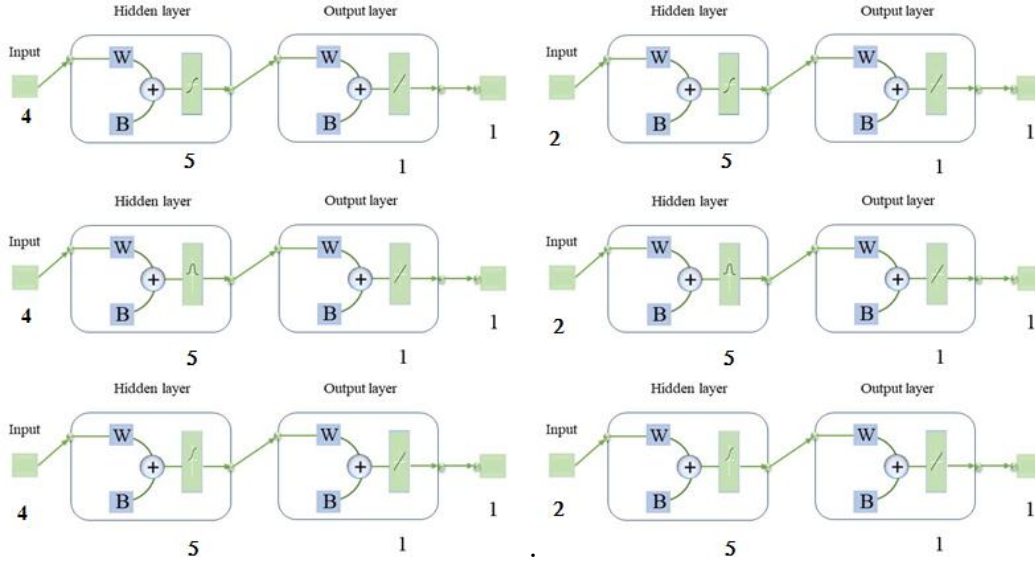


Figure 2- The structure of the MLPNN model for estimating the discharge capacity of SMBF flumes under free-flow (a) and submerged (b) conditions

Group Method of Data Handling (GMDH) Model

The Group Method of Data Handling (GMDH) is a machine learning algorithm belonging to the class of polynomial neural networks. It operates based on the principles of self-organization and evolutionary selection. The primary objective of GMDH is to construct an optimal mathematical model through the gradual combination and competitive selection of basis functions (typically polynomials). Consider an input variable x and an output variable y . In each layer of the GMDH model, all possible pairs of input variables (or outputs from the previous layer) are taken as inputs to simple transfer functions. The most common transfer function is the bivariate quadratic polynomial, expressed as (Bahrami-Yarahmadi et al. 2023):

$$\hat{y}_k = a_0 + a_1x_i + a_2x_j + a_3x_i^2 + a_4x_j^2 + a_5x_ix_j \quad (5)$$

Where x_i and x_j are the two paired input variables in the current neuron. $\hat{y}_k$ is the predicted output for the k -th neuron in this layer. The coefficients $a_0, a_1, \dots, a_5$ are estimated using the Least Squares Method on the training data. The GMDH process is carried out iteratively and layer-by-layer:

1. First Layer: All possible pairs of the original input variables $x_0, x_1, \dots, x_n$ are selected, and for each pair, a second-degree polynomial model is fitted.
2. Evaluation and Selection: The output of each model (neuron) is evaluated on the validation set. The selection criterion is typically the Root Mean Square Error (RMSE) or Mean Absolute Error (MAE):

$$RMSE = \sqrt{\frac{1}{m} \sum_{p=1}^m (y_p - \hat{y}_p)^2} \quad (6)$$

Only the neurons with the lowest error (e.g., the top N neurons) are selected as inputs for the next layer.

3. Subsequent Layers: In each new layer, possible pairs of the selected outputs from the previous layer are used as new inputs for the second-degree polynomial functions. This process continues until a stopping criterion is met, such as no improvement in validation error, reaching a predefined number of layers, or reaching a specified number of final neurons.

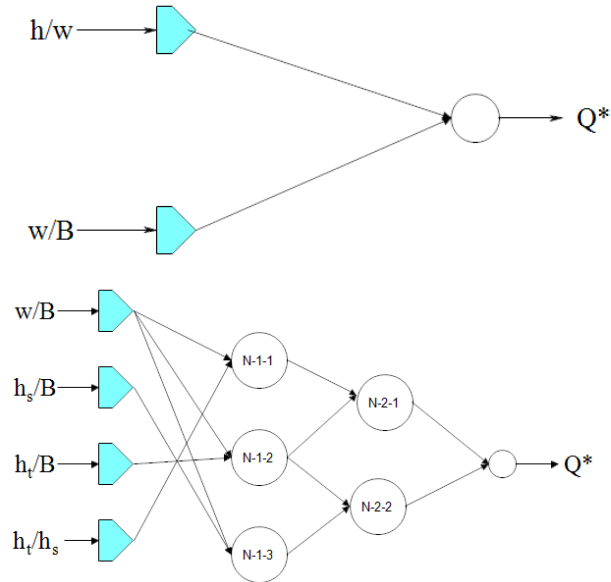


Figure 3- Structure of the developed GMDH model for estimating the discharge capacity of SMBF flumes under free-flow conditions

Results and Discussion

Before developing the soft-computing models, the experimental data related to the geometric and hydraulic parameters of the SMBF flume under both free-flow and submerged flow regimes underwent statistical analysis. To this end, their statistical properties are given in Table 1. For both conditions, Pearson correlation coefficients between the raw variables were calculated (Table 2) and presented in Figure 5.

Table 2- Correlation matrix of variables for estimating the discharge capacity

Condition		B	W	h	ht	hs	Q
Submerged	B	1					
	W	0.75	1				
	h	0.52	0.44	1			
	ht	-	-0.42	0.56	1		
	hs	0.10	-	-0.43	0.48	0.95	1
	Q	-	-0.47	0.46	0.97	1.	1
		0.20				0	
free-flow	B	1					
	W	0.82	1	0.67			
	h	0.19	-0.08	1			
	Q	0.66	0.58	0.67			1

Under free-flow conditions, the strongest direct correlation was observed between discharge (Q) and upstream depth (h) ($r = 0.67$). In contrast, under submerged conditions, the correlation coefficients between discharge and other variables showed a significant decrease, indicating greater complexity of hydraulic relationships in this regime. Supplementary analyses, including violin plots, paired histograms, and correlation heat maps, visually confirmed the distribution and interdependencies of the variables.

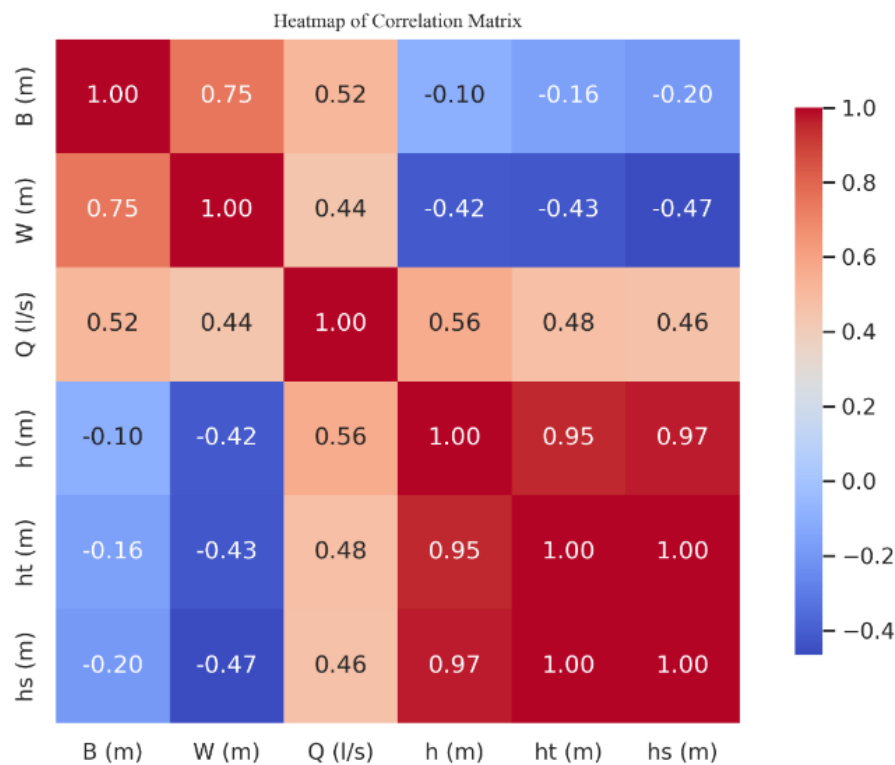


Figure 4-Heatmap of the correlation coefficients for raw variables involved in estimating the discharge capacity of SMBF flumes.

Results of soft-computing Models

This section presents the combined results of developing, training, and testing the two soft-computing models (MLPNN and GMDH) for flow discharge estimation under free-flow and submerged conditions. Following the dimensional analysis, the collected data were randomly divided into training and testing subsets using three different split ratios (60-40, 70-30, and 80-20). Through a trial-and-error process, an MLPNN with a single hidden layer containing five neurons was identified as the optimal structure for both flow regimes (Figure 2). The tangent sigmoid (tansig) activation function consistently yielded the best performance among the tested functions (tansig, logsig, and radbas) and was selected for the final model (Table 3).tansig) activation function consistently yielded the best performance among the tested functions

Table 3- Performance of the MLPNN model under Free-Flow Conditions

Test Set		Train Set		Ratio (Train- Test)	Activation Function
RMSE	R ²	E	RMS	R ²	
2×10 ⁻³	0.951		1×10 ⁻³	0.986	
1×10 ⁻³	0.991		1×10 ⁻³	0.992	Logsig
2×10 ⁻³	0.982		1×10 ⁻³	0.990	
1×10 ⁻³	0.985		1×10 ⁻³	0.989	
1×10 ⁻³	0.987		1×10 ⁻³	0.992	Radbas
2×10 ⁻³	0.981		1×10 ⁻³	0.990	
1×10 ⁻³	0.988		1×10 ⁻³	0.986	
1×10 ⁻³	0.983		1×10 ⁻³	0.987	Tansig
1×10 ⁻³	0.984		0	0.991	

Note: RMSE values of '0' may represent values smaller than the displayed precision (e.g., $< 1 \times 10^{-4}$).

As shown in this table, all three activation functions, across all three split ratios, exhibit suitable accuracy in estimating the discharge capacity of the SMBF flume. Furthermore, varying the percentage share of training and testing data from 60-40 to 80-20 does not significantly affect prediction accuracy for the SMBF flume discharge capacity. prediction accuracy This is because the data are sufficient across the ranges of both the training and testing sets. The 70% training–30% testing split was selected. The distribution of results for the developed neural network model during the training and testing phases is shown in Figure 5. As is evident from these figures, the data corresponding to the neural network results are highly concentrated along the line of perfect fit.

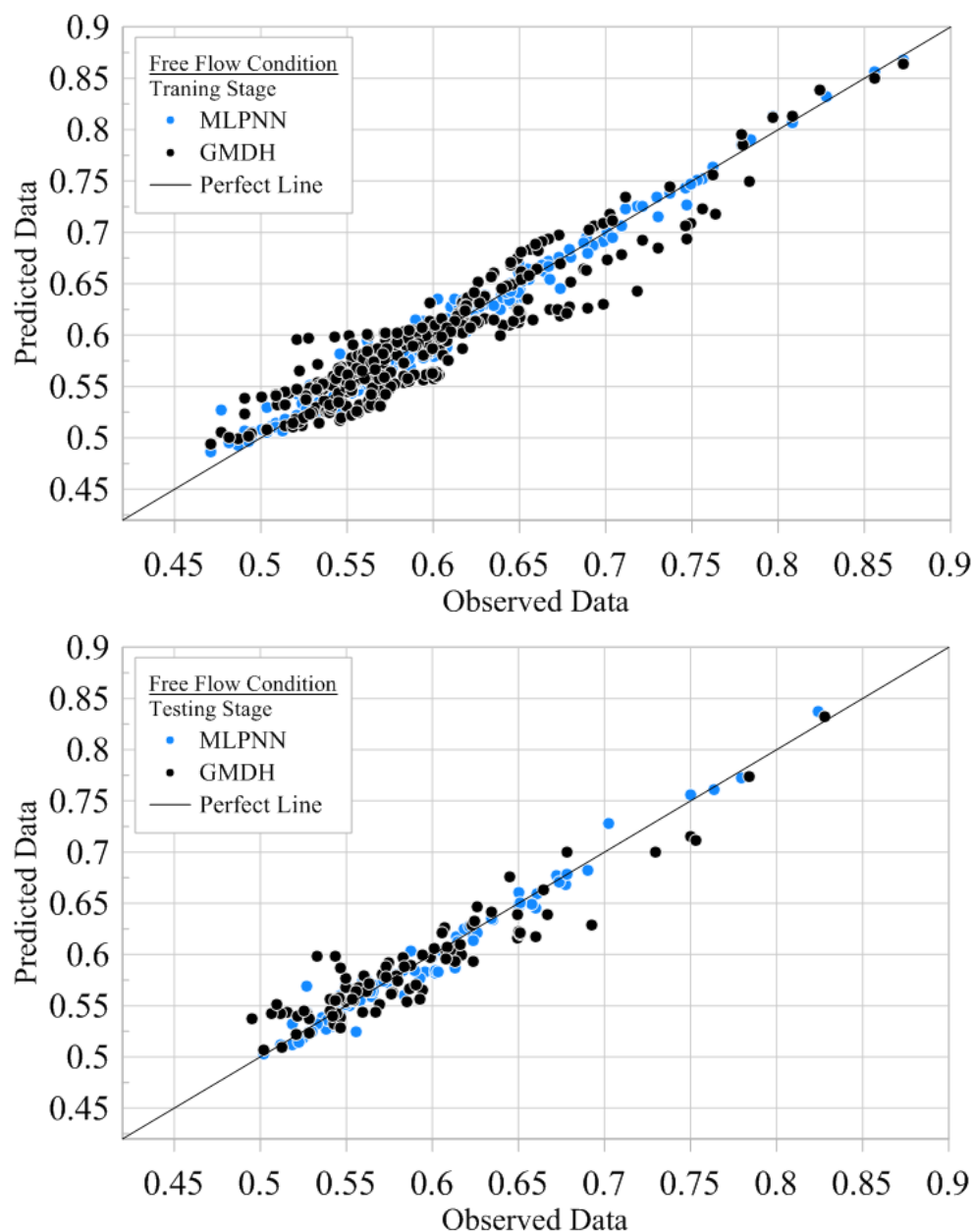


Figure 5- Performance of the developed MLPNN model for estimating the discharge capacity of SMBF flumes under free-flow conditions

The performance of the developed MLPNN under submerged-flow conditions was also evaluated, and its results in the training and testing stages are shown in Figure 6. Notably, four parameters were used as inputs under submerged-flow conditions, in submerged flow conditions (Eq. 4). The statistical indices used to evaluate the models are given in Table 4. As evident from this table, the MLPNN model demonstrated exceptional accuracy, achieving R^2 values above 0.98 and extremely low RMSE for both flow regimes, confirming its powerful capability. An examination of Table 4 and the figures indicates that despite the significant decrease in the correlation coefficients between the effective variables under submerged conditions, the modeling accuracy using the neural network model has not decreased

substantially. It still predicts the discharge capacity of this structure under submerged conditions with adequate accuracy.

Table 4- Consolidated Performance Summary of Optimal MLPNN and GMDH Models

Testing Set		Training Set		Performance (70-30 Split)	
RMSE	R ²	RMSE	R ²	Model	Flow Regime
1×10 ⁻³	0.983	1×10 ⁻³	0.987	MLPNN	Free-Flow
0.021	0.88	0.022	0.87	GMDH	
1×10 ⁻³	0.987	1×10 ⁻³	0.992	MLPNN	Submerged
0.020	0.96	0.016	0.88	GMDH	

Given that the neural network model is a black-box model, the influence of each dimensionless parameter on the output is not explicitly clear. Therefore, sensitivity analysis significantly aids in identifying the more influential parameters. Sensitivity analysis examines changes in the output in response to variations in input parameters (e.g., increases of 10% or 20%). Table 5 presents the sensitivity analysis of the developed MLPNN model. Examination of this table shows that increases of 10% and 20% in the relative head parameter (h/w) lead to proportional increases of 10% and 20%, respectively, in the neural network output for all activation functions. In contrast, a 10% and 20% increase in the cross-section reduction parameter (w/B) result in decreases of 15% and 23%, respectively, in the neural network output.

Table 5-Sensitivity Analysis of the Artificial Neural Network Model for Free-Flow Conditions

20%	10%	Parameter	Activation Function
+0.20	+0.10	h/w	Logsig
-0.23	-0.15	w/B	
+0.20	+0.10	h/w	Radbas
-0.23	-0.15	w/B	
+0.20	+0.10	h/w	Tansig
-0.23	-0.15	w/B	

Note: Values indicate the proportional change in model output (e.g., +0.10 = 10% increase).

The physical significance of the sensitive parameters is clear. Under free-flow conditions, the upstream depth (h) directly controls the approaching velocity and specific energy. The throat width (w) represents the contracted section where critical flow occurs. Thus, h/w physically reflects the degree of flow concentration and the available energy head driving the discharge. This parameter's dominance is consistent with Bernoulli's principle, where discharge is primarily a function of upstream head in critical-flow measuring devices. Under submerged conditions, the tailwater submerges the control section, reducing the influence of upstream depth. In this regime, the contraction ratio (w/B) determines the severity of flow contraction and the resulting energy losses due to eddy formation and boundary shear. A smaller w/B ratio (a narrower throat) creates stronger acceleration and larger head losses, which directly affect the discharge capacity under backwater effects. This finding aligns with classical weir and flume hydraulics, where geometric contraction governs flow behavior under submerged regimes. Sensitivity analysis was also conducted for the neural network model under submerged flow conditions, and the results are shown in Table 6. Examination of this table indicates that increases of 10% and 20% in the relative upstream head (h_s/w) result in increases of 8% and 12% in the output, respectively. Increases of 10% and 20% in the relative submergence cause decreases of 3% and 9%, respectively. h_t/h_s causes a 3% and 9% decrease in the results, respectively.

Table 6. Sensitivity Analysis of the Artificial Neural Network Model for Submerged Flow Conditions

20%	10%	Parameter	Activation Function
<hr/>			
+0.12	+0.08	h_s/w	Logsig
+0.09	+0.06	h_t/w	
-0.09	-0.03	h_t/h_s	
-0.18	-0.12	w/B	
+0.12	+0.08	h_s/w	Radbas
+0.09	+0.06	h_t/w	
-0.09	-0.03	h_t/h_s	
-0.18	-0.12	w/B	
+0.12	+0.08	h_s/w	Tansig
<hr/>			

20%	10%	Paramete r	Activation Function
+0.09	+0.06	h_t/w	
-0.09	-0.03	h_t/h_s	
-0.18	-0.12	w/B	

The GMDH model, operating according to the principles of self-organization, constructed its architecture automatically. Under free-flow conditions, the first hidden layer of the GMDH network contains a maximum of one neuron; under submerged conditions, it can contain a maximum of six neurons (Figure 3). The performance of GMDH under both flow regimes (free and submerged) is given in Table 4. As can be seen from this table, varying the percentage share of training and testing data from 60-40 to 80-20 does not significantly affect modeling accuracy. The 70% training–30% testing split was selected. The distribution of GMDH model results in free-flow conditions in the training and testing stages is shown in Figure 5, and for submerged-flow conditions in the same stages is shown in Figure 6. As is evident from these figures, the GMDH model does not exhibit a specific systematic overestimation or underestimation tendency.

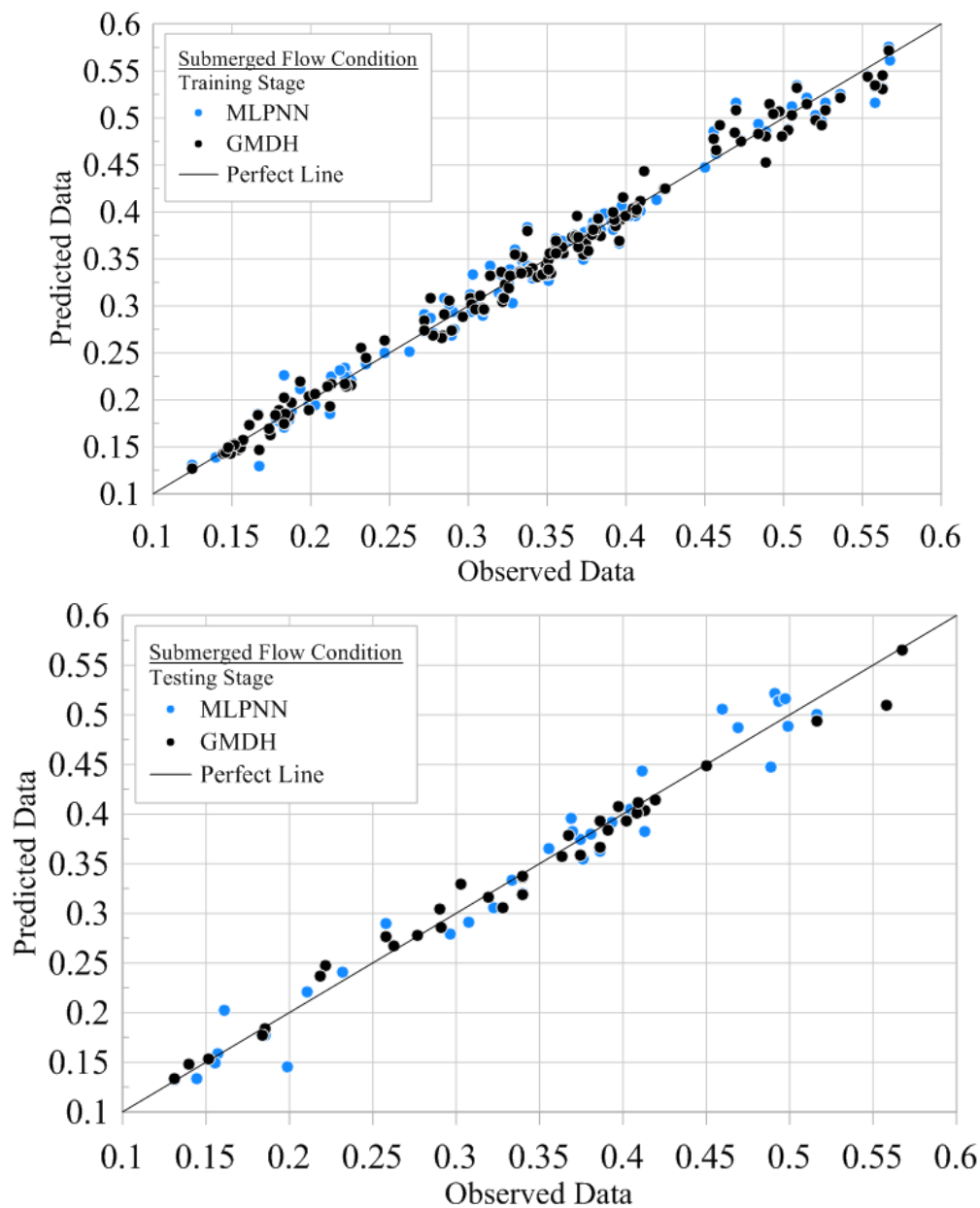


Figure 6- Performance of the developed MLPNN model for estimating the discharge capacity of SMBF flumes under submerged-flow conditions

The same approach used for the sensitivity analysis of the MLPNN model was applied here. The results of the sensitivity analysis for the GMDH model under free-flow conditions show that increases of 10% and 20% in the relative head (h/w) lead to average increases of 17% and 36%, respectively, in the GMDH model outputs. Conversely, a 10% and 20% increase in the relative throat width (w/B) result in decreases of 13% and 39%, respectively. The results of the sensitivity analysis for the GMDH model under submerged conditions are presented in Table 7. Examination of this table reveals that changes of 10% and 20% in the relative upstream head (h_s/w) increase the GMDH model outputs by averages of 12% and 17%, respectively.

Compared to the MLPNN model, the GMDH model exhibits greater sensitivity to input variations.

Table 7- Sensitivity Analysis of the GMDH Model for Submerged Flow Conditions

20%	10%	Parameter
+0.17	+0.12	h_s/w
+0.12	+0.08	h_t/w
-0.16	-0.07	h_t/h_s
-0.16	-0.09	w/B

Comparison with Previous Studies

Previous research has predicted the discharge capacity of SMBF flumes using Support Vector Machine (SVM), Multivariate Adaptive Regression Splines (MARS), and Multilayer Perceptron Neural Network (MLPNN) models. The statistical indices for the SVM model were $R^2 = 0.99$, RMSE = 0.011 for training and $R^2 = 0.98$, RMSE = 0.014 for testing. For the MARS model, the indices were $R^2 = 0.99$, RMSE = 0.007 (training) and $R^2 = 0.98$, RMSE = 0.018 (testing). The superior performance of MLPNN over GMDH can be attributed to its flexible non-linear mapping capability through multiple interconnected neurons with trainable weights and biases. Unlike GMDH, which restricts interactions to second-degree polynomial combinations of paired inputs, MLPNN can approximate arbitrarily complex functions through its layered structure and non-linear activation functions (tansig). This allows MLPNN to capture higher-order interactions among hydraulic parameters that GMDH's quadratic surface cannot adequately represent. Additionally, MLPNN's backpropagation algorithm optimizes all network weights simultaneously, whereas GMDH employs layer-wise local optimization, which may lead to suboptimal global solutions.

Conclusion

This study aimed to develop and evaluate soft-computing models for the accurate prediction of discharge capacity in rectangular flumes contracted with side semi-cylinders (SMBF) under free-flow and submerged conditions. Two models, the Multilayer Perceptron Neural Network (MLPNN) and the Group Method of Data Handling (GMDH), were developed using reliable laboratory data, and their performance was rigorously assessed using statistical indices and sensitivity analysis. Both MLPNN and GMDH models demonstrated a very high capability in predicting discharge under both flow regimes. The MLPNN model, with a single hidden layer containing five neurons and appropriate activation functions, achieved R^2 values of 0.99 for free-flow and 0.98 for submerged conditions. Under free-flow conditions, the h/w and, under

submerged conditions, the contraction ratio (w/B) had the most significant influence on discharge prediction. Sensitivity analysis revealed that the MLPNN model was more sensitive to changes in the h/w parameter under free-flow, while the w/B parameter was more influential under submerged conditions. Although the GMDH model exhibited higher sensitivity to input variations in free-flow, it demonstrated acceptable stability under submerged conditions. In terms of prediction accuracy and stability, the MLPNN model showed superior performance to GMDH. However, due to its self-organizing structure, mathematical transparency, and interpretability, the GMDH model can be a suitable choice in scenarios where understanding the relationship between parameters is crucial. Future studies should combine these models with optimization algorithms for more precise determination of the flume's geometric and hydraulic parameters.

Author Contributions

“Conceptualization, Abbas Parsaie; writing—original draft preparation, Farid Ahmadi; writing—review and editing, Mohammad Bahrami Yarahmadi. All authors have read and agreed to the published version of the manuscript. Bahrami Please turn to the Credit taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

All authors contributed equally to the conceptualization of the article and writing of the original and subsequent drafts.

Data Availability Statement

Data are available from the authors upon request.

Ethical Considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

Funding

The study was funded by the Shahid Chamran University of Ahvaz, Ahvaz, Iran, and Grant No. SCU.WH1402.72091.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) did not use AI.

References

- Achour, B., Amara, L., 2023. Discharge coefficient relationship for the SMBF flume. *Larhyss Journal*, 123–143. ASJP.
- Achour, B., Mehta, D. Azamathulia, H., 2024. A New Trapezoidal Flume for Open Channel Flow Measurement Design, Theory, and Experiment. *Larhyss Journal* P-ISSN 1112-3680/E-ISSN 2521-9782, (59): 157–179.
- Aminpour, Y., Vatankhah, A. R., Farhoudi, J. 2020a. Experimental modeling of flumes with two semi-cylinder contractions (free and submerged flows). *Flow Measurement and Instrumentation*, 76: 101844. <https://doi.org/10.1016/j.flowmeasinst.2020.101844>.
- Aminpour, Y., Vatankhah, A. R., Farhoudi, J. 2020b. Experimental modeling of flumes with two semi-cylinder contractions (free and submerged flows). *Flow Measurement and Instrumentation*, 76: 101844. <https://doi.org/10.1016/j.flowmeasinst.2020.101844>.
- Bahrami Yarahmadi, M., Basitnezhad, M., Parsaie, A. 2026. An experimental investigation of the discharge coefficient in compound pivot weirs. *Flow Measurement and Instrumentation*, 112: 103511. <https://doi.org/10.1016/j.flowmeasinst.2026.103511>.
- Bahrami-Yarahmadi, M., Parsaie, A., Shafai-Bejestan, M., Heydari, M., Badzanchin, M. 2023. Estimation of Manning Roughness Coefficient in Alluvial Rivers with Bed Forms Using soft-computing Models. *Water Resources Management*, 37 (9): 3563–3584. <https://doi.org/10.1007/s11269-023-03514-z>.
- Baiamonte, G., Ferro, V. 2007. Simple Flume for Flow Measurement in Sloping Open Channel. *Journal of Irrigation and Drainage Engineering*, 133 (1): 71–78. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2007\)133:1\(71\)](https://doi.org/10.1061/(ASCE)0733-9437(2007)133:1(71)).
- Bijanvand, S., Asgharzadeh-Bonab, A., Parsaie, A., Afaridegan, E. 2025. Enhanced Prediction of Discharge Coefficients in Harmonic Plan Circular Weirs Using Advanced Machine Learning and Ensemble Techniques. *Flow Measurement and Instrumentation*, 102812. Elsevier.
- Bijanvand, S., Mohammadi, M., Parsaie, A. 2023a. Estimation of water's surface elevation in compound channels with converging and diverging floodplains using soft-computing techniques. *Water Supply*, 23 (4): 1684–1699. <https://doi.org/10.2166/ws.2023.079>.
- Bijanvand, S., Mohammadi, M., Parsaie, A., Mandala, V. 2023b. Modeling of discharge in compound open channels with convergent and divergent floodplains using soft-computing methods. *Journal of Hydro informatics*, 25 (5): 1713–1727. <https://doi.org/10.2166/hydro.2023.014>.
- Bos, M. G. 1989. Discharge measurement structures. International Institute for Land Reclamation and Improvement, (third revised edition): 464.
- Carollo, F. G., Di Stefano, C., Ferro, V., Pampalone, V. 2016. New Stage-Discharge Equation for the SMBF Flume. *Journal of Irrigation and Drainage Engineering*, 142 (5): 04016005. [https://doi.org/10.1061/\(ASCE\)IR.1943-4774.0001005](https://doi.org/10.1061/(ASCE)IR.1943-4774.0001005).
- Carollo, F. G., Pampalone, V., 2021. Testing the Stage-Discharge Relationship in Sloping SMBF Flumes. *Journal of Irrigation and Drainage Engineering*, 147 (5): 04021010. [https://doi.org/10.1061/\(ASCE\)IR.1943-4774.0001558](https://doi.org/10.1061/(ASCE)IR.1943-4774.0001558).
- Ghasemi, M., Vatankhah, A. R., 2024. Experimental study of simple flumes with converging triangular walls. *Flow Measurement and Instrumentation*, 97: 102623. <https://doi.org/10.1016/j.flowmeasinst.2024.102623>.
- Majedi Asl, M., Momeni, M. R., Nikmehr, S., Omidpour Alavian, T., 2026. Laboratory and Numerical Investigation of Flow Rate in SMBF Flumes Using Flow3D and Comparison with Energy Equations. *Journal of New Approaches in Water Engineering and*

- Environment, 5 (1): 58–75. Gonbad Kavous University. <https://doi.org/10.22034/nawee.2025.517806.1152>.
- Moglen, G. E. 2022. Fundamentals of open channel flow. CRC Press.
- Parsaie, A. 2025. Impact of Surface Roughness on Discharge Coefficient of Crump Weirs: An Analytical Investigation. *New Approaches in Water Engineering and Environment*, 4 (2): 180–187. Gonbad: Gonbad Kavous University. <https://doi.org/10.22034/nawee.2025.510942.1146>.
- Parsaie, A., Dehdar-Behbahani, S., Devi, G. S. L., Haghiabi, A., Afaridegan, E., 2023. The discharge coefficient of SMBF flumes under free and submerged conditions. *Applied Water Science*, 13 (12): 236. <https://doi.org/10.1007/s13201-023-02048-4>.
- Parsaie, A., Haghiabi, A., 2026. Investigation of discharge coefficient and energy dissipation in free-flowing Quarter-Circular Gates. *Journal of Hydraulic Structures*, 12 (1): 1–8. Shahid Chamran University of Ahvaz. <https://doi.org/10.22055/jhs.2025.49153.1341>.
- Puri, D., Sihag, P., Sadeghifar, T., Dursun, O. F., Thakur, M. S., 2023. soft-computing-based model development for estimating the aeration efficiency through Parshall flume and Venturi flumes. *Multiscale and Multidisciplinary Modeling, Experiments and Design*, 6 (3): 401–413. <https://doi.org/10.1007/s41939-023-00153-0>.
- Salamati, S., Masoudian, M., 2025. Analysis of the Hydraulic Performance of a Middle-Hinged Gate in Weir and Gate Modes. *Journal of New Approaches in Water Engineering and Environment*, 4 (1): 40–53. Gonbad Kavous University. <https://doi.org/10.22034/nawee.2025.484734.1111>.
- Samani, Z., 2017. Three Simple Flumes for Flow Measurement in Open Channels. *Journal of Irrigation and Drainage Engineering*, 143 (6): 04017010. [https://doi.org/10.1061/\(ASCE\)IR.1943-4774.0001168](https://doi.org/10.1061/(ASCE)IR.1943-4774.0001168).
- Samani, Z., Magallanez, H., 1993. Measuring water in trapezoidal canals. *Journal of irrigation and drainage engineering*, 119 (1): 181–186. American Society of Civil Engineers.
- Samani, Z., Magallanez, H., 2000. Simple Flume for Flow Measurement in Open Channel. *Journal of Irrigation and Drainage Engineering*, 126 (2): 127–129. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2000\)126:2\(127\)](https://doi.org/10.1061/(ASCE)0733-9437(2000)126:2(127)).
- Shahinejad, B., Parsaei, A., Yonesi, H., Shamsi, Z., Arshia, A., 2022. Modeling and Estimating Flow Rate in SMBF Flumes using Soft Computation Models. *Journal of Water and Soil Science*, 26 (4): 91–104. *Journal of Water and Soil Science*.
- Sihag, P., Dursun, O. F., Sammen, S. S., Malik, A., Chauhan, A., 2021. Prediction of aeration efficiency of parshall and modified venturi flumes: application of soft-computing versus regression models. *Water Supply*, 4068–4085. IWA Publishing.
- Vatankhah, A. R., Mohammadi, M., 2020. Stage–discharge equation for simple flumes with semi-cylinder contractions. *SN Applied Sciences*, 2 (3): 510. <https://doi.org/10.1007/s42452-020-2317-z>.