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Original Research

Evaluation of ANN, GEP, and Regression Models to Estimate the Discharge Coefficient for the Rectangular Broad-Crested Weir

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Abstract

Broad-crested weirs are structures used to measure and control the water flows in rivers, canals, and irrigation and drainage networks. Accurate estimation of spillway discharge is one of the most striking elements in measurement structures. So far, many researchers have studied this issue based on various experimental conditions and a specific range of optional variables. They also have presented several relations. In the present study, 113 data sets of Bos were used for applicability of Artificial Neural Network (ANN), Gene expression programming (GEP), regression models to estimate the discharge coefficient for the rectangular broad-crested weirs. The effectiveness of the models was calculated using statistical criteria, including the coefficient of determination (R^2), Root Mean Square Error (RMSE), and mean absolute error (MAE). Comparing the models showed that the ANN with the highest R^2 coefficient (0.9916), lowest RMSE = 0.0012, and MAE = 0.00052 has the best discharge coefficient estimation than GEP models, regression models, and other empirical relations for the rectangular broad-crested weirs.

Keywords: rectangular broad-crested weirs, discharge coefficient, ANN, GEP, regression model

Introduction

Weirs are important hydraulic structures that have been used extensively to measure and control water flow in irrigation and drainage networks, reservoirs, sewage disposal systems, flood control, and river. These structures, such as valves, are vital components in water management in irrigation canals [1-3]. Weirs are different types, and they are provided with particular forms for various applications. Weir of multiple classes is offered specific conditions for numerous applications. The essential spillways are Ogee spillway, Chute spillway, Side Channel spillway,

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Morning Glory spillway, Stepped spillway, Labyrinth spillway, Sharp-crested spillway, and wide edge side used in water engineering constructions. Because of the big weir, large divisions for these structures are usually considered.

Recently, rapid progress has been made in the precise calculations in the field of water engineering. With progress on these matters, costs tend to be minimal, and project accuracy approaches to the maximum. Estimation of flow discharge in water science is fundamental and perhaps one of the most complex issues because the discharge is associated with various factors such as slope, roughness, cross-section, sedimentation, etc. Therefore, it is necessary to have a more accurate discharge estimation in the different water transmission and distribution institutions [4-7].

In irrigation, drainage, flood, and other broadcast facilities, projects need installations such as weir. Weirs have different types, such as broad-crested weir. The rectangular broad-crested weir is the most widely implemented among various structures. A rectangular broad-crested weir is a hydraulic device with a simple geometry used to measure and control the flow in rivers and irrigation canals. This spillway has a horizontal crown, and lines over this weir are straight and parallel.

For this reason, the pressure distribution over this type of weirs is considered hydrostatic [8, 9]. Broad-crested weir hydraulic study was conducted in the 19th and 20th centuries. Bazin [10] proposed and examined broad-crested weir for the first time after that; other researchers continue his approach as well [11, 12]. Singer [13-15] showed that discharge coefficient is a function of elevation changes of weir (P) and its length (L). Hager and Schwalt [16, 17] studied a more detailed on the hydraulic rectangular broad-crested weir. He showed that by increasing the length of the rectangular broad-crested weir crown, the submergence limit increases, and the weir discharge coefficient decreases. Sargison and Percy [18-20] investigated the water flow broad-crested weir with 2H:1V and 1H:1V slopes upstream and downstream. Their results show that using 2H:1V in comparison to 1H:1V provides a higher discharge coefficient. Structural performance can be optimized by changing the slope downstream. The downstream's pitch has no significant effect on the discharge coefficient instead of the vertical gradient. Zahiri, Eghbali [21] modeled flood discharge using genetic programming and concluded that genetic programming provides better accuracy than Genetic Algorithms (GA) and Artificial Neural networks (ANN) methods [22, 23]. Khosrojerdi, Kavianpour [24] examined the effect of crest length of the weir discharge coefficient by performing experiments on a broad-crested weir [25].

The closer estimation of the coefficient discharge using experimental methods is one of the basic principles to measure the flow accurately. So far, diverse and complex relationships and equations have been proposed for this purpose. Some of the most important relationships to calculate the discharge coefficient of a rectangular broad-crested weir is shown in Table 1, along with the researcher's name.

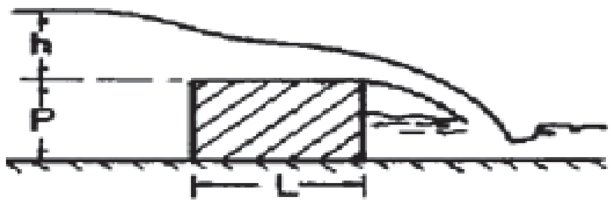


Fig. 1. Schematic design of rectangular broad-crested weirs (Hager & Schwalt, 1994).

This table shows the broad crested weir height, H is the water depth on the weir crest upstream, L is the length of the weir, Cd is the discharge coefficient of the weir. The geometric characteristics of the studied weir are shown in Fig. 1.

Today, the black box of artificial intelligence has high functionality to model and predict complex problems as self-compatible and self-learning functions. Including methods of artificial intelligence are ANN and Gene Expression Programming (GEP) used in water engineering. Expanding the use of neural networks in various scientific fields is due to their ability to solve complex problems (otherwise, they would not have a good answer).

According to recent experiments, neural networks present predictable results in water resources hydraulic structures. Hydrological factors include rainfall-runoff modeling, flow estimates, expected reservoir inflow, suspended sediment load estimation, discharge coefficient, and reservoir performance [26-29].

ANNs have a flexible mathematical structure to detect complex nonlinear relationships between input and output data. On the other hand, GEP is a computer programming technique that presents a suitable solution. GEP is a member of the evolutionary algorithm family [30-33].

The significant advantages of these models are that they can be used for the following conditions:

1. The relationship between decision variables is not well defined
2. The Final Solution to the problem is complex.
3. There is no standard analytical solution to the problem.
4. The approximate solution is an accepted method.
5. The number of data which should be tested by computer is large. (Such as satellite data) [34-36].

Most studies on the use of artificial intelligence methods for forecasting and simulating parameters indicate the ability of these methods. It can be noted in predict of subsiding in the rock fill dam crest [37-39], Local scour downstream of hydraulic structures [40-43], and the simulation flow of rainfall and runoff in a basin [44-48], modeled the phenomenon of sediment transport, using Genetic Programming. The

Table 1. Some of the proposed relations of discharge coefficient for broad crested rectangular. Weir.

Researcher Name (Year)	The proposed relations for discharge coefficient	Considerations
Hager and Schwalt [6]	$C_d=0.326\left[1-\frac{2}{9}\right]^{-1}\left[1-\frac{\frac{2}{9}}{1+(\frac{h}{L})^4}\right]$	
Bos [3]	$C_d=0.93+0.1\,(\frac{h}{L})$	
Rao and Muralidhar [11]	$C_d=0.913+0.049\left(\frac{h}{l}\right)$	$0\leq\frac{h}{l}<0.1$
Azimi and Rajaratnam [12]	$C_d=0.9+0.147\left[\frac{h}{h+p}\right]$	0.1< (h / L) < 0.4
Doeringsfeld and Barker [13]	$C_d=\frac{9}{8}\left\{\frac{1+\frac{h}{p}}{2\left[1+\frac{h}{p}\right]-\left(\frac{h}{p}\right)}\right\}^{1/2}$	
Khosrojerdi, Kavianpour [9]	$C_d=\left(0.5+0.33\frac{h}{p}+\frac{h}{L}\right)^{0.06}$	
Felder and Chanson [14]	$C_d=0.92+0.153\left(\frac{h}{L}\right)$	0.02 <h/L < 0.3
Salmasi, Poorescandar [15]	$C_d=0.612+\frac{h}{L}$	h/L≤0.27
Zachoval, Knéblová [16]	$C_d=0.038\ln\frac{h}{p}+0.87$	$0.52\leq\frac{h}{p}<7$

results of the GP had a good match with the intensity of sediment charts and multiple linear regression. Guven, Azamathulla [49] predicted the scour downstream of hydraulic structures using genetic programming [41, 50-51]. Bilhan, Emiroglu [52] used two neural network methods to study the horizontal flow over the rectangular side weir in a direct channel [28, 53]. Comparison of results showed that the neural network method is suitable for predicting the discharge coefficient. Emiroglu, Bilhan [54] used 2500 laboratory data by ANN to predict the discharge coefficient of Labyrinth triangular weirs in the direct channel [28, 55-56]. ANN performance was compared with nonlinear multiple regression. The results showed a good correlation between experimental data and the consequences of ANN. Roushangar, Akhgar [57] used an ANN and the GEP to investigate the energy losses on the stepped weir. They presented experimental data related to 17 physical models of the stepped weir as input and output of network in 3 scenarios: Falling stream regime data, skimming flow regime, and the combination of both. The results showed that both models (ANN and GEP) had performed well in estimating energy loss in stepped weir in various streaming [58-60].

So this study was conducted to assess the performance of ANNs, regression, and GEP in estimating the discharge coefficient of rectangular broad-crested weirs. The model results were compared with other empirical equations obtained by other researchers.

Materials and Methods

The following variables effectively describe the characteristics of the non-submerged rectangular broad-crested weirs that have upstream and downstream vertical sides and locate ed in the rectangular straight channel [61, 62].

$$f\,(h,V,\rho,\mu,L,b,\sigma,g,P)=0 \tag{1}$$

In this release, we have:

L: Length of the weir, b: width of the weir, h: water level on the weir crest, g: the acceleration of gravity, ρ: density, μ: the dynamic viscosity, σ: surface tension, v: speed and p: weir height

According to surveys conducted by different researchers [8, 63, 64], dimensionless parameters, h/p, h/L and h/(h+p) have the greatest impact on rectangular broad-crested weir discharge coefficient. In other wordss:

$$C_d=f\left(\frac{h}{p},\frac{h}{L},\frac{h}{h+p}\right) \tag{2}$$

The study also examined the effects of these three significant parameters on the discharge coefficient of the broad-crested weir that is easily measurable in the laboratory. This study used laboratory studies conducted on various rectangular broad-crested weir sizes (8). Characteristics of the weir are provided

Table 2. Main specifications of physical models in a rectangular broad-crested weir.

Symbol	Feature of weir	Length (cm)
L	Weir length	100-75-50
b	Weir width	200-50
p	Weir height	20
q	Discharge per unit width (liters per second)	0.0106-1.191

Table 3. The range of used parameters in the neural network model.

$(\frac{h}{h+p})$	$(\frac{h}{L})$	$(\frac{h}{p})$	C_d
0.1489-0.778	0.0667-0.7	0.175-3.5	0.9497-1.477

in the Table 2, and the range of parameters is summarized in Table 3.

According to the survey conducted by the tests, a total of 113 data sets were used in this study.

Artificial Neural Network (ANN)

ANNs are computational models that can determine the relationship between inputs and outputs of a physical system by a network of connected nodes, even if they are complex and nonlinear. The structure of neural networks (also called network architecture) is arranged in categories called layers. The typical architecture of these networks consists of three layers: input layer, hidden layer, and output layer. The input layer distributes the data over the network. The hidden layer processes the data, and the output layer extracts the results for specific inputs. Each network can have multiple layers [65-67]. An ANN works based on the learning of the problem-solving process. In other words, it works by finding hidden relationships in the process. For this purpose, the model is trained with a set of data. The trained model calculates the appropriate output using new inputs and the given relationship found in the training phase. Determination of the properly hidden layers of neurons is one of the most important in using ANNs. This recognition is essential in training the network and ultimately for performance. However, various relations calculate the number of hidden layer neurons [68-71]. The Multi-Layer Perceptron (MLP) network and Radial Basis Function (RBF) network are two types of ANNs widely used in water engineering sciences. In this study, we used an MLP neural network in the environment of Matlab 7.10 software.

Gene Expression Programming (GEP)

The GEP method was proposed in 1999 by Ferreira. This method combines Genetic Programming (GP) and

Table 4. Parameter values used in the GEP.

The parameter used in GEP	Value
The number of chromosomes	30
Length each vertex	8
The number of genes	3
Rate of Return	0.1
Genetic transposition rate	0.1
Mutation rate	0
The combination of single-point rate	0.3
Combining the two-point rate	0.3
Rate gene combinations	0.1

Genetic Algorithms (GA). The linear and straightforward chromosomes are combined with fixed length (similar to what is used in genetic algorithms) and branch structures with different sizes and shapes (similar to the parse tree in Genetic programming). Phenotype and genotype are separated in this method because all branch structures (with different sizes and shapes) are encoded in linear chromosomes in fixed length. The system can benefit from all the evolutionary advantages due to them. In summary, the GEP improvements happened in a linear structure then expressed as a tree structure, and this causes the modified genome to be transferred to the next generation. Therefore, it does not require heavy structures for the crossover and mutation [72, 73].

In this method, different phenomena can be modeled using a set of functions and a set of terminals. A group of parts usually includes essential arithmetic functions, trigonometric functions or any other mathematical function, or user-defined functions suitable for interpretation of models. The Terminal set comprises constants and variables problems [21, 40, 44, 72, 73]. For using GEP, the GenXproTools 4.0 software was used. In summary, the parameters used in each model run are provided in Table 4.

Regression

Regression analysis is a statistical method that uses quantitative relationship between two or more variables (independent or predictor variables) to predict the dependent variable (response variable). SPSS software was used for modeling and in order to use of multivariate linear and nonlinear regression, the following functions were used:

$$C_d = a\left(\frac{h_1}{L}\right) + b\left(\frac{h_1}{p}\right) + c\left(\frac{h_1}{h_1+p}\right) + d \tag{3}$$

$$C_d = a\left(\frac{h_1}{L}\right)^b \left(\frac{h_1}{p}\right)^c \left(\frac{h_1}{h_1+p}\right)^d \tag{4}$$

At this stage, finally, nonlinear equation four was presented as a desirable equation by using a variety of nonlinear equations.

Statistical Measures

The following statistical methods were used to compare the estimated discharge coefficient by ANN models and multivariate linear regression with the measured values and compare this model with other mentioned relations in this paper.

– The coefficient of determination (R^2)

The accuracy of any empirical relationship presented in this field depends on the values of this parameter. If the value of the coefficient of determination is closer to 1, it can better estimate the relationship between the discharge coefficient rectangular broad-crested weirs.

$$R^2=\frac{\left[\sum\left(C_{dm}-\overline{C_{dm}}\right)\left(C_{dp}-\overline{C_{dm}}\right)\right]^2}{\sum\left(C_{dm}-\overline{C_{dm}}\right)^2\sum\left(C_{dp}-\overline{C_{dp}}\right)^2} \tag{5}$$

– Mean Absolute Error (MAE)

$$MAE=\frac{1}{N}\sum_{i=1}^{n}\left|C_{dm}-C_{dp}\right| \tag{6}$$

– Root-Mean-Square Error (RMSE)

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(C_{dm}-C_{dp}\right)^2} \tag{7}$$

Where N is the number of data, C_{dm} is the measured values of discharge coefficient, C_{dp} is the estimated values of discharge coefficient, $\overline{C_{dm}}$ is the average measured values of discharge coefficient, and $\overline{C_{dp}}$ is the average estimated values of discharge coefficient. In each method, as RMSE and MAE values are closer to zero, their accuracy of models to estimate the discharge coefficient is higher.

Data Preparation

The input data must be normalized before training the neural network model. Using raw data reduces the speed and accuracy of the neural network model. This study uses Equation (8) to standardize the input data to the neural network model, between zero and one.

$$x_n=\frac{x_i}{x_{max}} \tag{8}$$

X_n is the normalized input, X_i is the input value, and X_{max} is the maximum amount of data.

In the next step, the data set was divided into two parts: training and testing. In this study, 70% were dedicated to training, and 30% were assigned to test the model. The selection of data for training and testing is random. The stir arrangement of rows of data from its original state was due to the randomization of data. After randomization of data, the highest and lowest values of observed output are placed on the training data. For this reason, the network can experience the most crucial states. Also, the closer data from maximum and minimum observed output data must be randomized to be validated.

Results and Discussion

The Results of ANN

In this study, we used Multilayer Perceptron (MLP) to estimate the discharge coefficient of the rectangular broad-crested weir, one of the most helpful feedforward ANN models. Three parameters are carried out in the neural network model: (h/p), (h/L), and (h/h+p) as input and (Cd) as output. The network training process began with a small number of neurons, and adding the additional neurons continued until the increasing neurons had nothing to improve the error. The tangent sigmoid function and log-sigmoid function were used in the hidden layer as a transfer function. Also, a linear function was used with a neuron in the output layer. Two thousand five hundred epochs are considered for each network, and the best neural network arrangement was obtained by trial and error. The results are shown in the Table 5. As a result (Table 5), the best arrangement for the neural network model has occurred when the transfer function for the hidden layer is the log-sigmoid function, a linear function is for the output layer, and the number of neurons in the hidden layer is four neurons (Fig. 2).

In this case, RMSE and MAE values for network training are 0.00028 and 0.00017, respectively, and these values to test the network are obtained 0.0012 and 0.00052. Also, the coefficient of determination (R^2) is estimated at 0.9993 for the training mode, and the testing mode is 0.9916.

As shown in Table 4, ANN has been extended to implement testing sections such as training sections. In Fig. 3, there is a good match between the test and training of ANN's model with the observed data for the discharge coefficient of the weir.

The GEP results

GEP was used because of the ability to choose the effective variables in the model, remove variables with less impact, and as well as the ability to provide the explicit relationship for estimating the discharge coefficient for rectangular broad-crested weirs. The first step in the GEP model is choosing a suitable fitness function that can take different forms. In the present study, Root Mean Square Error (RMSE) was selected as a standard fitting. The next step is to select the main operators to build a parse tree, and the last step involves finding the appropriate link. This study evaluated

Table 5. Different used ANN models (with one hidden layer).

Transfer function	# of neurons in the hidden layer	Training			Test		
		R^2	RMSE	MAE	R^2	RMSE	MAE
Tansig-purelin	3	0.99980	0.00037	0.00021	0.96300	0.00290	0.00023
Tansig-purelin	4	0.99910	0.00095	0.00016	0.98640	0.00140	0.00096
Tansig-purelin	5	0.99920	0.00031	0.00017	0.98970	0.00110	0.00097
Losig-purelin	3	0.99900	0.00034	0.00021	0.99070	0.00100	0.00078
Losig-purelin	4	0.99930	0.00028	0.00017	0.99160	0.00120	0.00052
Losig-purelin	5	0.99930	0.00029	0.00016	0.86710	0.00500	0.00029

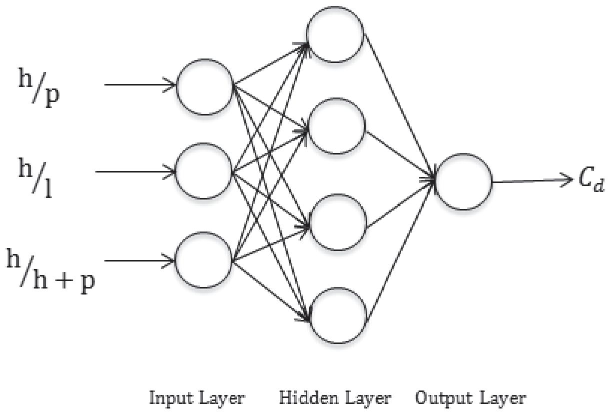


Fig. 2. The optimum neural network structure with three input parameters.

the GEP model with several mathematical models and four functions links (addition, subtraction, multiplication, and division) to estimate the discharge coefficient. The best results of the implementation of the model are displayed in errors format in the Table 6. According to the Table 6, based on the values of RMSE = 0.0032, R^2= 0.9074 and MAE = 0.0025 for training phase and RMSE = 0.0031, R^2 = 0.9107 and MAE = 0.0026 for testing phase, F2 function associated with the function subtraction link is the best performance for estimating the discharge coefficient for rectangular broad-crested weirs.

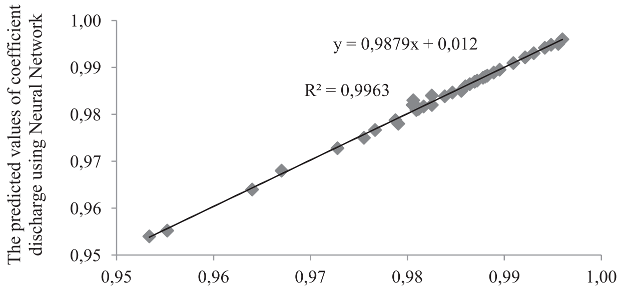


Fig. 3. Scatter plot between observed and calculated optimized values of ANN model for testing data.

Providing a mathematical equation between the dependent variable and the other independent variables is the GEP model's additional features than other intelligent models. It is significant for future predictions. The equation provided by the GEP model for estimating the discharge coefficient of rectangular broad-crested weirs based on function F2 is presented in Equation (9). Fig. 4 shows, tree expression of mathematical relationship for Equation (9).

$$C_d = 1 - \left(e^{\left(\frac{H}{L}\right)}\left(\frac{H}{L}\right)\right)\left(e^{-4.93}\left(\frac{H}{H+P}\right) + e^{\left(-9.026-\left(\frac{H}{P}\right)\right)}\right) \quad (9)$$

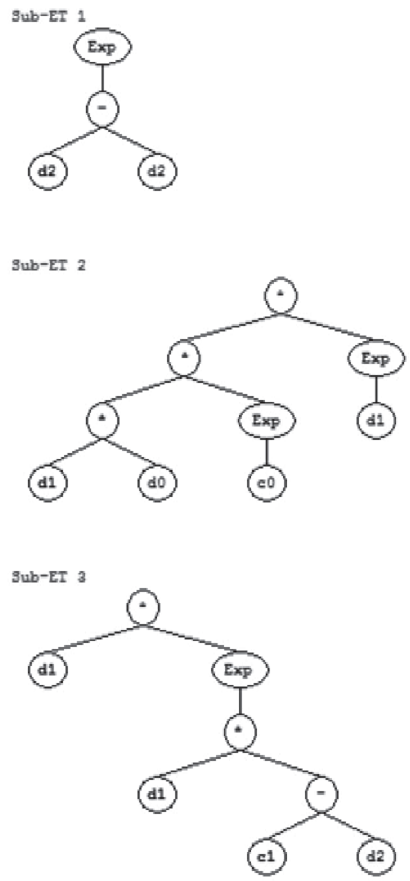


Fig. 4. The expression tree for the relationship of GEP (output).

Table 6. Results of GEP model using various mathematical functions.

Function	Link function	Mathematical Model	Train			Test		
			R^2	RMSE	MAE	R^2	RMSE	MAE
F_1	Addition	+, -,×,÷	0.6476	0.0069	0.0040	0.6703	0.0064	0.0035
F_2	Subtraction	+, -,×,÷,lnx, e^x	0.9074	0.0032	0.0025	0.9107	0.0031	0.0026
F_3	Addition	+, -,×,÷, √ , x^3 , x^2	0.8581	0.0046	0.0029	0.8482	0.0044	0.0030
F_4	Division	+, -,×,÷,lnx, e^x, √ , x^3 , x^2	0.9033	0.0035	0.0029	0.8952	0.0033	0.0028
F_5	Multiplication	+, -, ×, ÷,lnx, ex, √ , x^3 , x^2 , sinx, cosx, Arctg x	0.8440	0.0086	0.0051	0.8414	0.0085	0.0049

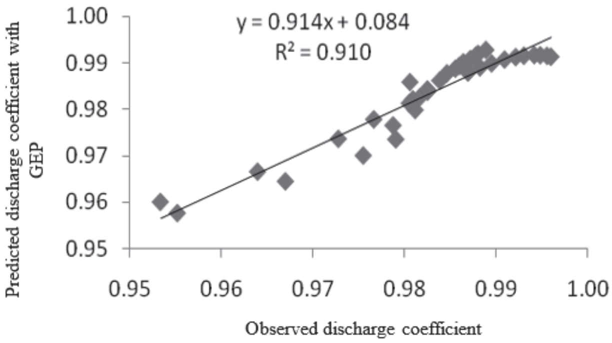


Fig. 5. Scatter plot between observed and calculated values in the GEP model for data used in the test phase.

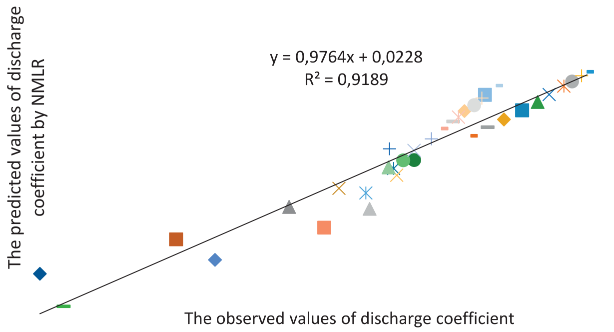
Fig. 5 shows the measured and calculated discharge coefficient values for rectangular broad-crested weirs by the GEP model in the test phase. According to Fig. 5, this model has performed well in estimating the discharge coefficient value so that estimates predicted amounts are equal to their actual values (calculated values).

Results of Regression Models

In this study, to estimate the discharge coefficient of rectangular broad-crested weirs, Multivariate Linear Regression (MLR) and Multivariate Non-Linear Regression (MNLR) were used. The results of the calculation are as follows:

$$C_d = 0.022\left(\frac{h_1}{L}\right) - 0.004\left(\frac{h_1}{p}\right) + 0.06\left(\frac{h_1}{h_1+p}\right) + 0.95 \quad (10)$$

$$C_d = 1.004\left(\frac{h_1}{L}\right)^{0.012}\left(\frac{h_1}{p}\right)^{-0.001}\left(\frac{h_1}{h_1+p}\right)^{0.012} \quad (11)$$



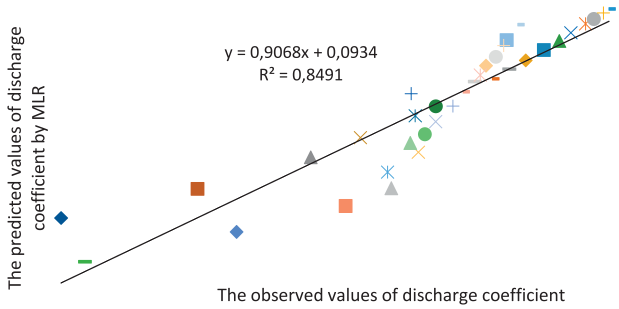


Fig. 6. Scatter plot between observed and calculated values of multivariate linear and nonlinear regression models for user data in the testing phase.

The multivariate linear and nonlinear regression analysis results are shown in Table 7. Fig. 6 shows the measured and calculated discharge coefficient values for rectangular broad-crested weirs by the two models in the test phase. Although the proposed nonlinear relationship is more accurate than the linear relationship, there is a good correlation between measured and computed values by the two models.

Table 7. The results of the statistical analysis of regression models.

Model	Train			Test		
	R^2	RMSE	MAE	R^2	RMSE	MAE
Multivariate Linear Regression	0.859	0.0043	0.0032	0.849	0.0044	0.0034
Multivariate Non-Linear Regression	0.926	0.0029	0.0021	0.919	0.003	0.0023

Table 8. Comparison of different relationships to estimate the discharge coefficient for rectangular broad-crested weirs using statistical criteria.

Model	R^2	RMSE	MAE
ANN	0.9916	0.0012	0.0005
GEP	0.9107	0.0031	0.0026
MLR	0.8490	0.0044	0.0034
MNLR	0.9190	0.0030	0.0023
Hager and Schwalt [6]	0.4080	0.6540	0.6540
Bos [3]	0.7410	0.0190	0.0170
Rao and Muralidhar [11]	0.7410	0.0520	0.0510
Azimi and Rajaratnam [12]	0.8120	0.0160	0.0140
Doeringsfeld and Barker [13]	0.7880	0.0660	0.0540
Khosrojerdi, Kavianpour [9]	0.8340	0.5030	0.0320
Felder and Chanson [14]	0.7140	0.0210	0.0190
Salmasi, Poorescandar [15]	0.7140	0.1820	0.1560
Zachoval, Knéblová [16]	0.8220	0.1090	0.1070

Compare the Performance of the Models

As shown in Table 8, it can be seen by selecting the optimal solution for each model and comparing them. In other experimental relations, it was found that most models can simulate flow with reasonable accuracy. Among the used models, the ANN model with the highest R^2 (0.9916), lowest RMSE (0.0012), and MAE (0.00052) have the best results in the validation phase.

In Fig. 7, the results of all four models are shown concerning the observed data. As shown in Fig. 7, all models have acceptable performance in estimating the discharge of coefficient.

Conclusion

This study tried to evaluate the performance of several models for estimating discharge coefficient for rectangular broad-crested weirs using the experimental data of Bos (1989). The models used were ANN, GEP, MLR, and MNLR. The observed discharge coefficient values were compared with the estimated discharge coefficient values in the mentioned models (ANN, GEP, MLR, and MNLR). The results proved that all methods (ANN, GEP, MLR, and MNLR) could estimate discharge coefficient for rectangular broad-crested weirs according to the evaluation criteria with relatively with 80-99 percent accuracy level. The ANN model showed better performance due to highest R^2 (0.9916), lowest RMSE (0.0012), and MAE (0.00052). This study also proved that using ANN, GEP methods will improve the discharge coefficient estimation and the following approach can be applied for various structures with different criteria.

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Conflicts of Interest

The authors declare no conflict of interest. The founding sponsors had no role in the study's design, in the collection, analyses, or interpretation of data, in the

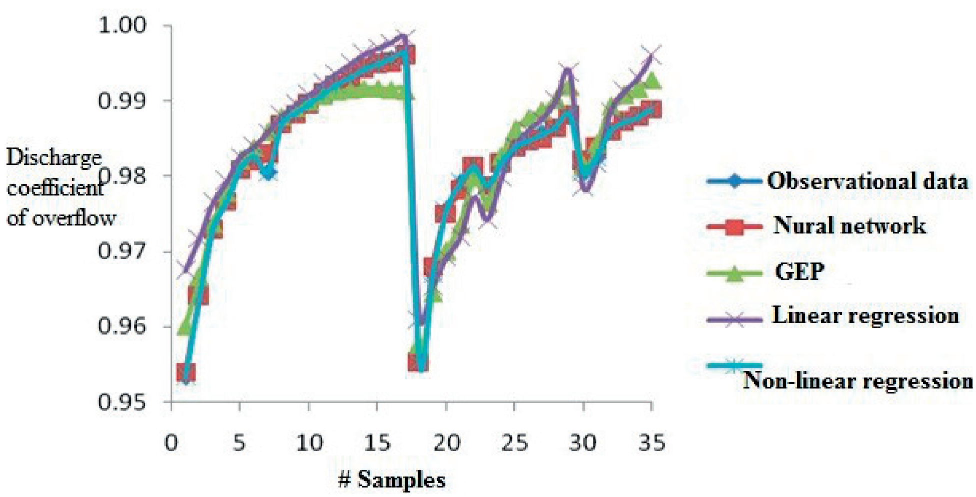

Fig. 7. Comparison between the observed and predicted discharge coefficient for rectangular broad-crested weirs by the models.

writing of the manuscript, and in the decision to publish the results.

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