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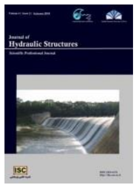

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Performance Evaluation of Artificial Intelligence Models in Estimating the Discharge Coefficient of Labyrinth Weirs with Semicircular Crests

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Abstract

In this study, the performance of ANN and SVM in estimation of the discharge coefficient of the labyrinth weirs with semicircular crests was investigated. For this purpose, 454 experimental data were used. Dimensionless parameters of HT/P, L/W, W/P, and a were introduced as inputs and CD parameters as outputs in the models. The performance of the ANN model with RMSE, R and, DC was 0.019, 0.971 and 0.971 respectively more acceptable and closer to the experimental data than the SVM model.

Keywords: Labyrinthine Weir, Artificial Neural Network, Support Vector Machines.

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1. Introduction

The volume of flow through the weir is dependent on the length and shape of the weir, so far, a lot of research has been done on the effect of hydraulic and geometric parameters on discharge coefficient and discharge rate over weirs. One of the effective ways to increase the length of the weir at a given width is to use the weirs with nonlinear plan, such as triangular, trapezoidal plan, circular, parabolic and so on. As a result of the construction of this type of the weir will increase the volume of flow through them and lower free elevation will be required upstream than linear weirs. This is very important when it acts as a flood discharge structure and facilitates the flow of the flood [1, 2].

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The first research on the labyrinth weir was conducted by [3] [3]. After the studies of Taylor (1968), Hay & Taylor, (1970) proposed a method for calculating the discharge and design of these weirs [4], and¬ followed another method for designing the labyrinth weirs. Juma et al., (2014) [5] analyzed the hydraulic properties of semicircular weirs using artificial neural networks (ANNs). They showed that the results of artificial neural networks were in good agreement with laboratory results. Goel, (2014) [6] used neural networks technique to predict the discharge and discharge coefficient of triangular weirs. This study showed that the results of ANN (MLP) performed better than the results and equations presented by Kumar et al., (2011) [7].

Roushangar et al., (2018) [8] investigated the discharge coefficient of labyrinth and arc weirs by using support vector regression. Their results showed that support vector regression method has high efficiency in determining the discharge coefficient of the labyrinth weirs. Karami et al., (2018) [9] examined rectangular labyrinthine weirs with models of vector machine [10, 11], artificial neural network and genetic algorithm. They examined the results of these models with laboratory data that provided better results than other models. (Gupta et al., (2014) [12] investigated the flow characteristics of the W-shaped weir in plan. The results showed that the efficiency of these weirs is better than conventional weirs. Using the laboratory data carried out in this study, equations were also presented for the discharge. These equations calculate the discharge value with 5% of fault fluctuations. The susceptibility of the weir to the water head was also investigated and the results showed that the weir is very sensitive in low and small apex angles.

According to the sources, it is observed that limited studies have been conducted with intelligent models to estimate the discharge coefficient of labyrinth weirs with semicircular crests. Therefore, in this study, using the laboratory data of [9], the performance of intelligent models of ANN and SVM in order to estimate the discharge coefficient of the labyrinth weir with a semicircular crest the study was conducted.

2. Methods

The one-dimensional flow equation on the labyrinth weirs is a function of total water charge (H_t), length of weir (L) and flow coefficient (C_D) without dimension and is obtained from relation 1 (Henderson, 1966).

$$Q = \frac{2}{3} \mathrm{CD} \sqrt{2g}\, \mathrm{Lc}\, H_t^{\frac{3}{2}} \tag{1}$$

Using dimensional analysis and considering geometrical, kinematic and dynamic parameters, the parameters affecting the flow coefficient in the labyrinth weirs include upstream water charge (Ht), weir nose length (A), effective crest length (Lc), total weir width (W), wall angle (a), weir height (P), weir thickness (tw) and the shape of the weir crest.

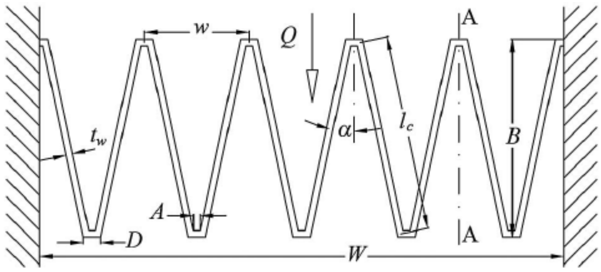


Figure 1. A view of the labyrinthine weir studied by Croston and Tullis (2013)

The data used in this study are the laboratory data of Kirkston and Tollis (2013). They have conducted studies on the labyrinth weirs with semicircular crests where the effective parameters are visible in Figure 1.

2.1. Artificial Neural Network (ANN)

Artificial neural networks (ANNs) consist of a number of neurons that are layered together in layers. Each artificial network consists of introductory, hidden and output layers that are the input network for data supply. The output layer contains the values predicted by the neural network and the hidden or intermediate layer is composed of processor nodes. The selection of type and number of network inputs has a great effect on the quality of the network performance and the hidden layers have the role of organizing the performance of a neural network. Different layers in the neural network as well as neurons in the layers can have different or similar stimulus functions. Neural networks are divided into different groups in terms of structure and communication between neurons.

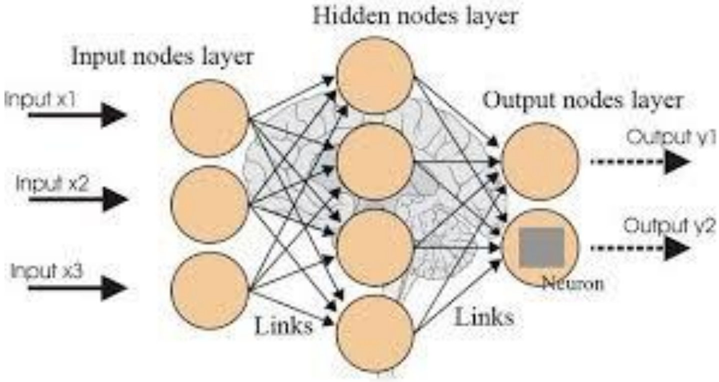


Figure 2. A general view of artificial neural network (Heykin ،1999)

2.2. Support Vector Machine (SVM)

Support vector machines act like other AI methods based on data mining algorithms. The first application of this method in water problems was proposed by (Dibike et al., 2001; Guo et al., 2008) [13, 14] to simulate runoff precipitation. Support vector machines are an efficient learning system based on constraint optimization theory that uses the principle of structural error minimization induction and leads to a general optimal solution. The way the SVM algorithm works is like most intelligent methods in training and testing, but unlike other artificial intelligence methods, instead of reducing computational errors, the operational risk of correct non-segmentation as the target function and achieves its optimal value. Figure 3 shows the structure of the backup vector machine.

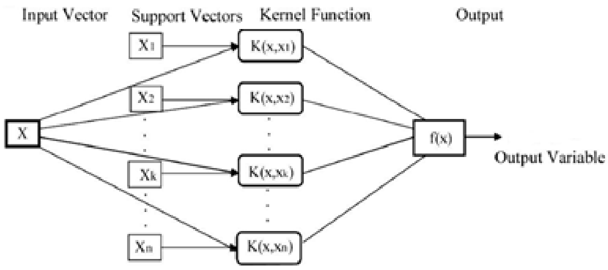


Figure 3. Structure of Support Vector Machine

In the SVM model, a function associated with dependent variable y is estimated as a function of several independent variables x. Similar to other regression problems, it is assumed that the relationship between independent and dependent variables with an algebraic function such as f(x) plus some perturbation (the allowable error ε) (relation1).

$$f(x) = W^T . \emptyset(x) + b \tag{2}$$
$$y = f(x) + noise \tag{3}$$

If W is the vector of coefficients and b constant of the attributes of the regression function and ∅ is the kernel function, then the goal is to find the functional form for f(x). This is achieved by calibration of the SVM model by a set of samples (calibration set). This process involves sequential optimization of the error function. Depending on the definition of this error function, two types of SVM model are defined:

In this study, due to its extensive application in regression studies, the regression model ε-SVM has been used to predict the discharge coefficient of a labyrinth weir with a semicircular crest. Support vector machines change the dimension of the problem through Cornell functions to solve nonlinear problems. The choice of kernel for SVM depends on the volume of training data and feature vector dimensions. In other words, according to these parameters [15], Cornley function should be selected that has the ability to train for the inputs of the problem. In this study, radial base kernel (RBF) has been used (relational 3):

$$K(x_i,x_j) = \exp\left(-\|x - x_i\|^2/\sigma^2\right) \tag{4}$$

In this research, intelligent models of artificial neural networks (ANNs) and support vector machines (SVM) models have been used to estimate the value of weir coefficient of a labyrinth with a semicircular crest (CD) using four dimensionless parameters H_t/P, L/W, W/P, and a. In the models used, four dimensionless parameters Ht/P, L/W, W/P, and a were introduced as inputs and the dimensionless parameter of C_D as output. In the models used, 75% of all available data were used for training and 25% for the test period.

2.3. Accuracy Assessment Criteria

Three statistical indices have been used to evaluate the ability and accuracy of performance of artificialneural network (ANN) and SVM models in estimating the discharge coefficient. Evaluation criteria for estimating the parameter of discharge coefficient, including correlation coefficient between observational and computational values, root mean square error (RMSE) Linear correlation between predicted and observed values (DC) are calculatedfrom 4, 5 and 6 respectively. A better model would be that R and DC have close to one and the root mean squares close to zero [16].

$$R=\frac{\sum_{i=1}^{n}(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2\sum_{i=1}^{n}(P_i-\bar{P})^2}} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \tag{6}$$

$$DC = 1- \frac{\sum_{i=1}^{n}(P_i-O_i)^2}{\sum_{i=1}^{n}(P_i-\bar{P})^2} \tag{7}$$

In these relationships, the values obtained from the $O_i P_i$ observational values (extracted from the laboratory), the values obtained from the predictive model method, the mean values obtained from the observational $\bar{O}\bar{P}$value, the mean values of the predictive models' method and n is the amount of data.

3. Results and Discussion

Discharge coefficient of the labyrinth weir with a semicircular crest was performed through the results of ANN and SVM models. In this study, the laboratory data of Crookston and Tullis (2013) were used to evaluate and compare the results of the models.

Dimensionless parameters of H_T/P, L/W, W/P, and a as inputs and C_D parameters as outputs were introduced in the models used.

In Table 1, the statistical parameters of the data set for the training period and the test are shown.

Table 1. Parameter range for input and output data in the test and training course Parameters

	a	**L/W**	**W/P**	**Ht/P**	**C_D**
At least	6	1	2.008	0.023	0.199
Maximum	90	7.607	4.015	0.8	0.81
Average	22.36	3.92	2.21	0.34	0.524
Coefficient of Change	1.09	0.5	0.27	0.151	0.252
Deviation Criteria	24.42	1.98	0.612	0.23	0.132

To model the discharge coefficient, neural network has 4 neurons in the input layer (A, HT/P, L/W, W/P) and one neuron in the output layer (discharge coefficient). The high correlation coefficient between observed and estimated values in training and test data for the estimated parameters indicates the high capability of the designed neural network to estimate the discharge coefficient of labyrinth weirs with semicircular crests.

Table 2. Simulation results of a semicircular crested weir flow coefficient using neural network model

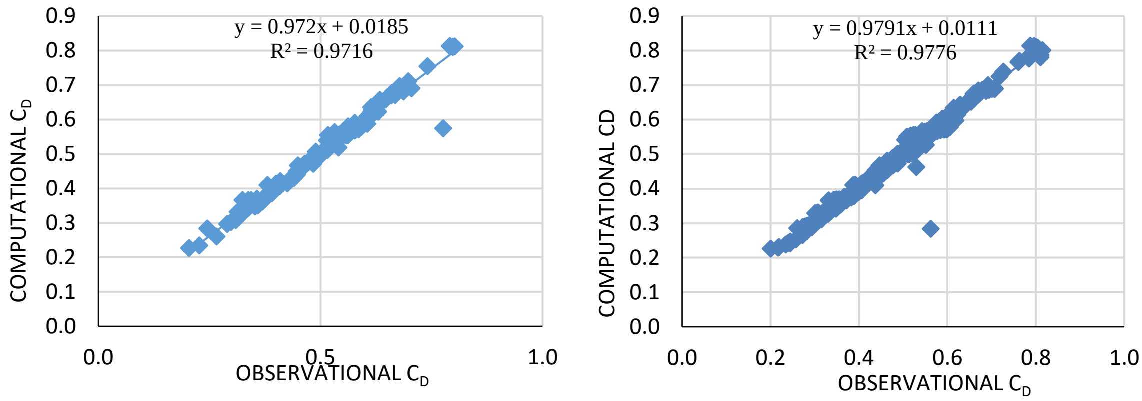
Parameter Name	Neural Network Models	Number of hidden layers	Number of neurons.
C_d	ANN	4	1-4

In order to evaluate the efficiency of the method used to estimate the discharge coefficient in labyrinth weirs with semicircular crests, Table 3 is presented.

Table 3. Accuracy of Estimation of Artificial Neural Network Model in Estimation of Discharge Coefficient

	Training			Test		
Model	RMSE	DC	R	RMSE	DC	R
ANN	0.023	0.978	0.988	0.019	0.971	0.985

In Figure 4, the scattering of observational-computational values of training stage and test of artificial neural network model are shown. According to Figure 4, it is observed that most of the points are located on or near the semi-structure line, which shows the acceptability of both models in estimating the value (C_D) but artificial neural network model. The results are very close to the observed values and therefore have a high accuracy in estimating the desired parameter (C_D) value.



A. Test **B. Training**

Figure 4. Scatter Graph of Observational-Computational Value of Training and Test of Artificial Neural Network Model

In the present study, the performance of SVM in estimation of discharge coefficient of a labyrinth weir with a semicircular crest was investigated. Considering that the selection of input models in intelligent systems can affect the accuracy of the results of the analysis, it was tried to use the input of the neural network model in the input layer (a, Ht/P, L/W, W/P) and a neuron is used in the output layer (discharge coefficient) to evaluate the yield (ANN) relative to the SVM. The performance of the support vector machine was evaluated using the RBF kernel function. According to Table 4, the results showed that the RBF kernel function with R, RMSE and DC is 0.978, 0.027 and 0.956, respectively. The syntax was such that the optimum values of ε and c were obtained for the fixed value γ, then the value was changed and the optimum value was calculated by calculating statistical parameters.

Table 4. Statistical parameters of SVM model with RBF kernel function

	Training			Test		
Kernel function type	RMSE	DC	R	RMSE	DC	R
RBF	0.031	0.942	0.971	0.027	0.956	0.978

In Figures 5 and 6, the scattering of the observational-computational values of the training stage and the support vector machine test is displayed. As can be seen in Table 4, the coefficient of explanation and determination coefficient are 0.957 and 0.956 respectively and the root mean squares are 0.027 in the test stage.

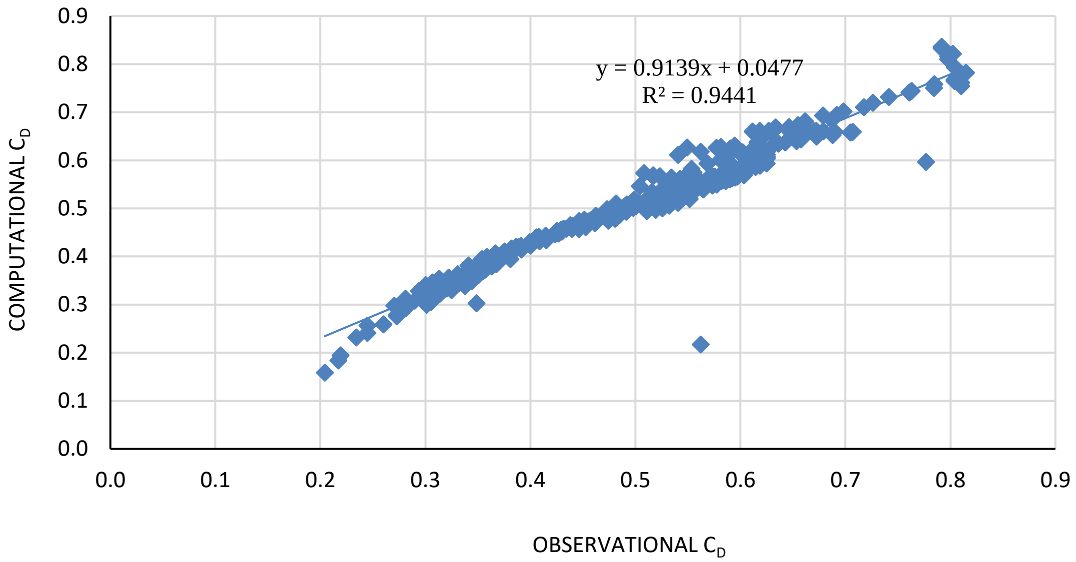


Figure 5. Scatter Graph of Observational Values - Computational SVM-RBF Training Stage

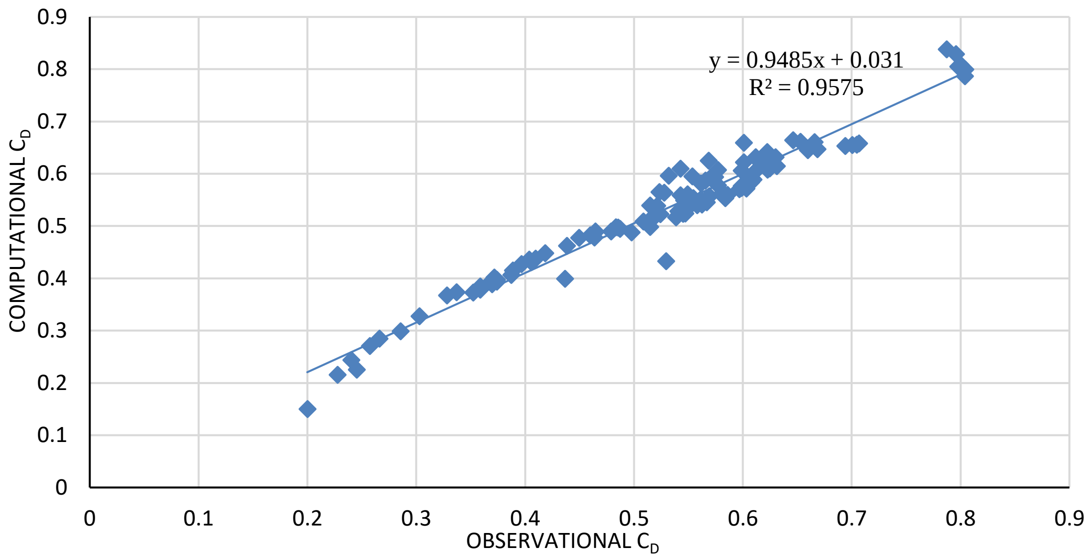


Figure 6. Scatter Graph of Observational- Computational Values of SVM-RBF Test

Statistical criteria show that ANN model has high accuracy of SVM method (Table 5).

Table 5. ANN and SVM model results for test period

Parameter	RMSE		DC		R	
	SVM	ANN	SVM	ANN	SVM	ANN
C_D	0.027	0.019	0.956	0.971	0.978	0.985

4. Conclusion

In this research, two models of artificial neural networks (ANNS) and support vector machines (SVMs) have been used to estimate the discharge coefficient of the labyrinth weir with a semicircular crest. Discharge coefficient data were obtained from the Crookston and Tullis (2013) laboratory study. Then, the estimated values (CDs) were compared with the mentioned models using the evaluation criteria. It should be noted that by random selection method of total data (454 numbers) as test and training data, with 25% and 75%, respectively, in a way that after repeating several random selections different from all available data, the data related to the conditions with the highest explicability coefficient (R) were performed. It has the lowest square mean square root (RMSE) called for the estimated process using the artificial neural network (ANN) model.

The results of this study showed that both intelligent models have better accuracy in estimating CD. However, the artificial neural network model compared to SVM machines with R, RMSE and DC was equal to 0.971, 0.019 and 0.971 for SVM and 0.957, 0.027 and 0.956 for SVM model, respectively. It is of high precision.

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