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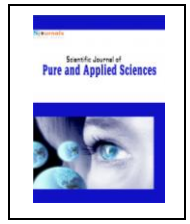

Original article

Predicting the side weir discharge coefficient using the optimized neural network by genetic algorithm

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A B S T R A C T

Side weir is one of the structures which are widely used in water engineering projects So study on the flow characteristics especially discharge coefficient (Cd_{sw}) of this type of weir is important. Several Empirical formulas proposed to calculate the Cd_{sw} that they usually associated with significant errors. Thus, using mathematical methods based on artificial intelligence is inevitable. Artificial neural network (ANN) is a very useful data-modeling tool that is able to capture and represent complex input and outputs relationships. In this study, accuracy the some famous empirical formula was assessed and Borghei and Parvaneh was most accuracy formula with ($\mathrm{R}^2 = 0.83$). To increase the accuracy of production the Cd_{sw} multi-layer neural network (MLP) has developed. This model, in the first, trained by a back propagation method such as levenberg_marquardt and its performance was determined. the error indexes in the train and testing process are equal to ($R^2_{train} = 0.93$ and $R^2_{test} = 0.96$). To increase the accuracy of MLP model, instead of increasing the size of the network (increase in the number of neurons and layers), Genetic Algorithm was used to train this model (GANN)and obtained an optimized value for Bias and weights. The final results show that using the GA to training the MLP model cased to increase in accuracy .The performance of the optimized neural network (GANN) in training and testing is equal to ($R^2_{train} = 0.98$ and $R^2_{test} = 0.97$).

1. Introduction

Modeling and Prediction of hydraulic phenomenon is an important part of hydraulic engineering activities. Estimating the flow rate through the Hydraulic structure is one of the most important issues in water engineering. side weir is an over flow structure which widely used in water engineering projects, such as river engineering, dams, irrigation networks and drainage, flood control to remove exceed water(Hager, 1987; Ghodsian, 2003; Ghodsian, 2004). When the water level reaches above the side weir crest it, divert a certain amount of discharge. Like all typical weirs, side weir can be, sharp, broad crested with various geometric and flow in the main channel can be sub-critical and supercritical (Emiroglu et al., 2011b;Kaya et al., 2011;Kumar et al., 2013). Many studies was done to defin the hydraulic behavior of this type of weir, which are often experimental method. The flow over a side weir is a typical case of spatially varied flow(SVF) with decreasing discharge (AL-TAEE, 2012). De Marchi with assuming constant energy, obtained equation of the (SVF) and to calculate the outflow discharge form the side weir, he solved analytically the (SVF). Finally, he proposed an equation for side weir discharge coefficient that today is known as the De Marchi coefficient (Swamee et al., 1994; Haddadi and Rahimpour, 2012). Sharp crested rectangular side weirs have been studied extensively by many researchers and usually used in water engineering projectbecause of the ease in construction and operation of this type side weir(Emiroglu et al., 2011b). More recently, Laboratory Studies have been done to improve the performance of this structure (Emiroglu et al., 2010; Kaya, 2010; Kaya et al., 2011). Experimental and theoretical investigations done on the flow over labyrinth, Oblique, semi-elliptical, Curved Plan-form and trapezoidal sharp and broad-crested side weir in rectangular channels at under subcritical and supercritical flow conditions. results shows that discharge coefficient is related to the Froude number at the upstream of the weir, ratios of weir height to depth of flow, weir length to width of main channel and length of broad-crested weir to width of main channel. The end result of all this research is show the effect of each geometric shape of the Side weir on the rising the performance of the this structure And for each specific geometric shape of the Side weir a mathematical formulas was proposed. (Cosar and Agaccioglu, 2004; HONAR and JAVAN, 2007; Kaya et al., 2011; Kumara et al., 2011; Kumar et al., 2012; Kumar et al., 2013). The flow over the side weir is the type of spatially varied flow (SVF) with decreasing discharge. To computer simulating flow over side weir the suitable numerical method such as Fourth Runge Kutta method should (AL-TAEE, 2012; Rahimi, 2012). In Table (1), some of the famous empirical equation that proposed for the Sharp crested rectangular side weir is collected. In addition, to predict the side weir Discharge coefficient, the studies base on mathematical modeling and artificial intelligence also has been done. In Artificial Intelligence (AI) Studies, a network is developed Instead of a relationships that results from the linear or nonlinear regression. The multilayer perceptron (MLP) and Adaptive Neuro Fuzzy Inference System (ANFIS) are most common AI models that In the field of artificial intelligence techniques has been used (Bilhan et al., 2010; Emin Emiroglu et al., 2010; Emiroglu et al., 2010; Bilhan et al., 2011; Bilhan et al., 2011; Emiroglu et al., 2011c). Based on the reported, AI models are much more accurate than empirical equation. The conclusion that can be derived from a review of literature is that study on hydraulic of side weir started with Laboratory investigation and recently the classical intelligent method are used for prediction of side weir discharge coefficient. In intelligent models to increase the efficiency, usually size of model will be increased such as (increase in number layer and increase in number of neuron in each layer). In this study, the MLP model was developed to predict the Cd_{sw} and and then to increase the accuracy of the model, optimization of the model structure done with Genetic algorithm.

2. Methodology

First, using dimensional analysis to extract important dimensionless factors influencing in the Cd_{sw}. Then to assess the empirical equation, some data that published in reputable journals collected in table (2). The number of these data is about 140. In the Following the MLP model was developed. The training and testing process of this model done with the same data collected to increase the accuracy of the MLP model, the training process will be done with Genetic algorithm.

Table 1
Some famous empirical formulas that presented to the calculation of side weir discharge coefficient.

Row	Author	Equation
1	Nandesamoorthy et al.	$C_d = 0.432\left(\frac{2-Fr_1^2}{1+2Fr_1^2}\right)^{0.5}$
2	Subramanya et al.	$C_d = 0.864\left(\frac{1-Fr_1^2}{2+Fr_1^2}\right)^{0.5}$
3	Yu-Tech	$C_d = 0.623 - 0.222Fr_1$
4	Ranga Raju et al.	$C_d = 0.81 - 0.6Fr_1$
5	Hager	$C_d = 0.485\left(\frac{2-Fr_1^2}{2+3Fr_1^2}\right)^{0.5}$
6	Cheong	$C_d = 0.45 - 0.221Fr_1$
7	Singh et al.	$C_d = 0.33 - 0.18Fr_1 + 0.49\left(\frac{P}{h_1}\right)$
8	Jalili et al.	$C_d = 0.71 - 0.41Fr_1 + 0.22\left(\frac{P}{h_1}\right)$
9	Borghei	$C_d = 0.7 - 0.48Fr_1 + 0.3\left(\frac{P}{h_1}\right) + 0.06\left(\frac{L}{h_1}\right)$

Table 2
Range of data collected.

Range	F1	p/h1	L/b	L/h1	C_d
min	0.09	0.34	0.30	0.35	0.28
max	0.83	0.91	3.00	10.71	1.75
mean	0.41	0.77	1.60	3.99	0.57
STDV	0.20	0.14	1.11	3.10	0.26

3. Dimensional analysis

Referring to Fig. 1 the discharge coefficient (Cd_{sw}) can be written as a function of width of channel (b), flow depth in the main channel (h_1), mean velocity of flow at upstream end of side weir (V_1),length of side weir (L), acceleration due to gravity (g), slope of main channel bed (So), deviation angle of flow (ψ),

$$C_d = f(v_1, L, b, h_1, P, \psi, s_0) \tag{1}$$

Using the Buckingham π theorem, nondimensional equations in functional forms can be obtained as below:

$$C_d = f_1\left(Fr_1 = \frac{v_1}{\sqrt{gh_1}}, \frac{L}{b}, \frac{L}{h_1}, \frac{P}{h_1}, \psi, s_0\right) \tag{2}$$

$$\sin(\psi) = \sqrt{1-\left(\frac{V_1}{V_s}\right)^2}$$

El-Khashab also mentioned that the dimensionless length of the side weir (L/b) includes the effect of the deviation angle on the discharge coefficient. Therefore, the deviation angle ψ is not existed in the Cd_{sw}. Thus, the discharge coefficient (Cd_{sw}) depends on the following dimensionless parameters(Emiroglu et al., 2011a).

$$C_d = f_2\left(Fr_1, \frac{L}{b}, \frac{L}{h_1}, \frac{P}{h_1}\right) \tag{3}$$

4. Artificial neural network (ANN)

The ANN is a nonlinear mathematical model that is able to simulate arbitrarily complex nonlinear processes that relate the inputs and outputs of any system. In many complex mathematical problems that lead to solve complex nonlinear equations, A Multilayer Perceptron network with definition of appropriate functions, weights and bias can used. Due to the nature of the problem, different Activity functions in neurons can be implementing. An ANN maybe has one or more hidden layers. Fig. 2 demonstrates a two-layer neural network consisting of hidden layer (layers) and outputs layer. As shown in the fig.2, $w_i$is the weights and b_i is the bias for each neuron. Initial assigned weight values are progressively correct during a training process that compares predicted outputs to known outputs. Such networks are often trained using back propagation algorithm. In the current study, the MLP model was trained with using two Levenberg–Marquardt technique and Genetic Algorithm (Wesley Hines, 1997).

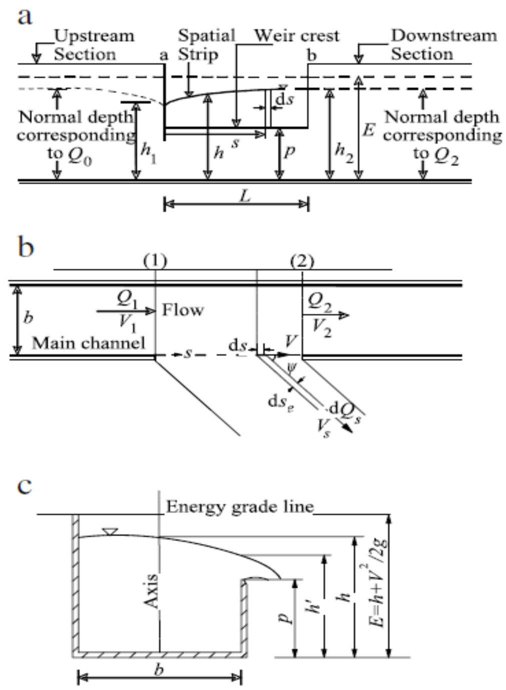

Fig. 1. Definition sketch of subcritical flow over a rectangular side weir.

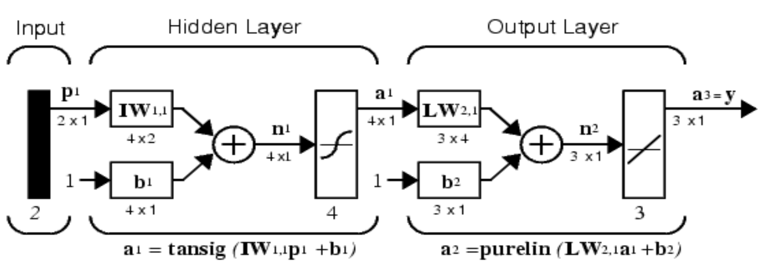

Fig. 2. A three-layer ANN architecture.

5. Genetic algorithm approaches

Genetic algorithms (GA or GAs) are a part of evolutionary computing that derives from Darwinian evolution. This algorithm introduced by John Holland in the 1970's at the University of Michigan. These algorithms are best suited to solving combinatorial and complex optimization problems, which cannot solve by using more methods that are conventional. Genetic algorithms are stochastic numerical search procedures inspired by biological evolution, crossbreeding trial solutions and allowing only the fittest solutions to survive and propagate to successive generations. They deal with a population of individual (candidate) solutions, which undergo constant changes by means of genetic operations of reproduction, crossover, and mutation. These solutions are rank according to their fitness with respect to the objective function where the fit individuals are more likely to reproduce and propagate to the next generation. Based on their fitness values, individuals (parents) are selected for reproduction of the next generation by exchanging genetic information to form children (crossover). Then the parents removed and replaced in the population by the children to keep a stable population size. The result is a new generation with (normally) better fitness. Occasionally, mutations introduced into the population to prevent the convergence to a local optimum and help generate unexpected directions in the solution space. The more GA iterates, the better their chance to generate an optimal solution. After a number of generations, the population expected to evolve artificially, and the (near) optimal solution will be reach. The measure of success is the convergence to a population with identical members. The global optimum solution however cannot be guarantee since the convexity of the objective function cannot be proving.

6. Optimized multilayer perceptron neural network

Multilayer Perceptron is one of the common type of neural networks that used in many field of application. The value of the weights and biases will be defined in the training process. Therefore, determine the optimal values of them can be regard as an optimization problem. To resolve these problem the powerful methods such as genetic algorithms can be implement. Combining Neural Nets with Evolutionary Algorithms leads to Evolutionary Artificial Neural Networks (EANNs). We can use Evolutionary Algorithms like the GA to train Neural Nets, choose their structure or design related aspects like the function of their neurons. The sections below outline these techniques, starting with the most common using a GA to train a Neural Net. As shown in fig(3) GA can be used effectively in the evolution to find a near-optimal set of connection weights globally without computing gradient information and without weight connections initialization.(L. Haupt and Haupt, 2004; Sivanandam and Deepa, 2008).in this paper to determine optimal value of weights and bias for each neuron the GA has been implemented. The dimension of the optimization problem is equal to total weights and biases that used to design in network architecture.

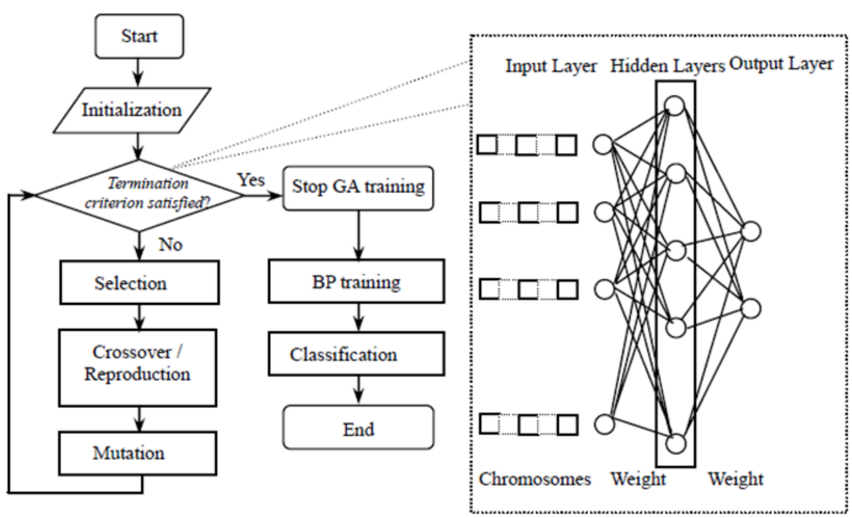

Fig. 3. flowchart of Combining Neural Network and GA.

7. Results

evaluation of empirical equation was done with data that the range of them given in table (1). Approximately 140 data used that published in journal by researchers the range of these data gives in the table (2). The results of empirical equation for these data calculate and then compare with the observer data and error indexes (Eq (4))) calculate and give in table (3). As shown in Figure (4) and table (3) the Borghei equation has suitable results ($R^2 = 0.83$) and other equation has not acceptable results ($R^2 \leq 0.4$).

$$RSME = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(C_{d-real} - C_{d-\mathrm{model}})}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} abs\,(C_{d-real} - C_{d-\mathrm{model}})$$

$$APE = \frac{1}{N}\sum_{i=1}^{N} abs\left(\frac{C_{d-real} - C_{d-\mathrm{model}}}{C_{d-real}}\right) \qquad (4)$$

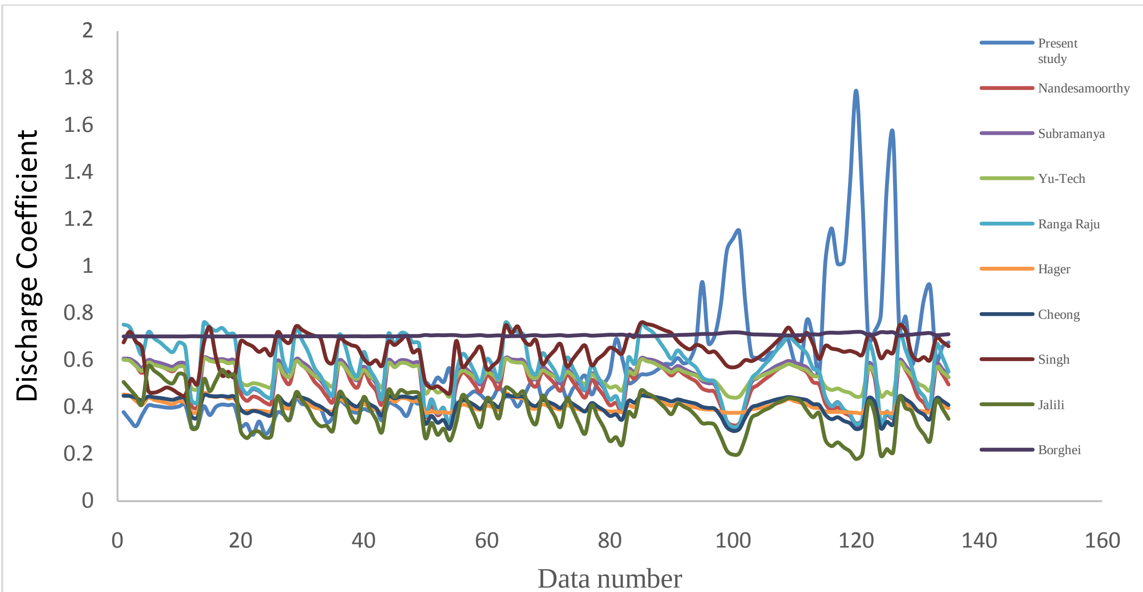

Fig. 4. Compression between and result of empirical equation and observation data.

Table 3
The RMSE, MAE,AP and R2 statistics of the empirical equations.

Equation	R^2	**RSME**	**MAE**	**APE**
Nandesamoorthy	0.29	0.315	0.205	32.53
Subramanya	0.34	0.315	0.207	33.88
Yu-Tech	0.277	0.285	0.192	32.23
Ranga Raju	0.277	0.336	0.237	41.72
Hager	0.17	0.312	0.19	25.53
Cheong	0.34	0.325	0.194	25.89
Singh	0	0.273	0.209	40.86
Jalili	0.337	0.372	0.235	32.41
Borghei	0. 834	0.288	0.247	51.79

For more accurate prediction Cd_{sw} The MLP model has been developed. The structure of MLP model as shown in the figure (5) included two layer, one layer for hidden layer and one layer to Output Variable. Firstly, The MLP model trained with levenberg_marquardt Algorithm. The 75 percent of data used to training and 25 percent also used to model testing. Characteristics of MLP model such as number of the neurons in each layers, transform function presented in Table 4. The inputs parameter for MLP model is the dimensionless parameter that extract in Dimensional Analysis stage ($\mathrm{Fr}_1, \frac{\mathrm{L}}{\mathrm{b}}, \frac{\mathrm{L}}{\mathrm{h}_1}, \frac{\mathrm{P}}{\mathrm{h}_1}$) and outputs is Cd_{sw} .the result of the classical MLP model in training and testing process shown in the figures (6 and 7). To assessment the performance of the classical MLP model, error statistical indexes such as RSME and R^2 and other statistics indexes calculated and shown in the Table 5. The accuracy of the MLP model in training and testing stage given in the Table (5) ($R^2_{train} = 0.93$ and $R^2_{test} = 0.96$) and the performance of the MLP are very suitable and in compare with empirical formulas, the MLP model is more accurate. To increase the performance of MLP model, instead increase in the structure of MLP model such as increase the number of the layers or increase the number of neurons. Defining the optimal value for weights and biases has considered so obtain the optimum value for the weights and biases for each done is a optimization problem that proposed doing with the GA. the Goal function that must optimized is Mean Square Error (MSE). The number of variable of optimization problem is equal to total number of weights and biases that used in the MLP model structure. As shown in the figure (4) total number of weights and biases is 25. Figure (8) show the training process the MLP model with GA and reduction the error during the iterations. The results of this network after optimization process for training and testing giving in the table (6) and show in the figure (9 and 10). Training the MLP model with GA cased to increase accuracy about 5.4 percent in the training and about 2 percent in the testing stage.

Table 4
Characteristics of MLP model.

Layer	Number of neurons	Transform function
hidden layer	4	tansig
Outputs Layer	1	tansig

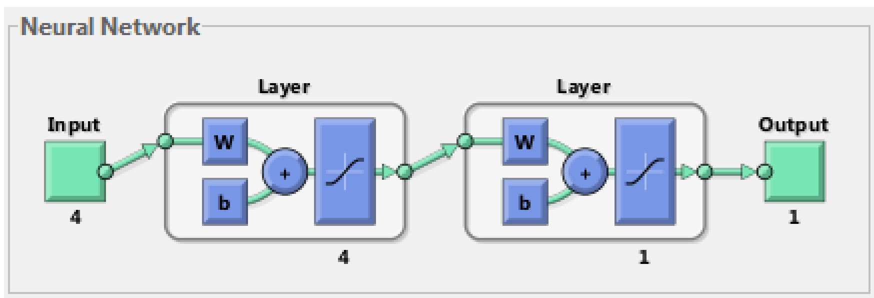

Fig. 4. structure of MLP model.

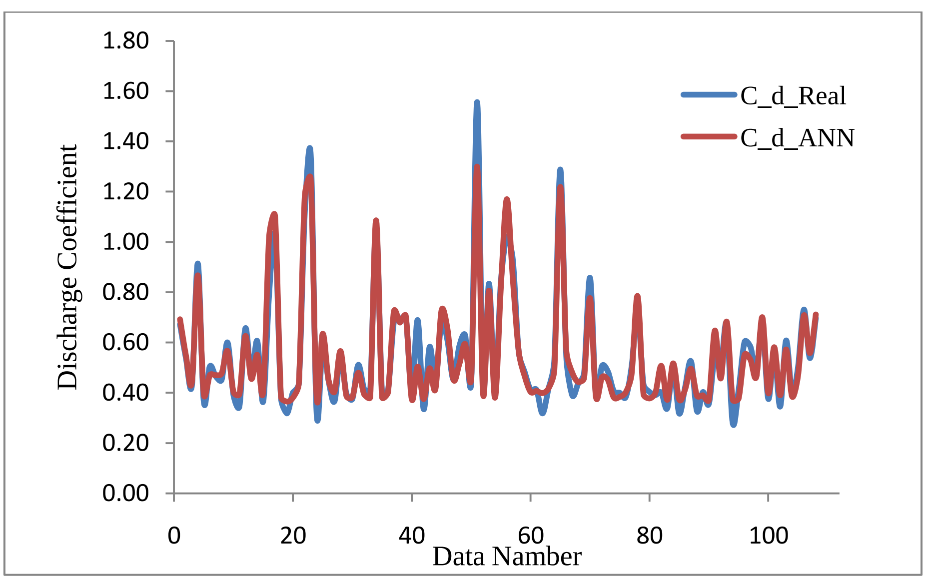

Fig. 6. Performance of classical MLP models during the training Stage.

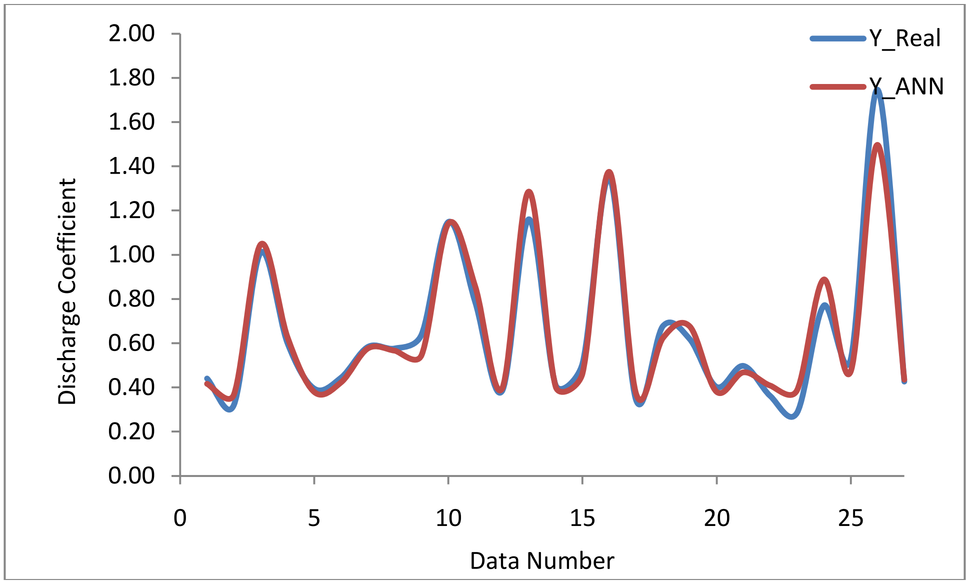

Fig. 7. Performance of MLP models during the Test Stage.

Table 5
Error statistics indexes of the classical MLP model.

stage	R^2	RSME	APE	MAE
Train	0.93	0.0571	2.26	0.02
Test	0.96	0.071	4.32	0.03

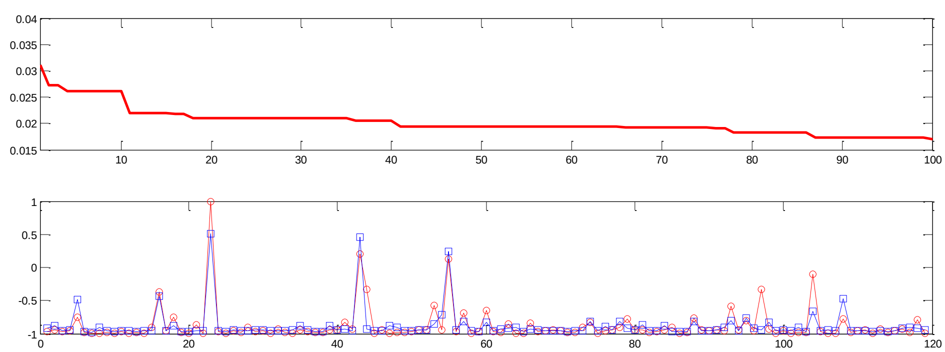

Fig. 8. schematic as training the neural network with Genetic Algorithm.

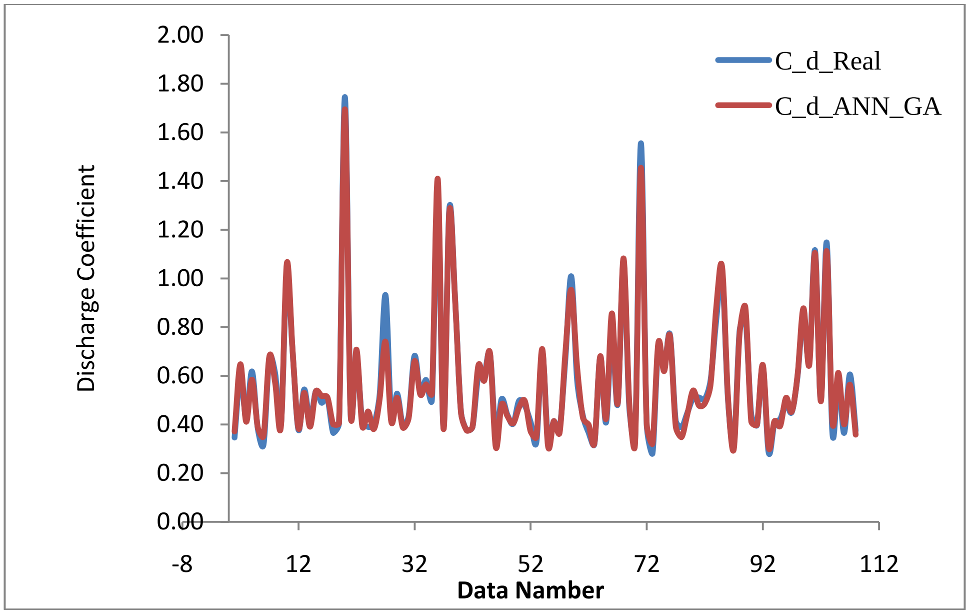

Fig. 9. Performance of optimized MLP models with the training data.

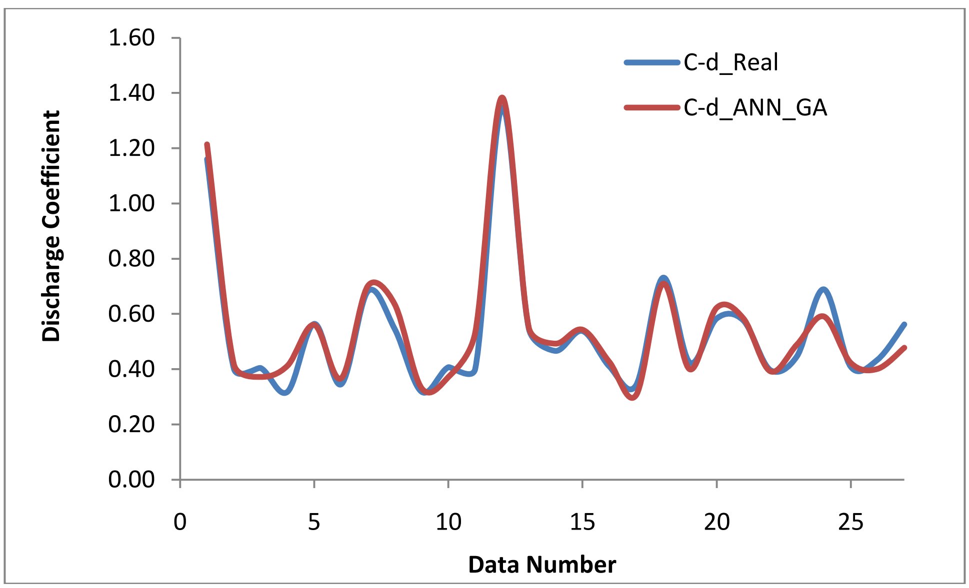

Fig. 10. Performance of optimized MLP models with the Test data.

Table 6
Error statistics indexes of the optimized MLP model.

stage	R^2	RSME	APE	MAE
Train	0.98	0.033	1.12	0.02
Test	0.97	0.05	3.42	0.03

8. Conclusion

In recent years, many researchers have welcomed the artificial intelligent modeling of Hydraulic phenomena. One of the structures is very important in hydraulic engineering are side weirs. Side weirs are widely used for flow diversion in irrigation, land drainage, urban sewage systems and in intake structures. The accurate estimates of this parameter helps to better manage water-engineering projects. Estimating of the discharge coefficient with using the empirical equations has considerable error; therefore, engineers have turned to using artificial intelligence techniques. In this paper the accuracy of empirical equation was evaluated, among of empirical equation the Borghei is suitable ($R^2 = 0.83$) and other formulas may contain significant error ($R^2 \leq 0.4$). For better of the estimation of side weir discharge coefficient the MLP model has been development .the dimensionless parameter that extract with dimensional analysis are considered as model inputs parameters. To increase the performance of the model the training process does with the Genetic Algorithm. The final result shows that the accuracy of the classical MLP model in Compare with the almost empirical equations is more better. The compare of the accuracy of the classical MLP and optimized MLP shows that with replacing the optimal value for weights and biases the performance of the MLP model will increased without any change in number neurons and layers.

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