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Prediction Of Discharge Coefficient For Cylindrical Weirs Using Adaptive Neuro Fuzzy Inference System ANFIS and Multilayer Neural Networks MLP

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Abstract

Cylindrical weir shape provides a stable overflow pattern , since this type of weirs can ensure the ease to pass floating debris and can provide simplicity in design. This research presents a prediction of discharge coefficient of cylindrical shape crest weir using different diameters , different angles of inclination, and different bed slopes . The adaptive neuro fuzzy inference system ANFIS and multilayer neural network (MLP) models were used by applying 143 laboratory test results for the prediction operation. The results indicated to high efficiency of ANFIS technique for modelling discharge coefficient with a very good performance of MLP neural networks.

Key words: Cylindrical weir , ANFIS, ANN, MLP , Hidden layer , Membership function .

INTRODUCTION

Due to changes in climate and weather, the probability of probable maximum flood in rivers has been increased[1]. For this reason, it is necessary to give high attention to study the discharge capacity of weirs to avoid reduction of its factor of safety . Increasing discharge capacity of weirs means using un conventional types of weirs [2]. The most common types of weirs are sharp crested weirs, broad crested weir , Circular crested weir and oblique or cylindrical weirs . Cylindrical weirs were first studied by De rries (1959) as was cited by [3].

A relatively early report about side weirs was provided by Singh et al. (1994) [4] based on a particular weir geometry and experimental work. Authors were determined sill height, main stream flow and weir crest as parameters of the experimental work for a rectangular weir assessment. For subcritical flow conditions, they searched for the discharge coefficient of the rectangular side weir. They used an experimental setup including a flow channel with 23 m length, 0.25 m width and 0.35 meter depth in which head was measured from 17 different points. The branch channel is 90^o alignment with the main channel. Authors emphasized that the upstream Froude number and sill height over upstream flow depth are related with the discharge coefficient. They proposed some empirical linear correlations for estimation of the discharge coefficient. It is important to see that the discharge coefficients can be represented by linear equations. The range of the discharge coefficient is reported to be between 0.45 and 0.65 while there is some limited number of results between 0.65-0.84.

Another similar experimental work on the discharge of a rectangular sharp edge side weir was reported by Borghei et al. (1995)[5]. They conducted 250 experiments in order to evaluate the flow related to the side weir while assessing the validation of the constant energy assumption of the De-Marchi for the utilization of the discharge coefficient. They found that the discharge coefficient can be used for subcritical flow. In addition to the report of the Singh et al. (1994) who denoted that the discharge coefficient is a function of upstream Froude number and sill height, authors found correlation between discharge coefficient and Froude number, weir height and weir length. They also denoted that they couldn't find a significant correlation between channel slope and the discharge coefficient. Results of four different empirical correlation equations (regression equations) are compared to the experimental results and a first order polynomial correlation is proposed as giving better results close to the experiments. It can be said that the experimental uncertainty of the results are not provided in the paper. An interesting finding of this work is the average 3.7% decrease in the energy due to the presence of the weir.

The discharge capacity of a triangular side weir connected to n open water channel was predicted by Emiroglu et al. (2010) [6].using ANFIS approach based on a previous extensive experimental work and its data. Since side weirs are used in various applications and the mass flow rate of the fluid is regulated by the geometry of the weir passively and main stream flow rate actively, the prediction of the discharge coefficient of a particular weir with fixed geometrical parameters and varying operational parameters is very important. Therefore the authors employed ANFIS method and tools in order to make the prediction. The lab data for the ANFIS depends on 2500 trials. They evaluated the performance of the ANFIS not only by the experimental data but also with the results of various multiple non linear regression methods. Statistical indicators such as RMSE, MAE and R were employed in the assessment of the approach and it was concluded in the paper that the ANFIS prediction can be employed for the triangular side weir case for the discharge coefficient.

Another good experimental study on geometrical parameters for side weirs was published in 2011 by Kaya et al. (2011)[7].

They compared and examined a semi-elliptical weir shape by using the data of a previous work on triangular side weir. This time 677 trials for the experimental results were said to be done for the determination of the discharge coefficient of the semi-elliptical side weir. Authors relate the discharge coefficient with 5 different parameters that are upstream Froude number, lengths of weir and the effective length, weir height and ratio of the ellipse diameters. They proposed an empirical equation for the discharge coefficient while correlating it to the parameters by using a regression technique. The proposed equation is valid for subcritical flows. Although the semi-elliptical side weir is said to yield better results in terms of De-Marchi discharge coefficient, triangular side weir has better values as stated in the conclusion part of the paper.

Multiphase free surface channel flow in the presence of a triangular side weir was analyzed and reported by Aydin (2012) [8] using numerical computational methods. Based on a comprehensive experimental work that is referred in the paper, Aydin (2012) used Fluent CFD code in order to obtain surface profile of the flow due to the existence of the side weir. Author investigated geometrical parameters of the triangular side weir while also compares the effects of the turbulence models in the code. Additionally Grid Convergence Index (GCI) was utilized in order to assess the uncertainty due to the discretization errors. RSM turbulence model was denoted to be a more accurate model in respect of the surface profile. Surface profile has a lower height at the upstream part of the side weir and recovers to the centerline at the downstream part. From the general layout of the work, it can easily be concluded that there is a potential of geometrical parameters for research in side weirs for the open channel flows. CFD can be used safely and effectively in such works judging by the experimental data.

Later in 2016, Parsaie et al. (2016)[9] used ANFIS in order to predict or estimate the discharge coefficient of a cylindrical weir. Their paper comprises of 46 references which can give an insight for the usage of the ANFIS for the weirs. As a different structure, the used weir is not a labyrinth side weir. Instead, weir-gate structure is the focus of the work. Weir-gate is proposed for a solution considering accumulation of sediments and materials behind gates and weirs. As authors denoted that this solution enjoys sufficient support from literature, methods for determining discharge coefficient are of interest. Authors used ANFIS and MLP as soft-computing methods for prediction of the discharge coefficient. They concluded that ANFIS and MLP results are very close to each other while ANFIS a bit ahead. As expected, they found the significant effects of upstream Froude number and gate opening height on the discharge coefficient.

There are other soft-computing or machine learning methods applied to the weir research. For instance Parsaie et al. (2017) [10]again used such a method in order to predict the discharge coefficient of the weir. This time particle swarm optimization (PSO) was used in order to train the Group Method of Data Handling (GMDH). The results of the GMDH-PSO are compared to multi-layer perceptron neural network and support vector machine. Again all methods are reported to have similar and close results while support vector machine is a bit ahead. Authors give basic information with the support of schematics and related literature in the text. Therefore the paper can also be evaluated for the comparison of the methods.

Better prediction accuracy of discharge coefficient of a sharp edge rectangular weir was aimed by Ebtehaj et al. (2018) [11]by utilizing multi-objective machine learning methods. They used adaptive neuro-fuzzy interference system and generalized group method as their main tools while supporting this system with genetic algorithm in order to define membership functions and data handling. With the existence of single value decomposition, their prediction system becomes a multi-objective data prediction tool. Various single objective data prediction systems and some regression based methods are also compared to the multi-objective system and the work can be considered as a comprehensive literature in this respect. They proposed that their design for the discharge coefficient prediction is superior to the compared tools and methods. However the reader should consider that this superiority is very relative and in absolute terms, the differences are very small such as 0.001 or similar. Another thing is; multi-objective methods have less parameter than the single objective methods.

Although side weirs and pivot weirs are different in terms of structures, aims, objectives and their effects on the flow, the discharge coefficient related to their effect on the flow and flow patterns downstream of the weir structures are similar in terms of their trends and effecting mechanisms. The recent work of Azimfar et al. (2018)[12] is an example for the works on discharge coefficient of pivot weirs. They developed discharge coefficient for flow of free and submerged conditions. Discharge coefficient is very important in this field, because it doesn’t have a dimension and this makes it to be applied to a wider range of applications. Authors of this work focused on Bernoulli approach and used momentum equations. They also utilized experimental results. They claimed to have better accuracies relating to their calculations comparing to the early works and they also claimed that their approach is less complex.

It seems that most of the references and literature about the discharge coefficients of the weirs are originating from developing countries in the last two decades so far. Some other instances are given below in order to exemplify the recent state of the topic.

In-reservoir arced labyrinth weirs are another type of weirs that are encountered in the engineering designs of hydraulics. Sangsefidi et al. (2018)[13] conducted an experimental study about this type of weirs. Especially photographs illustrating the flow patterns in the work are much appreciated. Another interesting side of the work is; a method for design of the arc labyrinth weir is presented. They examine effects of the headwater, the sidewall angle, and the weir arc angle on the discharge coefficient of the weir, flow efficiency and flow patterns. They reported a 4.5 efficiency increase due to the arced weir utilization.

A relatively short report was done by Ferro and Ayding (2018)[14]. They used data of a slit weir in order to show the validity of the Malcherek outflow theory. This theory allows to measure flow rate of the discharged fluid. By using data of an experimental work that was conducted for the range of 0.05 to 0.25 weir widths over channel width, authors claimed ± 5% error between calculated results with measured rates. The theoretical flow includes the deduction of the state-discharge coefficient. Results of the work indicate that the average velocity over a slit weir can be given in terms of head over weir and the contraction ratio.

Another comprehensive experimental work has been conducted by Shariq et al. (2018)[15] about an open water channel and a side rectangular weir setup. The setup was used previously and this paper enhances the experimental data from it. Flow is visualized by dye visualization techniques while the channel has very similar structure to real world open water irrigation systems. Authors evaluate the surface profiles along the channel width through the weir. The work not only compromises the experimental results but also examines a lot of correlations from the literature. And they also propose another empirical correlation for the discharge coefficient by non-linear regression techniques. The experimental results and the calculations of the empirical correlations are compared by means of statistical indicators such as RMSE, R, R^2, MAPE and such.

In this paper an experimental work data was used for developing adaptive neuro fuzzy inference system ANFIS for prediction of discharge coefficient of cylindrical weirs . The performance of ANFIS model was decided after applying multilayer perceptron (MLP) neural network .

LABORATORY CHANNEL AND EXPERIMENTAL WORK DISCRPTION.

Laboratory experiments were performed in the Hydraulics Laboratory of Northern Technical University / Technical Institute /Mosul, where the used channel dimensions were (0.2m) width and (0.25m) height and (4 m) length. The channel bottom is made from aluminum and side walls made of glass. The channel is provided with water from a tank beside the channel through pump discharges water into the stilling tank then to the channel. The channel contains crows to control the channel slope, Fig(1). The channel is also provided with suppressed rectangular sharp crested weir at the end to calculate the channel discharge. The Channel contains point gage to measure water level. In laboratory, cylindrical Weirs were used with different diameters, made from plastic and placed with different angles with channel wall. The weirs were putted at a distance (1.5 m) from the channel entrance. The experiments on cylindrical weir were performed by separating them into three groups. In the first group it was used three diameters of weirs (11 cm, 9 cm, 6.35 cm) and put at (90°) angle (as a normal weir) with channel wall. The second and third groups include the use of the same diameter sizes used in the first group with (45°, 30°) angles (oblique weir) . All the above trials were done with different bed slopes which are horizontal bed slope, 0.2 and 0.4 slopes .

Through these experiences, the data of water depth above the standard rectangular sharp crested weir (h) were taken to calculate the discharge in equation (1) (Rehbook formula[16]).

$$q_w = C_d * \frac{2}{3}\sqrt{2g} * h^{3/2} \ldots\ldots\ldots\ldots\ldots(1).$$

The value of (H1), which represents the total head, was calculated using the following equation:

$H_1 = d_1 + \frac{q_{w^2}}{2*g*d_{1^2}}$……….(2) where d_1 is the depth of water upstream the circular weir under study (in the case of vertical and oblique weirs)

The value of total head above the weir crest (Hw) was calculated using the following equation:

$$H_w = H_1 - D \quad \ldots\ldots\ldots\ldots\ldots\ldots(3).$$

Where: D is weir diameter.

The value of discharge coefficient of cylindrical weir (Cd) is calculated using the following equation.

$q_w = C_d * \frac{2}{3} * \sqrt{\frac{2g}{3}} * H_{w^{1.5}}$……..(4).while the value of Cd(weir) can be calculated as

$$C_{d(weir)} = 0.602 + 0.083 * \frac{h}{p} \ldots\ldots(5).$$

Where:

qw = discharge per unit width of the channel (m3/s/m).

Cd(weir) = discharge coefficient of rectangle sharp crested weir.

g = ground acceleration.

p = height of rectangle sharp crested weir (m).

h = height of the water upstream rectangle sharp crested weir (m).

Through the above experiments 143 value of Cd was found for the cylindrical weir .

Another two parameters which are measured(d crest and dc) in each trial can be defined as :

dc: flow depth measured at the weir crest (m).

dc:critical flow depth in a rectangular channel (m). [17].

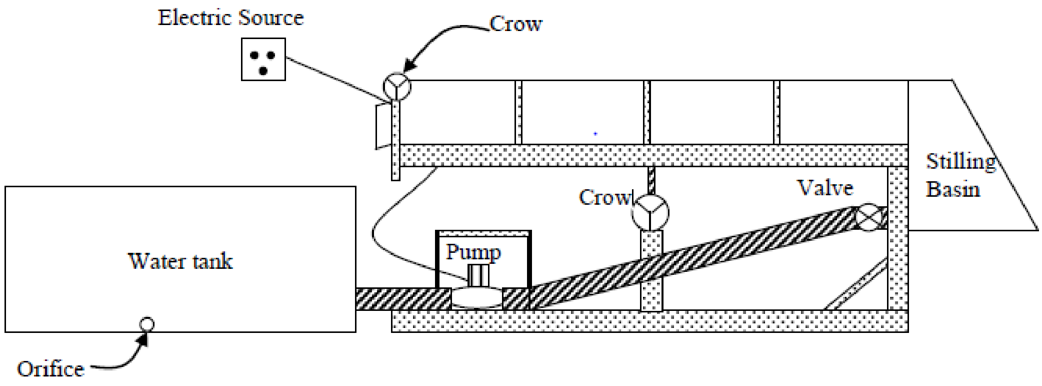

Figure 1. Channel setup

METHODOLOGY.

Adaptive Neuro Fuzzy Inference System ANFIS.

The most mathematical complicated problems can be solved and expressed by the Adaptive Neuro fuzzy Inference Systems (ANFIS) which can be considered as the most powerful tool for modelling most difficult problems based on input and output data. Zadeh (1965) presented Fuzzy logic approach in order to express complicated systems [18] . ANFIS are realized by an appropriate combination of neural and fuzzy systems. This combination ensures using both the numeric power of intelligent systems. In adaptive neuro fuzzy inference system different fuzzification and defuzzification strategies with different rule are considered for inputs parameter[19].Three stages are very important in fuzzy logic system modelling . The most important stage is the selection of the membership function for each inputs variable. [20] .Gaussian function for example could be selected for each of inputs variables. In first order Sugeno′s system, a typical rule set with two fuzzy IF/THEN rules can .be expressed as:

Rule 1: If x is A_1 and y is B_1, then

$f_1= p_1x+q_1y+ r_1$……………(6).

Rule 2: If x is A_2 and y is B_2, then

$f_2= p_2x+q_2y+ r_2$……………(7).

where A_1; A_2 and B_1; B_2 are the MFs for inputs x and y; respectively; p_1; q_1; r_1 and p_2; q_2; r_2 are the parameters of the output function. ANFIS structure is illustrated in Fig(2). All the inputs variable in the first layer gave the grade membership with membership function while in the second layer all the membership grade will be multiplies together. In the layer 3, all the grade of member will be normalized . In the fourth layer contribution of all the rule will be computed and in the last layer output variable will be computed as weighted average of grade membership.[21]

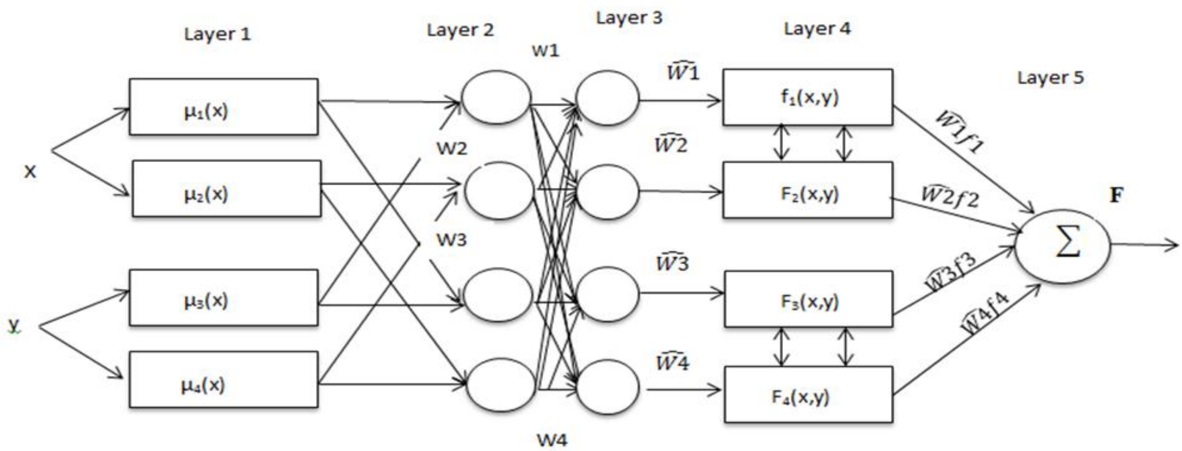

Figure 2: The structure of ANFIS Model.

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The membership functions are sometimes described by generalized bell functions.

$$\emptyset A_i(x) = \frac{1}{1+[\frac{x-c_i}{a_i}]^{2b_i}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(8).$$

where {ai, bi, ci} is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions on linguistic label Ai. [20]

Artificial Neural Networks

The artificial neural network as it is presented in Fig (3)is combined from input layer which includes the input variables and has one or more hidden layers with different number of neurons and the last layer in the network is the output layer which is the required output . Fig (3) presents s a three-layer neural network consisting of layers i, j, and k, with the interconnection weights Wij and Wjk between input, hidden and output layers. Initial assigned weight values are progressively corrected during a training process that compares predicted outputs to known outputs, and back propagates any errors (from right to left in Fig.). Different algorithms are available to obtain the appropriate weight adjustments necessary to minimize the errors. [22].

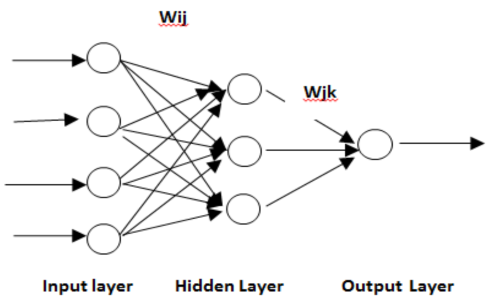


Figure 3. Structure of Artificial neural network.

Structure Of Multilayer Perceptron Neural Network (MLP).

MLP neural networks consist from nodes which are arranged in layers. Each layer is composed of nodes and in the fully connected network considered here each node connects to every node in subsequent layers. Each MLP network is composed of a three layers at least an input layer, one or more hidden layers and an output layer. The input variables are distributed to subsequent layers. Input nodes or neurons have liner activation functions and no thresholds. Each neuron in hidden and output layers have thresholds associated with them in addition to the weights.[2].

RESULTS

Results of Adaptive neuro fuzzy inference system ANFIS.

In this study the experimental data obtained were used in ANFIS model after using a dimensional analysis on the experimental work data base , which can be expressed as:

$Cd=f(D, H, Hw/R, Q, d_{crest}/dc, \alpha, ß)$ ...(9).

A program code including fuzzy logic tool box was designed and written by MATLAB. The parameters considered in this study as was mentioned in the experimental work representation were D diameter of the cylindrical weir , H the total head at upstream side above the crest ,Qdischarge, the dimensionless parameters which are Hw/R and d_{crest}/dc , R is the radius of the cylindrical weir , α is the longitudinal slope of the bed while β, is the angle of inclination. All the mentioned parameters were used to predict the discharge coefficient Cd. Totally 143 experimental data sets were used for ANFIS simulations. The data set was divided into two parts training(100) and testing (43). It is important to mention that the data set which were used for training and testing were all normalized before the start of the operation . The utility of ANFIS model leads to produce an optimal structure. The optimal structure of ANFIS model was tested as using all parameters as inputs and also by trying to minimize the number of inputs parameters with different membership functions since the optimal structure for soft computing causes an increasing in the conformity of results of any model due to influence of each parameter on getting more membership function . The performance of ANFIS models for training and testing data were evaluated according to statistical parameters R^2, RMSE, E_{nash}. These parameters can be described as :

$$R^2 = \frac{(\sum_{t=1}^{n}(A_t-A_{mean})(E_t-E_{mean}))^2}{\sum_{t=1}^{n}(A_t-A_{mean})^2 \sum_{t=1}^{n}(E_t-E_{mean})^2} \ldots\ldots.(10).$$

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}(A_t-E_t)^2 \ldots\ldots\ldots\ldots\ldots\ldots(11).$$

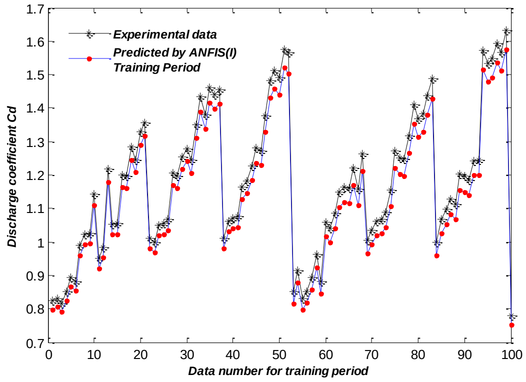
$$ENash = 1-\frac{\sum_{t=1}^{n}(A_t-E_t)^2}{\sum_{t=1}^{n}(A_t-E_{mean})^2} \ldots\ldots\ldots.(12).$$

where A_t is the observed value from experimental work and E_t is the Estimated value and E_{mean}, A_{mean} are the mean value of the series which are the observed and estimated [23, 24, 25]. Table (1) shows the results of the mentioned parametes for training and testing periods with some information on the ANFIS models parameters. The best results were selected among all the different trials to be showed . The best membership function is found after many trials then finding best performance. Figures (4, 5, 6, 7) show the performance of best applied ANFIS models.

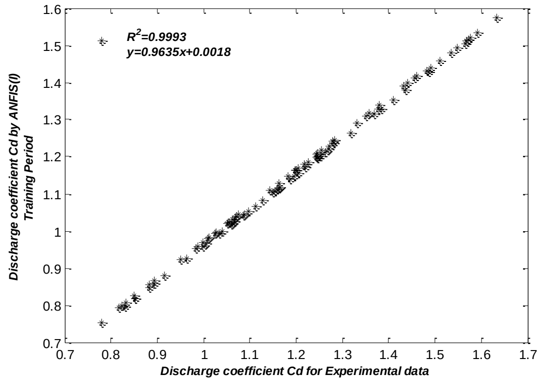
Table 1. Results of applied ANFIS Models.

Input parameters	BEST MF	Training Period			Testing Period		
		R^2	RMSE	E_{nash}	R^2	RMSE	E_{nash}
(D,H,Hw/R,Q,dcrest/dc,α,ß)- ANFIS(I)	**Gaussmf**	**0.9993**	**0.0332**	**0.9990**	**0.9983**	**0.0341**	**0.9983**
(D,H,Hw/R,Q,dcrest/dc,α)	Gaussmf	0.991	0.0471	0.991	0.978	0.0482	0.977
(D,H,Hw/R,Q,dcrest/dc,)	tiangularr	0.965	0.0612	0.9643	0.951	0.0671	0.954
(D,H,Hw/R,Q)	Trapezoid	0.971	0.0578	0.974	0.944	0.061	0.941
(D,H,Hw/R)	Generlized Bell	0.886	0.0623	0.885	0.876	0.0645	0.876
(D,H,)	Gaussmf	0.89	0.0656	0.891	0.87	0.0666	0.865
(D, α,ß))	Trapezoid	0.776	0.0771	0.777	0.763	0.0774	0.7631
(H)	Gaussmf	0.765	0.0762	0.766	0.71	0.77	0.741
(Hw/R)	Gaussmf	0.78	0.0645	0.778	0.712	0.0661	0.712
(Q)	Gaussmf	0.76	0.073	0.76	0.74	0.076	0.739
(dcrest/dc)	Gaussmf	0.86	0.058	0.867	0.85	0.0589	0.851
(dcrest/dc,α,ß)	Gaussmf	0.81	0.0591	0.812	0.83	0.0593	0.831
(D,H,Hw/R, dcrest/dc,α, ß)- ANFIS(II)	**Gaussmf**	**0.9911**	**0.0424**	**0.9912**	**0.9962**	**0.0441**	**0.996**
(D,H,Hw/R,α, ß)	Gaussmf	0.932	0.0585	0.932	0.93	0.05462	0.927
(D,Q,dcrest/dc,α,ß)	Generlized Bell	0.954	0.0623	0.96	0.911	0.0634	0.912

MF: Membership function

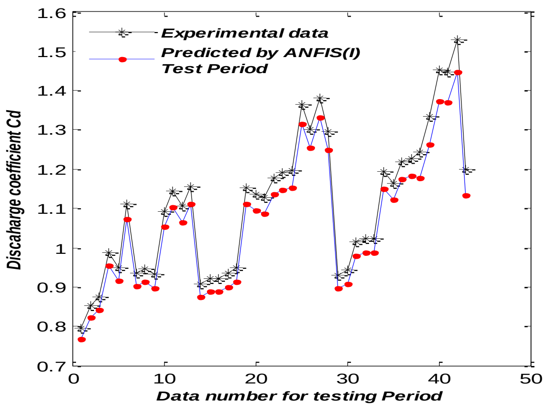


(a)

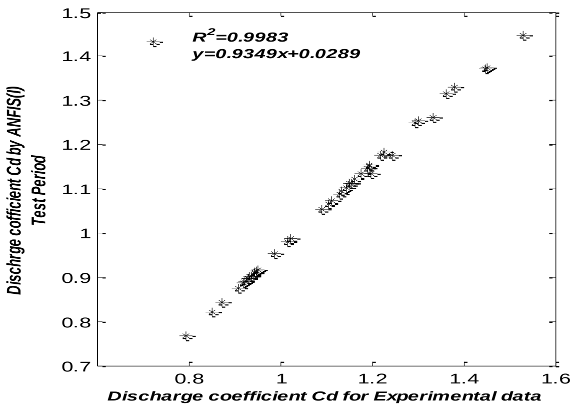


(b)

Figure (4-a, 4- b): Performance of model ANFIS(I) during training period.

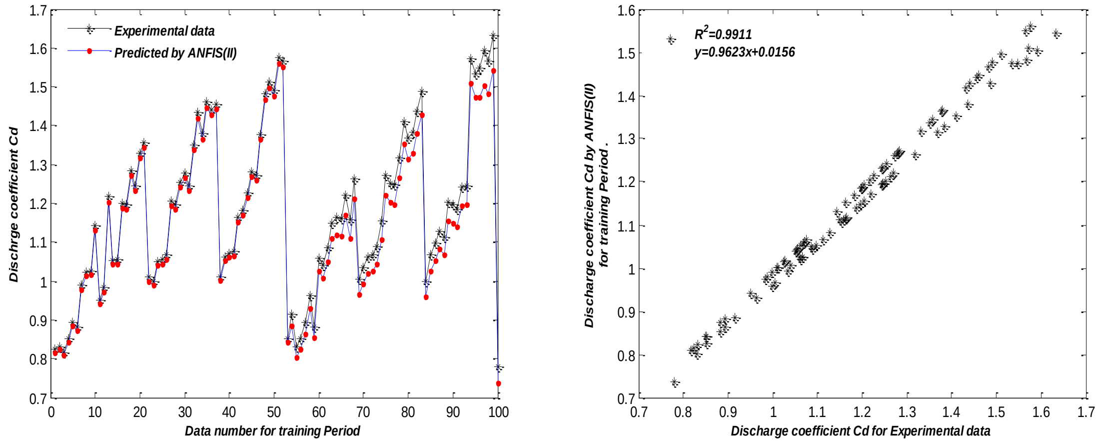


(a)



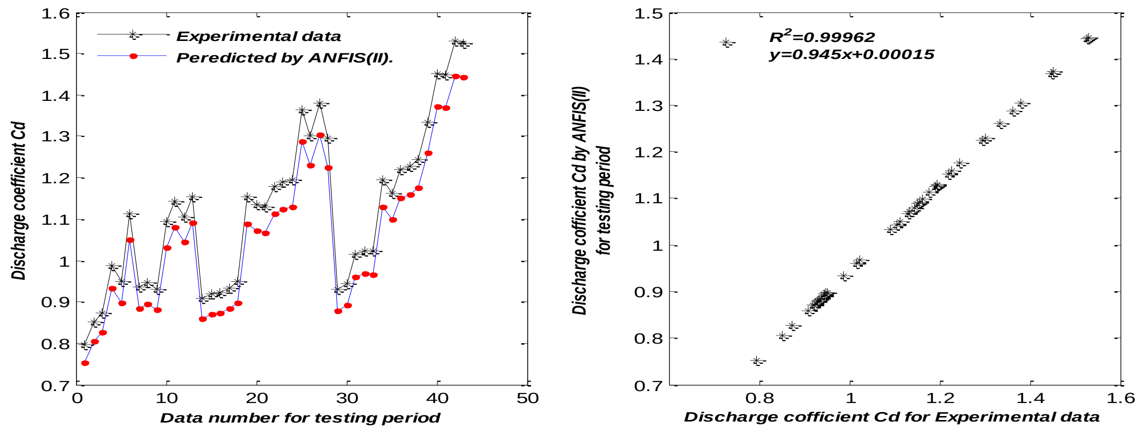
(b)

Figure 5-a, 5-b: Performance of ANFIS(I) model during testing period.



(a) (b)

Figure(6-a, 6-b): Performance of ANFIS(II) model during training period.



(a) (b)

Figure(7-a, 7-b): Performance of ANFIS(II) model during testing period

It is clear from the Table(1) and figures (4, 5, 6, 7) that there are two best ANFIS models which are remarked as ANFIS(I) and ANFIS(II). The results of the statistical parameters of ANFIS(I) were R^2=0.993 , RMSE =0.032, E_{nash} =0.0990 for training and R^2=0.9983, RMSE =0.03412, E_{nash} =0.09983 for testing Period while for ANFIS(II)the results were R^2=0.9911, RMSE=0.0424, E_{nash}=0.9912 for training and R^2=0.9962, RMSE =0.0441, E_{nash} =0.9961 for testing. The high influence of the most input parameters in the two models is very clear.

Results Of Multilayer Perceptron (MLP) Neural Network.

The collected data from the experimental work had been prepared to be suitable for artificial neural network therefore the data set was divided into two groups as training and testing. Designing the MLPNN model consists determination of number of neurons in each layer, number of hidden layers, determination of the transfer function for hidden layers neurons and the output layer and determination of learning algorithm. The optimum structure of MLP NN was investigated by avoiding the over parameterization of the network model . This was done by trying different input parameters which were chosen from the experimental work and by trying different number of hidden layers and also by using different number of neurons in each layer. In addition, the best transfer function for hidden layer and output layer was investigated also. Various types of transfer functions such as log-sigmoid(logsig),tan-sigmoid (tansig) and linear (pureline) were tested. The preparation and investigation of MLPNN was conducted in the environment of MATLAB software. Table (2) shows the results for the optimum structure for training and testing periods with different number of inputs , different number of hidden layers and different number of neurons in each hidden layer . The decision was made according to the common statistical parameters R^2 , RMSE , E_{nash}

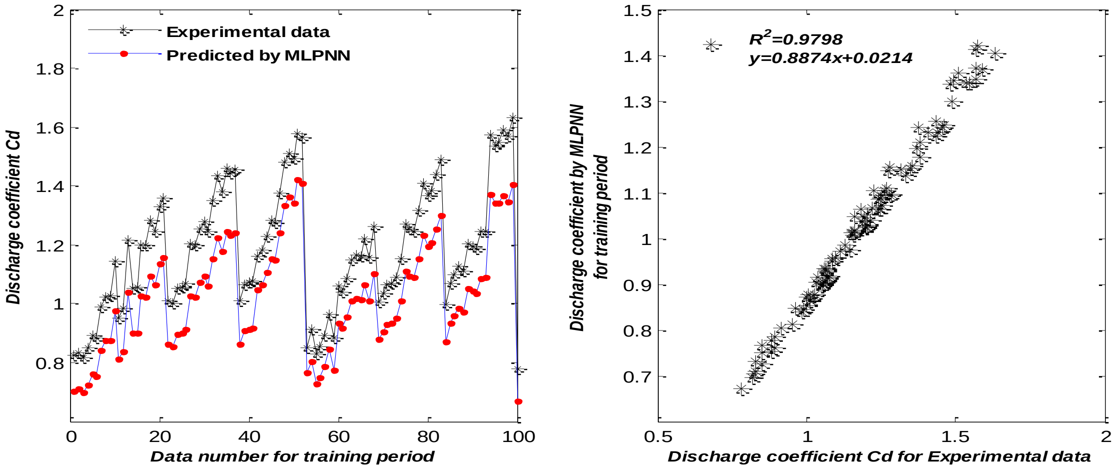
Table 2. Results of applied MLPNN Models.

Input parameters	BEST MLP Structure I-H-O	N1H-N2H	Transfer function For 1st layer –second layer	Training Period			Test Period		
				R^2	RMSE	E_{nash}	R^2	RMSE	E_{nash}
(D,H,Hw/R,Q,dcrest/dc,α,ß)	7-2-1	12-14	Tansig-Tansig	0.897	0.086	0.9867	0.976	0.087	0.9761
(D,H,Hw/R,Q,dcrest/dc,α)	6-1-1	7	Tansig	0.93	0.0723	0.934	0.923	0.0756	0.923
(D,H,Hw/R,Q,dcrest/dc,)	5-1-1	6	Tansig	0.965	0.065	0.9655	0.954	0.0654	0.9544
(D,H,Hw/R,Q)	4-2-1	21-5	Purelin-Purelin	0.90	0.0899	0.90	0.90	0.093	0.89
(D,H,Hw/R)	3-1-1	7	Tansig	0.91	0.088	0.92	0.911	0.0877	0.90
(D,H,)	2-1-1	11	Tansig	0.76	0.0956	0.76	0.74	0.0982	0.743
(D, α,ß)	3-2-1	5-6	Tansig-Purelin	0.81	0.093	0.81	0.82	0.095	0.82
(H)	1-2-1	4-3	Purelin-Tansig	0.67	0.111	0.65	0.66	0.099	0.66
(Hw/R)	1-1-1	7	Purelin-	0.751	0.099	0.751	0.743	0.0993	0.741
(Q)	1-1-1	10	Purelin-	0.81	0.077	0.82	0.81	0.0766	0.81
(dcrest/dc)	1-2-1	12-14	Purelin-Purelin	0.85	0.065	0.854	0.83	0.0671	0.834
(dcrest/dc,α,ß)	3-1-1	7	Tansig	0.94	0.0699	0.94	0.921	0.0699	0.921
(D,H,Hw/R, dcrest/dc,α, ß)	6-2-1	21-9	Tansig-Tansig	0.951	0.0691	0.952	0.934	0.0693	0.932
(D,H,Hw/R,α, ß)	5-1-1	8	Tansig	0.964	0.0683	0.964	0.944	0.069	0.943
(D,Q,dcrest/dc,α,ß)-MLPNN	**5-1-1**	**8**	**Tansig**	**0.9798**	**0.0571**	**0.9797**	**0.9117**	**0.0577**	**0.9116**

I-H-O: no of neurons in input layer-no of hidden layers-no of output neurons.

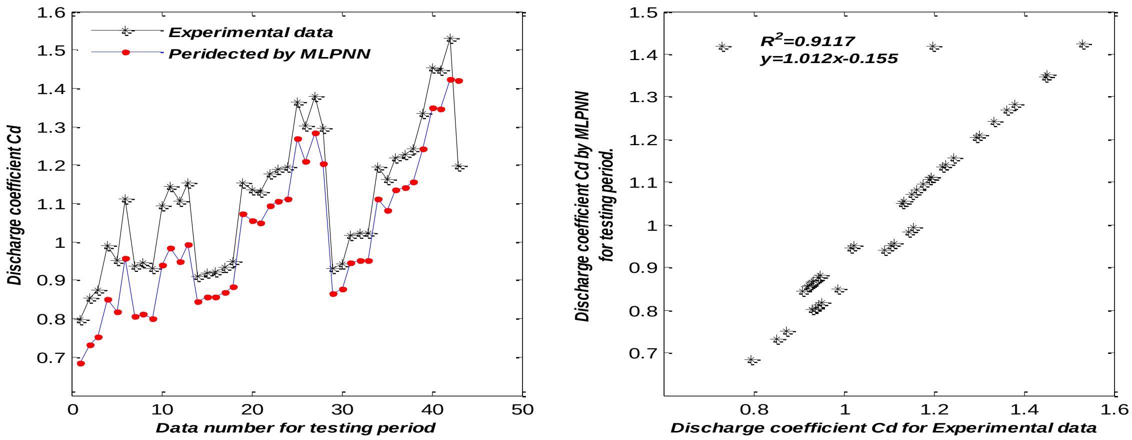
N1H-N2H: no of neurons in 1st hidden layer- no of neurons in the 2nd layer.

From Table (2) , it is clear that the best model which showed approximate conformity with experimental values of Cd was the last model . The model presented perfect predicting of discharge coefficient . The best number of hidden layer was one with eight neurons at the hidden layer as shown in the optimum structure. Results of the best MLPNN models are also illustrated by comparing the experimental results of Cd and the MLPANN results , this is shown in figures (8, 9) for training and testing periods . Scatter plots for training and testing periods are plotted also .



(a) (b)

Figure(8-a, 8-b): Performance of MLPNN model during training period.



(a) (b)

Figure (9-a, 9-b): Performance of MLPNN model during testing period.

An overview of the results gives an idea about the highly effect of bed slope of the channel and the angle of inclination since the high values of R^2 and E_{nash} for example were obtained in the models including these two factors. By comparing the best models of ANFIS and MLPNN , it is obvious that the adaptive neuro fuzzy inference ANFIS method performs better than MLPNN.

CONCLUSIONS.

In this study two theoretical models were developed which are ANFIS and MLPNN to determine discharge coefficient for cylindrical weir with different diameters and different angle of inclinations and bed slopes . 143 experimental data series with different input combinations were used for both models. Various membership functions for ANFIS models were investigated . The similar investigations were done for MLPNN models such as trying different input parameters combinations , different number of hidden layers and different number of neurons in hidden layers. The best transfer function in each layer was also investigated. The optimum ANFIS models were obtained after trying the different structures . The same optimum structure of MLPNN model was found with five input parameters and eight neurons in one hidden layer. It was concluded from the study that both models are suitable for modelling discharge coefficient but the ANFIS model was more efficient than MLP-ANN model .

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