



## Prediction of Discharge Coefficient of Crump Weir Using Artificial Neural Network (ANN)

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### ABSTRACT

The flow characteristics changes with varying geometry of the hydraulic weir and how the weir is inclined to the direction of flow in a channel. In this way, several studies have investigated the performance weirs experimental with paying much attention to the accurate prediction of discharge coefficient. Thus, the main objective of this study is to employ artificial intelligence (AI) techniques to predict the discharge coefficient ( $C_d$ ) of crump weir models. Hence, the precision and use of seven data-driven models including Bayesian neural network (BNN), multiple linear regression (MLR), multi-layer perceptron neural network (MLPNN), genetic algorithm (GA), support vector machine (SVM), Radial Basis Function (RBF) and curve fitting neural network (CFNN) were examined for estimating of the  $C_d$ . To achieve this, experiments were conducted on eighteen crump weir models of different apex angles  $80^\circ$ ,  $90^\circ$ ,  $100^\circ$ ,  $110^\circ$ ,  $120^\circ$  and  $130^\circ$ . The upstream angles of the weir models were set in decreasing order of  $85^\circ$ ,  $70^\circ$ ,  $55^\circ$ ,  $40^\circ$ ,  $25^\circ$  and  $10^\circ$ . While the downstream angles were increased to  $15^\circ$ ,  $20^\circ$ ,  $25^\circ$ ,  $30^\circ$ ,  $35^\circ$  and  $40^\circ$  respectively. 360 laboratory test results were used, 70% for training, 15% for testing, and 15% for validation. And statistical parameters of coefficient of determination ( $R^2$ ), root-mean-square error (RMSE), and mean absolute error (MAE), were employed as the criteria for the comparison of the model's performance. Results showed good agreements between the observed and estimated values using the AI-based models. However, among these models, the CFNN managed to estimate the  $C_d$  of the weir with the highest precision and accuracy than the rest of the models (RMSE= $0.1635 \times 10^{-4}$ ,  $R^2=0.9981$ ). Also, it was found that the most efficient crump was weir model 17 for having the least  $C_d$  of 1.14914 and least percentage error of 12.97412, which has been optimized using GA with a  $C_d$  value of 1.14815.

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### INTRODUCTION

The Crump section flat-vee weir is favored by hydrometrics because of the accuracy and range of flow measurement it exhibited. It is comparatively insensitive to submerged conditions and ease of determination of flow curves for any width, and its coefficient of discharges remain through undrown condition. However, this type of weir is disliked by fishermen because it can present a barrier to migration of fish (Rickard *et.al.*2003). As such it becomes necessary to investigate the behavior of the flow over the crump weir. In this way, few studies have

been devoted to evaluating the flow over crump weirs, for example, Bos, 1989 was the first to study the flow characteristics of trapezoidal profile weirs systematically. He conducted a series of experiments on these types of weirs with both upstream and downstream side slopes. The discharge coefficient was determined for free flow conditions using different discharge values (Daneshfaraz *et al.* 2019). Similarly, Khalifa & Umar, 2018 conducted experiments on crump weir models of different apex angles, they demonstrated that increase in the apex angle resulted in decrease in discharge coefficient.

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Hence, controlling the amount of discharge over different hydraulic structures was always a field of interest for researchers, with a view of decreasing sedimentation in reservoirs (Zahabi et al. 2018).

## THEORETICAL BACKGROUND

### Governing Equations

The discharge was estimated using the equation governing the modelling of flow over crump weir by determining the upstream flow head (h). Point gauge was used to measure the, h, above the crump weir (Arora, 2005). Thus, for modular flow over the crump weir, when the weir operates undrowned, the modular discharge is expressed as follows:

$$Q_m = C_d \sqrt{g} \cdot b H_o^{\frac{3}{2}} \quad (1)$$

$C_d$  and  $H_o$  can be determined using Equations (2) and (3) respectively

$$C_d = 1.163 \left( 1 - \frac{0.0003}{h} \right)^{1.5} \quad (2)$$

$$H_o = y_o + \frac{v_o^2}{2g} \quad (3)$$

Where,  $Q_m$  = Discharge for modular flow ( $m^3/s$ ),  $C_d$  = Modular discharge coefficient,  $g$  = gravity ( $m^2/s$ ),  $b$  = Breadth of weir (m),  $H_o$  = Total head upstream of the weir crest (m),  $y_o$  = upstream water level (m),  $\frac{v_o^2}{2g}$  = upstream velocity head (m).

However, dimensionless reduction factor is introduced to correct the non-modular flow as given by Equation (4):

$$f = Q/Q_m \quad (4)$$

Where,  $Q$  = Discharge for non-modular flow ( $m^3/s$ )

### Artificial Neural Networks

Artificial neural network (ANN) is a nonlinear mathematical model that is able to simulate arbitrarily complex nonlinear processes, which relate inputs and outputs of any system. In many complex mathematical problems that lead to solving complex nonlinear equations, multilayer perceptron networks are common types of ANN widely used by researchers (Parsaie 2016; Moazamnia et al. 2019).

### Support Vector Machines

Support vector machines operate based on data mining algorithms and are like other artificial intelligent methods. It was used in different fields of hydrology (e.g., Nadiri et al.

2017) and Hydraulics (e.g., Sadeghfam et al. 2019). Support vector machines are an efficient learning system based on the theory of optimization that uses the inductive principle of minimization of structural errors and lead to a general optimal response.

### Multi-layer Perceptron Neural Network (MLPNN)

MLPNN is a computational method which tries to propose a mapping between input space (input layer) and optimal space (output layer) by understanding the inherent relationships among data with the help of learning process and using simple processors called neurons (Heidari et al., 2016). The high speed of processing and flexibility in the face of unwanted errors are the features of this model. Its main advantage is its high speed and optimal precision in the prediction of complex variables with linear and non-linear mapping.

Mohammad Zounemat et al., 2019 have examined the precision and use of six data driven models including BNN, MLR, MLPNN, GEP, LSSVM and CHAID for estimation of discharge passing triangular Arced labyrinth weir. MLPNN managed to estimate the discharge passing the weir with the highest precision (RMSE = 0.00385,  $R^2 = 0.999$ ).

Reza Norouzi et al., 2019 have investigated the performance of MLP, RBF and SVM in predicting the discharge coefficient ( $C_d$ ) of labyrinth weirs. The performance of the MLP model was excellent with RMSE and  $R^2$  of 0.019 and 0.985 respectively.

In the studies of Zounemat et al., 2019, they applied various hybrid meta-heuristic MLPNN and ANFIS for predicting flow parameters of piano key weir flow.

## METHODOLOGY

### Fabrication of the Experimental Models

The experimental work was conducted on eighteen crump weir models of different apex angles of  $80^\circ$ ,  $90^\circ$ ,  $100^\circ$ ,  $110^\circ$ ,  $120^\circ$  and  $130^\circ$ . Accordingly, the upstream angles of the models were decreased to have the following values  $85^\circ$ ,  $70^\circ$ ,  $55^\circ$ ,  $40^\circ$ ,  $25^\circ$  and  $10^\circ$ , and to as well increasing the downstream angles as  $15^\circ$ ,  $20^\circ$ ,  $25^\circ$ ,  $30^\circ$ ,  $35^\circ$  and  $40^\circ$  respectively, which will sum

up to give 180° as the total angles in a triangle as shown in Figure 1. Plywood of 22 mm thickness

was used in fabricating the main body of the crump weirs.

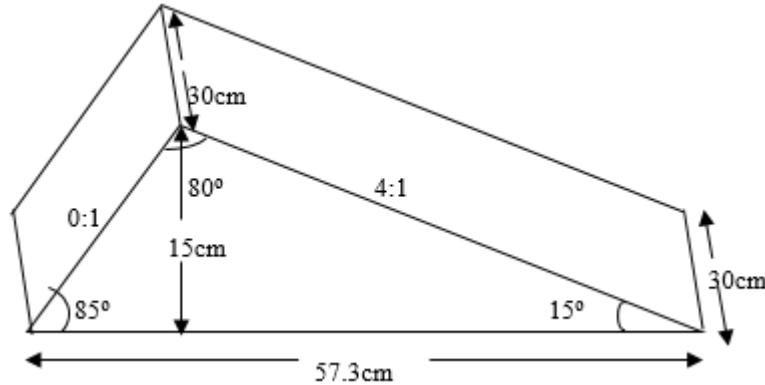


Figure 1: The schematic view of crump weir model 1 of apex angle 80°, upstream angle and slope, 85° and 0:1, downstream angle and slope, 15° and 4:1 respectively.

**Table 1: Geometric Factors of Crump Weir Models**

Model	Upstream Slope	Downstream Slope	Model width 'b' (cm)	Crest Height 'P' (cm)	Apex Angle (degree)	Upstream Angle (degree)	Downstream Angle (degree)
1	0.1:1	4:1	30	15	80	85	15
2	0.4:1	3:1	30	15	90	70	20
3	0.7:1	2:1	30	15	100	55	25
4	1:1	2:1	30	15	110	40	30
5	2:1	1:1	30	15	120	25	35
6	6:1	1:1	30	15	130	10	40

#### Experimental Procedure:

The crump weirs were installed in the flume with the help of sealants to prevent leakage, which has to be levelled. One vernier were located downstream the weir and the other upstream. The verniers were zeroed with the bed of the channel.

Seventy-two models were fabricated for which the angles were varied, 80°, 90°, 100°, 110°, 120°, and 130°. Experiment were then be ran for each model and various heads and their corresponding discharges were recorded. The procedure has five (5) runs. Each run has a different flow rate and a set of four (4)  $y_0$  and  $y_1$  depths; two sets for modular flow condition and the other two sets for non-modular flow condition. The initial flow rate were set. Then,  $y_0$  and  $y_1$  depths were recorded for the following conditions: Modular flow: without stop block (gate). Modular

flow: one full stop block (gate) ( $y_1$  should be the only depth that changes). Non-modular flow: Add a half of one stop block (gate). ( $y_1$  and  $y_0$  depth that change). Non-modular flow: Add one quarter of a stop block (gate). The flow rate were increased at constant interval.

Heights ( $P=10\text{cm}$ ,  $15\text{cm}$ ,  $20\text{cm}$ ) were used as a crump weir models. For each type of crump three types of surface roughness were used. The first one were a smooth PVC, the second one is coated with a uniform sand  $D_{50}=0.72\text{ mm}$  ( $D_{50}$  is the sieve diameter in which 50% of material are finer), while the third is covered by gravel of  $D_{50}=3.6\text{ mm}$ . Eighteen models were used to conduct the experimental study. In each run the selected model were inserted along the width of the flume. Then the pump started at desired flow rate and after the flow stability were



achieved the water surface level upstream and above the weir model were measured using point gauge. For each type of the crump weir a series of tests under different flow rates were conducted. The pump were activated and the discharge were adjusted using a control valve and the reading of the point gauge were recorded to give the head above crump weir required for the calculation of estimated discharge; At the beginning of each run the control valve were adjusted to alter the head; For each head recorded, the actual discharge were measured by direct method using the weighing arrangement provided at the tail end of the flume. The previous steps were repeated for each of the five runs of experiments to be conducted for each model. A total of 360 runs were conducted.

#### Determination of Observed Discharge ( $Q_o$ )

The observed discharge,  $Q_o$ , was measured experimentally using the gravimetric method. Throughout the experiment, 100kg of water were collected by means of the weighing balance (see plate II) attached to the flume and stopwatch was used to obtain the time taken to collect the 100kg for onward determination of discharge.

Volume,  $V = \text{mass/density}$

Observed discharge,  $Q_o = \text{Volume / average time}$

$$\text{Average time} = \frac{(t_1 + t_2)}{2} \quad (5)$$

#### Determination of Estimated Discharge ( $Q_e$ )

The discharge equation for the crump weir was used to compute the estimated discharge using the flow heads.

Point gauge will be used to measure the flow head ( $h$ ) above the crump weir (Arora, 2005).

$$Q_m = C_d \sqrt{g} \cdot b H_o^{\frac{3}{2}} \quad (1)$$

$$C_d = 1.163 \left( 1 - \frac{0.0003}{h} \right)^{1.5} \quad (2)$$

$$H = y + \frac{v^2}{2g} \quad (3)$$

#### Derivation of Discharge Coefficient

In order to validate the suitability of the theoretical equations, the maximum of the absolute value of the deviation of the data from the model was obtained as:

$$\text{MaxErr} = \max(\text{abs}(C_{do} - C_{de})) \quad (7)$$

Where,  $C_{do}$  = Experimental Discharge Coefficient =  $Q_o / Q_e$

$C_{de}$  = Estimated Discharge Coefficient

$$Cd = (D_{50}, P, h, Q, \theta) \quad (8)$$

Thus, by dimensional analysis and using the approach of Buckingham's  $\pi$ -theorem, Equation (8) becomes:

$$Cd = f \left( \frac{D_{50}}{P}, \theta, \frac{h}{P} \right) \quad (9)$$

It follows that Equation (9) can be expressed as Equation (10) based on dimensional homogeneity:

$$C_d = k_1 \left[ \frac{D_{50}}{P} \right]^a + k_2 \left[ \frac{h}{P} \right]^b \quad (10)$$

Where,  $K_1$ ,  $K_2$ ,  $a$ , and  $b$  are parameters to be estimated by regression analysis.

## RESULTS AND DISCUSSION

#### Computation of Discharge Coefficients ( $C_d$ )

Tables 2 show the values of  $C_d$  obtained from Equations 1 and 2 respectively. The head measurements were obtained by means of the point gauge.

**Table 2:** Discharge characteristics for model 1

$Q_o = V/t/m^3/s$	$y_o/m$	$h_o = y_o - 0.10/m$	$y_1/m$	$H_o/m$	$H_1/m$	$C_d$	$Q_e/m^3/s$	% Error
0.001515	0.120	0.020	0.060	0.121	0.065	1.13693	0.00133	12.04391
0.001563	0.160	0.060	0.110	0.175	0.115	1.15429	0.00135	13.36654
0.001613	0.194	0.094	0.135	0.210	0.140	1.15744	0.00139	13.60220
0.001667	0.210	0.110	0.130	0.228	0.150	1.15825	0.00144	13.66252
0.001724	0.218	0.118	0.100	0.235	0.160	1.15857	0.00149	13.68652
Average						1.15310	0.001400	13.27234

**Table 3:** Summary of the statistical analysis of Cd predicted by MLP using different neurons

No of neurons	Training		Validation		Testing	
	MSEx(10 <sup>-6</sup> )	R <sup>2</sup>	MSEx(10 <sup>-6</sup> )	R <sup>2</sup>	MSEx(10 <sup>-6</sup> )	R <sup>2</sup>
1	9.0141	0.9123	7.5607	0.9152	4.5334	0.9613
2	5.0244	0.9392	5.8012	0.9301	23.735	0.8881
3	8.6095	0.9116	6.2662	0.9356	6.7934	0.9419
4	7.5581	0.9154	7.8690	0.9376	7.0532	0.9386
5	8.1319	0.9172	7.4021	0.9139	25.307	0.8497
6	7.7184	0.9283	6.2652	0.9111	7.1875	0.9115
7	1.9925	0.7902	2.4047	0.6565	17.668	0.8180
8	9.0060	0.8856	5.1653	0.7087	16.042	0.8045
9	8.1825	0.9234	7.0573	0.9161	1.8738	0.9821
10	8.1417	0.9251	4.6387	0.9309	6.2766	0.9290
11	1.0583	0.9090	3.7310	0.9579	7.0051	0.9331
12	4.3199	0.9458	2.1757	0.8691	7.2633	0.9435
13	7.8978	0.9175	6.1824	0.9432	6.5836	0.9363
14	9.4249	0.9035	8.5379	0.9214	6.3073	0.9325
15	4.7196	0.9475	4.2265	0.9404	23.272	0.8592
16	9.1488	0.9180	5.5131	0.8933	8.6496	0.9166
17	7.7760	0.9240	8.3009	0.9161	5.6503	0.9328
18	3.9774	0.9525	2.2298	0.8719	189.13	0.5615
19	8.3764	0.9227	7.4020	0.9137	0.9750	0.8849
20	1.0319	0.9037	6.4052	0.9190	7.6421	0.9132

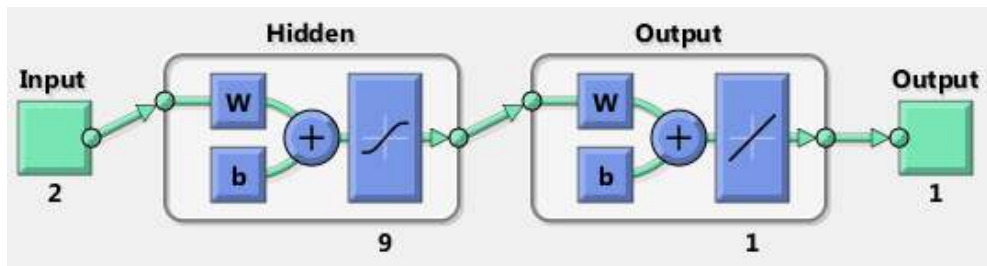


Figure 2: MLP Levenberg Marquardt Neural Network Diagram

## DISCUSSION OF RESULT

### *Predicting the Cd of crump weir using ANN*

Results of evaluating the precision of the data-driven models in the estimation of Cd of crump weirs in the training and testing sets are presented in Tables 5 and 6 respectively. Comparison of the values provided in Table 6 shows that CFNN managed to estimate discharge passing the weir with the highest accuracy (RMSE=  $0.1635 \times 10^{-6}$  MAE= $0.4713 \times 10^{-3}$  R<sup>2</sup>=0.9981). Also, CFNN was followed by MLPNN, BNN, GA, MLR, RBF and SVM.

Eqs. (15), demonstrate the extracted relationships between independent and

dependent variables in the CFNN model. Scatter plots presented in Figs. 14 and 15 show the results of BNN and MLPNN respectively indicating their good precision in estimating the performance of the crump weir.

In this study, the precision of seven data-driven models was evaluated for the estimation of Cd for crump weir. Final results showed that CFNN could estimate the discharge passing the weir with the highest precision. Also, due to the effect of input parameters of the model on the estimation accuracy, CFNN precision was evaluated using the various combination of the input parameters. 2 different independent



variables were used for constructing the applied models. In order to investigate the importance of each variable in the final performance of the models.

Table 7 shows the sensitivity analysis of Coefficient of discharge, Cd. The sensitivity analysis was carried, in order to evaluate the significance of input variables on the Coefficient of discharge. The sensitivity analysis was performed

using the ANN model due to the high value of correlation coefficient and minimum error it produced.

Consequently, the parameter ( $\frac{h}{P}$ ) was found to be the most effective parameter with R = 0.9971, MSE =  $3.8513 \times 10^{-4}$  on the prediction of Cd. While the function ( $\frac{D_{50}\theta}{P}$ ) was found to be the least effective parameter on the prediction of Cd.

Relation of Model Cd and Observed Cd

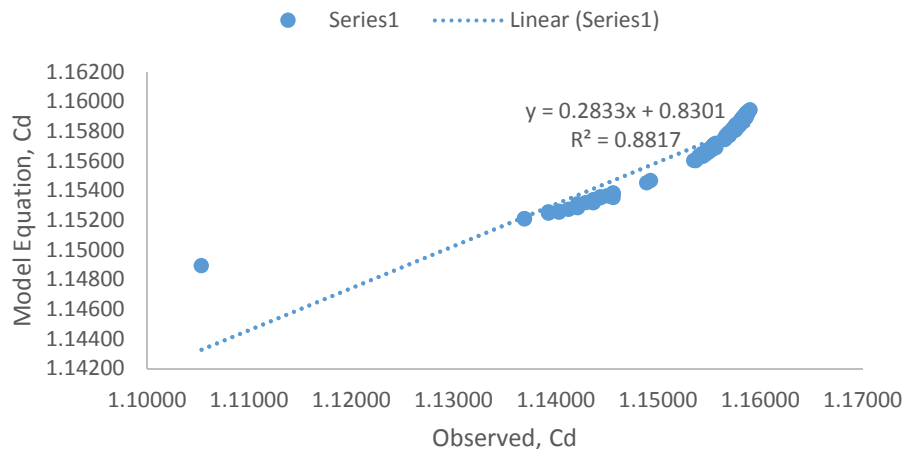


Figure 8: ANN verification of Cd from Model Equation

**Table 4.** Results of evaluating the performance of data driven models in the training phase.

Models	MSE $\times(10^{-6})$	MAE $\times(10^{-3})$	R <sup>2</sup>
MLP	8.1825	0.9874	0.9234
BNN	7.9003	0.8452	0.9192
RBF	2897.6	1.7652	0.8400
SVM	4232.7	2.6745	0.7300

**Table 5:** Results of evaluating the performance of all the applied models in the testing phase.

Models	MSE $\times(10^{-6})$	MAE $\times(10^{-3})$	R <sup>2</sup>
CFNN	0.1635	0.4713	0.9981
MLP	1.8738	0.6704	0.9821
BNN	3.4682	0.7461	0.9669
GA	3.9641	0.8452	0.9573
MLR	2611.7	1.4233	0.8700
RBF	2672.6	1.5712	0.8600
SVM	3288.7	2.1005	0.7900

Finally, the precision of the models in estimating the discharge passing the weir was evaluated using the root-mean square error

(RMSE), mean absolute percentage error (MAE), R<sup>2</sup> (coefficient of determination). The best values of these criteria were 0, 0, and 1 respectively.

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_j)^2} \quad (12)$$

$$MAE = \frac{1}{n} \sum_{j=1}^n |y_j - \hat{y}_j| \quad (13)$$

$$\hat{R}^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (14)$$

In Eqs. (12) – (14),  $y$  is the actual Cd,  $\hat{y}$  is their average,  $n$  is the number of estimations.

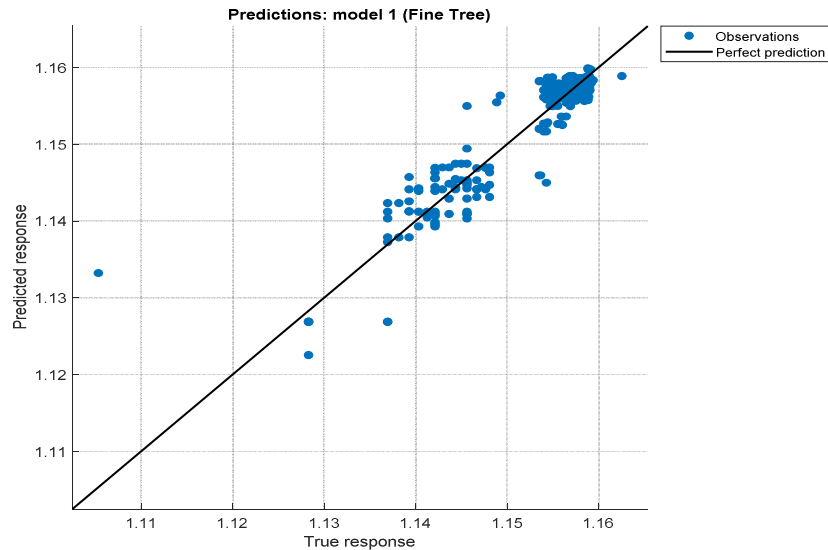


Figure 3: Relation of Cd predicted and Actual value using (MLR) model

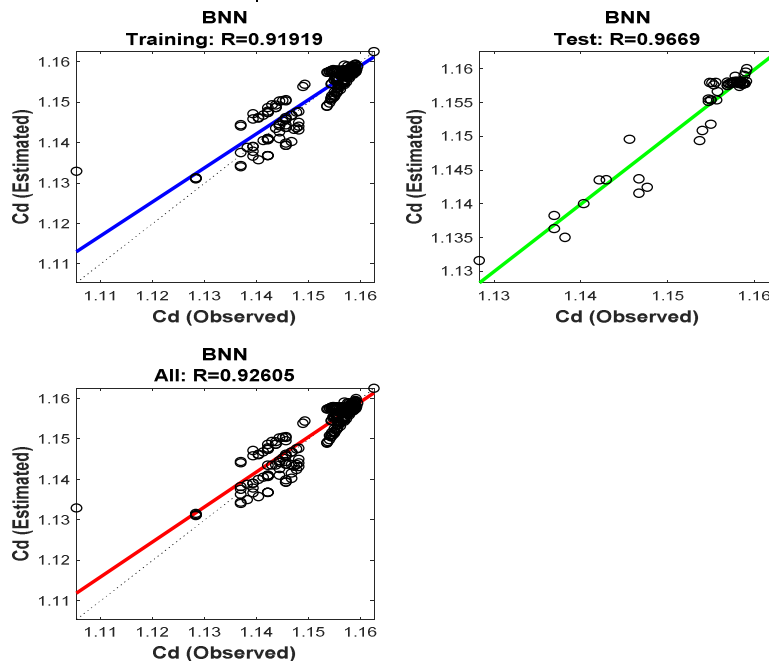
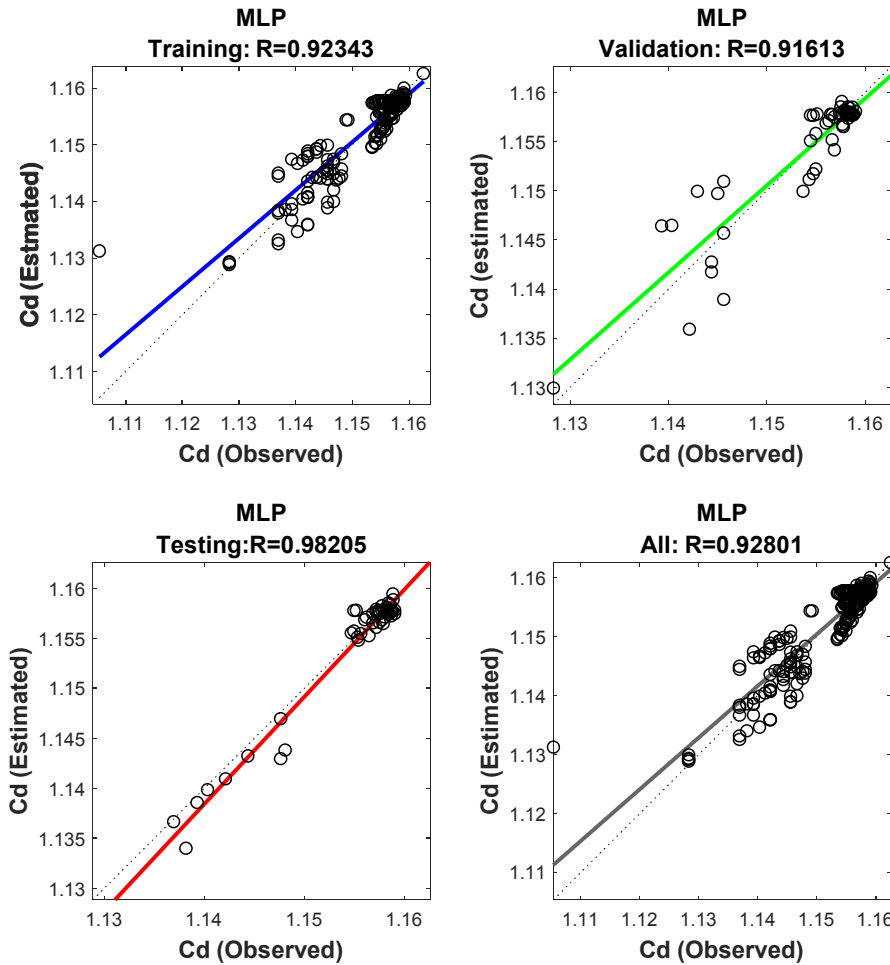


Figure 4: Distribution diagram of the observational-computational values in training and testing stages of Bayesian Neural Network (BNN) Model varification of Cd.



**Figure 5:** Distribution diagram of the observational-computational values in training and testing stages of MLP model

Thus, the parameters  $K_1$ ,  $K_2$ ,  $a$  and  $b$  in Equation (10) were determined through regression analysis and Curve Fitting Neural Network as expressed by Equation (15) as follows:

$$Cd = 0.5785 \left[ \frac{D_{50}\theta}{P} \right]^{6.593 \times 10^{-5}} + 0.58 \left[ \frac{h}{P} \right]^{0.006761} \quad (15)$$

The model equation has  $R^2 = 0.9981$ .

**Table 6:** Sensitivity analysis of Cd's for input parameters with ANN model.

Function	Training		Testing	
	MSE $\times (10^{-4})$	R <sup>2</sup>	MSE $\times (10^{-4})$	R <sup>2</sup>
$Cd = \left[ \frac{D_{50}\theta}{P} \right]$	7.5421	0.9782	7.6801	0.9884
$Cd = \left[ \frac{h}{P} \right]$	3.7313	0.9841	3.8513	0.9971
$Cd = \left( \frac{D_{50}}{P} \theta, \frac{h}{P} \right)$	0.1534	0.9883	0.1635	0.9981



Table 6 shows the sensitivity analysis of Coefficient of discharge, Cd. The sensitivity analysis was carried, in order to evaluate the significance of input variables on the Coefficient of discharge. The sensitivity analysis was performed using the ANN model due to the high value of correlation coefficient and minimum error it produced.

Consequently, the parameter ( $\frac{h}{P}$ ) was found to be the most effective parameter with  $R = 0.9971$ ,  $MSE = 3.8513 \times 10^{-4}$  on the prediction of Cd. While the function ( $\frac{D_{50}\theta}{P}$ ) was found to be the least effective parameter on the prediction of Cd.

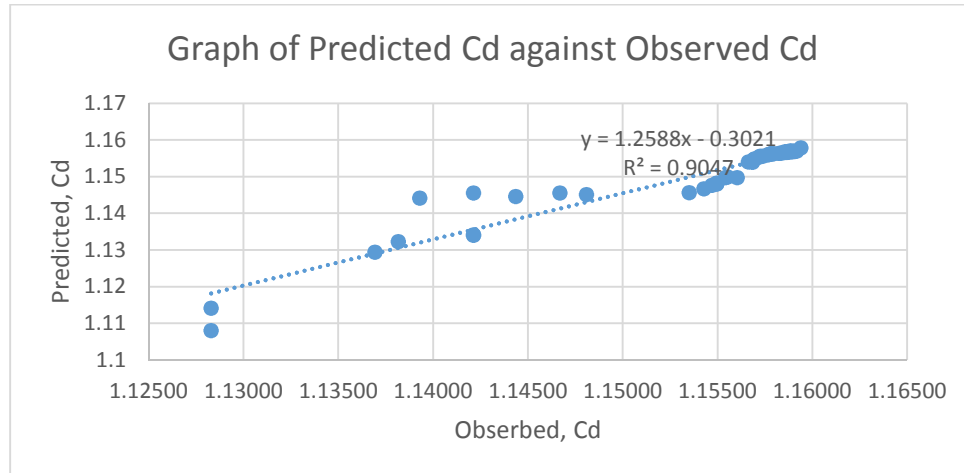


Figure 6: Relation of predicted Cd and observed Cd using (MLP) model

## CONCLUSION

By using the equations which has been discussed in the literature, the raw data was calculated and processed using ANN. Based on the results of the investigation, the following conclusions are reached:

1. Cd increases with the increasing flow rate.
2. The effect of  $h/P$  on Cd values increases with the increase in weir height.
3. Cd decreases from model 1 to model 18 with model 17 having the least Cd close to unity and least percentage error making model 17 to be more efficient.
4. The Mathematical Model equation generated using CFNN performed better than other models such as MLP, BNN, GA, MLR, RBF and SVM with  
 $RMSE = 0.1635 \times 10^{-6}$   
 $MAE = 0.4713 \times 10^{-3}$   $R^2 = 0.9981$

## RECOMMENDATIONS

The recommendations below are some of the improvements that can be carried out for further study:

1. Depth of weir and width of channel in variable value are suggested to get the best flow rate for hydraulic structure of crump weir design.
2. Calibration device for better data collection suggested using a volume meter to get the flow rate over a crump weir.
3. Similar study should be carried out using stones and cement models instead of wooden models.

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