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Modeling of flow characteristics beneath vertical and inclined sluice gates using artificial neural networks

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KEYWORDS

Sluice gate;
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Abstract In this paper, artificial neural networks (ANNs) modeling method with back propagation algorithm was employed to investigate the flow characteristics below vertical and inclined sluice gates for both free and submerged flow conditions. Two ANN models were developed yielding two generalized equations to predict the discharge coefficient (C_d) values for both modes of flow. The model network for free flow entailed four input variables, namely, dimensionless upstream water depth, Froude number, Reynolds number, and inclination angle, whereas, the C_d value represented the only single output variable. For submerged flow ANN model, a fifth input variable was added, which is the dimensionless tailwater depth. The two ANN models were trained and validated against 420 data sets collected from previous experimental studies. The results indicated that ANNs are powerful tools for modeling flow rates below both types of sluice gates within an accuracy of ±5%.

1. Introduction

Policy of water saving relies on the precision of flow discharge measurements. Sluice gates are widely used for controlling discharge and flow depth in irrigation channels and in hydraulic structures such as barrages. Thus, accurate flow rate computations below sluice gates in all flow conditions are inevitably required. Sluice gates are classified into different categories based on different criteria. Based on the downstream water level, they are classified as sluice gate discharging free and submerged flow, whereas, on the basis of alignment with channel axis Mansoor [1] classified them as normal sluice gate, if the gate is normal to the axis of the channel, side sluice gate, if the gate is parallel to the axis of the channel, and skew sluice gate when the gate is inclined to the axis of the channel. Further, a gate inclined with vertical is classified as inclined or planar gate (Fig. 1).

Flow through the opening of normal vertical sluice gates has been the subject of investigation for many academicians and researchers. On the other hand, little work has been done on flow under inclined sluice gates. Henry [2] studied the diffusion of submerged jet downstream of a normal sluice gate and

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Notations

ANN	artificial neural networks	L	length of sluice gate (m)
B	gate width (m)	Q	discharge (m^3/s)
b	sluice gate opening height (m)	Re	Reynolds number (dimensionless)
BPN	back propagation network	RMSE	root mean square error
C_d	discharge coefficient (dimensionless)	Y_1	upstream flow depth (m)
Fr	Froude number (dimensionless)	Y_t	tailwater flow depth (m)
g	gravitational acceleration (m/s^2)	θ	sluice gate angle (radians)

developed a useful diagram for discharge coefficient (C_d) in free and submerged flow conditions. Based on the experimental curves demonstrated in [1], Swamee [3] proposed equations for both free and submerged flows as well as criterion for submergence. Ferro [4] carried out experimental study on simultaneous flow over and under a sluice gate. Clemmens et al. [5] examined submerged radial gates. Spulveda [6] explored various calibration methods for C_d of submerged sluice gates. Belaud et al. [7] studied the contraction coefficient under free and submerged sluice gates. Cassan and Belaud [8] investigated flow characteristics under normal sluice gates using both experimental and numerical methods. Wu and Rajaratnam [9] explored solutions to rectangular sluice gate flow problems.

The side sluice gates and skew sluice gates are often used to divert the discharge in the side channel in irrigation, urban sewage system and during flood operation. Little published work namely [10–12] is available on side sluice gates. On skew sluice gates, Swamee et al. [13] conducted experimental study under free and submerged flow conditions covering a wide range of hydraulic parameters. Montes [14] developed method of solution for flow under planar sluice gates and suggested that the discrepancy between experimental and theoretical values of contraction coefficient is due to the energy loss associated with the vortex formation at the upstream region of the gate.

Flow under sluice gate (Fig. 2) may be evaluated quite simply through the one-dimensional equation of energy. The more direct form of the discharge relationship is as follows:

$$Q = C_d\, b\, B\sqrt{2gY_1} \tag{1}$$

where C_d is the gate discharge coefficient; Q is the discharge; b is the gate opening; B is the gate width; and Y_1 is the upstream water depth.

The artificial intelligence based modeling represents an efficient tool to investigate flow characteristics below gates. Buyalski [15] discussed several algorithms to predict discharge under radial gates. The use of artificial neural networks (ANNs) modeling for prediction and forecasting variables in water resources engineering has been increasing rapidly. An ANN is a mathematical model based on some features of human brain and nervous system storing and dealing with information. It has an ability to capture a relationship from giving patterns, and hence is suitable for application in the solution of complex problems, such as classification, nonlinear modeling, forecasting, fitting, control and identification as stated in [16,17]. In this context, a number of applications of ANNs for prediction, forecasting, modeling and estimation of water resources variables (water discharge, sediment discharge, rainfall runoff, ground water flow, precipitation and water quality, etc.) were examined by Mustafa et al. [18]. The back-propagation network (BPN) is one of the most popular feed-forward networks in ANNs. The BPN has the advantages of a simple structure, mature algorithm and powerful function, so it becomes a useful technique for solving hydroscience problems.

In this paper, two ANN models using the back propagation algorithm were developed to investigate the flow for both free and submerged flow conditions under vertical and inclined sluice gates. The developed ANN models yielded two simple generalized equations to predict the C_d value and to account

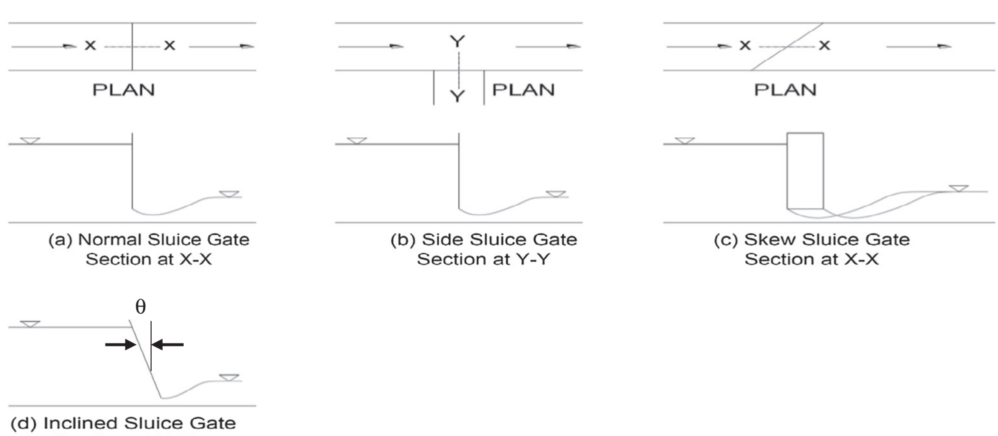

Figure 1 Types of sluice gates after Mansoor [1].

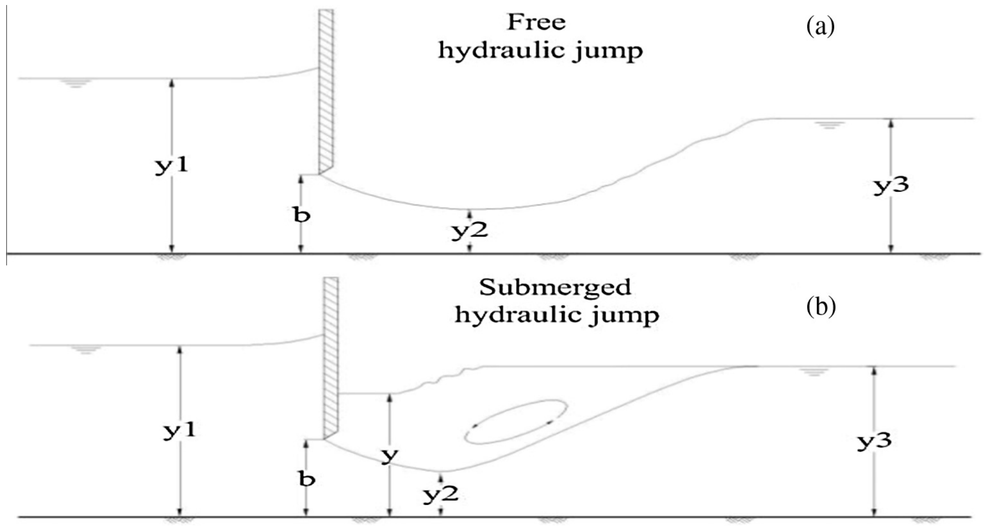

Figure 2 Flow beneath sluice gate under free (a) and submerged (b) condition.

for the inclination angle effect on flow characteristics in both modes of flow conditions.

2. Data collection

Four groups of data sets were collected from previously published experimental work for the purpose of developing the two ANN models in this study. The distinguishing conditions for type of flow were based on the Equations developed by Swamee [3]. The first group entailed 120 data sets for free flow condition below vertical sluice gates and were collected from 3 different experimental studies, namely, Nago [19], Hager [20], and Cassan and Belaud [8]. The second group of data sets consisted of 100 data sets for submerged flow under vertical sluice gates and were collected from Swamee [3], Belaud et al. [7], and Cassan and Belaud [8]. The other two groups were concerned with free and submerged flow beneath inclined sluice gates and were extracted from Montes [14] and Nago [19]. The third group comprised 90 data sets for free flow, whereas, the fourth group included 110 data sets for submerged flow. Table 1 illustrates the range of variables for the 4 groups. The collected data included the flow rate (Q), upstream water depth (Y_1), tailwater depth (Y_t), gate openings (b), Froude number (Fr) at the upstream section, Reynolds number (Re), and inclination angle (θ). The data sets of both the first and third group were together used to develop the ANN model for free flow conditions, while, the second ANN model was built using the whole data sets of the second and fourth groups.

3. Development of artificial neural networks models

The ANN determines a relationship (i.e. create a model) between the input and the output of the available data set of any system. These models are then used to predict the output from the known input values of the same system, thus requiring sufficient number of data to create and test the models. In this research, the BPN training algorithm was used to develop two ANN models for free and submerged flow conditions, respectively. A three-layer BPN consists of an input layer, an output layer, and a hidden layer. In BPN, the input quantities (X_i) are fed into the input layer neurons that, in turn, are passed onto the hidden layer neurons (h_i) after multiplication

Table 1 Range of parameters used for ANN models development.

θ	Q (m^3/s)	b (m)	Y_1 (m)	Y_t (m)	Re	Fr
Free flow						
0	0.002–0.124	0.02–0.12	0.107–0.220	–	19,450–123,535	0.08–0.44
Π/4 (45°)	0.005–0.062	0.01–0.06	0.077–0.572	–	45,435–86,053	0.16–0.31
Π/3 (60°)	0.004–0.053	0.01–0.05	0.060–0.562	–	38,214–66,192	0.12–0.24
5Π/12 (75°)	0.004–0.045	0.01–0.05	0.086–0.574	–	36,486–58,230	0.10–0.23
Submerged flow						
0	0.021–0.103	0.03–0.24	0.201–0.313	0.103–0.297	22,460–127,054	0.04–0.25
Π/12 (15°)	0.009–0.036	0.01–0.06	0.082–0.374	0.060–0.359	31,763–71,025	0.06–0.14
Π/6 (30°)	0.005–0.045	0.01–0.06	0.047–0.580	0.033–0.427	27,508–79,408	0.05–0.15
Π/4 (45°)	0.007–0.025	0.01–0.06	0.075–0.572	0.054–0.420	29,320–63,527	0.06–0.12
Π/3 (60°)	0.004–0.017	0.01–0.05	0.051–0.573	0.053–0.407	25,416–89,490	0.07–0.17
5Π/12 (75°)	0.003–0.016	0.01–0.05	0.052–0.498	0.050–0.402	23,150–55,016	0.06–0.11

by connecting to weights (W_{ij}). A hidden layer neuron adds up the weighted input received from each input neuron ($x_i W_{ij}$) and associates it with a bias (b_j) as follows:

$$S_j = \Sigma(x_i W_{ij} - b_j) \tag{2}$$

The result (S_j) is then passed on through a non-linear transfer function to produce an output (e.g. logistic sigmoid function):

$$\mathcal{F}(S_j) = \frac{1}{(1 + \exp^{-S_j})} \tag{3}$$

The output neurons do the same as the hidden neurons. The BPN finds the optimal weights by minimizing a predetermined error function. A gradient descent method is often used to modify the network weights. In this research, the ANN architecture used for modeling is a multilayer perceptron network with steepest descent back-propagation training algorithm. The steepest descent optimization method employs instantaneous gradients in adapting the weights of the neural network. The steepest descent method is the simplest of the gradient methods. By using simple optimization algorithm, this method can easily find the local minimum of a function. It starts by simply picking an arbitrary point that is within a function's range and takes small steps toward the direction of greatest slope changes, which is the direction of the gradient, and eventually, after many iterations, the minimum of the function is located.

For adjustment of the weight and threshold coefficients it holds that:

$$w_{ij}^{(k+1)} = w_{ij}^{(k)} - \lambda \left\{ \frac{\partial E}{\partial w_{ij}} \right\}^{(k)} \tag{4}$$

$$v_i^{(k+1)} = v_i^{(k)} - \lambda \left\{ \frac{\partial E}{\partial v_i} \right\}^{(k)} \tag{5}$$

where λ is the rate of learning ($\lambda > 0$). The key problem is calculation of the derivatives $\frac{\partial E}{\partial w_{ij}}, \frac{\partial E}{\partial v_i}$.

The steepest descent method has the advantages of minimal storage requirements, very low computational costs, conceptual simplicity, with fast iterations and it can always locate an existing minimum. However, the steepest descent sometimes lacks fast convergence. In this context, the steepest descent version used in this research forces the gradients in a one-dimensional subspace as the iterations progress, to avoid the classical zigzag pattern of steepest descent, which is the main responsible for the slow convergence of the method. In this paper, a number of trials were carried out to reach at the various user defined parameters required for the neural network based algorithm using WEKA software.

3.1. Free flow artificial neural network model

The model network consists of three layers: Input layer of 4 neurons to represent the input variables as ratio of upstream water depth to gate opening (Y_1/b), inclination angle (θ), Froude number (Fr), and Reynolds number (Re); an output layer to characterize the single output variable C_d; and the hidden layer between the input and the output layers to receive the input, perform computations, and send outputs to the output layer. The hidden layer uses a transfer or activation function to modify the input to the neuron. The transfer function may be linear, logistic sigmoid, or tanch. To investigate the effect of inclination angle on the flow field under sluice gates, the flow was analyzed for inclination angles of 45°, 60°, and 75° as well as for normal sluice gate ($\theta = 0$).

The following steps summarize the network training process based on BPN algorithm:

i. The values of the weights were set to initial random values.
ii. The normalized input pattern Xp (Y_1/b, Fr, Re, and θ) and the normalized target pattern (C_d) were shown to the network.
iii. The output from each node in a layer was calculated.
iv. The weight between nodes was adjusted, starting from the output layer and working backwards as in (4) and (5).

The steps from ii to iv were repeated until the error between the desired and the neural network output reaches a global minimum. In this study, a ten-fold cross-validation was used, while one hidden layer was used as it works well for this data set. The logistic sigmoid function was used as the activation function at both hidden and output layers. Other user-defined parameters used were as follows – momentum = 0.0, learning rate = 0.3, hidden layer nodes = 8, training time = 600 and, iterations = 1000. These values were obtained after a large number of trials by using different combination of these parameters carried out on used data sets. From a total number of 220 data sets, 170 data sets were used for training the model, while the remaining 50 data sets were utilized for model validation. In order to check the reliability of the developed ANN model to predict the flow characteristics under vertical and inclined sluice gates for free flow condition, the model was operated for all configurations presented in Table 1. The ANN model of the free flow sluice gate was obtained by learning the training flow conditions and then the predicted results were compared with those measured in experiments.

3.2. Submerged flow artificial neural network model

After being validated for free flow under normal and inclined sluice gates, another ANN model was developed for submerged flow condition with 200 new data sets. The flow was analyzed for vertical sluice gate and for inclination angles of 15°, 30°, 45°, 60°, and 75°. In order to establish a general relationship to predict the C_d value for sluice gates under submerged flow condition, the submerged flow ANN model entailed the addition of one more input variable, which is the ratio of tailwater depth to gate opening (Y_t/b). The model was trained and tested using the data sets presented in Table 1. Eighty percent of the data sets were used for training the model, while the remaining 20% were used for testing. Many trials were conducted to determine the best initial range of the weights of the network connections, the best activation function, the best number of neurons in the hidden layer and the best number of iterations. Then the network stability was checked. Analysis of the results of the conducted training indicated the following:

- The best range to initialize the weight matrix was +0.2.
- The best activation function was logistic sigmoid.

- The best number of neurons in the hidden layer was 9 neurons.
- The best number of iterations was 1500 iterations.

3.3. Statistical analysis

Two parameters namely correlation coefficient and root mean square error (RMSE) values were used for the performance evaluation of the two ANN models in predicting the value of C_d for both free and submerged flow conditions. The higher value of correlation coefficient and the smaller value of RMSE reveal better performance of the model. The results of the ANN based modeling of C_d using different combinations of input parameters with the used data sets are provided in Table 2 in terms of correlation coefficient and RMSE. The study revealed that the highest value of correlation coefficient and least value of RMSE were obtained for C_d with Y/b, followed by angle of inclination (θ) in radians, Fr, and Re for both flow conditions. This implied a very weak correlation between Re and C_d. The results of statistical analysis with respect to Re coincide with those obtained by Montes [14] who proved that for Re values greater than 10,000, the effect of Re could be neglected in flow rate computations. The effect of Fr was found to be minimal. Negative correlation was found between C_d and Fr in both flow conditions, whereas a negative correlation exists between C_d and angle of inclination (θ) for the case of submerged flow conditions.

The results of the ANN models revealed that both Fr and Re have very minor effect on the value of C_d. Hence, they were not included in the predicted formulas for estimating the C_d value for both free and submerged flow conditions.

4. Results and discussion

Many trials were carried out through the two ANN models with different combinations of the selected parameters to obtain the best fitted equations for predicting the value of C_d. The results for each flow condition are as follows.

4.1. Free flow

The best fitted nonlinear equation for free flow is given by

Table 2 Calculated correlation coefficient and RMSE.

Input combinations	Submerged flow		Free flow	
	Correlation coefficient	RMSE	Correlation coefficient	RMSE
Y_1/b	0.911	1.412	0.925	1.662
(θ) in radians	0.770	1.671	0.876	1.831
Y_t/b	0.634	2.123	–	–
Fr	–0.182	3.313	–0.223	2.849
Re	0.123	3.641	0.165	2.931
$Y_1/b + Re$	0.45	2.950	0.511	2.221
$Y_1/b + Fr$	0.52	2.163	0.580	1.953
$Y_1/b + Y_t/b$	0.926	1.121	–	–
$Y_1/b + (\theta)$	0.953	0.984	0.961	0.973
$Y_1/b + Y_t/b + (\theta)$	0.958	0.956	–	–

$$C_d = (0.042\theta + 0.443)(Y_1/b)^{0.11} \tag{6}$$

Fig. 3 displays a comparison between the prediction of the best network (4–8–1) and the experimental data with respect to C_d for free flow conditions below vertical sluice gates. The figure indicated that very good agreement was obtained. The equation shows that the discharge coefficient is greatly influenced by dimensionless upstream water depth. Figs. 4–6 depict C_d variation against Y_1/b for three different inclination angles. Figs. 4–6 indicated that there is a slight increase in C_d values with increasing the inclination angle from 45° to 75°. On the other hand, the values of C_d ranged from 0.40 to 0.78 for different angles as shown in below figures compared to a range of 0.45–0.60 in the case of free flow beneath vertical sluice gates (Fig. 3). This implies a maximum increase of 30% in the value of C_d for the case of inclined sluice gate. The results revealed that the average value of C_d for vertical sluice gate is 0.58,

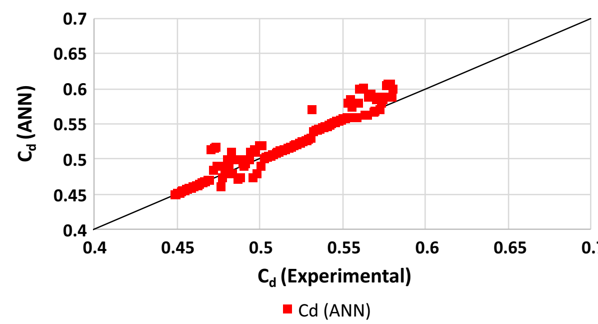

Figure 3 Measured versus predicted C_d values for free flow conditions below vertical sluice gate.

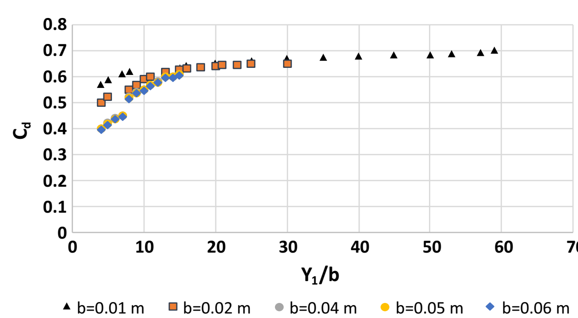

Figure 4 Variation of C_d versus Y_1/b for θ = 45° (free flow condition).

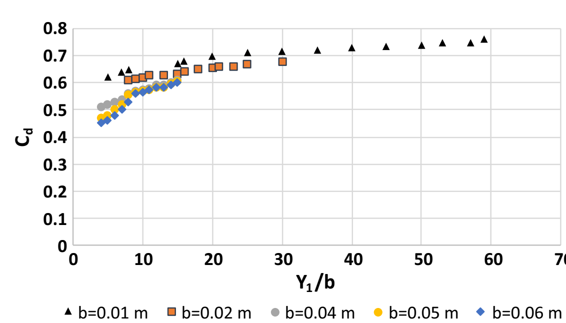

Figure 5 Variation of C_d versus Y_1/b for θ = 60° (free flow condition).

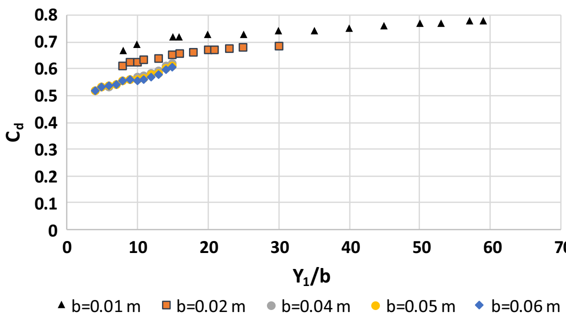

Figure 6 Variation of C_d versus Y_1/b for $\theta = 75°$ (free flow condition).

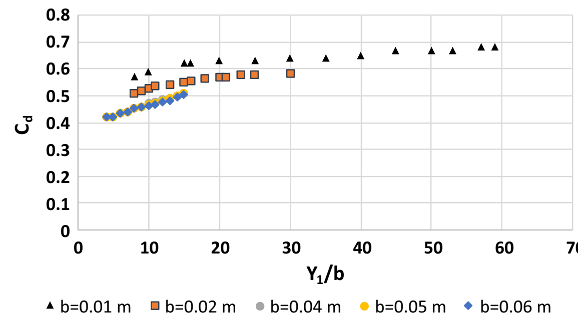

Figure 8 Variation of C_d versus Y_1/b for $\theta = 15°$ (submerged flow condition).

which is very close to the value of 0.56 obtained by Nago [19] and the value of 0.572 attained by Cassan and Belaud [8], whereas, for inclined sluice gates, the model results showed average C_d values of 0.67 and 0.73 for inclination angles of 45° and 60°, respectively. These two values are in good agreement with the values of 0.66 and 0.716 found by Nago [19] for the same two angles.

4.2. Submerged low

Many trials were performed through the ANN model in submerged flow with different combinations of the dimensionless parameters Y_1/b and Y_t/b, in addition to angle of inclination. The perfect fitted equation generated by the model is given by:

$$C_d = (0.053\theta + 0.243)(Y_1/b)^{0.45}(Y_t/b)^{-(0.20+0.03\theta^{6.2})} \tag{7}$$

Fig. 7 shows that the ANN model also yielded very comparable C_d values for submerged flow conditions under vertical sluice gates. Figs. 8–12 present variation of C_d with Y_1/b for five different angles of inclination. As it can be seen, discrepancy between these dimensionless parameters and C_d is higher than the case of free flow condition, but interaction of these parameters with each other results in high accuracy in predicting C_d values. Figs. 8–12 show that there is a marked variation of C_d with θ. An increase in C_d values of the inclined sluice gate with decrease in inclination angle was realized. For inclination angle of 15°, the values of C_d ranged from 0.4 to 0.69, while the range was from 0.20 to 0.43 for inclination angle of 75°. For inclination angles of 15° and 30° the trend of C_d variation for submerged flow is quite similar to that of inclination angles of 45° and 60° for free flow, whereas, the variation in C_d values

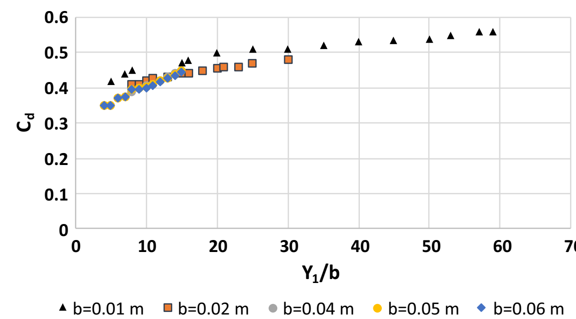

Figure 9 Variation of C_d versus Y_1/b for $\theta = 30°$ (submerged flow condition).

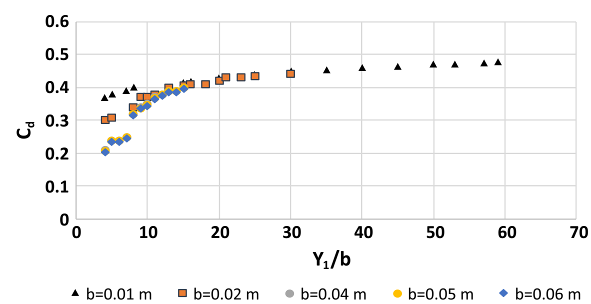

Figure 10 Variation of C_d versus Y_1/b for $\theta = 45°$ (submerged flow condition).

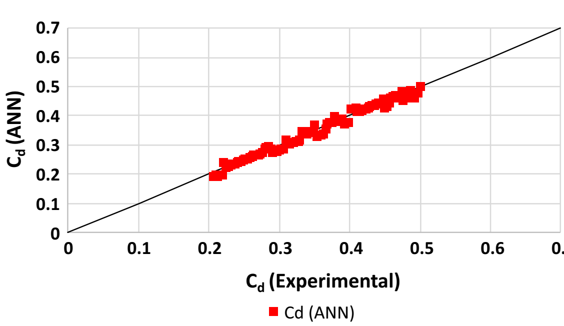

Figure 7 Measured versus predicted C_d values for submerged flow conditions below vertical sluice gate.

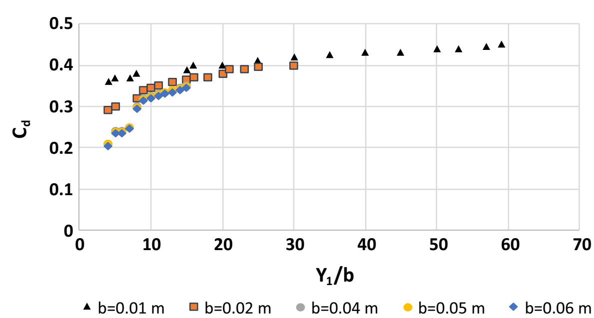

Figure 11 Variation of C_d versus Y_1/b for $\theta = 60°$ (submerged flow condition).

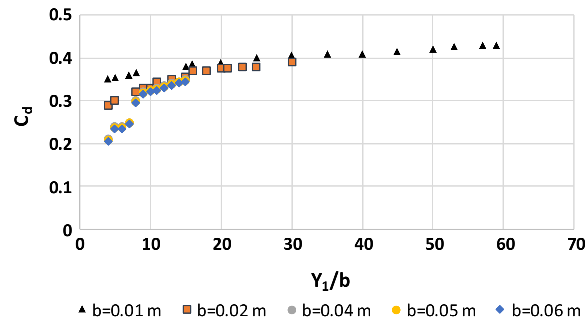

Figure 12 Variation of C_d versus Y_1/b for $\theta = 75°$ (submerged flow condition).

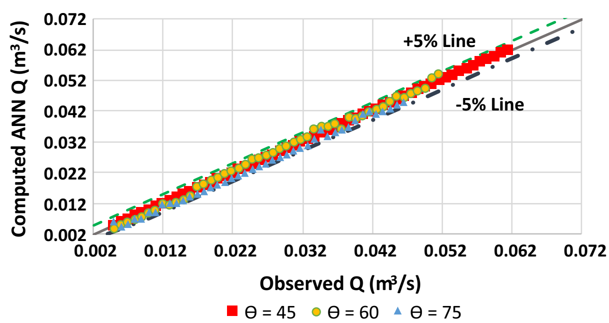

Figure 13 ANN computed versus observed Q for free flow condition.

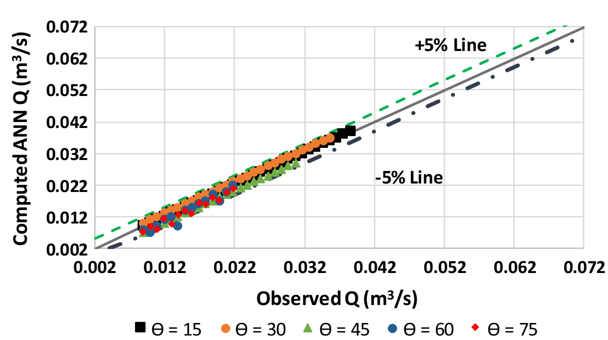

Figure 14 ANN computed versus observed Q for submerged flow condition.

for inclination angles of 45°, 60°, and 75° for submerged flow is different from that of same angles for free flow. The values of C_d for inclination angles of 15° and 30° were higher than those of vertical sluice gates (Fig. 7). On the contrary, the values of C_d for vertical sluice gates were higher than those of inclination angles of 60° and 75°. The average C_d value derived from the ANN equation for vertical sluice gate is 0.38 that is comparable to the value of 0.37 obtained by Cassan and Belaud [8] and the value of 0.365 that attained by Shivapur and Shesha [21], while, the average C_d values for inclination angles of 15°, 30°, and 45° are 0.62, 0.49, and 0.45, respectively. These values are in good agreement with the values of 0.596, 0.465, and 0.435 found by Shivapur and Shesha [21].

4.3. Accuracy of generalized equations

After being checked for the case of vertical sluice gate with respect to C_d values (Figs. 3 and 7), the accuracy of the two developed equations was examined for inclined sluice gates. For data set of each inclination angle, discharge values were computed for both free and submerged flow conditions using the two developed Eqs. (6) and (7). These computed values were plotted against the observed values of Table 1 as shown in Figs. 13 and 14 for free flow and submerged flow, respectively. It is evident from these figures that most of the data points lie within a tolerance limit of ±5%. This implies quite high accuracy of the two developed equations.

5. Conclusions

Two simple generalized equations for estimation of discharge coefficient of sluice gates in both free and submerged flow conditions were proposed via two developed ANN models using BPN algorithm that can be used to find C_d for any value of θ in the specified range of parameters. The predicted C_d is found to be dependent on the ratio between the depth of water in the upstream and the gate opening, and the angle of inclination for free flow conditions, whereas, for submerged flow conditions, one more variable affects the value of discharge coefficient that is the ratio between the depth of water in the downstream and the gate opening. The results revealed that an increase in discharging capacity of the inclined sluice gate with decrease in inclination angle was realized for submerged flow condition, while, no significant change in discharging capacity was recognized in case of free flow condition. Moreover, the values of C_d for inclined sluice gates were higher than those of vertical sluice gates in case of free flow, whereas, for submerged flow, the values of C_d for inclination angles of 15° and 30° were higher than those of vertical sluice gates. On the contrary, the values of C_d for vertical sluice gates were higher than those of inclination angles of 60° and 75°. Using these equations discharge through sluice gates can be obtained within an accuracy of ±5%. The results indicated that ANNs are powerful tools for modeling flow rates below both vertical and inclined gates.

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