Integrating Artificial Neural Networks for Enhanced Decision Making in Water Management

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Abstract

The structures, such as sluice gates, play a critical role in hydraulic structures and determine the flows internal and external management in them. This research focuses on the analysis of the behavior of the sluice gate in terms of the gate opening, the flow rate, and the coefficient of discharge (Cd). The experimental data show that the highest values of Cd are achieved at the least gate opening and the maximum value of Cd is 0.765 at the gate opening of 0.03 m. With the view of improving decision making capacity, the study uses Artificial Neural Networks (ANN) to forecast Cd using experimental data. In addition, a prediction accuracy of 0.999 is established by the ANN model, as shown by the R^2 value. This high level of precision underscores the capability of ANN in modelling of hydraulic behaviors and justifies its use in the improvement of sluice gate operations. With the incorporation of ANN based predictions, management of water resources may be enhanced and hence improve the designing, operation and decision-making processes in hydraulic infrastructural projects especially in cases of dynamic flow.

Keywords: Sluice gate, Artificial neural networking, Water management, coefficient of discharge, Predictive modelling

1. Introduction

Sluice gates are one of the most important types of the gated structures that are used for control of water flow and for discharge measurements in the irrigation canals, rivers and dam spillways [1]. These gates are used for free and submerged flow, and the estimation of the flow discharge is equally important for efficient control of water resources. One of the crucial steps in the process is the identification of the discharge coefficient depending on hydraulic parameters, upstream and downstream heads [2,3,4]. The discharge increases almost directly with increase in upstream head for free flow conditions but the head that controls the discharge in submerged conditions are both upstream and downstream heads [5,6]. A lot of work has been done in order to analyze the hydraulic characteristic of sluice gates.

Research has been carried out on the effects of gate position, sill geometry, and flow parameters on the discharge coefficient [5,7]. For example, sill length and width were found to have profound effect on flow characteristics [5,6]. Furthermore, the application of artificial intelligence has brought Machine learning models like Artificial Neural Networks (ANNs) into use, which are more accurate than empirical and analytical methods in estimating the discharge coefficients under complicated hydraulic situations [3,8,9]. ANNs in particular overcome deficiencies of conventional approaches successfully by dealing with non-linear dependencies and various flow conditions and offer accurate estimations of discharge coefficients. As the studies have shown, ANNs can reach good accuracy, with the coefficients of determination up to 0.99 [9,10]. These models have been proved to give reliable results in cases where the hydraulic conditions and the gate shapes are different, for example cylindrical gates or sills [2, 8].

This paper also uses experimental measurements with ANN modelling to predict the discharge coefficient (Cd) for sluice gates. These are discharge, Froude number (Fr), ratio of downstream water depth to upstream water depth, and relative sill height. The Cd values determined experimentally were 0.765 at the minimum gate opening of 0.03 m, highlighting the Cd/gate opening correlation [5,6]. The presented experimental data feed the ANN models which can predict Cd with unprecedented precision, exemplifying the ability of improving sluice gates and water management systems [3,9,11]. In addition to overcoming experimental challenges, the application of computational methods in hydraulic research improves structures of hydrological infrastructures and water resources. Thus, this work's conclusions support the use of experimental data coupled with machine learning algorithms in making precise predictions and improving hydraulic systems [9,10,12].

2. Methodology

2.1. Data Collection

The experimental setup consisted of a flow measurement system, data acquisition devices, and a hydraulic flume with a sluice gate as the primary control mechanism for managing flow rates. The flume, constructed with clear polymeric walls and a rectangular cross-section (Figure 1(a)) (10 m length, 0.3 m width, 0.5 m depth), provided a controlled environment for studying flow dynamics, with an adjustable horizontal channel slope. The sluice gate (Figure1(b)) that is made of durable materials to survive hydraulic forces was mounted perfectly without leakage and instability through the adjustable height and widths according to the various condition of flow. The experiments were first made by observing the average depth of flow for ten discharge values without the sluice gate. The schematic diagram of flow under sluice gate is shown in Figure 2. Then tests were performed for five different openings of the gate Yg = 0.03, 0.04, 0.05, 0.06, and 0.07 m. Discharge values (Q) varied between 0.0117 cumecs and 0.0222 cumecs to attain required upstream (Yo) and downstream (Y1) depths. For each gate opening, ten experiments were conducted at different discharges, amounting to a total of 60 tests for determining the relationships between the flow parameters and experimental errors. Upstream and downstream water depths, gate openings, and discharge rates were measured to calculate the discharge coefficient, specific energies, and forces on the sluice gate using the equation

$$\mathrm{Cd} = \frac{\mathrm{Q}}{\mathrm{b} \times \mathrm{Yg}\sqrt{2\mathrm{gYo}}} \quad \text{(a)}$$

Where, Cd = coefficient of discharge, Q = discharge, b = width of the channel (31cm), g = gravitational constant and Yo = depth on the downstream of sluice gate.

Figure 1. (a): Open channel flume ; **(b):** Sluice gate

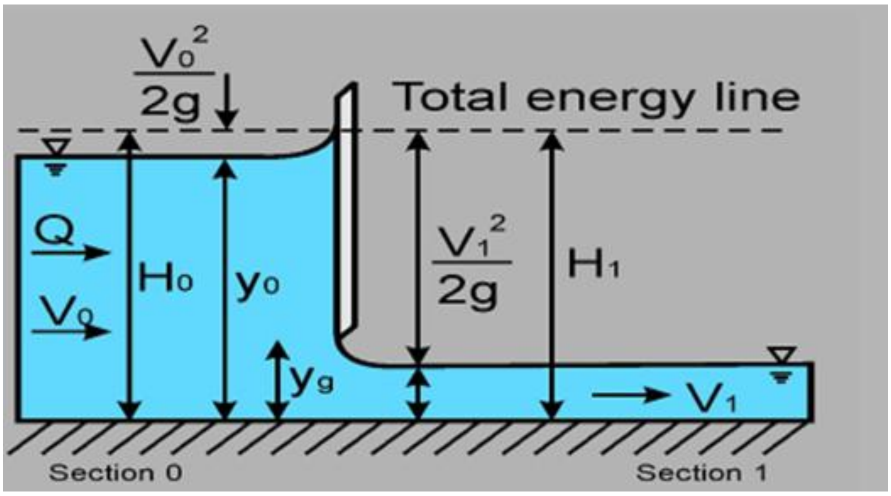


Figure 2. Schematic diagram of discharge beneath a sluice

2.2. ANN model in JMP

To design the artificial neural network model JMP was used to design and set up the neural network. The structure of the ANN model and the number of neurons in the model, input, hidden and output layer is depicted in Figure 3. In this study, the ANN architecture consisted of two hidden layers, with neurons varying across five different configurations: 3x3, 6x6, 9x9, 12x12, 15x15. The activation function used for both the above layers was TanH that can easily address non-linear relationships. The penalty method used was squared which reduces large weight values and hence guard against overfitting.

The performance of the training and validation of the model was assessed using R^2, RMSE and SSE. In order to cheque generalization abilities of the model, the holdback value was set to 0.33, which means that 33% of the data was used for the validation and 67% for the model training. This approach can help assess the model on other data, thus preventing overfitting and improving its accuracy.

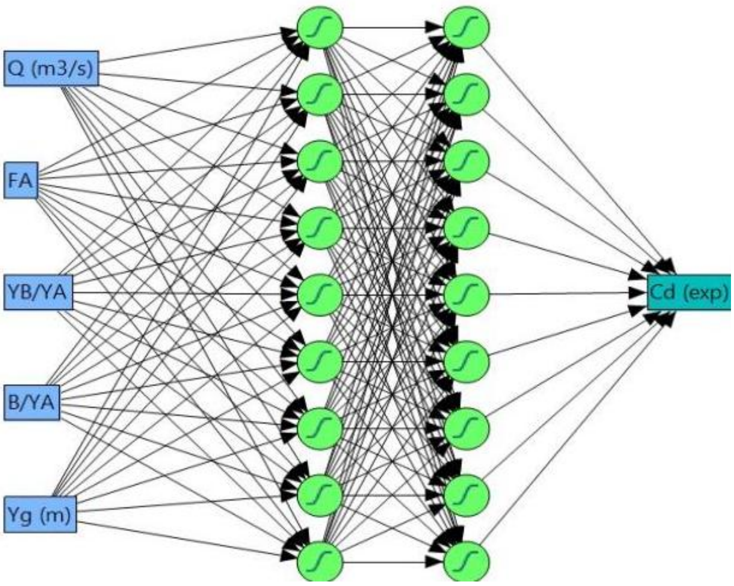


Figure 3. ANN Diagram Showing Inputs, Outputs, and Neurons

2.3. Model Evaluation and Performance Metrics

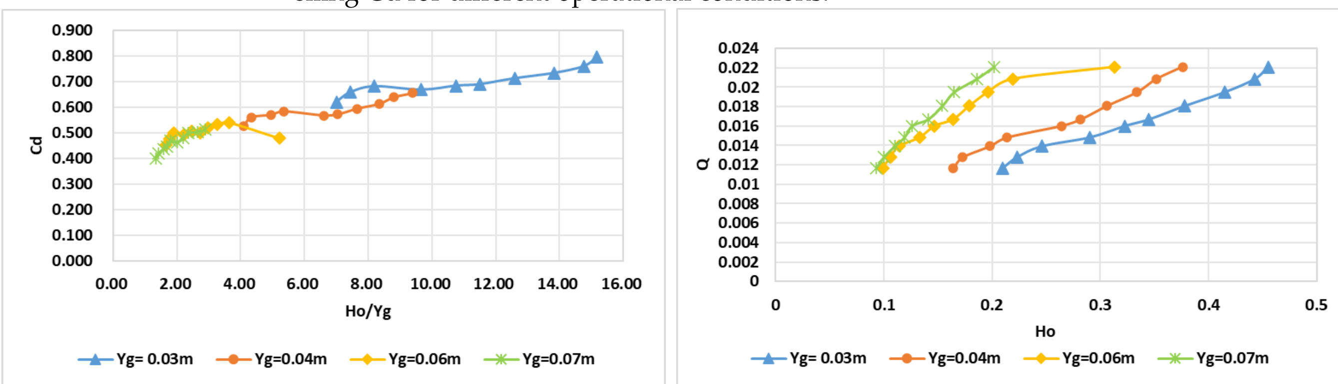
After that the model was evaluated on the test data set which was not used during the model training procedure. In order to evaluate the model predictiveness of the outflow, the R^2 value for both training and validation groups was measured. The training R^2

was 0.999 and validation R^2 was 0.996 which depicts that the current model is more appropriate to the training data set and reasonable on the validation data set.

3. Results and Discussion

3.1. Experimental Results

From figure 4a, it can be seen that the discharge coefficient (Cd) rises with the ratio H_0/Yg. As for the Cd, it is revealed that the curve presenting the relationship between it and the gate opening is inversely proportional to the gate opening but when the gate opening increases, the Cd decreases. From the study, it was found that the upstream water depth H_0 greatly influences the concentration of Cd. For larger openings, the upstream depth of water decreases as the sluice gate opening increases hence the decrease in the Cd as the opening increases. On the other hand, when the opening of the sluice gate is decreasing the area beneath the gate becomes small and the flow is contracted so that the Cd value is small. The observed maximum and minimum Cd values for a particular (H_0/Yg) ratio are 0.07 and 0.01 respectively as shown in figure 4a. In Figure 4b, the stage-discharge relationship for different sluice openings has been depicted. At a certain flow rate, the depth of water upstream of the dam reduces with the size of the opening of the gate. Based on the findings presented in this paper, the average Cd for a sluice gate opening of 0.01 m is higher than those for openings between 0.02 m and 0.07 m. In addition, the discharge coefficient is examined against the upstream water depth in figure 4b, which exhibits a non-linear behavior due to the complex interaction between the flow rate, the size of gate opening and hydraulic conditions. This nonlinearity results from the fact that the relationships between these variables are not independent, which presents difficulties when modelling Cd for different operational conditions.



(a) **(b)**

Figure 4. (a) Ho/Yg VS Cd relation; **(b)** Ho VS Cd relation

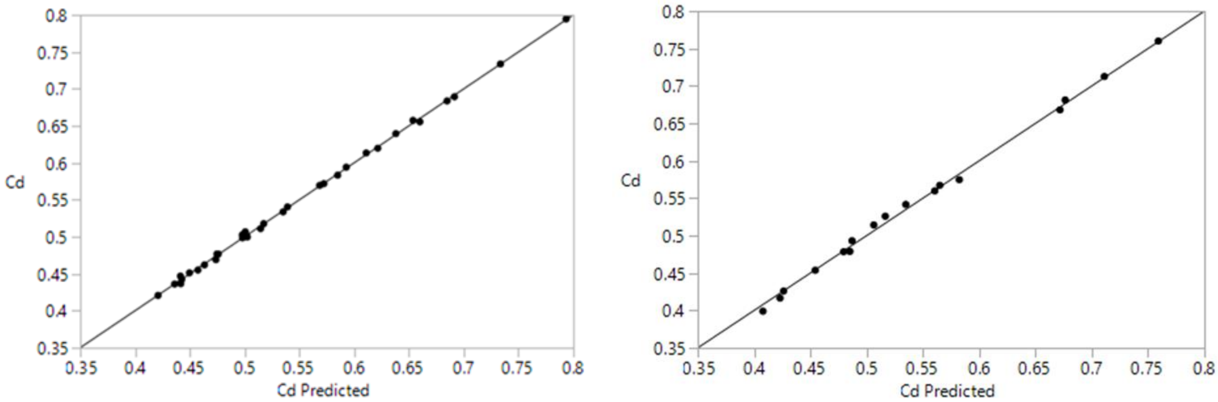
3.2. ANN Results

Several measures of performance were used to test the developed ANN model in JMP. It was 0.999 for the training data set and 0.996 for the validation set, which testifies high predictive power of the model. The findings of these analyses imply that the model fits well on the training data and has a promising capability to perform well on other data sets.

The RMSE and SSE for the training and validation data were also analyzed to provide support for the model. The low values of RMSE and SSE suggest that the proposed model accurately predicts coefficient of discharge values which will be useful in reservoir management

3.3. Prediction Performance

In order to compare the ANN model's accuracy, graphs of predicted vs observed Coefficient of discharge(cd) were plotted. These graphs (Figure 5 a, b) show how well the model fits the coefficient of discharge data across the whole data range. The actual and predicted cd values also had a near perfect positive correlation in that the points were clustered closely to the 45-degree line proving that the model had high prediction precision.



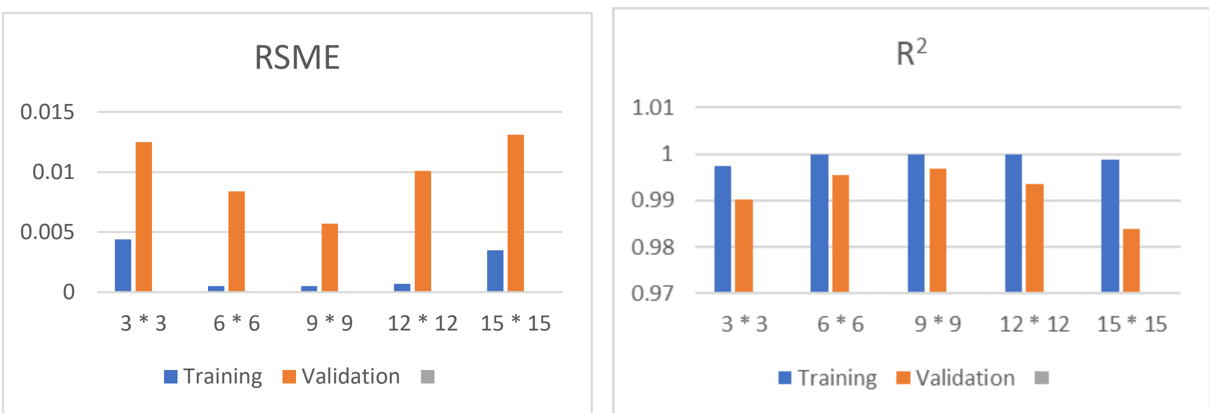
(a) **(b)**

Figure 5. (a) Predicted vs observed cd (training); **(b)** Predicted vs Observed cd (Validation)

3.4. Model Performance and Evaluation

Through these models, the Artificial Neural Network (ANN) models were tested using the coefficient of determination (R^2), and Root Mean Squared Error (RMSE) for the training and validation data set. From the results obtained, it can be concluded that the performance of the model increases with increase in the number of neurons in the hidden layers, and the 9x9 configuration offered the best results. Especially, it was observed that the 9x9 network had the highest training R^2 (0.999), the lowest training RMSE (0.0005) suggesting that this network provides a very good fit to the training data.

Subsequent computations also showed that the output performance was increased as the neurons increased from 3x3 to 12x12 but decreased in the 15x15 configuration. While the 15x15 model yielded a slightly smaller training RMSE of 0.0035, the validation R^2 was insignificantly higher and the validation RMSE was insignificantly lower than the 12x12 model, indicating that overly complex models may overfit, to mean that while the model would approximate the training data very well, it poorly approximated the unseen Thus, the 9x9 is determined to be the most appropriate network model because of its capability of capturing the training data and at the same time possessing an excellent ability to generalise new patterns, and it is for this reason that this configuration has been adopted in this study.



(a) **(b)**

Figure 6. (a) RMSE Training and Validation; **(b)** R2 Training and Validation

4. Conclusions and Recommendations

The coefficient of discharge for sluice gates was analyzed experimentally along with the ANN modelling study. Results from experimentation pointed out that gate opening sizes and upstream flow depth substantially affects (Cd). Inversion relationship between the smaller the gate openings and increase contraction in the flow enhancing with a larger (Cd), and conversely bigger size of opening diminish the effect of contraction as well as results in greater turbulence lowering its efficiency. Upstream flow depth was also found to be a significant parameter, and increasing gate openings resulted in a corresponding decrease in depth and (Cd). Comparison studies revealed that smaller openings at a given discharge produced higher (Cd) values because of sharper flow convergence. Larger openings resulted in lower (Cd). ANN modeling successfully captured the nonlinear relationships between flow parameters and gate geometry and closely matched experimental results and validated the reliability of the model.

These results highlight the role of (Cd) as a critical parameter for sluice gate optimization through its dependence on gate opening and upstream depth. The experimental and ANN-based approach provide an integrated framework for the prediction of (Cd), thereby making sluice gate design and operation more efficient. This research provides insight into adaptive water management strategies and hydraulic system performance improvement.

Conflicts of Interest: The authors declare no conflicts of interest.

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