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Application of ANN in Estimating Discharge Coefficient of Circular Piano Key Spillways

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ABSTRACT

Among all solutions for disrupted vortex formation in shaft spillways, an innovative one called Circular Piano Key Spillway, based upon piano key weir principles, has been experimented less. In this study, the potential of Artificial Neural Networks (ANN) in estimating the amounts of discharge coefficient of Circular Piano Key Spillway has been evaluated. In order to pursue this purpose, the results of some physical experiments were used. These experiments have been conducted in the hydraulic laboratory using different physical models of Circular Piano Key Spillway including three models with different angles of 45, 60 and 90 degrees. Data from those experiments were used in training and test steps of ANN models. Multilayer Perceptron (MLP) network with Levenberg-Marquardt backpropagation algorithm was used. The performance of artificial neural network was measured by these statistical indicators: coefficient of determination (R2), mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) and optimum quantities of statistical indicators for test step were assessed 0.9999, 0.4988, 0.5963 and 0.9999 respectively, for Circular Piano Key Spillway with an angle of 90 degree and for training step were assessed 0.9999, 0.5479, 0.6305 and 0.9999 respectively, for Circular Piano Key Spillway with an angle of 90 degree. In other words, Circular Piano Key Spillway with an angle of 90 degrees has the optimum performance, both in training and test steps. Artificial Neural Network model can successfully estimate the amounts of discharge coefficient of Circular Piano Key Spillway.

1. Introduction

“Piano Key Weir” is a new spillway which affect the specific flow and increase its amount more than four times. Not only this new free-flow spillway decrease the cost of new dams but also it can rise the safety, the storage and the flood control efficiency of existing dams. The first set of models were made in 1999 at the LNH Laboratory in France (owned by Electricité de France) and in 2002 2002 at Roorke University in India and Biskra University in Algeria [1,2].

The Piano Key Weir has some characteristics which are listed below:

- It has simple configuration which can be helpful in construction process by using prefabricated units,
- It highly reduces the cost of constructions for new dams and rise the safety of them,
- It can increase the storage capacity of existing dams,
- Its operation is just like the weirs with free surface but with better performance [3].

The Piano Key Weirs (PKW) are suitable for gravity dams or in spillway channels of earth dams. They are noticed mostly because of their structures and the flow condition on their upstream and downstream. The PKW has better performance compare with Creager weir for both cases of location [4].

The discharge of Morning glory spillways is limited by the capacity of the shaft but using PKW in combination with this spillway can increase the level and capacity of the reservoir. So using PKW linked with shaft inlet can be led to a better hydraulic efficiency [5].

At LNH hydraulic laboratory, different shapes of PKWs set on a morning glory spillway have been studied using hydraulic models. In cases like re-evaluation of the design flood which are required better hydraulic performance, they use PKW to decrease the required head of water as for straight crested spillways. Using this new solution, combination of PKW principles and morning glory spillway, better share the flow between inner part and outer part of the shaft. As the results show, even in higher flow, there is no vortex and the discharge is quite stable. The optimization can be used for any given project [6].

The combination of PKW principle and a morning glory spillway was tested on a model of Bage dam with the scale of 1/20. The comparison of hydraulic performance was taken between the current morning glory spillway and the combination of PKW and morning glory spillway called papaya spillway. The papaya spillway has better performance compare with the traditional morning glory spillway in a lower diameter, experimental results showed. The risk of vortex formation and air entrainment are avoided by the water supply of the shaft and submergence occurs on higher discharge. The discharge capacity is increased particularly at low heads and it can be four times more than traditional morning glory spillway. By increasing the head, the improvement of discharge capacity reduce but it is always more than 30% [7].

In 2013, the enlargement of Black Esk reservoir in Scotland by the innovative adoption of precast piano-key weirs around the rim of the bell-mouth spillway was undertaken by adapting published empirical relationships and then refined using computational fluid dynamics (CFD) analyses. The adopted design with the 24-cycle piano key weirs showed better performance [8].

The bell-mouth spillway of Scottish reservoir, Black Esk, was enlarged by installing a circular piano key extension consisting of 24 precast concrete sections. The new spillway is designed to pass higher flood and save 0.7 m from the amount of dam raising that would have been required for the alternative scheme, based on simple raising of the weir around the bell mouth rim [9].

The circular piano-key spillway constitutes a proper hydraulic structures to increase the design flow and capacity of the related dam reservoirs. It increase the release capacity approximately 2 and 1.5 times higher than morning glory spillway and papaya spillways, respectively, for the same original shaft spillway [10].

This paper discusses the potential of Neural Networks in estimating the discharge coefficient of circular piano key models. The results of an experimental study on physical models of different shapes of circular piano key spillway are used.

Artificial Neural Networks (ANN) have been successfully applied in a number of diverse fields including the field of civil engineering [11–14]. In a given study in Semnan University of Iran, Artificial Neural Network was applied to develop the strength properties of recycled aggregate concrete (RAC) based upon important input variables. ANN can be used as an efficient model to predict the compressive strength of RAC, the results showed [15].

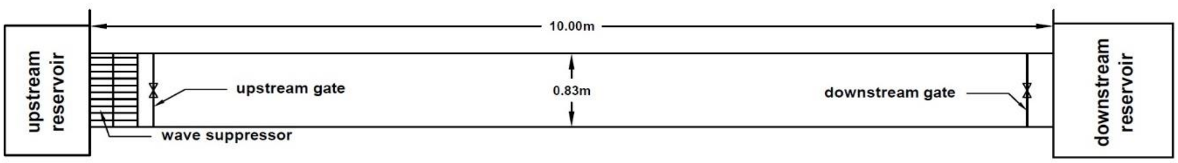
Artificial Neural Network method with back propagation algorithm were used to analyze the experimental data of different types of vortex breakers on morning glory spillway [16]. Also, Artificial Neural Network and multiple linear and nonlinear regressions were used to set up a new design equation for the discharge capacity of Piano Key weirs using the Levenberg-Marquardt backpropagation algorithm for neural network training [17].

In another study, the strength of concrete was predicted by data-driven models. Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models were constructed for predicting the strength of different concrete mix designs. This study shows that ANN can be used efficiently in this case [18].

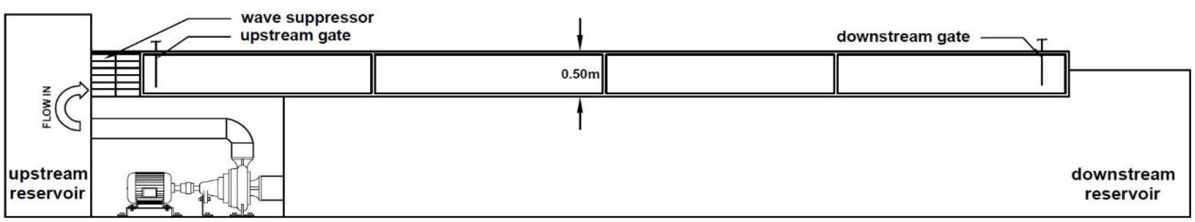
2. Experimental setup

The experiments were conducted in hydraulic laboratory of water engineering department, Bu-Ali Sina University, Hamadan, Iran. All experiments were carried out in a hydraulic flume with the dimensions of 10m, 0.83m and 0.5m, length, width and height respectively. Water flows through the reservoir by a centrifuge pump with 15kw power and 330 m3/h discharge. After passing through wave suppressor, water flows through the flume. Flume's walls were made of 1cm thickness glass. The range of discharge in this study was 1.8-22 m^3/h. The flume was equipped with a rolling point gage (±1mm accuracy) and flow discharge has been measured by an ultrasonic flowmeter which had been calibrated for this research Fig. 1. The sketch of hydraulic laboratory flume configuration is shown in Fig. 2.

Fig. 1. Ultrasonic Flowmeter and Point Gage.



(a)



(b)

Fig. 2. (a) Top view, (b) Front view of laboratory flume.

Overall 80 experiments have been carried out using physical models including three different models of circular piano key spillways. Circular piano key models were made using acrylic sheets. Thickness and texture of those sheets were selected considering the fact that the structure should not be affected by the swirling flow around the shaft and its weight should make it enable to be installed on the vertical shaft and the bend. So acrylic sheets with the thickness of 2 mm were used. Three different circular piano key models with the angles of 90, 60 and 45 were made, Table 1. Their dimensions are shown in Fig. 3.

Table 1.
Dimensions of Circular Piano Key models.

P(cm)	D(cm)	L(cm)	b(cm)	α
7.5	7.5	7.5	30	45,60,90

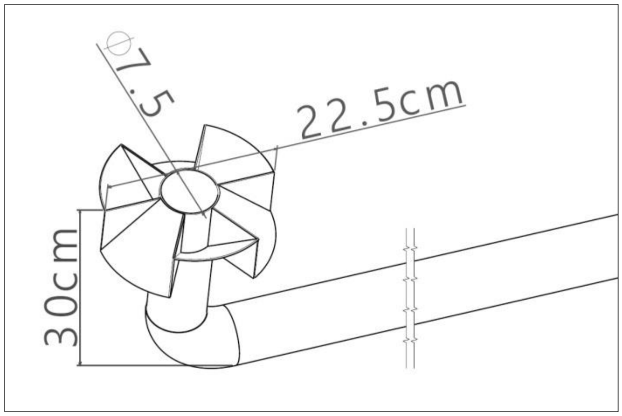


Fig. 3. Dimensions of Circular Piano Key model.

3. Methodology

A nonlinear mathematical model which can simulate difficult problems related by inputs and outputs is ANN. One of the most common types of ANN is Multilayer Perceptron (MLP) network which is so popular among researchers. The definition of suitable functions, weights and bias should be noticed in order to use MLP model [19]. Fig. 4 shows the architecture of MLP networks.

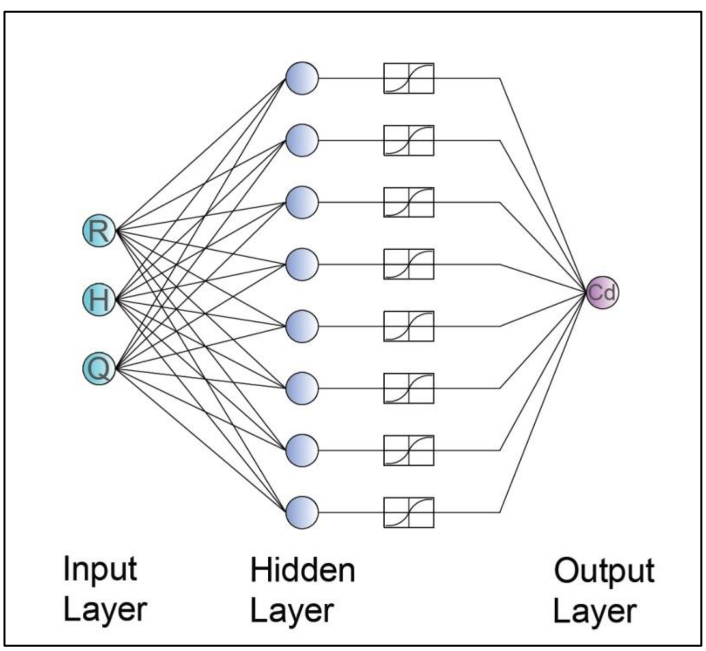


Fig. 4. Schematic drawing of multilayer perceptron neural networks.

Back propagation is a learning algorithm which is used by MLP and many other neural networks. In this algorithm, the input data is presented to the neural network repeatedly. The output is compared to the desired output in every presentation and an error is calculated. In training process, this error is fed back (back propagated) to the neural network and the weights are adjusted by using that. The error reduces in every iteration and neural model gets closer to achieving the desired output [20]. The validation step which comes after the Training step, is used indirectly while the ANN is trained to monitor the over-fitting of the neural network. It stops the training of ANN when the error of the Validation step begins to increase. The final step of the ANN modeling is called Test step which evaluates the accuracy of the machine learning algorithm [21]. In this study, 76 data sets including 1600 data were used for training and test steps, 90% of data were used for training step and 10% of data were used for test step [22]. Choosing data for training and test steps was randomly. The statistical properties of experimental data are illustrated in Table 2.

Table 2.
Statistical properties of experimental data.

Input Nodes	R (cm)	H (cm)	Q (m^3/s)
Mean	7.5	8.4	11.9
Minimum	3.75	1.5	1.8
Maximum	11.25	25.5	22
Standard Deviation	30.4	52.6	1.64

In this study, ANN was trained by Levenberg-Marquardt algorithm because this algorithm is the fastest one among all current back propagation algorithms. Although it needs more memory space to run but using this algorithm as the best possible choice among all other supervised algorithms is highly recommended. Transfer (activation) functions were used in hidden layer are included; Purelin Transfer Function, Log-Sigmoid Transfer Function, Tan-Sigmoid Transfer and Purelin Transfer Function was used in output layer. Mentioned functions were tested in different networks with different number of neurons in hidden layer.

This network was simulated using MATLAB software, 7.14 version. It was consisted of one input layer and one output layer. Input layer was included of radios (R), head (H), discharge (Q) and output layer was included of one neuron; discharge coefficient (C_d). The number of hidden layers and their neurons were chosen by trail and error.

Statistical indicators were calculated to evaluate the performance of networks' models. They are included: Coefficient of Determination (R2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The formulas of these indicators are presented as below.

$$R^2 = \frac{\left[\sum(C_{dm}-\overline{C_{dm}})(C_{dp}-\overline{C_{dp}})\right]^2}{\sum(C_{dm}-\overline{C_{dm}})^2(C_{dp}-\overline{C_{dp}})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(C_{dm} - C_{dp}\right)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|C_{dm} - C_{dp}\right| \quad (3)$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{C_{dm}-C_{dp}}{C_{dm}}\right| \quad (4)$$

In above mentioned equations, n, C_{dm}, C_{dp}, $\overline{C_{dm}}$, $\overline{C_{dp}}$ represent the number of data, the measured discharge coefficient value, the predicted discharge coefficient value, the average value of measured discharge coefficient and the average value of predicted discharge coefficient, respectively.

Discharge coefficient was calculated using the below formula. In this formula discharge is shown by Q, C_d represents discharge coefficient, r represents diameter, h represents head of water and g shows gravitational constant.

$$Q = C_d \pi r^2 (2gh)^{1/2} \quad (5)$$

4. Result and discussion

In this study, Artificial Neural Networks were used to estimate the discharge coefficient of circular piano key spillway. For the architecture of ANN, many different combinations with different numbers of neurons along with different combinations of input variables were compared. Appropriate combination of layers and neurons number was chosen considering the least test error. The number of hidden layers, the number of neurons, kind of transfer function, learning algorithm and the number of appropriate repeat were chosen based on Coefficient of Determination (R2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Finally, the accuracy of every transfer function in estimating discharge confident can be assessed according to the results of test error.

For circular piano spillway model with an angle (α) of 45 degrees, log-sigmoid transfer function with 10 neuron in hidden layer had the best performance among all. Root Mean Square Error (RMSE) for optimum network was $1.09\times e^{-11}$. The amounts of statistical indicators for optimum network model is shown in Table 3. Also, the comparison between the observed discharge confident values and the predicted discharge confident values for training and test steps are illustrated in Fig. 5.

Table 3.
Statistical indicators for optimum network model, circular piano key α=45.

Step	R^2	RMSE	MAE	MAPE
Training	1	0.597287	0.551727	0.999984
Test	0.917599	0.656664	0.590372	0.999986

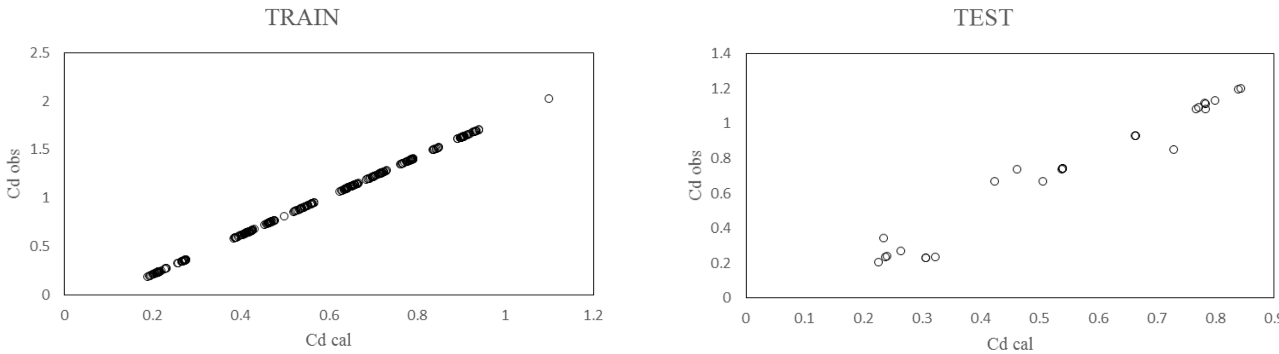


Fig. 5. Observed vs predicted amounts of discharge coefficient, circular piano key α=45.

Also, for circular piano spillway model with an angle (α) of 60 degrees, log-sigmoid transfer function with 10 neuron in hidden layer had the best performance among all. Root Mean Square Error (RMSE) for optimum network was $6.47 \times e^{-11}$. The amounts of statistical indicators for optimum network model is shown in Table 4. Also, the comparison between the observed discharge confident values and the predicted discharge confident values for training and test steps are illustrated in Fig. 6.

Table 4.
Statistical indicators for optimum network model, circular piano key α=60.

Step	R^2	RMSE	MAE	MAPE
Training	1	0.677905	0.623913	0.999986
Test	1	0.721338	0.677873	0.999985

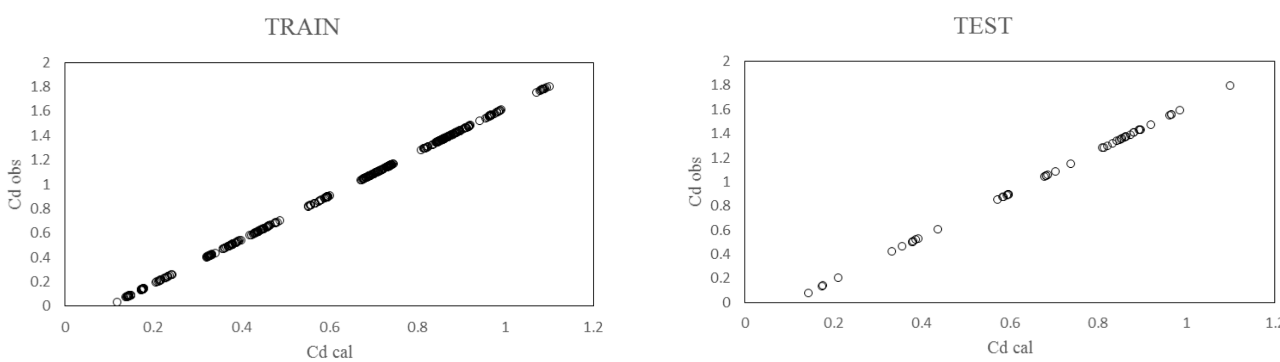


Fig. 6. Observed vs predicted amounts of discharge coefficient, circular piano key α=60.

And finally, for circular piano spillway model with an angle (α) of 60 degrees, log-sigmoid transfer function with 10 neuron in hidden layer had the best performance among all. Root Mean Square Error (RMSE) for optimum network was $2.53 \times e^{-8}$. The amounts of statistical indicators for optimum network model is shown in Table 5. Also, the comparison between the observed discharge confident values and the predicted discharge confident values for training and test steps are illustrated in Fig. 7.

Table 5.
Statistical indicators for optimum network model, circular piano key α=90.

Step	R^2	RMSE	MAE	MAPE
Training	0.9999997	0.63054	0.547931	0.999987
Test	0.999978	0.596339	0.498758	0.999987

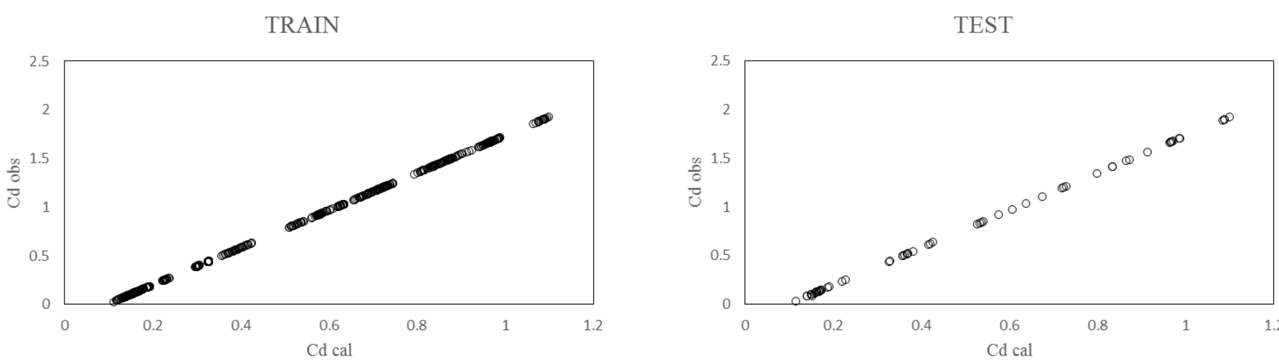


Fig. 7. Observed vs predicted amounts of discharge coefficient, circular piano key α=90

The circular piano key spillway with an angle of 90 degrees shows the optimum amounts, comparison between statistical indicators for different models in test step shows. Also, in training step, the optimum amounts of statistical indicators were obtained from circular piano key spillway with an angle of 90 degrees.

5. Conclusions

In this study, experimental data obtained from some experiments on different physical models of circular piano key spillway were used. All experiments had been conducted in hydraulic laboratory using three physical models of circular piano key spillway with different angles.

Artificial Neural Networks were applied to estimate the discharge coefficient of circular piano key spillway. Multilayer Perceptron (MLP) network with Levenberg-Marquardt algorithm was used. To evaluate the performance of ANN, some statistical indicators were calculated including; Coefficient of Determination (R2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

Artificial neural network has indicated a noticeable accuracy in predicting the amount of discharge coefficient of circular piano key spillway. In other word, ANN has the potential to estimate discharge coefficient of circular piano key spillway. Also, circular piano key spillway with an angle of 90 degrees has the optimum performance, both in training and test steps, statistical properties showed.

Using other methods such as Neuro Fuzzy, Gene Expression Programming etc. and comparison between the results of different models can be considered in further researches in this realm. Also using Computational Fluid Dynamic (CFD) models such as Flow 3D, Fluent and ANSYS for simulating flow over circular piano key models can be led to reasonable results, which can be noticed in future studies.

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