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Prediction of the discharge coefficient of steeply crested inclined weirs using different neural network techniques

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Oblique sharp-crested weir.

ABSTRACT

The main objective of this work is to accurately predict in irrigation and hydraulic systems the discharge coefficient of the used sharp-crested inclined dams. Training algorithms on radial basis function RBF and multilayer perceptron MLP, and input variables such as weir height, length, inclination, and flow rates. From a tilted weir, researchers have used these training techniques as a model for various neural networks. In addition, the performance of CFNN is better than other neural networks such as RBF and MLP. The discharge coefficient Cd was the output variable. 95 test results were analysed. CFNN achieved a significant reduction in mean square errors (MSE), with values of 9.4363×10-12 and 1.6336×10-05, respectively, in the training and testing phases.

Introduction

The discharge coefficient (CD) is considered very important in dam water control applications, and work in this field is considered very expensive because it requires the development of mathematical models to facilitate work on it. This is one of the reasons for the lack of research because it requires a high research budget compared to other research. Many researchers, including and Chilang et al. (2018), Norouzi et al. (2019), Ismail et al. (2021) These researchers explored the use of neural networks in classifying the hydraulic properties of inclined dams using RBFN. Significantly lower values are for the root mean square error types of RMSE and MSE, specifically 0.0082 and 6.8×. 10-05 respectively was the result of the exceptional performance and high efficiency of the RBFN model in accurate modeling of Cd [1,2].

The effectiveness of radial basis function networks and support vector machines for estimating the drainage coefficient of labyrinthine dams with quarter-circular vertices and multilayer perceptual networks was studied in [2]. Excellent results were obtained when using the superior training approach, and it was shown that the correlation coefficient R2, mean absolute relative error (MARE), and RMSE were also revealed. The particular approach showed exceptional accuracy in the simulation results. They all achieved very good results, with results of 0.884, 0.0327, and 0.0156. Particular emphasis has been placed on MLP and ANFIS methodologies when evaluating the discharge coefficient using theoretical techniques [3].

It is noticeable from the analysis results that the coefficient of the ANFIS approach is superior to the MLP strategy approach when estimating the results using the discharge coefficient. It is possible to use the results of this analysis to identify system users and determine those authorized to use wireless networks.[4]. A new alternative based on forward cascade neural network is proposed after analyzing the traditional strategy of using feed-forward neural networks (FFNNs) and updating theory-based prediction techniques. It is observed that there is a significant reduction in the probability of spectrum conflict in cognitive wireless networks when relying on CFNN. CFN-based multi-step prediction technique. Source [5] predicts the behavior of authorized users, by introducing a prediction technique for wireless satellite networks.This study contrasts the efficacy of CFNN with other prediction techniques, such as FFNN and update theory. By utilizing a step prediction strategy based on CFNNs, cognitive wireless networks can effectively steer clear of spectrum conflicts. To delve deeper into the data this study utilizes To analyze Cd, CFNN and training approaches were used. The CFNN models predict Cd values based on inputs such as H/P, B/L, Q, and. The goal of this research is to use prediction techniques to reduce estimation and more efficiently determine optimal Cd levels.

Experimental work

In a study researchers provided data that was used in this study. The experiment was conducted in a channel, with dimensions of 0.52m width, 0.8m height and 6.6m effective length. For this research we used crested weirs made of Plexiglas with varying lengths (L) from 0.52m to 0.1175m and a height of 0.46m.

The oblique weir had an inclination angle (α) ranging from 29.10 to 63.70 degrees while for free flow conditions a plain weir with an inclination (θ =900) was used. The discharge rate ranged from 8.45 l/s, to 37 l/s throughout the experiments.

A total of 95 runs were conducted for the free flow cases, divided into eight sets based on the weir length mentioned earlier and varying weir heights between 0.460m and 0.511m.The flow rate passing through a conventional sharp-crested weir can be expressed by the following equation:

$$Q = \frac{2}{3} * Cd * B * H\sqrt{2gh} \qquad \textbf{(1)}$$

where B refers to the width of the channel, Cd represents the discharge coefficient of the normal weir, H signifies the head over the weir, and g represents the acceleration due to gravity.

As a result, the discharge coefficient for an oblique sharp-crested weir can be defined by the equation:

$$Cd = (0.701 - 0.121 * \frac{B}{L} + \left(2.229 * \frac{B}{L} - 1.663\right) * \frac{H}{P} \qquad \textbf{(2)}$$

In their study, it was observed that when the length of the oblique weir (L) is greater than the channel width (B), the Cd decreases for a constant ratio of H to P (head over weir to weir height).

Theoretical part

A new and effective method called CFNN is introduced to predict Cd values. CFNN is a type of Artificial Neural Network (ANN). Has an architecture. In this model each preceding level connects, with every layer ensuring connectivity within the network. CFNN has an intriguing feature in that it includes weights (vw_ik) that connect the output layer to the input layer. Figure 1 shows a representation of the model.

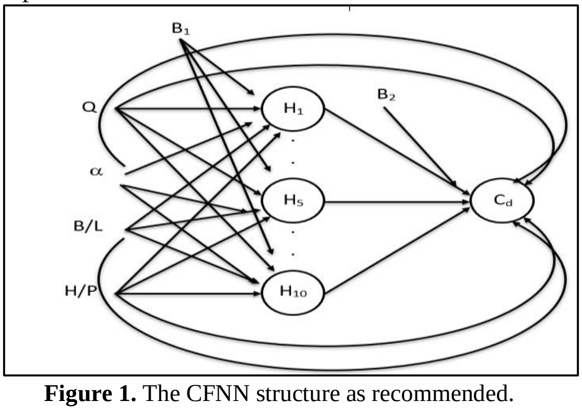

Figure 1. The CFNN structure as recommended.

$$z\_in_j = v_{0j} + \sum_{i=1}^{n} X_i v_{ij} \qquad \textbf{(3)}$$

$Z_j = f(z\_i\,n_j)$ **(4)**

$y\_i\,n_k = w_{0k} + \sum_{j=1}^{p} Z_j w_{jk} + \sum_{i=1}^{n} X_i v w_{ik}$ **(5)**

$Y_k = f(y\_i\,n_k)$ **(6)**

The calculations are denoted in the model as z_i n_j, where j ranges from 1 to p. In this example, the weights between the bias and hidden neurons can be represented as. In addition, input neuron weights are denoted by, while hidden neuron weights are denoted by, with values ranging from 1 to. The letters represent neuron computations.

Moreover in the CFNN model the inputs for each output neuron are calculated as, where ranges from 1 to. The weights between the bias and output neurons are represented by w0k, while the weights between the output neurons are represented by w0k. In addition, the CFNN model includes connections () between input and output neurons. [7] denotes the calculations of the output neurons.

Figures 2. 3 display regression analysis of the CFNN models outputs compared to their targets during both training and testing phases. Figure 4 illustrates how CFNN output values relate to desired target values, in the testing phase.

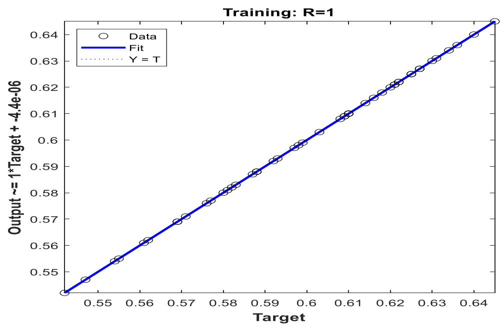

Figure 2. Regression between the CFNN model's outputs and their targets in the training phase.

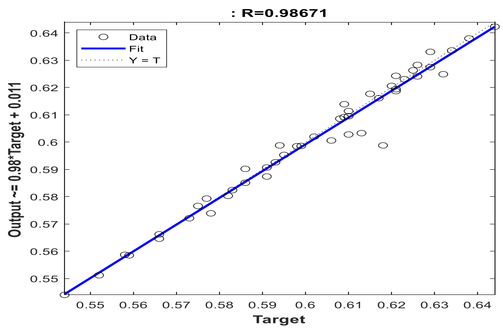

Figure 3. Regression between the CFNN model's outputs and their targets in the testing phase.

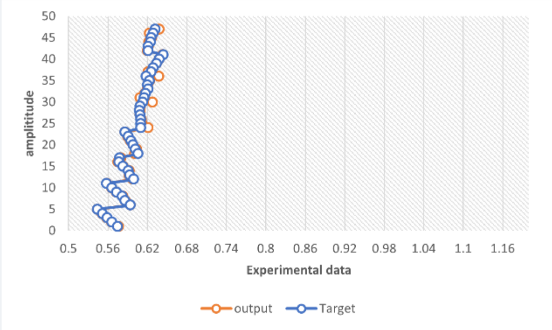

Figure 4. The relationship between the CFNN output values and the desired target values during the testing phase.

The evaluation of the proposed model's regression performance commonly involves statistical computation methods such as MSE and RMSE. Lower values of these statistical measures indicate a better model fit. The MSE can be calculated using the following equations:

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(exp_i - pred_i)^2 \qquad \textbf{(7)}$$

Where:

Where (N) represented the number of data, while (Ci) represented the discharge coefficient obtained from experimental work, the observed values were (at), while the estimated values were (Et). In addition, mein and A mean stand for the average values of the evaluated and observed series, respectively, in addition to using MSE and RMSE in the statistical calculations of this study because they provide a reliable way to evaluate how well the ANN models perform.

Result and discussion

For training and testing purposes the experimental data was actively pre-processed for use with the ANN and datasets were created. In terms of performance, the development and application of the CFNM model proposed in this study was conducted successfully, ahead of other neural networks such as Backpropagation Neural Network (BPNN) and CFNM.

The CFNN model utilized inputs such as H/P, B/L, Q, and α to predict the discharge coefficient (Cd). Notably, the CFNN model achieved exceptionally low mean square error (MSE) values, specifically 9.4363×10^{-12} during the training stage and 1.6336×10^{-05} during the testing stage. In contrast, the RBF and MLP models exhibited comparable MSE values of 0.003 and 0.0015, throughout the training phase, respectively. Less training time is needed because to the CFNN's enhanced connections between the input and output layers [8][9][10]. Figure 3 depicts an analysis of the regression connection between the desired goal and the actual output of the CFNN. Without a doubt, the figure demonstrates a significant and positive connection between the CFNN output and the targeted testing aim. The computed regression value of R^2 = 0.996, which is quite close to the ideal value of R^2 = 1, further supports the effectiveness of the CFNN model.

Table 1. MSE and R^2 of CFNN model in the training and testing stage

Statistical parameters	Training	Testing
MSE	$9.43*10^{-12}$	$1.63*10^{-5}$
R^2	1	0.969

Figure 5, which features scatter graphs, shows how the CFNN model performed throughout the testing phase. The CFNN model's R2 and MSE values in both. The training and testing steps are listed in Table 1. Comparisons between the CFNN with and other ANNs are given in Table 2.

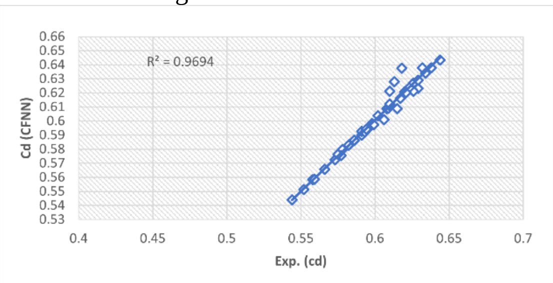

Figure. 5 Performance of the CFNN model during test phase.

Table 2. Comparisons between the CFNN with and other ANNs.

Neural Network Type	MSE
Multilayer Perceptron (MLP)	0.0015
Radial Basis Function (RBF)	0.003
Cascade-forward neural network (CFNN)	$9.43*10^{-12}$

Conclusion

This study's goal was to evaluate the CFNN model's performance in forecasting the discharge coefficient of oblique sharp-crested weirs. Statistical metrics including MSE and R2 were used to assess the effectiveness of the CFNN model. The research also focused on improving three theoretical models: CFNN, RBF, and MLP. The dataset consisted of 95 experimental data series with various inputs, specifically for different angles of inclinations in the weirs with inclined sharp crests. This paper's main goal was to calculate the Cd for the oblique sharp-crested weirs. Various ANN techniques were utilized with the experimental dataset. When comparing to the other models, the CFNN model exhibited superior performance, as evidenced by the results of the evaluation. The CFNN network achieved the lowest mean square error of 9.43×10-12 during the training stage. Additionally, it achieved a small testing error value of 1.63×10-5, further affirming its superior performance.

References

[1] A. A. Ismael, S. J. Suleiman, R. R. O. Al-Nima, and N. Al-Ansari, "Predicting the discharge coefficient of oblique cylindrical weir using neural network techniques", Arabian Journal of Geosciences, Vol. 14, No. 1670, 2021. https://doi.org/10.1007/s12517-021-07911-9 .

[2] Norouz R, Daneshfaraz R, Ghaderi A (2019) Investigation of discharge coefficient of trapezoidal labyrinth weirs using artificial neural network. Applied Water Science (2019) 9:14.8

[3] Chelang A, Abdul-Karim A, Ismael A (2018) Prediction of discharge coefficient for cylindrical weirs using adaptive Neuro fuzzy inference system ANFIS and multilayer neural networks MLP. Int J Appl Eng Res ISSN 0973-4562 13(9):7042–7051.

[4] Yang.M, Xie.B,Dou.Y. and Xue. G.Cascade Forward Artifcial Neural Network based Behavioral Predicting Approach for the Integrated Satellite terrestrial Networks. Mobile Networks and Applications2021

[5] Wang.F,Zheng.S,Ren.Y,Liu.W,and Wu.C. Application of hybrid neural network in discharge coefficient prediction of triangular labyrinth weir. Flow Measurement and Instrumentation (2022) 83,10210.

[6] Borghei, S.M., Vatannia, Z., Ghodsian, M. and Jalili, M.R. \Oblique rectangular sharp-crested weir", Proceedings of the Institution of Civil Engrg. (ICE), Water and Maritime Engineering, 156, WM2, pp. 185-191 (2003)

[7] Raid Rafi Omar Al-Nima, Farqad Hamid Abdulraheem, and Moatasem Yaseen Al-Ridha, "Using Hand-Dorsal Images to Reproduce Face Images by Applying Back propagation and Cascade-Forward Neural Networks", 2nd International Conference on Electrical, Communication, Computer, Power and Control Engineering (ICECCPCE19), IEEE, Mosul, Iraq, 13-14 February, 2019.

[8] Aditi Jahagirdar, Rashmi Phalnikar. Comparison of feed forward and cascade forward neural networks for human action recognition. Indonesian Journal of Electrical Engineering and Computer Science. Vol. 25, No. 2, February 2022, pp. 892~899.

[9] Md. Ayaz, Talib Mansoor, Discharge coefficient of oblique sharp crested weir for free and submerged flow using trained ANN model, Water Science, Volume 32, Issue 2, 2018, Pages 192-212, ISSN 1110-4929, https://doi.org/10.1016/j.wsj.2018.10.002 .

[10] Parsaie, A., Haghiabi, A. The Effect of Predicting Discharge Coefficient by Neural Network on Increasing the Numerical Modeling Accuracy of Flow Over Side Weir. Water Resour Manage 29, 973–985 (2015). https://doi.org/10.1007/s11269-014-0827-4