THE USE OF ARTIFICIAL NEURAL NETWORKS FOR PREDICTION OF DISCHARGE CAPACITY OF A SPILLWAY WITH A BREAST WALL

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Abstract: *The accuracy of discharge estimation is very important from an operational, environmental and economic point of view in irrigation or hydroelectric projects. This accuracy affects the safety in the activities and operation of the entire work systems. This paper describes the application of Artificial Neural Networks (ANNs) and Adaptive Network Fuzzy Inference System (ANFIS) models to predict the discharge capacity of a breast wall spillway. The performance of these models is compared to the conventional non-linear regression (NLR) and multi-linear regression (MLR) models based on experimental data. Root mean square errors ($RMSE$), average error (AE), average absolute deviation (δ) and correlation coefficient (R) statistical parameters are used as comparing criteria for the evaluation of these model's performance. The comparison result indicates that these neural networks could be employed successfully in the discharge prediction of the spillway with a breast wall. The results also show that the performance of the ANFIS and FFBP model are found superior to those of the MLR, NLR and FFCC models with the lowest error and the highest correlation coefficient.*

Keywords: Neural network, discharge, breast wall spillways, ANFIS, non-linear regression, multi-linear regression.

1. INTRODUCTION

Spillways with breast walls are extensively used in hydraulic and environmental engineering. This spillway is often applied in gated spillway to increase the regulating storage of flood discharge, reducing the gate height and number of spillway spans, reducing in cost of gates and operating mechanism, etc. The accurate discharge prediction of this spillway is very important from an operational, environmental and economic point of view in irrigation or hydroelectric projects. It affects the safety in the activities and operation of the entire work systems. The discharge capacity depends on many factors, such as the water upstream level, the sharp-edge of the gate, the crest downstream profile, the gated position on the crest spillway and the head loss of the flow over slot, and breast wall profile [1], etc.

In the past, the discharge capacity of the spillway with a breast wall has been obtained using physical model or theoretical methods[2]. In the recent decades, numerical method has been widely developed to simulate flow over hydraulic structure due to the development of computer power and the successes in the research of fluid dynamics. The simulated discharge is relatively precise and conducted by many researchers[3-5]. However, there are many factors affecting the precision of the results that gained from numerical modeling, e.g., the discretization and iterative methods, the basic domain meshing and/or the computation parameters setup[6], etc.

Currently, neural networks (NNs) are used for a wide tasks in hydraulic engineering. Recent research studies have shown that the NNs are able to provide a powerful tool in forecasting dependent variables for a wide range of scientific and hydraulic engineering problems. Emiroglu, et al (2011)[7] applied neural networks to estimate the discharge capacity of triangular labyrinth side-weir located on a straight channel. To predict the scour below the spillway, Azamathulla, et al (2008)[8] used ANNs and ANFIS model and compared to some traditional formulas in this field. In hydrology engineering, a comprehensive application of hydrology was presented by the ASCE Task Committee (2000)[9, 10].

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Karaboga, et al (2008)[11] presented the operation of the spillway radial gates of reservoirs during floods based on fuzzy logic control. Salazar, et al (2013)[12] applied both the numerical method and ANNs to analyze the discharge capacity of radial-gated spillways at Oliana Dam, Spain. Recently, Pektas and Erdik (2014)[13] used ANN to predict the peak discharges due to embankment dam failure. These studies indicated that the result of NNs model agreed well with the measured data or traditional models, such as regression methods.

The object of this study is to predict the discharge capacity of the spillway with a breast wall using the artificial neural networks. The ANNs architectures are the regular feed forward (FF) trained using the standard error back propagation (FFBP) as well as the cascade correlation (FFCC) training scheme. Furthermore, the ANFIS model was also considered in this work. These models were trained with the 80% measured data from an experiment study and testing with 20% remaining data. The predicted networks would be compared to the traditional statistical schemes, such as the MLR and NLR approach. The studies incorporated use of the neural network toolbox of MATLAB (2010) as well as the script files for developing ANN and ANFIS model.

2. NEURAL NETWORK MODEL

2.1 Artificial Neural Networks Approach

Artificial Neural Networks (ANNs) are considered to be a flexible modeling tool capable of learning the mathematical mapping between variables of the nonlinear systems, namely, input, hidden and output, with each neuron acting as an independent computational element (see Fig. 1). The results from the hidden layer are transferred to the output layer by multiplying the output of each neuron in the hidden layer by the corresponding connection weight between hidden and output neurons. The output layer produces the network output for further processing of the data[9]. At this stage, the network output is compared to the desired (target) output to compute the error. If the error is acceptable, then the output is assumed to be correct. Otherwise the weights of the connection are adjusted starting from the output layer and propagating backward[14].

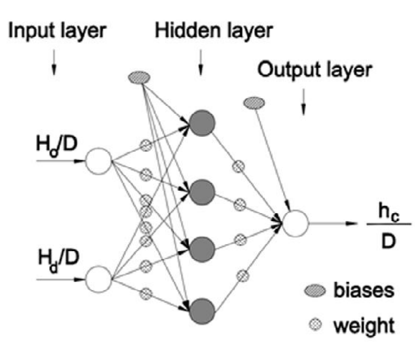

Fig.1. Structure shape of ANN

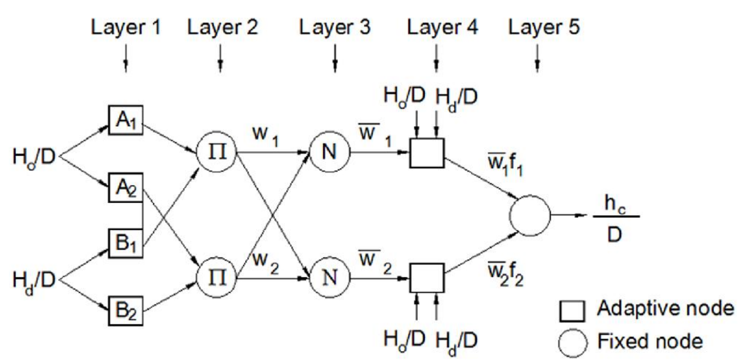

Fig.2. ANFIS network architecture

Most of the ANNs applications in water resources engineering involve the employment of conventional feed forward back propagation method (FFBP). Other ANN methods, such as the radial basis function (RBF), feed forward cascade correlation algorithm (FFCC) and generalized regression neural network (GRNN) could be used as an alternative. The mathematical details of the FFBP, FFCC and RBF models are described in Haykin (1995)[15].

2.2 ANFIS Approach

Adaptive Neuro - Fuzzy Inference System (ANFIS), firstly, which was introduced by Jang (1993)[16], is a universal approximate and capable of approximating any real continuous function on a compact set to any degree of accuracy. The

ANFIS is a hybrid scheme that uses the learning capability of the ANNs to derive the fuzzy if-then rules, with appropriate membership functions worked out from the training pairs leading finally to the inference[9]. The difference between the common neural networks and the ANFIS is that while the former captures the underlying dependency in the form of the trained connection weights, the latter does so by establishing the fuzzy language rules[8]. The input in ANFIS (Fig. 2) is first converted into fuzzy membership functions, which are combined together. After following an averaging process, this is used to obtain the output membership functions and finally the desired output.

3. DIMENSIONAL ANALYSIS

Respect to Fig. 3, the discharge capacity of the spillway with a breast wall (Q) in the free orifice flow can be written as a function of the total head (H_o), the orifice opening (D), the width of orifice (L), the acceleration due to gravity (g), the dynamic viscosity of the fluid (μ), the surface tension (σ), and the mass density of the fluid (ρ).

$$\Phi\left(Q, H_o, L, H_d, D, g, \mu, \sigma, \rho\right) = 0 \tag{1}$$

Where Φ is a functional symbol. Using as the dimensional independent variables D, g, μ, the non-dimensional equation in functional forms can be obtained using Π-theorem as follows:

$$F\left(\frac{H_o}{D}, \frac{L}{D}, \frac{H_d}{D}; \frac{Q^2}{gD^5}, \frac{D^{3/2}g^{1/2}\rho}{\mu}, \frac{\sigma}{D^{1/2}g^{1/2}\mu}\right) = 0 \tag{2}$$

After arranging the dimensionless parameter, the functional relationship, Eq. (2) can be rewritten in the following form:

$$\frac{h_c}{D} = F_1\left(\frac{H_o}{D}, \frac{H_d}{D}, Re, We\right) \tag{3}$$

where h_c is the critical depth, $h_c = Q^{2/3}L^{-2/3}g^{1/3}$, the Reynolds number ($Re = VD/\nu$) of the orifice flow and the Weber number ($We = V/(\sigma/\rho H)^{1/2}$). In fact, the influence of the viscosity and surface tension could be neglected due to the Reynolds and Weber numbers are big enough[17, 18] for the flow in this work (see Table 1). The measured data would be used to develop two discharge prediction formulas for the spillway with a breast wall basing on Eq. (3) and the MLR, NLR methods.

4. EXPERIMENTAL SETUP

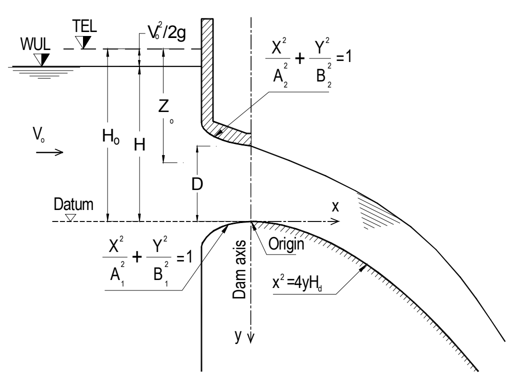

Fig.3. Diagram of a spillway with breast wall

Fig.4. The laboratory flume

The experiments were conducted by the author in the Hydraulic Structures Laboratory at the National University of Civil Engineering (NUCE), Hanoi, Vietnam. The spillways were designed with three design heads (H_d), namely, 15, 20, and 25cm with 30, 29, and 35 cm in height (P), respectively. The spillway's upstream quadrant profile was conformed to an ellipse, which is similar to the ogee profile of the free overflow spillway. Specifically, this profile was designed by equation $X^2/A_1^2+Y^2/B_1^2=1$ in this study. The downstream profile of the spillway was fabricated by the following equation $x^2=4H_d y$. In addition, the breast wall profile was conducted by the following equation $X^2/A_2^2+Y^2/B_2^2=1$ or $X^2/D^2+Y^2/(0.33D)^2=1$. It is notable that the upstream edge of the breast wall was in line with the upstream edge of the spillway, and the downstream edge was in line with the spillway crest axis as shown in Fig. 3. The spillway models were constructed and installed in a flume which consisted of a steel frame with transparent Plexiglas sides, 40 cm wide, 600 cm long, and 80 cm deep. The bottom of the flume was made of stainless steel with a horizontal slope (Fig. 4).

Table1. Experimental cases and parameters

Parameters	Values		
H_d (cm)	10	15	20
P (cm)	29	30	35
No. of experiments	33	40	44
Q_{ex} (m^3/s)	0.0178 ~ 0.0704	0.0265 ~ 0.0952	0.0289 ~ 0.0936
Re number	6.6e+4 ~ 2.4e+5	4.4e+4 ~ 1.7e+5	7.2e+4 ~ 2.3e+5
We number	74 ~ 205	90 ~ 267	99 ~ 232
D (cm)	5 ~ 10.5	5.5 ~ 13.5	7.3 ~ 15.3
H_o (cm)	8.9 ~ 28.3	11.3 ~ 43.4	12.7 ~ 27.6
A_1/B_1 (cm)	2.8/1.6	4.2/2.25	5.6/3.2
A_2/B_2 (cm)	(5 ~ 10.5)/(1.65 ~ 3.5)	(5.5 ~ 13.5)/(1.8 ~ 4.5)	(7.3 ~ 15.3)/(2.4 ~ 5)

The water surface from upstream to downstream was measured at the centerline of flume with a point gauge and with an accuracy of $\pm$ 0.1mm. Furthermore, the water upstream level of model was measured at position $1.5m$ from the origin of the spillway toward upstream. The orifice opening D was measured accurately with a meter fixed on the gate and the accuracy of $\pm 1mm$. In addition, the discharge come into the flume was also measured by a rectangular sharp-crested weir located in the gathering tank. Relative uncertainty in the discharged measurement was about 3%. The experiments were carried out for various the orifice opening D, and the water head H. The water surface profile, the discharge was measured carefully for each the orifice opening case in steady-state condition.

5. MODELING OF PREDICTED DISCHARGE CAPACITY USING FFBP, FFCC, ANFIS, NLR AND MLR MODELS

5.1. ANN models

To predict the discharge capacity of the spillway with a breast wall, the dimensionless parameter h_c/D was considered for the output layer. Two dimensionless parameters, namely, H_o/D and H_d/D were used for the input layer. The experimental data are divided into 80% of the data (94 sets) for the training of the network and the remaining 20% of the data (23 sets) for testing the network prediction. A neural network toolbox contained within the MATLAB (2010) package as well as the script files were used in this study. Several trials are conducted to have the best structure of the ANN. For the

ANN models, including the FFBP and FFCC models, with 2 nodes in the input layer, three hidden layers and twenty neurons together with the sigmoid transfer function give the best result. The training of these networks was stopped after reaching the minimum mean square of 0.001 between network yield and the true output during training patterns.

5.2 ANFIS model

With regard to the ANFIS model, several different models were employed and finally, the ANFIS model with 2 nodes in the input layer, and three triangle membership functions were considered sufficiently for modeling purpose. The previous 80% of data set is used to build the ANFIS model and the rest of observations for the testing process.

5.3 NLR and MLR models

The same 80% training data sets for building the ANNs and ANFIS models are also used to build the regression model. The following equations were obtained to estimate the discharge prediction formulas with the two independent parameters using the MLR and NLR methods, respectively.

$$\frac{h_c}{D} = 0.8535 + 0.2463\frac{H_o}{D} - 0.0447\frac{H_d}{D},\ R^2 = 0.962 \quad (4)$$

$$\frac{h_c}{D} = 0.9397\left(\frac{H_o}{D}\right)^{0.4741}\left(\frac{H_d}{D}\right)^{-0.049},\ R^2 = 0.985 \quad (5)$$

Testing (or validation) of the above formulas was made with the help of the remaining 20% of measurement (23 data), which was not involved in this derivation.

6. DISCUSSION OF RESULTS

6.1 A comparative study

The numerical results for testing data using FFBF, FFCC, ANFIS, NLR and MLR models were plotted versus the experimental results. Fig. 6 and Fig. 7 show the experimental data versus these techniques for both training and testing data sets, respectively. A quantitative comparison is shown in Table 2 in terms of the four error measures, namely, (i) the correlation coefficient (R); (ii) the average error ($+$ or $-$), AE; (iii) the average absolute deviation, δ, and (iv) the root mean square error, $RMSE$. Expressions for these measure quantities could be found in Azamathulla, et al (2008)[8].

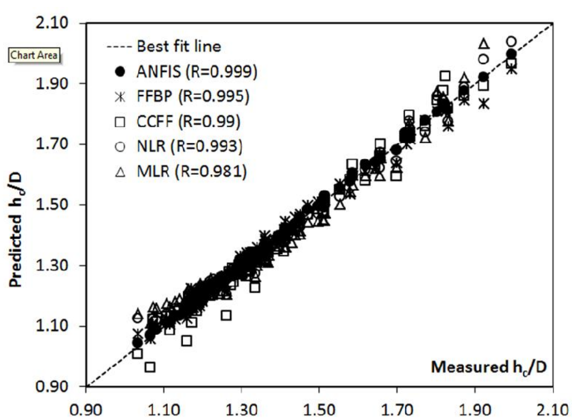

Fig. 6. Measured versus predicted h_c/D of the models for training data

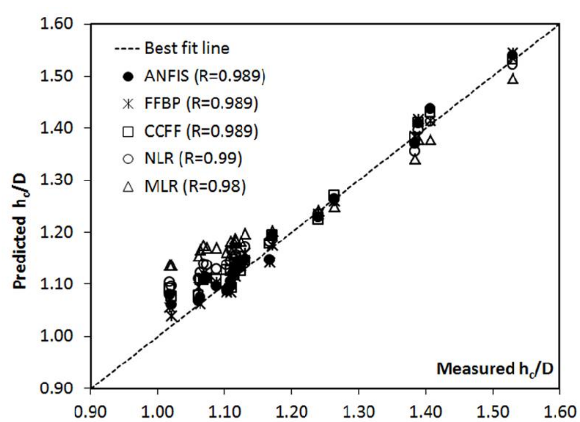

Fig. 7. Measured versus predicted h_c/D of the models for testing data

Table 2 Comparison of Predicted and Measured h_c/D

Model	Data set	R	AE	δ	RMSE
FFBP	Training data	0.995	0.1	1.19	0.02
FFCC		0.99	1.06	1.86	0.04
ANFIS		0.999	-0.01	0.6	0.01
NLR (Eq. (5))		0.993	-0.08	1.48	0.03
MLR (Eq. (4))		0.981	-0.14	2.47	0.04
FFBP	Testing data	0.989	-0.97	1.55	0.02
FFCC		0.989	-1.64	1.83	0.03
ANFIS		0.989	-0.98	1.54	0.02
NLR (Eq. (5))		0.99	-2.96	3.07	0.04
MLR (Eq. (4))		0.981	-4.65	5.22	0.07

It may be seen from Table 2 that the ANFIS model predicted the dimensionless parameter h_c / D for training and testing data with the lowest value of all other error measures $RMSE(0.01)$, $AE(-0.01)$, $\delta(0.6)$ and the highest $R(0.999)$ values in the training period, respectively. Furthermore, the error measures of the ANFIS and FFBP model are relatively small in comparison with the other models in testing period. These performances are almost similar in testing process. In short, table 2 shows that the outcome of the ANFIS model and FFBP are considered the best one compared to the MLR, NLR and FFCC models. Additionally, The NLR seems to be better than the MLR model.

6.2 Sensitivity analysis

Table 3. Sensitivity analysis using ANFIS and FFBP models

Model	Data set	R	AE	δ	RMSE
FFBP	Test data				
Without H_o / D		0.27	-18.28	19.06	0.27
Without H_d / D		0.972	-1.28	2.3	0.04
ANFIS					
Without H_o / D		0.6	-19.4	18.76	0.24
Without H_d / D		0.982	-1.74	2.07	0.03

The sensitivity tests are commonly carried out to ascertain the relative significance of each of the independent parameters on the dependent parameters. All the independent parameters reconsidered in term of the sensitivity analysis[19]. In this study, the sensitivity of each independent variable, namely H_o / D and H_d / D, in respects to dependent variables (h_c / D) used in establishing the models was analyzed. The results of sensitivity analysis for the input parameters are shown in Table 3. According to table 3, the value of H_o / D has the significant effect, whereas the value of H_d / D has the least effect on the discharge capacity of the spillway with a breast wall. This is also reflected by the coefficients in Eq. (4) and Eq. (5).

7. SUMMARY AND CONCLUSIONS

An alternative method to the conventional MLR and NLR approaches to predicting the discharge capacity of the spillway with a breast wall is introduced in this study. These methods are the Artificial Neural Networks (ANNs) and the Adaptive Network Fuzzy Inference System (ANFIS) model. The experimental data were used as training and testing sets in order to obtain the normalized value of h_c / D as a function of the relevant dimensionless parameters basing on the NLR and MLR approaches. After training and testing of the ANNs and ANFIS models, the ANFIS model and FFBP are found to be capable of predicting the discharge capacity of the spillway with a breast wall. The estimations of the ANFIS and FFBP model were clearly better than those of the conventional MLR, NLR equations (Eq. (4) and (5)) as well as the FFCC models, with the lowest errors ($RMSE(0.02)$, $AE(-0.97)$, $\delta(1.54)$) and the highest correlation coefficient $R(0.989)$ in testing period. The sensitivity analysis also indicates that the value of H_o / D has the significant effect in calculated the discharge for the flow in this field. In short, this study showed that the conventional NLR and MLR approaches could better be replaced by neural networks and similar soft computing schemes for predicting the discharge capacity of the breast wall spillways at the first designing stages.

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Tóm tắt*:*

ỨNG DỤNG MẠNG NƠ-RON NHÂN TẠO TRONG TÍNH TOÁN KHẢ NĂNG THÁO CỦA ĐẬP TRÀN CÓ SỬ DỤNG TƯỜNG NGỰC

Việc xác định chính xác khả năng tháo của công trình tháo lũ có vai trò quan trọng trong khai thác, vận hành các dự án thủy lợi, thủy điện. Sự chính xác này ảnh hưởng đến độ an toàn trong vận hành của toàn bộ hệ thống công trình. Bài báo này trình bày ứng dụng mô hình Artificial Neural Networks (ANNs) and Adaptive Network Fuzzy Inference System (ANFIS) trong dự báo khả năng tháo của đập tràn có sử dụng tường ngực. Kết quả của những mô hình này được so sánh với mô hình hồi quy tuyến tính (MLR) và không tuyến tính (NLR) dựa trên kết quả thí nghiệm mô hình thủy lực. Những đại lượng thống kê như sai số quân phương (RMSE), sai số trung bình (AE), độ lệch sai số trung bình (δ) và hệ số tương quan (R) được sử dụng để so sánh kết quả dự báo của những mô hình này. Kết quả tính toán chỉ ra rằng mô hình ANFIS và FFBP dự báo chính xác hơn so với các mô hình FFCC, MLR và NLR với sai số là thấp nhất và hệ số tương quan là cao nhất.

Từ khóa: Neural network, ANFIS, lưu lượng, đập tràn có tường ngực, phân tích hồi quy.

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