

Determination of Aerated Steps Number over Broad-Crest Stepped Spillways under Jet Flow Regime by using Artificial Neural Network

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ABSTRACT

Recently, particular attention has been paid to the stepped spillways due to the increasing effect of energy dissipation and the reduction of cavitations risks with the development of Roller Compacted Concrete (RCC) technique. Flow regimes on the spillways divide into three groups, namely skimming, jet and transition flow. Compared to the numerical methods, the majority of performed studies in this field have been done using experimental methods, which requires a lot of time and expenditure. This paper has attempted to train an Artificial Neural Network (ANN) which includes two layers for determination of the number of aerated steps over broad-crest stepped spillways under the jet flow regime condition using MATLAB. The best network was trained entailing one neuron on each layer. Results show that the number of aerated steps can be obtained by having the critical depth, steps height, chute length, chute angle, and total number of steps. The obtained nonlinear relationship was validated using testing data. The predicted results have been compared to experimental data. Proper conformity of outputs and experimental data has been investigated using SPSS. The P-Value of Man-Whitney Test of the training and testing data compared to experimental data are 0.89 and 0.77, respectively. Good agreement was shown between experimental data and predicted results using ANN.

Keywords

Stepped Spillway; Number of Aerated Steps; Jet Flow; Neural Network; Roller Compacted Concrete; P-Value

1. Introduction

Stepped spillways have become popular in the last decade due to the low cost and the speed of construction with the development of roller compacted concrete technique. Stepped spillways cause a significant energy dissipation of the flow and a reduction in the size of the energy dissipater needed below the spillway and decrease the cavitations risk

due to the intense aeration over them. The flow over a stepped spillway is divided into three kinds of flow regimes in jet, transition and skimming flow. Jet flow occurs at small discharges and skimming flow occurs at large discharges. The transition flow regime appears for passing from jet flow to skimming flow.

Some researchers performed a lot of studies in this field. Essery and Horner

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(1971), and also Sorensen (1985), were the first researchers who classified the flow regimes over stepped spillways. Considering the results of the performed experiments on the stepped spillways, it is significant that the transition from the jet flow to the skimming flow occurs when $\frac{y_c}{h}$ is approximately equal to 0.8, where y_c is the critical depth and h is the height of steps (Chanson 1994). By collecting the results of other researchers experiments Chanson showed that in addition to nonlinear parameter of $\frac{y_c}{h}$, the chute slope is effective to transfer jet flow to skimming flow. He presented a correlation equation based on the two mentioned non-dimensional parameters (Chanson 1994).

Experimental results of Chamani and Rajaratnam (1999) presented that the fully developed aerated flow over stepped spillways can be divided into upper and lower regions in which the air concentration distribution shows a proper conformity with Straub-Anderson equations (1958). They presented equations to describe the creation of the skimming flow, and also explained the skimming flow characteristics over stepped spillways (Chamani and Rajaratnam 1999). Sorensen (1985) investigated the energy dissipation using the hydraulic models. Peyras et al. (1992) produced graphs for calculating the energy dissipation over the gabion stepped spillways.

Pegram (1999), and other researchers studied the effect of flow pattern, steps geometry and chute slope on the energy dissipation by performing the experimental tests over stepped spillways. Christodolou (1993) obtained an approximate method to evaluate the energy dissipation including the number of the steps. By the measuring velocity at aerated region, Tozzi (1994)

estimated the energy dissipation from 47% to 74%. Chanson et al. (2000) presented relations for estimating the energy dissipation over spillways at the skimming flow. Sanchez et al. (2000) studied the pressure field of the skimming flow. In contrast to Chanson's theory, many researchers such as Peyras et al. (1992), Chammani and Rajaratnam (1999), Matos and Quintela (1994) believe that the energy dissipation in the jet flow is more than skimming flow. They proposed the error of entering the air in the chute when measuring flow depth, and regarded the Chanson's statements as challenging.

They didn't regard the utilization of the aerated water depth as correct for computing energy dissipation and stated that it is overestimated due to the use of the aerated water depth instead of the clear water depth. So, Matos and Quintela, by collecting previous researcher's findings and using the secondary depth of hydraulic jump (the clear water depth) for determining the first depth of the hydraulic jump and finally computing the relative energy dissipation over stepped spillways showed that calculated energy dissipation will be less than Diez-Cascon et al. (1991) and Chanson's experimental results. By applying the indirect method of using secondary depth of the hydraulic jump, Tozzi (1992) and Peyras et al. (1999) determined the energy dissipation.

In the numerical studies, Olsen and Kjellesving (1998) modeled the flow over ogee spillways in the two and three dimensional space for the different geometrical parameters, and solved the Navier-Stokes equations using $k-\varepsilon$ turbulence model, and also presented the discharge coefficient of the ogee spillway.

Chen et al. (2002) analyzed the flow over the stepped spillway using finite volume method and used the standard $k-\varepsilon$

turbulence model for determining the turbulence of the flow. Also, Tabbara et al. (2005) analyzed the stepped spillway by using finite element method and the standard $k-\epsilon$ model. Carvalho and Martins (2009) studied a large stepped spillway model giving a circular profile on the tip of steps and also baffles and stills on the horizontal face of steps, physically and numerically. Gonzales and Chanson (2007) conducted an experimental study to gain a better understanding of the flow properties in stepped chute with typical slopes of embankment dams. Sanchez-Juny et al. (2007), (2008) presented a pressure field analysis on the vertical and horizontal faces of the steps in fully developed skimming flow regime zone of a stepped spillway in an RCC dam. Salmasi (2010) presented an artificial neural network for calculating the energy dissipation of the flow over stepped chutes.

Due to the importance of air entrainment over the stepped spillways, it is essential to know the flow conditions in this regard. In this paper, it has been tried to train suitable artificial neural network for determination of the aerated steps number over broad-crest stepped spillways under jet flow regime conditions.

2. Material and Methods

2.1. Artificial Neural Network

The human's neural network (the brain) - as a parallel processor- has been made from the basic units named neurons. The synapses are basic and operating elements which behave as a link among neurons. The brain has the ability to do many calculations (like pattern identification, perception, etc.) higher than the fastest digital computers because of the ability in organizing basic elements that are neurons. fig. 1 shows a neural neuron.

Artificial neural networks are a form of the artificial intelligence which tries to simulate the action of human's brain and the neural systems. These networks learn by giving sample information in order to get the accurate functional relations existing among information. In other words, it makes an output pattern based on the input pattern given to the network. The method used for teaching to is called the Learning Algorithm which is responsible for modifying weights and biases of the network. The computational capability of the neural network is due to its wide parallel structure, learning ability and generalization. The generalization means producing logical output from

the data which have not been included in the process of learning. The artificial neural networks are usually used in the form of software in digital computers. These networks need a large amount of connections among processor units (the neurons) for a better operation. Each network consists of a set of layers which include neurons.

2.2. Feed Forward-Multilayer Neural Network

The most common neural network includes the feed forward-multilayer networks which are the set of one or several hidden layers which are located between input and output layers, and output of a layer acts as the input of the next layer (Cheung and Cannons 2002).

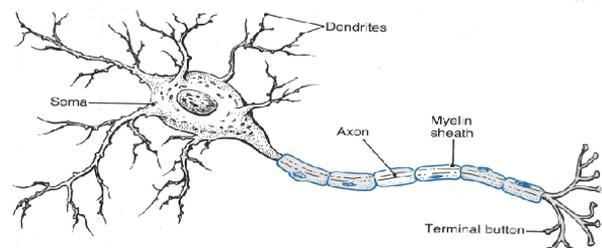


Fig. 1. Schematic of a neural neuron

The layers have relations (Synaptic joints) serially (fully or partly adjoined) with a feed forward method and without any joint among units in an equal layer (Jain et. al. 1996). A feed forward- multilayer network including l input neurons, m_1 neurons at the first hidden layer, m_2 neurons at the second layer and n neurons at the output layer is written with $l-m_1-m_2-n$ (Rajasekaran and Vijayalakshmi Pai 2007). Figure 2 shows a neural network with a hidden layer, joints among neurons, etc (Dawson et al., 2000).

2.3. Neural Network Data and Transfer Functions

In many cases, division of available data is performed in three sets of training, validation, and testing. Generally, using the following percentages will lead to the best results.

In this paper 10 percent of the data have been selected as testing data and the rest of them as training data. Following this, each set has been classified in the form of input and target data. It is necessary for the data to be normalized because multilayer neural network usually uses the Log-Sigmoid transfer function which is in the range of $\{0, 1\}$. Tansig and Purline functions can also be used instead of Log-Sigmoid function. If the layers of a multilayer network have sigmoid neurons, the output of the network will be limited to a small range.

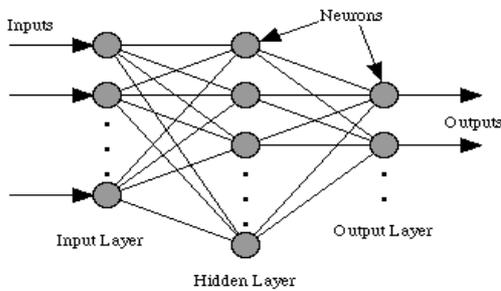


Fig. 2. A neural network with a hidden layer

2.4. Neural Network Learning

In this paper, we use MATLAB software. The input and target data are defined to the software for training of the network until a nonlinear relationship is created among the input and target information. Attaining to the ideal response is the base in achieving the minimum error, (MSE), corresponding to equation 1, and also 40000 epochs.

$$Mse = \frac{1}{N} \sum_{i=1}^N (y_i - \bar{y})^2 \quad (1)$$

At the first step, weights and biases are zero, predictably. Then, the training function estimates the MSE value at any repetition. If it reaches to the defined error limit or the maximum of the repetitions, the training will stop and it will come back to a new network and training responses. We can achieve to a better response, but we will never achieve an error value equal to zero, because the abilities of the network are limited. Considering the abilities of the feed-forward networks in modeling the nonlinear processes, the multilayer perception network has been used, which is based on back propagation learning algorithm. Equation 2 shows the general form of the obtainable nonlinear relationship.

$$Target = Purline(w_2 \times Tansig(w_1 \times I) + b_1 + b_2) \quad (2)$$

Where I is a perpendicular matrix of the input data at the normalized space, w and b indicating weight and bias values, respectively. In fact, the relation between the defined elements is corresponding to Equation 3.

$$Target = w_2 \left(\frac{1 - e^{-2((w_1 \times I) + b_1)}}{1 + e^{-2((w_1 \times I) + b_1)}} \right) + b_2 \quad (3)$$

2.5. Case Study

The 36 initial experimental data of a broad-crest stepped spillway with 0.3 m width, (Baylar et al. 2003, 2006, and 2007) was used as trained data for training the network. The input data matrix with size 536 consists of the information related to the first to fifth data (the critical water height over spillway, the steps height, the chute length, the chute slope angle, and the number of total steps over spillway). The target data matrix with size 1*36 consists of the number of aerated steps which show the number of steps that the air enters to the fluid flow over them. This air entrainment procedure increases the energy dissipation and cavitations risks. Table 1 indicates the minimum and maximum of the experimental data which have been used to train the network.

3. Result

After running the program, the weight and bias values are determined and a nonlinear relationship is obtained. For choosing the best network among the trained networks, we defined the testing data of the network as the input value for the obtained nonlinear relationship and compared the attained number of aerated steps from this relationship to the experimental data. So, a neural network was accepted with the number of one neuron for each layer. Then, testing data have been applied to the nonlinear relationship. Fig. 3 compares the experimental data and evaluated results by the neural network for training and testing data. Table 2 expresses the weights and biases of the chosen network with 1 neuron for each layer. Finally, the obtained relation for this network is in the form of Equation 4.

$$Na = w_2 \times \left(\frac{1 - e^{-2((w_1 \times c) + b_1)}}{1 + e^{-2((w_1 \times c) + b_1)}} \right) + b_2 \quad (4)$$

Table 1. The minimum and the maximum of the experimental data used

	$Q : (m^3 / s) * 10^{-3}$	$h : (m)$	$L : (m)$	$\alpha : deg ree$	N	Na
Max.	5.001	0.05	3.26	14.48	8	6
Min.	30.001	0.15	5	50	50	48

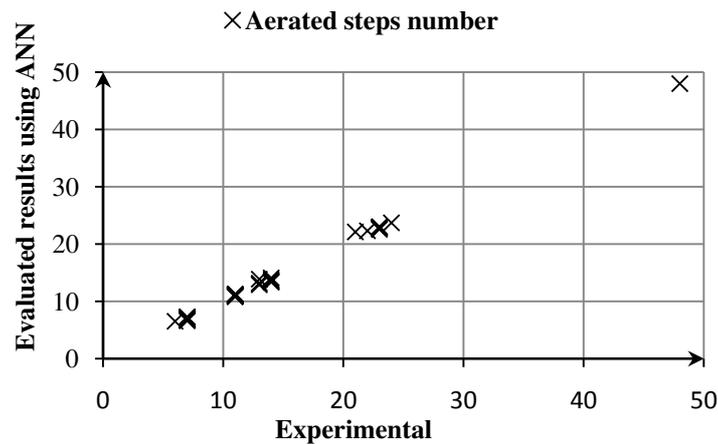


Fig. 3. A) Comparison of the experimental data and evaluated results by the neural network for the training data

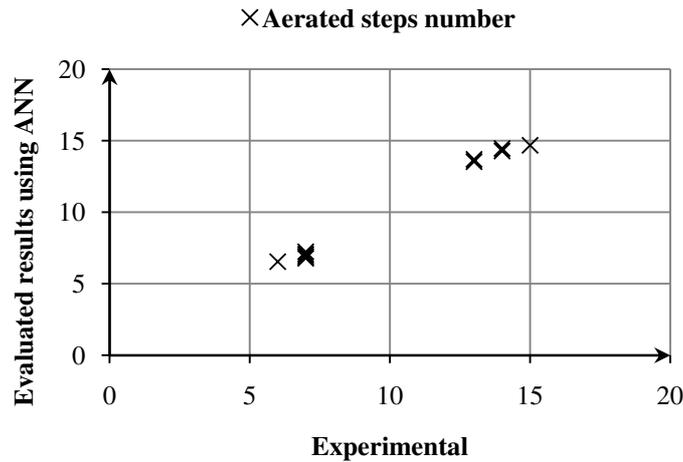


Fig. 3. B) Comparison of the experimental data and evaluated results by the neural network for the testing data

Table 2. Weights and Biases

W1	[0.078508 -0.071434 -0.01764 0.02035 -0.7191]
W2	[-1.3413]
b1	[0.66602]
b2	[0.86386]

Where cis is the perpendicular matrix with size 5×1 which is related to the input data (that, its elements from top to the bottom include hc, h, L, α, N , respectively), and Na is the number of aerated steps over the spillway at the normalized space. Also, w_1, w_2, b_1 and b_2 are given in table 2

4. Conclusions

In order to compare the training data obtained from the neural network to the experimental data, the SPSS software has been used. The P-Value of Man-Whitney Test of training and testing data compared with experimental data are 0.89 and 0.77, respectively. If the obtained P-Value is nearer 1, it would represent a better conformity between the compared values, and if it is less than 0.5, it would represent an egregious difference between them. Therefore, the trained network will not be

accepted. Results of a network with one neuron for each layer have the suitable P-Value. On the other hand, this network gives more suitable P-Value than other networks for the testing data. So, the mentioned network is selected.

The neural network model can give a proper non-linear relationship for evaluating the number of aerated steps over the stepped spillway and jet flow regime according to its ability. Using equation 4, we can calculate the number of aerated steps by having the main properties of the stepped spillway (the critical water height over the spillway, the step height, the chute length, the chute slope angle, and the total number of all the steps). The number of aerated steps is important due to the air entrainment phenomena. If the number of aerated steps is large, the air entrainment will be much more. So, the energy dissipation will be more and the cavitations risk will be less. Results of this paper can be used to determine the amount of the air entrainment as a result of estimating the number of aerated steps. Determining the number of aerated steps over the spillway by using equation 4 removes the need to the

experimental measurements relating to concentration, etc, and saves a lot of time and cost. According to the results, the agreement between the obtained results from the network and the experimental results is well. No previous research results were found for the comparison to present results, and hence the present study is one of the few researches in this field.

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