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ANALYSIS AND ESTIMATION OF SEEPAGE DISCHARGE IN DAMS

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Abstract

Analysis and estimation of seepage discharge in dams is presented in this paper. First of all the continuity Laplace equation is solved for a dam and piezometric head are computed under the dam. Based on piezometric head data values of seepage discharge of dam are obtained for different conditions. After that a procedure for estimation of seepage discharge under a diversion dam using feed forward multi layer perceptron artificial neural network is presented. Neural network are trained based on pizometric head data for seepage discharge estimation in different conditions and its test results are compared with actual data. Finally it is observed that estimated seepage discharges are in good agreement with actual results.

Keywords: Seepage Discharge, Dams, Analysis, Estimation, Laplace Equation

1. Introduction

Dams are barrier constructed to save and hold back water and raise its level, the resulting reservoir being used in the generation of electricity or other beneficial things. Because of high level importance of dams several studies have been performed on analysis and investigation of dams. Rezk and Senoon [1] presented an analytical solution for the same problem and also comparisons between two solutions. Effect of relative permeability of core on each relative seepage discharge and relative drop of phreatic surface due to core is investigated. Rochon-Cyr and Léger [2] presented a review study about Shake table sliding response of a gravity dam model consist of water uplift pressure. They performed a series of shear tests and shake table sliding tests on a 1.5 m high concrete gravity dam model with a smooth concrete–concrete frictional interface corresponding to a cold lift joint. Javanmardi et al. [3] developed a theoretical model for transient water pressure variations along a tensile seismic concrete crack with known crack wall motion history. They performed Experimental tests to validate the proposed model. Then the proposed model was implemented in a nonlinear discrete crack finite element program for seismic analysis of concrete dams. Wei et al. [4] in a study used an anisotropic laminar layer element with thickness to simulate mechanical deformation properties of weak-bed intercalations at a dam's foundation as well as a contact friction interface element without thickness to simulate joints and fissures of the rock mass at the dam's foundation. They used nonlinear finite element analysis to compute the resistance to sliding of a high-concrete gravity dam at the dam's foundation. Yan et al. [5] presented a systematic analysis on the factors that may contribute to the uplift. They performed three dimensional numerical analysis and rock mechanical model to confirm the uplift mechanism of the confined hot aquifer test. Plizzari [6] studied uplift pressure effects in cracked concrete gravity dams. He investigated influence of uplift pressure on stress intensity factors and crack-propagation angle. Liu et al. [7] used a coupled hydro-mechanical model to study of the uplift mechanism of Tongjiezi dam. They used a numerical model for appraise the representative elementary volume and to investigate related parameters to hydraulic and mechanical properties of the rock mass. They found if hydro-geological conditions at the Tongjiezi dam site are specific, hydro-mechanical coupling during and after the reservoir

impoundment is the most important factor to make the uplift, and the rheological behavior of rock masses cause the time-dependent deformation under seepage pressure.
Nowadays a new method that often used for investigation and design of different characteristics and parameters of dams in recent decades is ANN. Wang and He [8] presented an article about numerical simulation and the model experiment upon a hypothetical concrete arch dam in order to crack detection using the reduction of natural frequencies and effect of crack characteristics on the dynamic property of the arch dam was investigated. Mata [9] studied the differences between multiple linear regression and ANN models for the characterization of dam behavior under environment loads. Then they investigated the horizontal displacement recorded by a pendulum in a large Portuguese arch dam. Hasebe and Y. Nagayama [10] presented an article about multipurpose dam with drainage area relatively smaller compared with dam capacity. They made a comparison between reservoir operation using the fuzzy and ANN systems and actual one by operator, by using examples of floods during flood and non-flood seasons. Kim and Kim [11] developed an ANN model for the estimation of relative crest settlement of concrete-faced rockfill dams. The settlement values that were predicted using the ANN model were in good agreement with these field data.
In this paper analysis and estimation of seepage discharge in dams is presented. The continuity Laplace equation is solved for a dam and piezometric head are computed under the dam. Using piezometric head data values of seepage discharge of dam are obtained for different conditions. A procedure for estimation of seepage discharge under a diversion dam using feed forward multi layer perceptron artificial neural network is presented. Trained network used to seepage discharge estimation in different conditions and compared with actual results.

2. Analysis

2.1. Derivation of the Laplace Equation

In reality, the flow of water through soil is not in one direction only, nor is it uniforms over the entire area perpendicular to the flow. In such cases, the groundwater flow is generally calculated by the use of graphs referred to as flow nets. The concept of the flow net is based on Laplace's equation of continuity, which governs the steady flow condition for a given point in the soil mass. Laplace equation is the combination of the equation of continuity and Darcy's law [12].
A small element with dimensions of dx, dy and dz is considered in order to study of flow in point A (Fig.1).

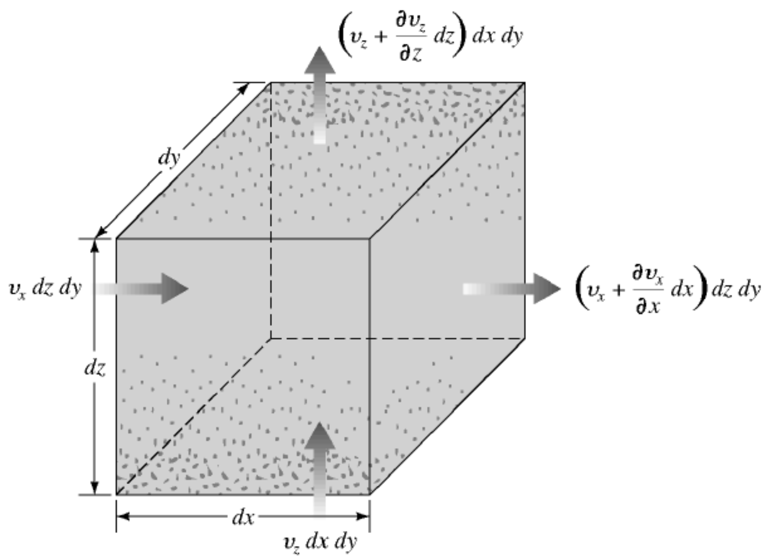

Figure 1. Flow in point A [12]

In Fig.1, v_x , v_y and v_z are flow velocity component in main three directions, $v_x.dz.dy$, $v_z.dx.dy$ and $v_y.dx.dz$ are inlet water discharge and $\left(v_x+\frac{\partial v_x}{\partial x}dx\right)dz.dy$, $\left(v_z+\frac{\partial v_z}{\partial z}dz\right)dx.dy$ and $\left(v_z+\frac{\partial v_z}{\partial z}dz\right)dx.dy$ are outlet water discharges.

By assuming water as an incompressible flow and considering that volume to be constant, total inlet discharge flow is equal to total outlet discharge flow.

So:

$$\left[\left(v_x+\frac{\partial v_x}{\partial x}dx\right)dz.dy+\left(v_z+\frac{\partial v_z}{\partial z}dz\right)dx.dy\right]-\left[v_x.dz.dy+v_z.dx.dy\right]=0 \tag{1}$$

$$\frac{\partial v_x}{\partial x}+\frac{\partial v_y}{\partial y}+\frac{\partial v_z}{\partial z}=0 \tag{2}$$

From darcy's law, flow velocity can be written as:

$$\begin{aligned} v_x &= k_x i_x = k_x\frac{\partial h}{\partial x} \\ v_y &= k_y i_y = k_y\frac{\partial h}{\partial y} \\ v_z &= k_z i_z = k_z\frac{\partial h}{\partial z} \end{aligned} \tag{3}$$

That k_x and k_z are coefficient of permeability in horizontal and vertical directions. By replacing Eq.e in to continuity equations (Equation (2)), the following equation is obtained.

$$k_x\frac{\partial^2 h}{\partial x^2}+k_y\frac{\partial^2 h}{\partial y^2}+k_z\frac{\partial^2 h}{\partial z^2}=0 \tag{4}$$

If soil be isotropic, so:

$$k_x=k_y=k_z \tag{5}$$

Then the preceding continuity equation simplifies to:

$$\frac{\partial^2 h}{\partial x^2}+\frac{\partial^2 h}{\partial y^2}+\frac{\partial^2 h}{\partial z^2}=0 \tag{6}$$

Equation (6) is called Laplace equation.

In an isotropic medium the continuity equation represents two orthogonal families of curves:

1. Flow lines: the line along which a water particle will travel from upstream to the downstream side in the permeable soil medium;
2. Equipotential lines: the line along which the potential (pressure) head at all points is equal [12]

The combination of flow lines and equipotential lines is called flow nets (Fig.2).

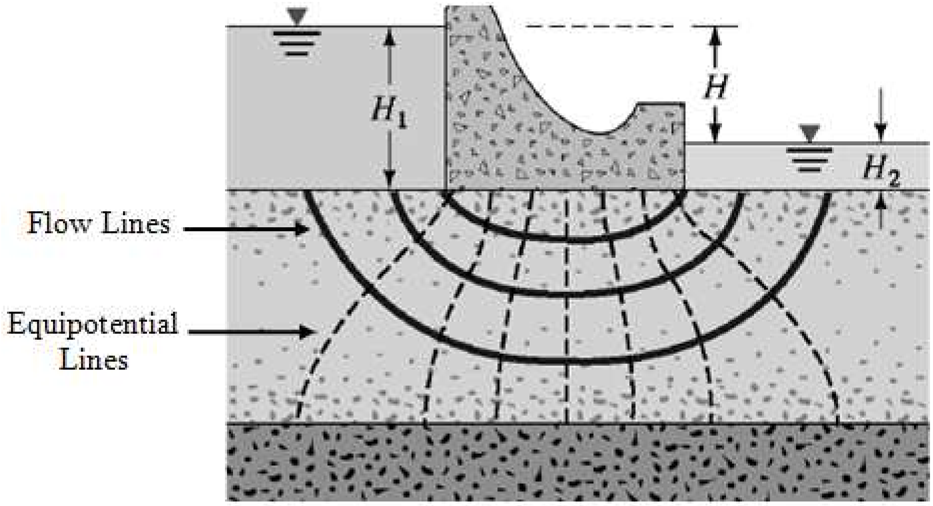

Figure 2. Flow Net [12]

2.2. Solving Laplace Equation

In present study using PDE toolbox of MATLAB, Eq.6 has been solved in 2 dimensional. Firstly geometry of diversion dam has been drawn. Characteristics of considered diversion dam have been shown in Fig. 3.

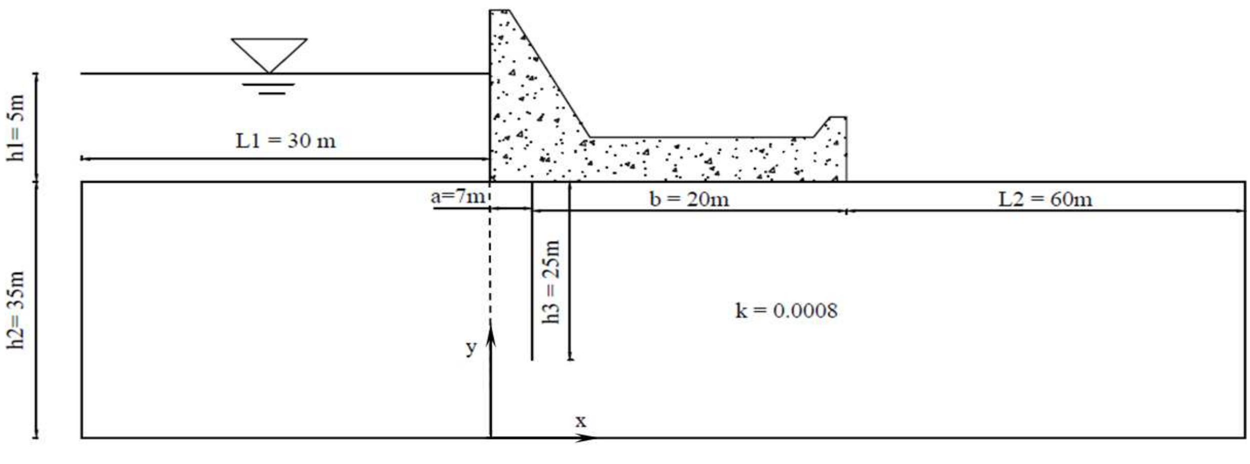

Figure. 3. Characteristics of considered diversion dam

For solving Eq.6 boundary conditions must be defined. There are two types of boundary conditions that are natural (Neumann) and essential (Dirichlet). Piezometric head values and passing flow flux are specified using Dirichlet and Neumann boundaries, respectively. In this study, except of upstream and downstream boundaries, all of boundary conditions are Neumann. In Neumann boundaries flow passing is zero and piezometric head values are 40 m and 35 m in upstream and downstream boundaries, respectively. After meshing of model, Laplace equation is solved.

By solving Laplace equation, piezometric head in several points of considered model was derived. Then uplift pressure under the diversion dam is obtained using following equation:

$$P_u = \gamma(U - Y) \tag{7}$$

where P_u is uplift pressure, U is piezometric head, γ is Specific gravity of water and Y is height of base level.

2.3. Seepage Discharge

In the next step, using derived piezometric head in different nodes and following equation seepage discharge per unit width is calculated.

$$q = kiA \tag{8}$$

where i is hydraulic gradient and obtains from Equation (8):

$$i = \frac{\Delta u}{\Delta x} \tag{9}$$

also

$$v = ki \tag{10}$$

that $v = ki$ is velocity.

3. Estimation of Seepage Discharge

Multi-**L**ayer **F**eed **F**orward (**MLFF**) is the most popular type of neural network. ANNs offer a procedure to tackle complex problems, and are applied in different fields of engineering. A schematic diagram of typical MLFF neural-network architecture was illustrated in Fig. 4. In MLFF neural networks knowledge is stored as a set of connection weights. The process of modifying the connection weights, in some orderly fashion, using a suitable learning method is call training [13]. In this study, an ANN was trained based on the Back Error Propagation (BEP) technique for the estimation of pizometric head in different points under the dam. The inputs of the mentioned ANN were coordinates of different points under the dam, and target outputs were corresponding pizometric head. Also the same ANN was trained based on the BEP technique. In this table, W_{ij} is the weight of link that relates neuron number i from input layer to neuron number j from hidden layer. Also V_{ik} is the weight of link that relates neuron number j from hidden layer to neuron number k from output layer. B_{1j} is the weight of the link that relates bias of input layer to neuron number j of hidden layer and B_{2k} is the weight of the link that relates bias of hidden layer to neuron number j of output layer. In each network, transfer functions for neurons of hidden and output layers are Tansig and are defined as equation (11).

$$H(n) = 2/[(1+\exp(-2n))-1]. \tag{11}$$

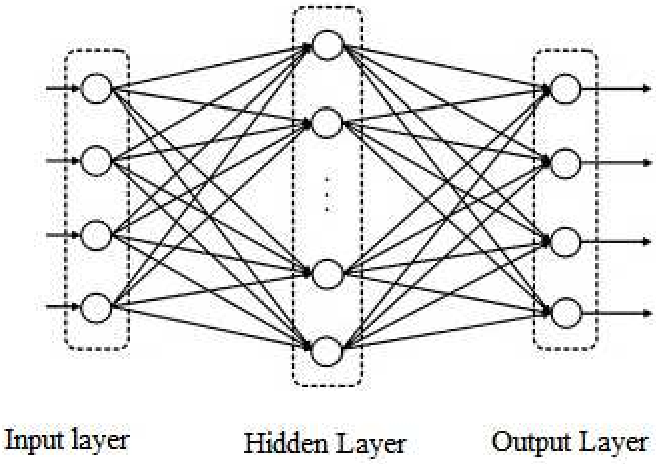

Figure 4. Diagram of typical MLFF neural network

The estimation procedure of the present study consists of three main stages. In the first stage, a MLFF neural network was created with an input, a hidden and an output layer with 2, 10 and 1 neuron, respectively. The inputs of the ANN were coordinates of different points under the diversion dam, and the target output was corresponding pizometric head. In the second stage, ANN training was performed by data of 56 different points that were obtained by solving continuity Laplace equation. For training ANN, BEP technique was applied and layer weights of ANN were obtained. In the third stage, some data were not used in the training process were used to test the trained ANN. For this propose, coordinates of these data were applied as inputs to trained ANN and corresponding outputs were obtained. All the data were applied to ANN of this article in normalized form. Then, the outputs of the trained ANN were compared with corresponding pizometric heads from analytical data. In the training procedure, BEP iteration was assumed to be 1000 epochs.

4. Result

Piezometric head and then seepage discharge in several points of considered model was computed by solving continuity equation, and using equation (9). Coordinates of 56 different points under diversion dam and corresponding pizometric heads were applied as inputs and outputs to ANN, respectively.

The BEP technique was used to training the ANN and the calculated weights using BEP method was obtained that were tabulated in Table 1. The test results of ANN for 16 other points were obtained which were tabulated in Table 1. As it can be seen, the average error between actual and predicted data for the ANN that trained by BEP methods was 3.14% and therefore it can be concluded that there is good agreement between predicted and actual data and for this problem.

The actual seepage discharge value in the considered condition was 0.00138 (m^2/s) which was estimated 0.00132 (m^2/s). It means that the estimation error in this case was less than 4.5% that is very good result for this problem. So the proposed procedure can be used for estimation and investigation of discharge's seepage under the diversion dams. The main advantage of the proposed procedure is respond to the points that the prizometric head data aren't available there, and therefore ANN can be used to estimation of prizometric head and then discharge's seepage with good approximation. In the

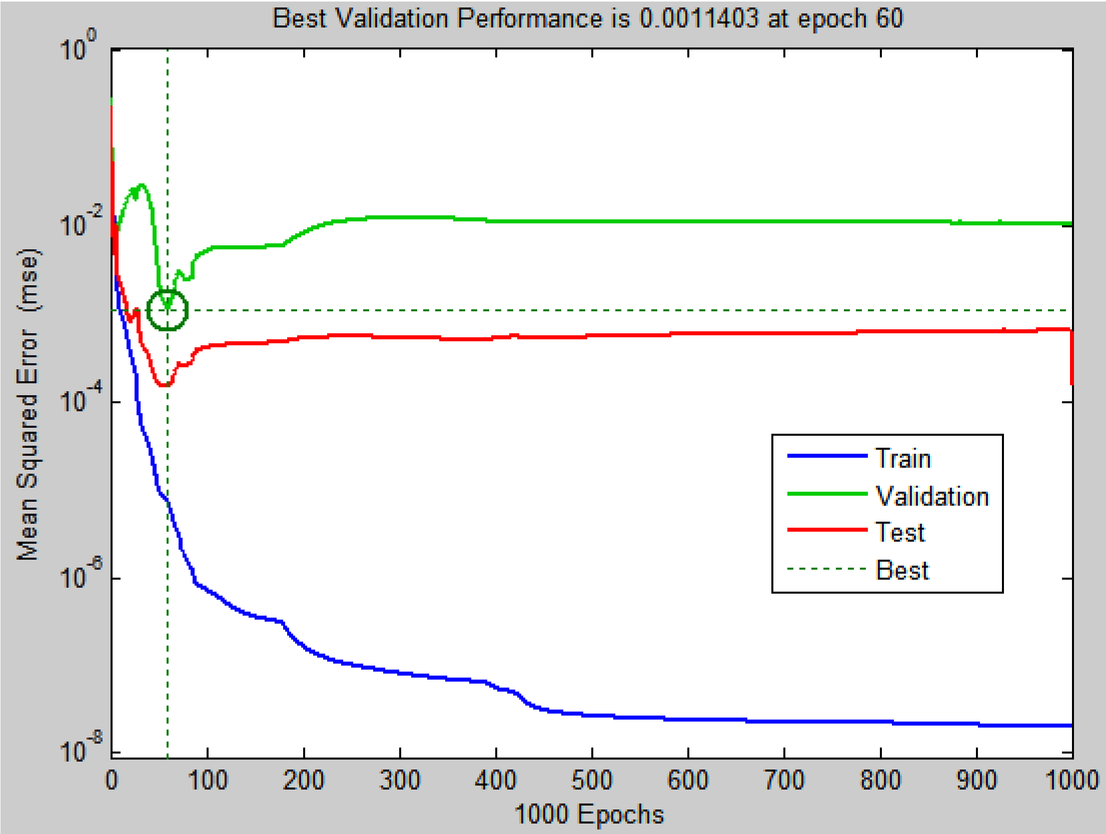

Figure 5. Training procedure of ANN using MATLAB

Table 1. Comparison of actual and predicted pizometric head under the diversion dam

Number	X (m)	Y (m)	Actual Head (m)	Estimated Head (m)	Error (%)
1	31	0	38.2293	38.95242	1.891538
2	31	5	38.2327	38.87403	1.677447
3	31	10	38.4857	39.12392	1.658338
4	31	15	38.7884	39.30735	1.337911
5	31	20	39.115	39.44971	0.855719
6	31	25	39.3803	39.57033	0.482551
7	31	30	39.6344	39.71655	0.20726
8	31	35	39.8166	39.88174	0.163601
9	36	0	37.7085	37.44185	0.707123
10	36	5	37.7574	37.56109	0.519934
11	36	10	37.986	36.78514	3.161328
12	36	15	38.6572	36.44846	5.713663
13	36	20	39.0678	36.28089	7.133516
14	36	25	39.3291	36.22683	7.887976
15	36	30	39.6517	36.24364	8.594999
16	36	35	39.6383	36.37492	8.232897

5. Conclusion

In dams is presented in this paper Analysis and estimation of seepage discharge. First of all the continuity Laplace equation is solved for a dam and piezometric head are computed under the dam. Based on piezometric head data values of seepage discharge of dam are obtained for different conditions. After that a procedure for estimation of seepage discharge under a diversion dam using feed forward multi layer perceptron artificial neural network is presented. Neural network are trained based on pizometric head data for seepage discharge estimation in different conditions and its test results are compared with actual data. Finally it is observed that estimated seepage discharges are in good agreement with actual results. All in all, it is shown that analysis and estimation of seepage discharge which is very important parameters in dams using proposed procedure of this study is so accurate and time consuming.

6. References

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