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PREDICTION OF UPLIFT PRESSURE UNDER THE DIVERSION DAM USING ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM

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Abstract

*This paper proposed a procedure for prediction of uplift pressure under a diversion dam using **A**rtificial **N**eural **N**etwork (**ANN**) and **G**enetic **A**lgorithm (**GA**). In this study, firstly the continuity Laplace equation is solved for a diversion dam and piezometric head and uplift pressure are computed under the diversion dam. Then two similar ANNs are trained based on GA and **B**ack-**E**rror **P**ropagation (**BEP**) technique for uplift pressure prediction in different points of considered diversion dam and their test results are compared with each other and with actual data. The inputs and outputs of ANNs are coordinates of different points under the dam and corresponding uplift pressures, respectively. The test results show that the uplift pressure is predicted with good accuracy using this procedure in different locations.*

Keywords: Artificial Neural Network, Diversion Dam, Genetic Algorithm, Uplift Pressure

1. Introduction

One of the most important hydraulic structures which have significant role in production of hydroelectric energy, supply of drinking water, development of agriculture and etc, are dams. Since dams is built for saving and control waters of river and considerable volume of water is gathered behind of them, so break of them make great floods and damages in cities and industrial facilities. Different factors cause instability in dams such as piping, overtopping, uplift pressure, failure in body of dams and etc. Several studies have been done about dams and effects of different parameters on them. Plizzari [1] 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. [2] 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. Rochon-Cyr and Léger [3] 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. [4] 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. [5] 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. [6] 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.

A new technique often used for investigation and design of different characteristics and parameters of dams in recent decades is ANN. Hasebe and Y. Nagayama [7] 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 [8] developed an ANN model for the prediction 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. Wang and He [9] 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 [10] 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.
This paper using ANN and GA proposed a procedure for prediction of uplift pressure under the diversion dam using ANN and GA toolboxes of MATLAB. The continuity Laplace’s equation was solved for a diversion dam using PDE toolbox of MATLAB. The inputs of ANNs were coordinates of different point of dam and the outputs were corresponding uplift pressure. GA and BEP technique were used for training the ANNs and finally their test results were compared with each other and with actual data.

2. Analysis

Usually, flow of water in soil not only isn’t in one direction but also isn’t consistent in all of the surfaces that are perpendicular to flow direction. So in these states, calculation of underground water flow is done by flow net. Concept of flow net is defined based on the continuity Laplace’s relations that define conditions of steady flow for a point in the soil mass. For study of flow in point A, a small element is considered with dimensions of dx, dy and dz. v_x and v_z are flow velocity in horizontal and vertical directions, respectively. Flow discharge in horizontal direction is $v_x.dz.dy$ and in vertical directions is $v_z.dx.dy$. Therefore outlet water discharges of the small element in horizontal and vertical directions are as follow:

$$\left(v_x + \frac{\partial v_x}{\partial x} dx\right) dz.dy \qquad (1)$$

$$\left(v_z + \frac{\partial v_z}{\partial z} dz\right) dx.dy \qquad (2)$$

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:

$$\left[\left(v_x + \frac{\partial v_x}{\partial x}dx\right)dz.dy + \left(v_z + \frac{\partial v_z}{\partial z}dz\right)dx.dy\right] - \left[v_x.dz.dy + v_z.dx.dy\right] = 0 \tag{3}$$

$$\frac{\partial v_x}{\partial x} + \frac{\partial v_z}{\partial z} = 0 \tag{4}$$

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

$$v_x = k_x i_x = k_x \frac{\partial h}{\partial x} \tag{5}$$

and

$$v_z = k_z i_z = k_z \frac{\partial h}{\partial z} \tag{6}$$

That k_x and k_z are coefficient of permeability in horizontal and vertical directions. Using equations 4, 5 and 6 the following equation is written.

$$k_x \frac{\partial^2 h}{\partial x^2} + k_z \frac{\partial^2 h}{\partial z^2} = 0 \tag{7}$$

If soil be isotropic, above continuity equation for 2D flow can be written as follow:

$$\frac{\partial^2 h}{\partial x^2} + \frac{\partial^2 h}{\partial z^2} = 0 \tag{8}$$

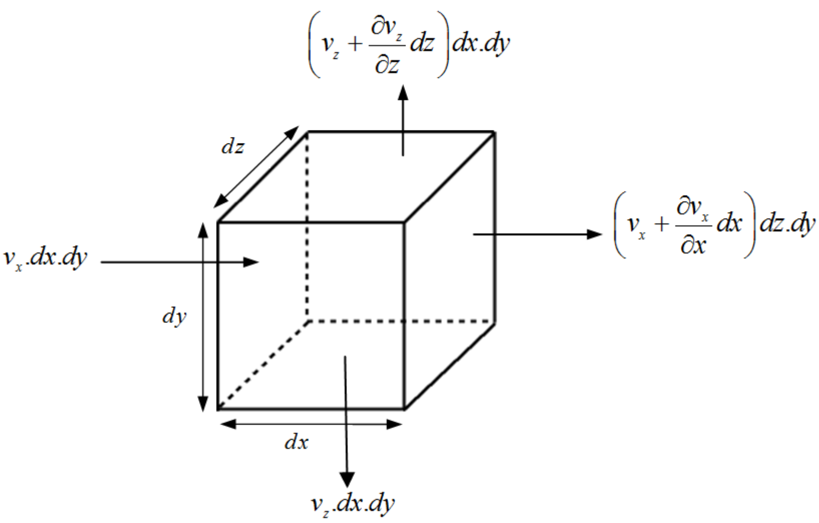

Fig. 1. Flow in point A

In this paper for solving continuity equation PDE toolbox of MATLAB has been used. Firstly geometry of diversion dam has been drawn. Characteristics of considered diversion dam have been shown in Fig. 2.

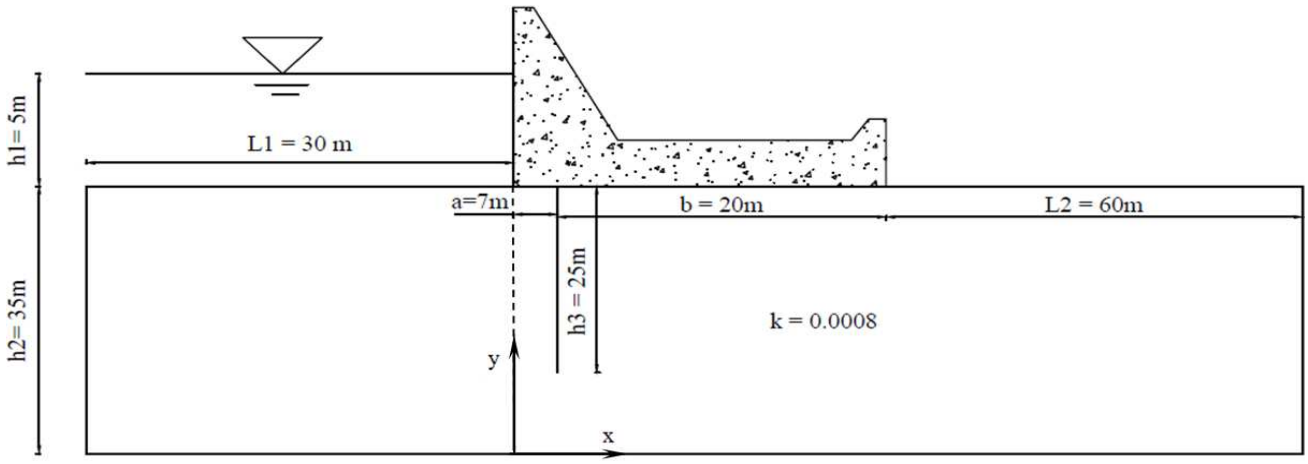

Fig. 2. Characteristics of considered diversion dam

Then boundary conditions must be defined. Boundary conditions are natural (Neumann) or essential (Dirichlet). In Dirichlet boundaries values of piezometric head and for Neumann boundaries passing flow flux should be specified. In this model all of boundary conditions are Neumann except of upstream and downstream boundaries that are Dirichlet. Flow passing in Neumann boundaries is zero and value of piezometric head in upstream and downstream boundaries is 40 m and 35 m, respectively. After meshing of model, continuity equation is solved.
By solving continuity equation, piezometric head in several points of considered model was calculated. Using bellowing equation uplift pressure under the diversion dam is obtained.

$$P_u = \gamma(U - Y) \tag{9}$$

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

3. Prediction

3.1. Artificial Neural Network

ANNs offer a procedure to tackle complex problems, and are applied in different fields of engineering. **M**ulti-**L**ayer **F**eed **F**orward (**MLFF**) is the most popular type of neural network. A schematic diagram of typical MLFF neural-network architecture was illustrated in Fig. 3. 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.
In this study, an ANN was trained based on the GA for the prediction of uplift pressure 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 uplift pressure. Also the same ANN was trained based on the BEP technique. In each network, transfer functions for neurons of hidden and output layers are Tansig and are defined as equation (10).

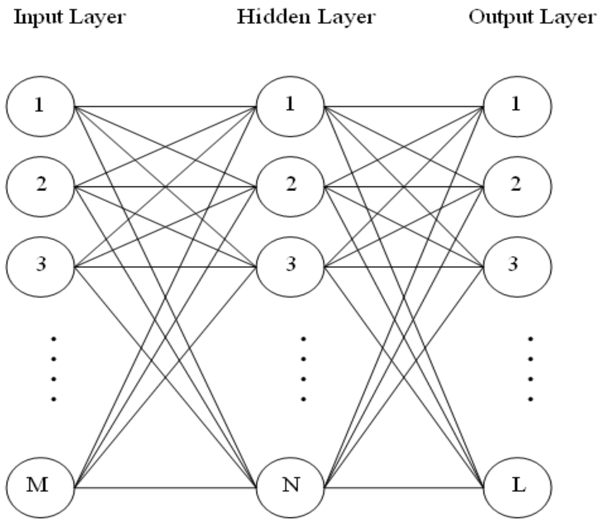

Fig. 3. Schematic diagram of typical MLFF neural network

$$f(x) = \frac{2}{(1 + \exp(\text{-}2x))\text{ -}1}. \tag{10}$$

3.2. Back-Error Propagation Technique

BEP is one of the most powerful learning algorithms in ANNs that was presented by Rumelhart and Mcclelland [11]. The structure of the back-propagation was illustrated in Fig. 3. In this study the structure of neural network includes input layer, hidden layer, and output layer. The variables M , N and L show total neuron number in the input layer, hidden layer and output layer, respectively. Values w_{MN} are the weights between the input and the hidden layer. Values w_{LN} are the weights between the hidden and the output layer. The operation of BEP consists of three stages:

1- Feed-forward:

$$v_j = w_{LN}(n).u_{j+1}(n); \tag{11}$$

$$o_j(n) = \varphi(v_j(n)) = \frac{2}{1 + \exp(-v_j(2n))}; \tag{12}$$

Where, o_j is output, u_j is input, u_{j+1} is output of hidden layer and φ is transfer function.

2- Back-propagation:

$$\delta_j(n) = e_j(n).\varphi'(v_j(n)) = (d_j(n)\text{ - }o_j(n))o_j(n)(1\text{ - }o_j(n)); \tag{13}$$

Where, δ_j represents the local gradient function, e_j shows the error function, o_j means the actual output and d_j is desired output.

3- Adjust weighted value:

$$\delta_j(n) = e_j(n).\varphi^{'}(v_j(n)) = (d_j(n) - o_j(n))o_j(n)(1 - o_j(n)); \qquad (14)$$

where, η is the learning rate. Repeating these three stage results to the value of the error function will be zero or a constant value.

3.3. Genetic Algorithm

A common optimization method in engineering applications is GA that popularized by Holland [12]. GA in all iterations generates a population of points that using stochastic and not deterministic operators approach the optimal solution. By initializing a set of individuals and is submitted to genetic operators, resulting in the evolution of populations through generations the first population is formed. This algorithm in each generation evaluates the individuals according to objective function and selects the best individuals. The individuals that are better, according to the objective function, have a higher possibility of attending in the recombination procedure. Mutation is the main operator for protecting GA from permanently losing genetic material through the evolution of generations, which changes parts of the individuals periodically. Also for the recombination of genetic exchange among individuals crossover is used. Migration is defined as the movement of individuals among sub-populations of existing individuals, with the best individuals from one sub-population replacing the worst individuals in another sub-population. The best individual is proposed as the solution to the problem by this algorithm. Fig. 4 shows the flowchart of basic GA.

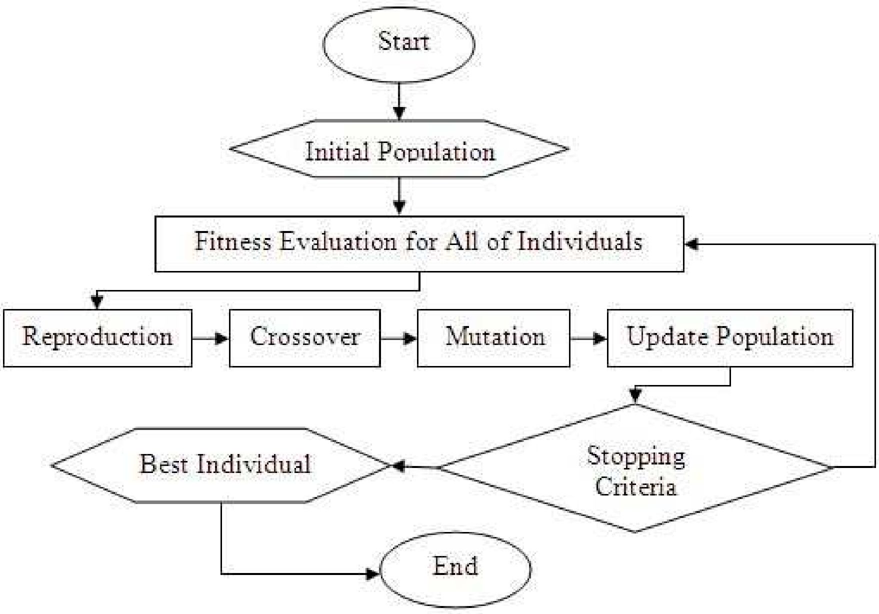

Fig. 4. Flowchart of basic genetic algorithm

3.4. Prediction Procedure

The prediction procedure of the present study consists of three main stages. In the first stage, two MLFF neural networks were created with an input, a hidden and an output layer with 2, 5 and 1 neuron, respectively. The inputs of the ANNs were coordinates of different points under the diversion dam, and the target output was corresponding uplift pressure. In the second stage, ANN trainings were done based on data of 104 different points that were obtained by solving continuity Laplace equation. For training ANNs, GA and BEP techniques were 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 ANNs. For this propose, coordinates of these data were applied as inputs to trained ANNs and corresponding outputs were obtained. Then, the outputs of the trained ANN based on GA and BEP were compared with corresponding uplift pressures from analytical data. In this procedure, the GA generation, population size and BEP iteration were assumed as 1000, 105 and 1000 respectively. It should be mentioned that the data were applied to all ANNs of this article in normalized form.

4. Result

Piezometric head and then uplift pressure in several points of considered model was computed by solving continuity equation, and using equation (9). Fig. 5 shows the diagram of uplift pressure under the diversion dam respect to variation of X for $Y = 35(m)$.

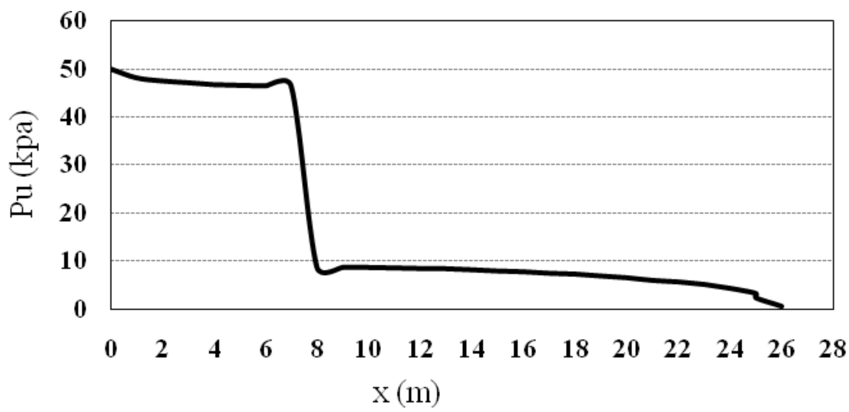

Fig. 5. uplift pressure under the diversion dam

Coordinates of 104 different points under diversion dam and corresponding uplift pressures were applied as inputs and outputs to ANNs, respectively. The GA and BEP technique were used to training the ANNs and the calculated weights using these two methods were obtained that were tabulated in Table 1. The procedure of optimizing weights of ANN that was performed by GA toolbox of MATLAB has been illustrated in Fig. 6. The test results of ANNs for 7 other points were obtained that were tabulated in Table 2. As it can be seen, the average error between actual and predicted data for the ANN that trained by BEP and GA methods were 1.77 and 4.85 and therefore it can be concluded that there is good agreement between predicted and actual data and for this problem and with the assumed parameters for BEP and GA, the BEP better trained the ANN. So the proposed procedure can be used for prediction and investigation of uplift pressure under the diversion dams. The main advantage of the proposed procedure is respond to the points that the pressure data aren’t available there, and therefore ANN can be used to prediction of pressure with good approximation.

In the Table 1, 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.

Table 1. Calculated weights of ANN using GA and BEP technique

Weight	GA	BEP
W_{11}	17.435	4.256
W_{12}	-1.284	15.593
W_{13}	-0.693	-15.701
W_{14}	-0.931	0.204
W_{15}	8.740	0.283
W_{21}	11.963	-8.359
W_{22}	0.706	-0.584
W_{23}	-2.792	0.606
W_{24}	-7.597	0.526
W_{25}	-0.224	0.718
B_{11}	-0.309	-10.056
B_{12}	1.049	5.914
B_{13}	7.619	-5.986
B_{14}	2.867	1.606
B_{15}	1.086	1.190
V_{11}	0.506	0.010
V_{21}	1.156	12.592
V_{31}	0.129	13.080
V_{41}	1.782	-72.491
V_{51}	1.113	22.556
B_{21}	0.044	48.195

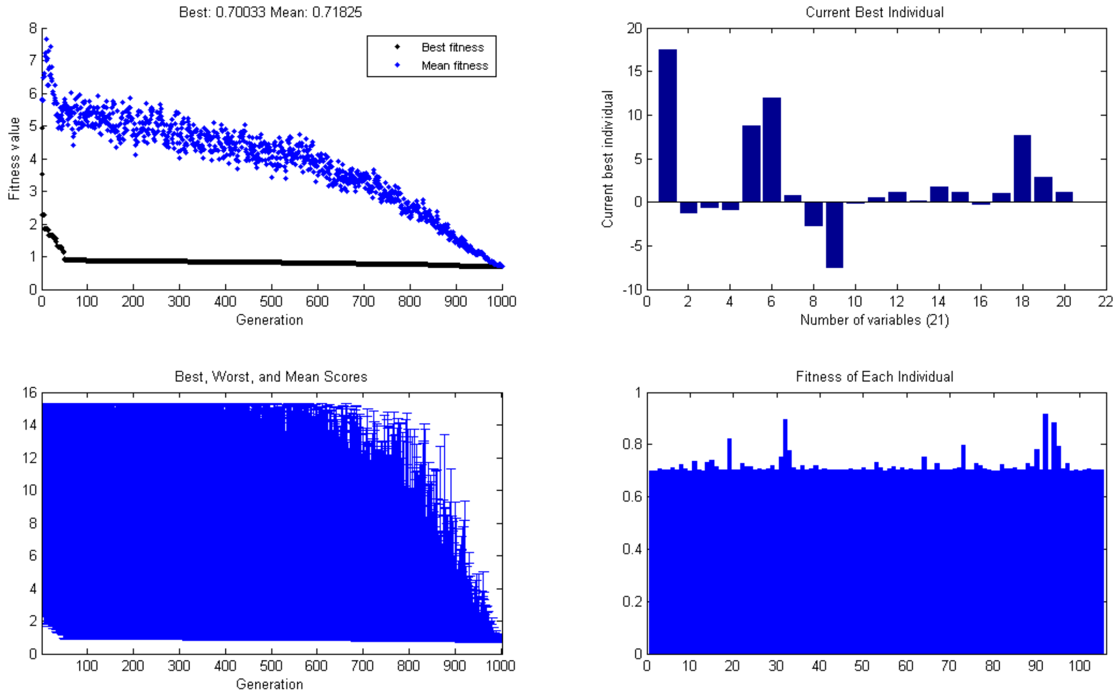

Fig. 6. Optimization procedure of ANN weights using Genetic Algorithm

Table 2. Comparison of actual and predicted uplift pressure under the diversion dam.

Number	1	2	3	4	5	6
X (m)	4	14	1	11	24	18
Y (m)	33	33	32	32	32	31
Actual Pressure (kPa)	17.384	66.549	28.161	77.122	38.646	47.395
Predicted Pressure using BEP (kPa)	69.379	27.955	75.228	38.854	33.791	47.395
Predicted Pressure using GA (kPa)	68.221	27.447	73.003	41.965	36.104	44.500
Error of BEP (%)	4.252	0.730	2.455	0.538	2.643	0.002
Error of GA (%)	2.513	2.533	5.340	8.588	4.021	6.106

5. Conclusion

In this paper a procedure for prediction of uplift pressure under a diversion dam using ANN and GA was presented. The continuity Laplace equation was solved for a diversion dam and piezometric head and uplift pressure were computed under the diversion dam. GA and BEP technique were used to training two similar ANNs for uplift pressure prediction in points of considered diversion dam. Test results of these trained ANNs were compared with each other and with actual data. It was found that there is good agreement between predicted results of ANNs and actual data. Also for this problem and with the assumed parameters for BEP and GA, the ANN was better trained using BEP rather than GA. Therefore it was concluded that the proposed procedure can be used for prediction and investigation of uplift pressure under the diversion dams.

6. References

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