A comparison of sophisticated neural network and Finite Element Method in estimating of variations in permeability of earth-dam body in leakage phenomenon

Ali R. Ahmadi¹, Foad Ghasemi², Ehsan Sadrossadat³, Ahmad Ghasemi⁴
1- Associate Professor of Kerman Graduate University of Technology
2 & 3- Master student of Kerman Graduate University of Technology
4-Master student of Shiraz university
1-iran.mahan@gmail.com, 2-zzfqassemi@yahoo.com, 3-ehsan.sadr12@gmail.com,
4-ahmadghasemi@yahoo.com

Abstract
Leakage is one of the most important problems in earth dam construction. Lake of leakage phenomenon analysis for earth dams can lead to destructive problems like increase in leakage forces, increase in pore water pressure and instability of the earth dam. In this study, leakage in two sections of an earth dam are modeled and analyzed by Finite Element Method (FEM), Multilayer Perceptron network (MLP) and Radial Basis Function network (RBF) and the results are compared. Based on the results, it can be concluded that FEM prediction are not compatible with actual data, whereas sophisticated neural network give acceptable results.

Keywords: sophisticated neural networks, leakage, finite element.

1. INTRODUCTION

In recent years, Artificial Neural Networks (ANNs), successfully being used in many engineering fields such as geotechnical engineering. The initial research of programming that knowledge, began from the mid-19th century by Parlf Lvrya and continued by scientists such as William James in the 19th century, Mac Klv and Pittsburgh in 1943, Hb in 1949, Frank Rosen Blatt 1958, have been continued until today.

Mathematical models need to determine the relationship between input and output, but (ANNs) transfer knowledge or the law lies beyond the data, by processing experimental data, to the network structure. Although, (ANNs) is more suitable when there are complex relationships between variables that can not be computed. On the other hand the mathematical functions cause large error in results if given incorrect or incomplete input, while (ANNs') results are exact and precise.

Considering to special geometry of large earth dams' body, one of parameters can cause effects on it, is leakage. Wide valley in river basin, earthquake region in Iran are reasons of building earth dams, because of the flexibility and resistance of them against incoming earthquake forces. Also, being available materials of earth dams can reduce the cost of construction. Inconsideration of earth dams' leakage analysis, may cause leakage forces, pore water pressure and instability of earth dams.

Earth dam's leakage (Sattar Khan Earth Dam), implemented by using black box models by Noorani and others. [5, 6] Also, a numerical modeled by FEM software is used for non-permanent leakage in earth dams by Taylor and others. [7]

2. ARTIFICIAL NEURAL NETWORKS (ANNs)

(ANN) is consists of arithmetic operators similar to a biological neural systems. In fact, all artificial neural networks include a series of simple computing elements that require a bit of memory to perform calculations and other tasks. Each neural network includes a series of inputs, number of hidden layers and output layer. Inputs are processed in hidden layer and after exit from output layer turn into the network's results. Within the network, data change into new values by weight linkage then used as variables of transmission functions. The process performs in each layer of a neural network until network's output ultimately obtained. This feature of neural network has the ability to achieve acceptable results, unlike conventional methods, in less time and without need to predefined criteria or rules. Several types of artificial neural networks with special features exist, so to achieve the desired results an appropriate neural network should be selected. Also, the
type and number of data for network training must be particularly considered to train neural networks correctly. [8, 9]

In this paper, two types of neural network known as the Multi Layer Perceptron Network and Radial Basis Function, respectively, which briefly called MLP and RBF are used.

3. MULTI-LAYER PERCEPTRON NETWORK (MLP)

In (MLP) each neuron in each layer is entirely connected to neurons in previous layer. The output of each layer after performance function effects, became the input for the next layer, this process continues until the output of network obtained.

According to the following equations network's behavior is expressed:

\[ a^{l+1} = p \]
\[ a^{l+1} = f^{-1}(W^{l+1}a^l + b^{l+1}) \]  

(1)

p = input vector, a = output vector, l = number of layers and superscript = the number of layer

Learning methods of MLP are based on Back Propagation (BP) algorithms. There are two calculation direction for BP algorithm: first forward path and second feedback path. In forward path network's parameters will not change during calculation and stimulus functions act on each neuron. In feedback path, beginning from the last layer (output layer), where error vector is available. Then the error vector distributed from right to left (last layer to first layer) and local gradient, calculated neuron to neuron by back propagation. [10]

The used stimulus function is a sigmoid function and the equation is as followed in figure 1.

![Figure 1 – sigmoid stimulus function](image)

4. RADIAL BASIS FUNCTION NETWORK (RBF)

Radial basis function networks (RBF) are precursor networks with three layers. (RBF) network has a middle layer and stimulus functions are radial functions like Gaussian Functions with special width and center and it's the major difference between (RBF) and (MLP). Moreover, against (MLP) network, the distance between each pattern with each neuron's center vector in middle layer calculated as input for radial stimulus function. Other notable point is the selecting middle layer, so more layers can be selected. Although, (RBF) can be applied to increase the speed of learning and to solve common problems in neural networks.[11,12].

Objective functions used in this study include: Root Mean Square Error (RMSE) and coefficient of fit (R2) and their relationship is as followed:

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_i - \hat{Q}_i)^2} \]  

(2)

Where \( Q_i \) and \( \hat{Q}_i \) are observation flow (m^3/s) and estimation flow (m^3/s) respectively.

The acceptance of received papers will be communicated with the corresponding author and can be tracked by all authors through the conference web site. A paper which receives final or conditional acceptance should be prepared regarding the requested corrections, and the paper should be sent again via conference web site.
5. **FLOW EQUATION**

Linear flow of water inside the cylinder of soil is simply followed by the Darcy law, , but issues such as water movement within the body of earth dams usually followed by two or three dimensional flow, however, the Darcy can also be held accountable for this, but sought an equation to clearly demonstrate hydraulic pressure distribution at any point. According to the modeling, in this study non-synchronous Richard's equation is reviewed:

\[
\frac{dM}{dt} = \frac{\partial (pc)}{\partial t} \Delta x \Delta y \Delta z
\]  (3)

Where \(c\) and \(\rho\), respectively, are the volume and density of water.

Assuming constant \(\rho\), the following equation resulted, in which \(k\) and \(t\), respectively, the permeability coefficient of time:

\[
\nabla(\rho k \nabla \Phi) = \frac{\partial (pc)}{\partial t}
\]  (4)

The equation represents the non-synchronous mode of Richard's equation, that if the flow were permanent and irreversible of a homogeneous environment, the equation would change into the two-dimensional Laplace equation as followed: [Vahid Nourani]

\[
\nabla^2 \Phi = \frac{\partial^2 \Phi}{\partial x^2} + \frac{\partial^2 \Phi}{\partial y^2} = 0
\]  (5)

6. **Modeling**

In this study, leakage of earth dam's body modeled by Finite Element Method (FEM). According to the data related to the pezometric head analysis made and results compared with numerical modeling results (in different modes of core geometry, homogeneous and heterogeneous) and (ANNS') modeling results in two cross-section of earth dam. Seep / w software used for FEM and numerical analysis.

Assuming equal amounts of \(K_y\), \(K_x\) and according to the reported permeability coefficient , 1/4 × 10-5 m/s, Esteqlal Dam (located 25 km Bastak city, Hormozgan province) modeled in isotrope mode and results are compared with reported observed pezometric head. Due to changes in water level behind the dam, the model performed with time steps non-synchronous mode (transient).

**Model A: a Homogeneous Core (Impermanent or transient State)**

An important issue in the case is, applying boundary conditions. In transient modeling, first a permanent state modeled then necessary steps of time applied so initial and boundary conditions of upstream and downstream of dam in transient state performed. [Vahid Nourani]

The model is composed of 1005 elements and 1120 nodes. Number of time steps, 10 units, increase size of first time step, 2/1 unit and expansion factor, 3/95, assumed so, after time calculations, transient state is equal to 1/21 × 10^7 s and Richard's equation for the range of 100 days and increase of 2/7 m of water level behind the dam, will be satisfied.

Network flow model is shown in figure 1 for transient state. It should be noticed, determining amount of increasing time steps and expansion factor performed by trial and error test and upper bound will be the ending time of increasing water level. Leakage flow line changes, depending on the level of increase, is shown in figure (2). According to figure (2), boundary conditions imposed on the upstream and downstream indicate the starting line of leakage in upstream and by increasing water level in reservoir, the line reaches the maximum height, although, in downstream, boundary conditions first above the foundation then at the end of time amplitude (100 days) will reach.
**Model B: a Heterogeneous Core (Impermanent or transient State)**

Figure (3) shows with the heterogeneous wedge-shaped core earth dam. Dam core is composed of different permeability coefficients and the smaller wedge-shaped core in downstream has less. The main reasons for choosing such geometry for the core section of dam are, filling the pores in the filter and drainage, and overturning moment on core toe that increased by increasing water level of reservoir [5].

Amounts of observed and calculated of pezometric head is given in Tables (1) and (2). For example, one of pezometers' results are compared in (5) to (7) charts.
7. RESULTS AND DISCUSSION

Artificial Neural Network Model
All phases of networks' modeling are performed in MATLAB (Version 7.6.0.324, The Math Works Inc.). To train MLP and RBF networks, back propagation algorithms are used and different types of back propagation algorithms can be seen in Figure 4:

<table>
<thead>
<tr>
<th>MATLAB function name</th>
<th>Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainbfg</td>
<td>BFGS quasi-Newton back propagation</td>
</tr>
<tr>
<td>traincgf</td>
<td>Fletcher–Powell conjugate gradient back propagation</td>
</tr>
<tr>
<td>traincg</td>
<td>Polak–Ribiere conjugate gradient back propagation</td>
</tr>
<tr>
<td>traindgr</td>
<td>Gradient descent back propagation</td>
</tr>
<tr>
<td>traingda</td>
<td>Gradient descent with adaptive linear back propagation</td>
</tr>
<tr>
<td>traingrad</td>
<td>Gradient descent with momentum and adaptive linear back propagation</td>
</tr>
<tr>
<td>trainlm</td>
<td>Levenberg–Marquardt back propagation</td>
</tr>
<tr>
<td>trainoss</td>
<td>One step secant back propagation</td>
</tr>
<tr>
<td>trainrp</td>
<td>Resilient back propagation (Rprop)</td>
</tr>
<tr>
<td>trainge</td>
<td>Scaled conjugate gradient back propagation</td>
</tr>
</tbody>
</table>

Figure 4 - different types of Back Propagation algorithms

Back Propagation algorithm is in fact generalized least squares method to the multi-layer network with nonlinear functions. For network training, Back Propagation algorithm error with methods of momentum and Levenberg-Marquardt used as shown in Figures 5 and 6.

Figure 5 shows that in spite of training error 0.085858 and after 10000 cycles, network is not converged so, the process is not successful.

An example of network training by Levenberg-Marquardt method is shown in Figure 6.
As seen in Figure 6 in 748th cycle, network training error is 0.0009976 and it's understood that network training is high.

8. COMPARISON OF ARTIFICIAL NEURAL NETWORK APPROACH WITH THE FINITE ELEMENT METHOD

In this section, at first, FEM, MLP and RBF models' results are presented then, compared by variation observed and calculated pezometric heads to time for one of pezometers.

Table 1: results of calculations for the heterogeneous wedged-shaped core

<table>
<thead>
<tr>
<th>Row</th>
<th>Heterogeneous Nuclear</th>
<th>RSME (average)</th>
<th>RSME (average)</th>
<th>RSME (average)</th>
<th>Calculated head using finite element (m)</th>
<th>Water Head (m)</th>
<th>Pizometers situation</th>
<th>Piezometer No.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>US</td>
<td>184/2/19</td>
<td>184/2/19</td>
<td>184/2/19</td>
<td>184/2/19</td>
<td>11/9</td>
<td>US</td>
<td>205</td>
</tr>
<tr>
<td>2</td>
<td>US</td>
<td>185/2/19</td>
<td>185/2/19</td>
<td>185/2/19</td>
<td>185/2/19</td>
<td>11/9</td>
<td>US</td>
<td>206</td>
</tr>
<tr>
<td>3</td>
<td>US</td>
<td>186/2/19</td>
<td>186/2/19</td>
<td>186/2/19</td>
<td>186/2/19</td>
<td>11/9</td>
<td>US</td>
<td>207</td>
</tr>
<tr>
<td>4</td>
<td>DS</td>
<td>187/2/19</td>
<td>187/2/19</td>
<td>187/2/19</td>
<td>187/2/19</td>
<td>11/9</td>
<td>DS</td>
<td>208</td>
</tr>
<tr>
<td>5</td>
<td>US</td>
<td>188/2/19</td>
<td>188/2/19</td>
<td>188/2/19</td>
<td>188/2/19</td>
<td>11/9</td>
<td>US</td>
<td>209</td>
</tr>
<tr>
<td>6</td>
<td>CL</td>
<td>189/2/19</td>
<td>189/2/19</td>
<td>189/2/19</td>
<td>189/2/19</td>
<td>11/9</td>
<td>CL</td>
<td>210</td>
</tr>
<tr>
<td>7</td>
<td>DS</td>
<td>190/2/19</td>
<td>190/2/19</td>
<td>190/2/19</td>
<td>190/2/19</td>
<td>11/9</td>
<td>DS</td>
<td>211</td>
</tr>
<tr>
<td>8</td>
<td>US</td>
<td>191/2/19</td>
<td>191/2/19</td>
<td>191/2/19</td>
<td>191/2/19</td>
<td>11/9</td>
<td>US</td>
<td>212</td>
</tr>
<tr>
<td>9</td>
<td>DS</td>
<td>192/2/19</td>
<td>192/2/19</td>
<td>192/2/19</td>
<td>192/2/19</td>
<td>11/9</td>
<td>DS</td>
<td>213</td>
</tr>
</tbody>
</table>

1-upstream, 2-downstream
Comparison between table and charts results ultimately derived:
- FEM is effective in modeling the problem, however its error (RMSE), because of inaccurate modeling of barrier filter and drainage system, can never reach zero; hence is the difference between finite element results and observed data.
- FEM’s transient model make better prediction than the steady state model.
- Modeling by ANNs is more successful than FEM since ANNs models have less error in least squares measure.
- Both MLP and RBF networks have provided good results; hence, utilization of either method seems reasonable.

9. CONCLUSIONS

In this study, modeling of phenomenon leakage in earth dams and effect of permeability variation on leakage were discussed. A brief introduction to Artificial Neural Networks, in particular the MLP and RBF networks were given next. Ultimately, results of those models were compared to observed data. Comparisons indicate good performance by models based on Artificial Neural Network approach and that the traditional of finite element modeling does not. Match the observed data as well.

10. REFERENCES


