Analysis of Seepage Under Concrete Dam Using Artificial Neural Networks

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1 INTRODUCTION

In recent years, there has been a growing interest in a class of computing devices that operate in a manner analogous to that of biological nervous systems. These devices, known as Artificial Neural Networks (ANN) are finding applications in almost all branches of science and engineering. As their names imply, ANN are inspired by the neuronal architecture and operation of the human brain. Because of their fundamental hardware similarity to that of the human brain, ANN have some unique, human-like capabilities in information processing. Probably, learning from examples is the most important capability of ANN, in which ANN are capable of learning complex, highly nonlinear relationships and associations from limited field data.

The unique capabilities of the ANN are proving very useful in a wide variety of engineering applications. ANN were successfully applied to some of civil engineering problems, see for example ASCE Journal of Computing in Civil Engineering, *special issue* on Neural Networks (1994). In groundwater flow, Aziz & Wong (1992) applied the ANN to analyze well and aquifer hydraulics from pumping tests, Ranjithan et al, (1993) applied the ANN for screening groundwater reclamation and contaminants control.

In the present study, back propagation ANN, Rumelhart et al. (1986) was utilized to characterize the porous media properties from a limited field data. In which the limited field data can be used to teach or code the neural network and after teaching or coding, mapping or encoding is performed in order to map the whole area of interest. Figure 1 shows the schematic of the concrete dam founded on geological formation indicating the boundary conditions of the problem as well as the field data locations. For deterministic analysis, we use the mean value of the field data to conduct the FEM calculation.

2 ARTIFICIAL NEURAL NETWORKS

The ANN shown in Figure 2, consists of three layers, input layer of two units, A_1 and A_2, hidden layer of 10 units, B_1 up to B_{10}, and output layer of one unit, C_1. The three layers are connected with connections represented by the weight matrices W_{ij} and V_{ij} and its biases. The number of units in the hidden layer was determined after trial and error procedure by changing the number of units in the layer and observing the convergence of the net to specific error and/or reach a number of iteration steps. Training, teaching or coding of the neural networks is a major concern for its development, in which the networks determine the appropriate set of weights that makes it perform the desired function. There are many ways that this can be done; the most popular class of these algorithms are based on supervised training. Typically, supervised training starts with a networks comprising an arbitrary number of hidden neurons, a fixed topology of connections, and randomly selected values for the weights. The networks is then presented with a set of training patterns, each comprising an example of the problem to be solved (the inputs) and its corresponding solution (the targeted outputs).

3 ANN FOR SEEPAGE FLOW ANALYSIS

The ANN technique discussed in section 2 was applied to characterize the geological media under a concrete dam, in which 9 field data of permeability coefficient were obtained randomly. The locations of these data are shown in Figure 3. The ANN was trained with the 9 data, in which the coordinate x and y were the input for each single data and the rank of the permeability coefficient was the output. The rank of the permeability in this case was set as very high, high, medium, low and very low, Figure 3.

After training the networks, encoding operation was conducted for all blocks over the area of interest. That was done by fixing the weight matrices and their biases, and feeding the networks with input data and obtaining the normalized permeability rank, Figure 2. Which in turn transformed to the true permeability rank. Finally, the domain was characterized into 5 different materials of different permeability coefficients, Figure 3, which were used as input parameters to conduct the FEM calculation.

FEM calculations were performed using VPFLOW code, Ohnishi et al. (1993 & 1994) The dimension of the domain was set as 25 m length and 10 m depth, discertized into mesh consists of 250 elements. The head difference between upstream and downstream of the dam is 10 m.

4 DISCUSSION

Figure 4 shows the water pressure distribution under the concrete dam for all conducted analysis. It is clear that ANN result is closer to the result of the reference case than the deterministic one. Table 1 summarize the exit discharge downstream of the dam for all analysis, which indicated that the exit discharge for ANN case more than both deterministic and reference results. Comparison between ANN and both reference and deterministic results, Figure 4 and Table 1, we can conclude that ANN is a promising tool for characterizing hydraulic properties of geological media from limited field data, which maybe used as a practical tools in real geotechnical applications.

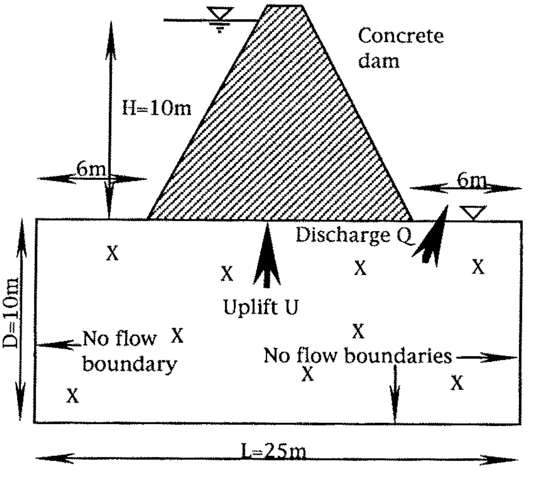

Figure 1 Schematic of concrete dam on geological formation and flow boundary conditions.
X indicate the field data location.

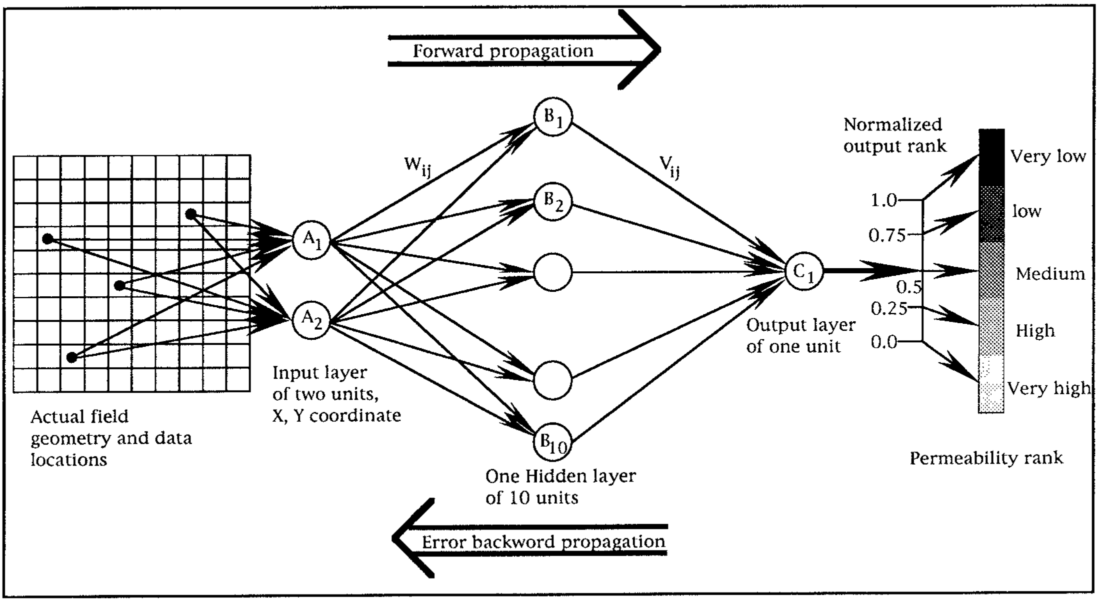

Figure 2 Schematic representation of ANN topology for permeability characterization using backward propagation algorithm.

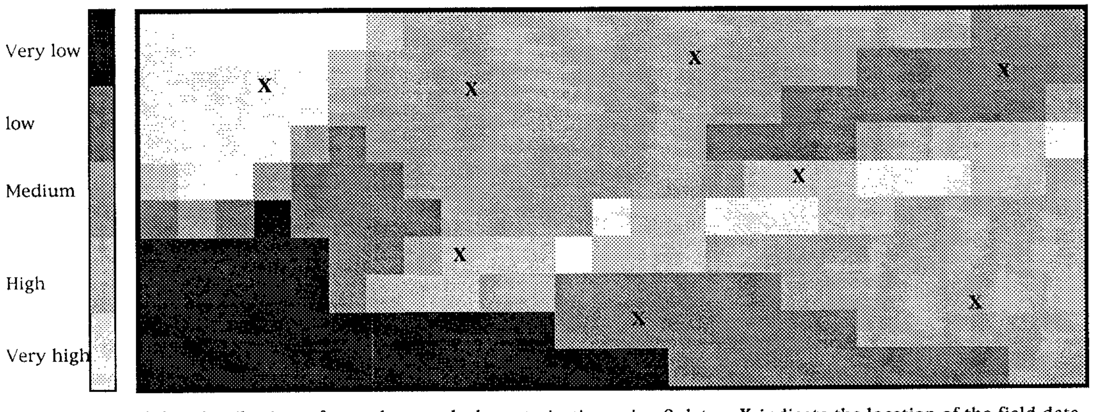

Figure 3 Permeability distribution of neural network characterization using 9 data. X indicate the location of the field data.

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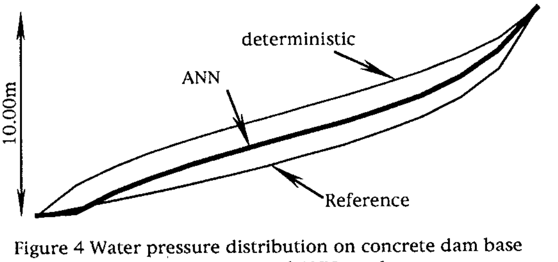

Figure 4 Water pressure distribution on concrete dam base for reference, deterministic, and ANN results.

	Q in m^3 /s/m
Reference	0.00003897
deterministic	0.00004360
ANN	0.00006353

Table 1 Exit discharge downstream of the dam for reference, deterministic, and ANN results.