Estimating variations in permeability of earth-dam body during leakage phenomenon by neural network

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Abstract

Leakage is one of the most important problems in earth dam construction. Lack of leakage phenomenon analysis for earth dams lead to destructive problems like increase in leakage forces, increase in pore water pressure and stability of the earth dam. In this study, leakage in two sections of an earth dam are modeled and analyzed by Finite Element Method (FEM), Multi Layer Perceptron network (MLP) and Radial Basis Function network (RBF). Predictions made by each of the methods are compared and it can be concluded that FEM prediction are not compatible with actual data, whereas sophisticated neural networks make acceptable predictions.

Key words: Earth-dam, Leakage, Neural Network

1. Introduction

In recent years, Artificial Neural Networks (ANNs) have successfully been used in many engineering fields, in particular geotechnical engineering. Research on knowledge programming began in mid-19th century by Parlf Lvrya and it has continued by scientists such as William James of the same periody, Mac Klv and Pittsburgh in 1943, Heb in 1949, Frank Rosen Blat in 1958, Vidroo, Minsky and Papert in 60 decade, Hopfield and Mackland in 1982 until 1985 until today.

In the context of knowledge mathematical models need to determine the relationship between input and output. In Artificial Neural Networks (ANNs) transfer knowledge or the law, lies beyond the data; and it is established by processing experimental data through the network structure. Field ANNs are well suited for cases in which there are complex relationships between field variables, and the complexity is such that the process cannot be modeled properly. In such cases the classical modeling techiquies have large errors in the predictions if incorrect or incomplete input is given, while ANNs' results remain acceptable.

The special geometry of large earth dams' body, can be affected rather seriously by leakage. Wide vallies at river basins and earthquake prone regions of Iran are well suited for earth dam construction. Because of the flexible nature of the earth dam, it can survive

high intensity earthquake forces. Furthermore, availability of materials for earth dam construction makes them economically attractive.
Interactive earth dams' leakage analysis is a necessary process to prevent increase in 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 Nourani and others [Nourani and Sharghi(2008)]. Also, a numerical modeled by FEM software is used for non-permanent leakage in earth dams by Tayoor and others.

2. Artificial Neural Networks (ANNs)

(ANN) consists of arithmetic operators similar to biological neural systems. In fact, all artificial neural networks include a series of simple computing elements that require a small amount of memory to perform calculations and other tasks. Each neural network includes a series of inputs, number of hidden layers and an output layer. Inputs are processed in hidden layers and after passing through the output they turn into the network's results. Within the network, data change into new values by weight linkages used as variables of transmission functions. In the process of the variable transmission passes through each layer of a neural network until network's output is ultimately obtained. This feature of neural network has the ability to provide acceptable results for problems that conventional methods fall short. Several types of artificial neural networks with special features exist in literature, so to achieve the desired results an appropriate neural network should be selected. Also, the type and number of data processing times for network training must be considered carefully so to train the neural networks correctly [Ameri and Molayem (2003), Menhag (2000)].
In this paper, two types of neural networks known as the Multi Layer Perceptron Network (MLP) and Radial Basis Function (RBF) are considered. A brief description of each network is presented next.

3. Multi-layer Perceptron Network (MLP)

The details of research methodology must be inserted here.

In this type of network every neuron in each layer is completly connected to neurons in the layer before it, in the sense of data processing. The output of each layer, after applynig function effects, becomes the input for the next layer, this process continues until network’s output is obtained.
Network’s behavior is expressed based on the following equations:

$$
\begin{gathered}
a^0 = p \\
a^{l+1} = f^{l+1}\left(W^{l+1}a^l + b^{l+1}\right)
\end{gathered}
\tag{1}
$$

p = input vector, a = output vector, l = number of layers, and superscript indicates the layer number
The learning methods of MLP are based on Back Propagation (BP) algorithms. There are two calculation directions for the BP algorithm: first, is the feed forward path and second is the feedback path.
In the feed forward direction, network's parameters will not change during calculations and stimulus functions act on each neuron as data proceeds through each layer. In the backward direction, beginning with the last layer (output layer), where error vector is available, the error is distributed from right to left (last layer to first layer) and local gradient of error distribution is through back propagation [Menhag (2000)].
Here the utilized stimulus function is a sigmoid function and the equation is presented in figure 1.

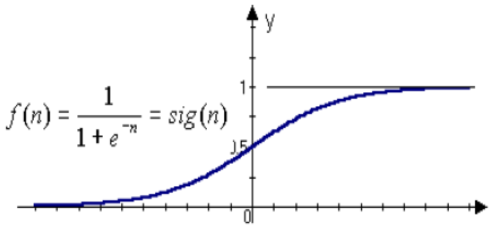

Fig 1: sigmoid stimulus function

4. Radial Basis Function network (RBF)

Radial Basis Function networks (RBF) are feed forward networks with three processing layers. RBF networks have a middle layer with stimulus functions that are radial functions like Gaussian Functions with special width and center; which is the major difference between RBF and MLP. Moreover, unlike MLP network, the distance between each pattern and each neuron's center vector, in the middle layer, is calculated as input for radial stimulus function. Other notable point is the selection of middle layer for this purpose, so that more layers can be selected. RBF can be applied to increase the speed of learning and to solve common problems in neural networks [Akbar-pour and Shokrollahi, (2004), Montazer et al. (2002)]. Objective functions used in this study include: Root Mean Square Error (RMSE) and coefficient of fit (R^2) and their relationship is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_i - \widehat{Q}_i\right)^2} \qquad (2)$$

Q_i =observational flow (m^3/s) ، $\widehat{Q}_i$ =approximate flow (m^3/s).

5. Flow Equations

Linear flow of water through a cylinder of soil is modeled using Darcy law, however there are issues such as water movement within the body of earth dams, especially in two or three dimensional flow. In this study non-synchronous Richard's equation is used:

$$\frac{dM}{dT} = \frac{\partial(\rho c)}{\partial t}\Delta x\Delta y\Delta z \qquad (3)$$

Where c and ρ are the volume and density of water respectively.
Assuming constant ρ, (Eq.3) yields the following relation, in which k is the permeability coefficient and t represents,

$$\nabla(\rho k\nabla\Phi) = \frac{\partial(\rho c)}{\partial t} \qquad (4)$$

This equation represents the non-synchronous mode of Richard's equation: and for steady state flow through homogeneous medium it reduces to Laplace equation as in two dimensions [Nourani and Sharghi (2008)]:

$$\nabla^2\Phi = \frac{\partial^2\Phi}{\partial x^2} + \frac{\partial^2\Phi}{\partial y^2} = 0 \qquad (4)$$

6. Modeling

In this study, leakage through earth dam's body is modeled using Finite Element Method (FEM). Models are based on data related to the pezometeric head analysis, results of which are compared to numerical modeling results (in different modes of core geometry, homogeneous and heterogeneous) and also to (ANNS') modeling results in two cross-sections of earth dam. Seep / w software was used for the finite element analysis.

Assuming equal permeability values of K_x and K_y based on the reported permeability coefficient of $1/4 \times 10^{-5}$ m/s, Esteqlal Dam (located 25 km Bastak city, Hormozgan province) is modeled in isotropic mode and results are compared with observed pezometeric head values. Due to changes in water level behind the dam, the model is time dependent (transient).

Model A: Homogeneous Core (Transient State)

An important issue in this case is the proper application of boundary conditions. In transient modeling, first a permanent state is modeled then necessary time steps are applied so that the initial and boundary conditions of upstream and downstream of the dam in transient state are satisfied [Nourani and Sharghi (2008)].

The model is constructed using 1005 elements wiyh 1120 nodes. Number of time steps, 10 units, increase in size for the first time step, 1/2 unit and expansion factor of, 3/95 is assumed so that for after time calculations, total time of the transient state is equal to $1/21 \times 10^7 s$ with rise in water level.

Network flow model is shown by figure 1 for the transient state. It should be noted that, determining the amount of increase in time steps and the expansion factor are set through trial and error, the upper bound of which is be the end time for water level rise. The leakage flow line changes depending on the water level as shown in figure (2). According to figure (2), conditions imposed on upstream and downstream boundaries define the starting line for leakage in the upstream which increases by the increasing water level; note that the downstream boundary conditions right above the foundation are satisfied at the end of transition time (100 days).

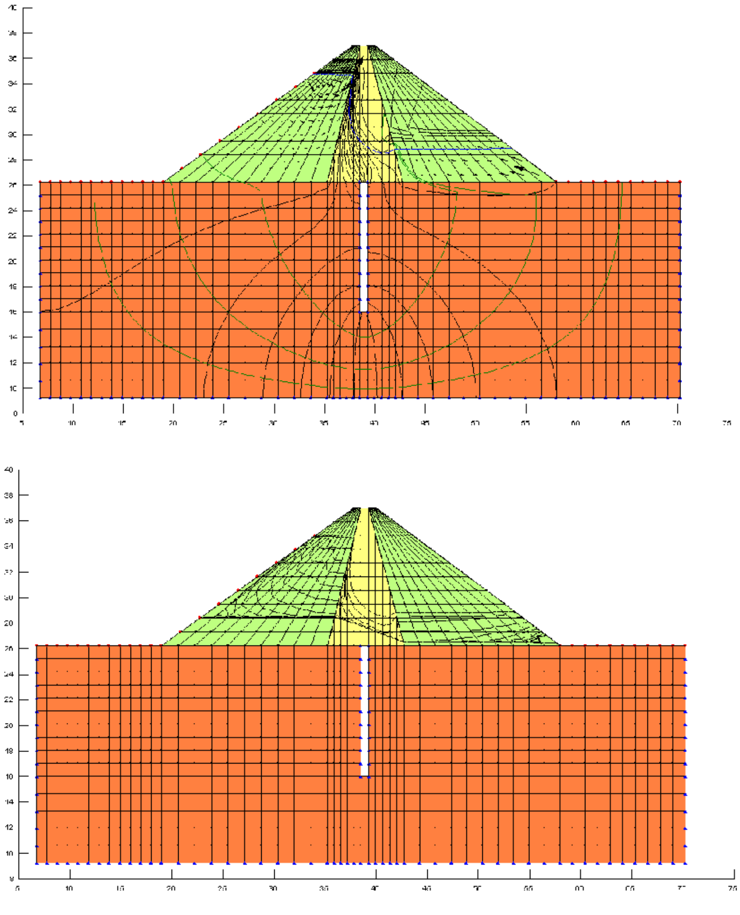

Fig 2: different types of Back Propagation algorithms

Model B: Heterogeneous Core (transient State)

Figure (3) displays the model for a heterogeneous wedge-shaped core earth dam. Dam's core non uniform permeability coefficients and the smaller wedge-shaped core in downstream have less. Main reasons for choosing such geometry for core section of the dam include filling of pores in the filter and drainage, and overturning moment about core's toe that is increased by rise in water level of the reservoir [Nourani and Sharghi (2008)].

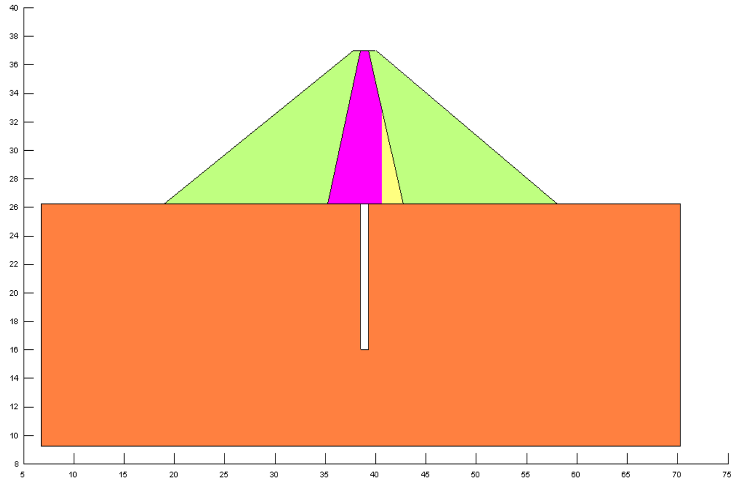

Fig 3: different types of Back Propagation algorithms

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:

MATLAB function name	Algorithm
trainbfg	BFGS quasi-Newton back propagation
traincgf	Fletcher–Powell conjugate gradient back propagation
traincgp	Polak–Ribiere conjugate gradient back propagation
traingd	Gradient descent back propagation
traingda	Gradient descent with adaptive linear back propagation
traingdx	Gradient descent w/momentum and adaptive linear back propagation
trainlm	Levenberg–Marquardt back propagation
trainoss	One step secant back propagation
trainrp	Resilient back propagation (Rprop)
trainscg	Scaled conjugate gradient back propagation

Fig 4: different types of Back Propagation algorithms

Back Propagation algorithm is in fact the generalized least squares method applied to the multi-layer networks with nonlinear functions. For network training, Back Propagation algorithm error with methods of momentum and Levenberg-Marquardt were used.

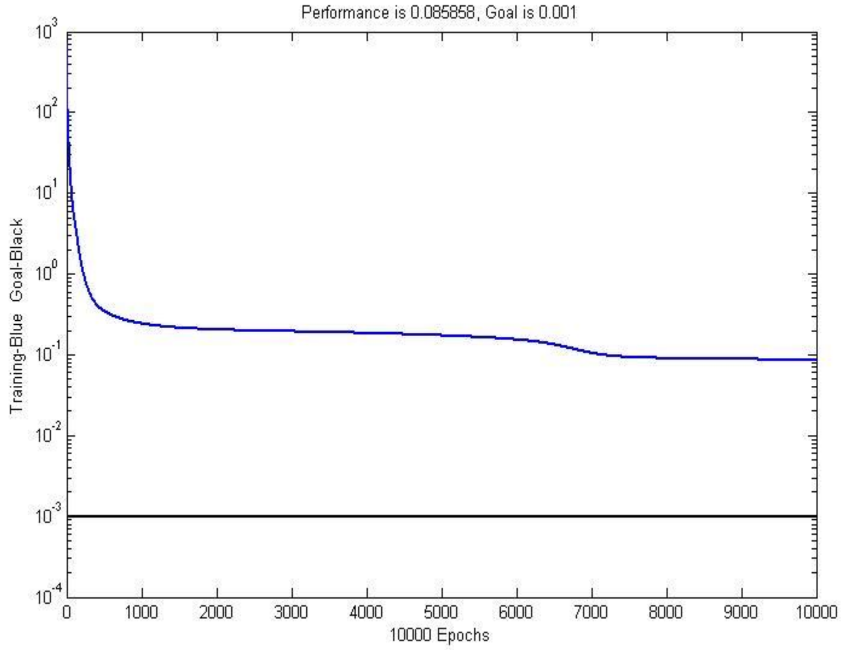

Fig 5: Sample of momentum method training

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

An example of network training by Levenberg-Marquardt method is shown in Figure 6.

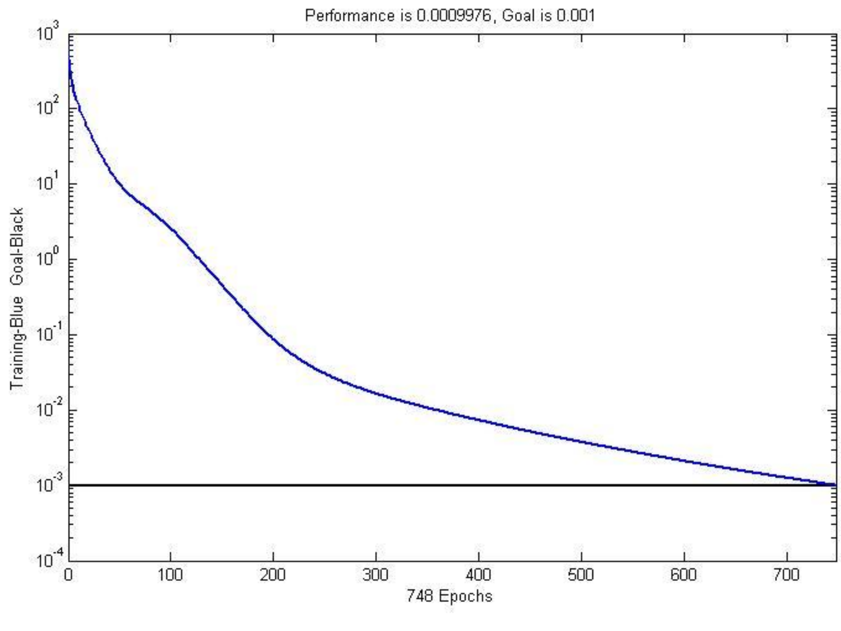

Fig 6: Sample of network training, Levenberg-Marquardt method

As seen from Figure 3 after the 748th cycle, with network training error of 0.0009976 the process converges.

8. Comparison of artificial neural network approach and the finite element method

In this section, FEM, MLP and RBF models' results are presented and are compared to variations observed and the calculated piezometeric heads versus time for one of piezometers.

Heterogeneous Nuclear										
RSME (average)	**RBF**	**RSME (average)**	**MLP**	**RSME (average)**	**Calculated head using finite element (m)**	**Local Observed head (m)**	**Water Head (m)**	**Piezometers situation**	**Piezometer No.**	*Row*
	۱۸۴۵/۵۱		۱۸۴۵/۱۹		۱۸۴۵/۹	۱۸۴۵/۲۱	۱۱/۹	*US*[1]	۲۰۵	۱
	۱۸۵۸/۰۱		۱۸۵۷/۹۱		۱۸۵۸/۱۴	۱۸۵۷/۵۰	۲۴/۱۴	*US*	۲۰۶	۲
	۱۸۵۵/۰۱		۱۸۵۵/۳		۱۸۵۶/۶	۱۸۵۵/۸۷	۲۳/۰۴	*DS*[2]	۲۰۷	۳
	۱۸۴۲/۴		۱۸۴۱/۹		۱۸۴۲/۷	۱۸۴۲	۸/۷	*DS*	۲۰۸	۴
۰/۹۸۵	۱۸۵۷	۰/۹۹۱	۱۸۵۶/۸۱	۰/۹۴۵	۱۸۵۷/۱۲	۱۸۵۶/۴۲	۲۳/۱۲	*US*	۲۰۹	۵
	۱۸۵۸/۶۵		۱۸۵۸/۴۵		۱۸۵۹/۴۵	۱۸۵۸/۷۹	۲۵/۴۵	*CL*	۲۱۰	۶
	۱۸۵۲/۵۱		۱۸۵۲/۲۱		۱۸۵۳/۱	۱۸۵۲/۳۱	۱۹/۱	*DS*	۲۱۱	۷
	۱۸۷۰/۸۶		۱۸۷۰/۹۶		۱۸۷۰/۷۹	۱۸۷۱/۱	۳۶/۷۹	*US*	۲۱۲	۸
	۱۸۷۳/۳۵		۱۸۷۲/۹۷		۱۸۷۲/۲۷	۱۸۷۳/۱۵	۳۸/۲۷	*DS*	۲۱۳	۹

1-upstream, 2-downstream

Table 1. Results of calculations for the heterogeneous wedged-shaped core

Observed and calculated head charts

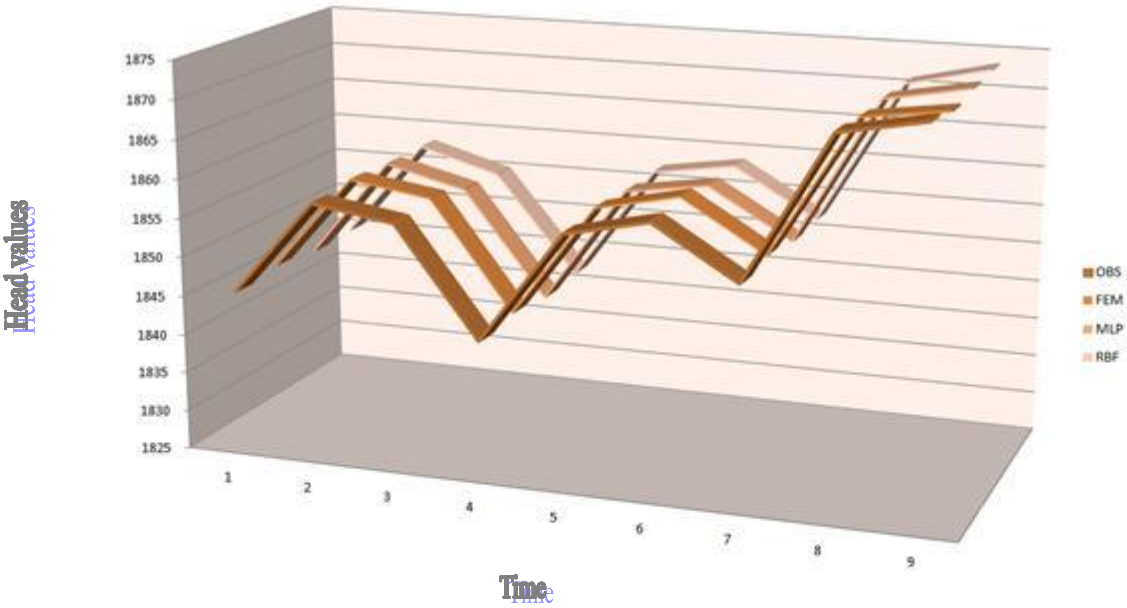

Fig 7: Observed and calculated head

Comparing the results yields the following conclusions:

- 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, thereby giving rise to 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 leakage phenomenon 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 finite element modeling does not include complexities of the actual structure and hence can not match the observed data as well.

10. References

Akbar-pour, M., & Shokrollahi, A. (2004). Basics neural networks The using sophisticated neural networks in estimation of river flows, Proc. Of the 1th National Congress on civil Engineering, Industry Sharif University, Tehran. (in Persian).

Ameri, M., & Molayem, M. (2003). The using sophisticated neural networks in analysis, Proc. Of the 6th International Congress on Civil Engineering, Industry Isfahan University, Isfahan, (in Persian).

Bart Kosko, Forewords by Lotfi A. Zade, James A. Anderson. (1992). *Neural Network and Fuzzy Systems*, Prentice-Hall Inc.

Hashash, Y. M. A., & Hook, J. J., & Schmidt, B., & Yao, J. I. C. (2001). The Seismic design and analysis of underground structures, *Tunneling Underground Space Technology*, 16, pp 247-293.

Marandi, S. M., & Bagheri-pour, M, H. (2003). The using sophisticated neural networks to determine resistance of asphalt concrete, Proc. Of the 6th International Congress on Civil Engineering, Industry Isfahan University, Isfahan, (in Persian).

Martin, T., & Hagan. & Howard, B. DEMUTH. (2000). *Neural Network Design*, Mark Beale MHB, Inc.PWS Publishing Company.

Menhag, M. B. (2000). *Basics neural networks*, Industry Amir-Kabir Press.

Montazer, Gh., & Ghodsian, M. & Dehghani, A. (2002). Presentation new approach intelligent for estimation maximum with The using sophisticated neural networks in estimation of river flows, Proc. Of the 6th International Symposium on River Engineering, Shahid Chamran University of Ahvaz, Ahvaz. (in Persian).

Neil, N., & Eldin, Ahmad, B. & Senouc. (1995). Condition Rating of Rigid Pavements by Neural Networks, *Can J. Civ. Eng*, 22,pp 861-870.

Nourani, V., & Fatehi-nobarian, B. investigation effect changes of permeability of body soil dam in numerical modeling phenomenon leakage Zenver soil dam, 5th National Congress on Civil Engineering, (in Persian).

Nourani, V., & Sharghi, A. (2008). A model of black cube for analyse leakage in soil dams, Proc. Of the 3th National Congress on Iran Water Management, Tabriz, (in Persian).