ORIGINAL RESEARCH

Integrated ANN model for earthfill dams seepage analysis: Sattarkhan Dam in Iran

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Received: May 2, 2012 **Accepted:** August 2, 2012 **Published:** December 1, 2012
DOI: 10.5430/air.v1n2p22 **URL:** http://dx.doi.org/10.5430/air.v1n2p22

Abstract

Piezometric heads in the core of Sattarkhan earthfill dam in Iran have been analyzed in this paper via Artificial Neural Network (ANN). Single and integrated ANN models were trained and verified using each piezometer's data, and also the water levels on the up and downstream of the dam. Therefore, in the single ANN modeling a single ANN was developed for each piezometer, whereas in the integrated ANN modeling only a unique ANN was trained for all piezometers at different cross sections of the dam. Three-layered Perceptron ANN trained with Back Propagation Levenberg-Marquardt scheme was employed in the single modeling; while, two different ANN algorithms, the feed-forward back-propagation (FFBP) and the radial basis function (RBF) were employed to develop integrated ANNs. The number of hidden neurons were determined 5 and 7 for single ANNs, whereas 6 hidden neurons for the integrated FFBP ANN, and the spread value of *0.5* for the integrated RBF. The results show good agreement between computed and observed water heads at different monitoring piezometers with validation determination coefficients higher than *0.7984* in the single and *0.87* and *0.67* in the FFBP and RBF integrated modeling, respectively. Thereafter, the results of the ANNs were satisfactorily compared with the results of a physically based model (Finite Element Model, FEM).

Key words

Piezometric head, Seepage, Artificial neural network, Feed-forward back-propagation network, Radial basis function, Finite element model, Sattarkhan earthfill dam

1 Introduction

Development and extension of the civilizations need optimum management of water resources. In this way, construction of dams to control, store and transfer water is one of the oldest and most important activities of engineering, which is nowadays regarded as one of the biggest and costliest projects of the Civil Engineering. In arid and semi-arid countries, due to low amount of rainfall, and rapid increase in water demand, it is necessary to control and optimize the available water resources. Therefore, dam construction on the path of surface flows is one of the basic choices to reach such an optimized goal.

One of the traits of earthfill dams is related to their cheap body material, which may be found in the construction site. Because of this, earthfill dams in comparison to other types of dams are more economical. In addition of economic aspects, in some cases constructing limitations make building of the earthfill dam necessary. In the past, design of the earthfill dams was completely based on the empirical knowledge and faith in the sections which had good performance, but in the last decades the behavior of dams, especially the collapsed dams, has been studied using modern soil mechanics. The most important improvement in this case is the analysis of seepage through the body of an earthfill dam and its influence on the stability of the dam. Terzaghi's one-dimensional consolidation theory for saturated soils introduced an approach to seepage problems [1].

Over the past few decades, significant improvement has been achieved in the issue of seepage modeling through the dams; for this purpose several methods have been suggested to model seepage analysis. Models based on their involvement of physical characteristics generally fall into three main categories: black box models, conceptual models and physical based models [2]. The conceptual and physical based models are the main tools for predicting variables and understanding the physical processes involved in a system. However, they have a number of practical limitations, including the need for large amounts of field data, sophisticated programs for calibration using rigorous optimization techniques, and a detailed understanding of the underlying physical process [3]. If sufficient data are not available, and accurate predictions are more important than understanding the actual physics of the situation, black box models remain a good alternative method and can provide useful predictions without the costly calibration time [4].

Recently Artificial Neural Network (ANN) as a black box model has been widely used for forecasting in many areas of hydraulic, hydrology and water resources. Also, a presented literature survey by Shahin et al. [5] reveals that ANN has been successfully applied to several geotechnical engineering problems. Goh [6] presented an ANN model to predict the friction capacity of piles in clays. Ni et al. [7] proposed a methodology of combining fuzzy sets theory with ANN for evaluating the stability of slopes. A number of hypothetical natural slopes were evaluated by both ANN and an analytical model, and the results of the ANN model were in a good agreement when compared with the analytical model. Sivakugan et al. [8] explored the possibility of application of neural networks to predict the settlement of shallow foundation on the granular soils. Similar studies have been conducted in different areas including soil properties and behavior, liquefaction, design of tunnels and underground opening, soil permeability and hydraulic conductivity, soil swelling and classification of soils by applying ANNs [5].

On the other hand, a number of mathematical techniques such as finite difference (FDM), finite volume (FVM), finite element (FEM) and boundary element (BEM) methods have been widely applied to solve the governing physical-based partial differential equation (PDE) regarding the seepage and flow field through an earthfill dam (i.e., Richards' equation) [9]. Celia et al. [10] compared results of different forms of the governing PDE to the unsaturated problem by presenting a numerical approximation. Ross [11] suggested two FDMs for solving Richards' equation in one dimension, and investigated their applications. Li [12] developed a FEM for solution of the nonlinear unsaturated flow equation. Bardet and Tobita [13] proposed a FDM for calculating unconfined seepage using spreadsheets. Tayfure et al. [14] developed a numerical method using FEM for two-dimensional unsteady state seepage through the saturated-unsaturated zone in an earthfill dam. The FEM model can be more effective when data on the spatial variation of the actual model parameters at every element of the numerical mesh are available. However, such extensive data throughout the entire dam body are rarely available, primarily due to time and budgetary constraints. Furthermore, the numerical solution of the highly nonlinear flow equations is prone to problems of instability and lack of convergence. Thus, an ANN model was used for predicting seepage in time and space and the locus of the seepage path. Nourani and Babakhani [9] offered the Radial Basis Function (RBF) spatial interpolation method to estimate the water potential heads through an earthen dam and the results of the model were compared with the results of FDM; then they employed the ANN model for handling non-linear time variability of the phenomenon to cope with the limitations of FDM and RBF methods in temporal modeling.

To the best of our knowledge, it seems there is not any study regarding integrated ANN-based modeling of seepage through earthfill dam and comparison of its results with a numerical method. Hereafter, the governing PDE of the seepage is reviewed. Then, after a brief explanation about ANN, a short description of the FEM approach is presented. The study area and data are then reviewed; following this, seepage through Sattarkhan earthfill dam has been simulated and verified using ANN. Finally, two integrated models based on two different algorithms, the feed-forward back-propagation (FFBP) method and the radial basis function (RBF), are developed, and the obtained results are compared with the single ANNs results and the FEM physical-based method.

2 Governing equation

The fluid motion is assumed to obey the classical Richards equation. This equation may be written in several forms, with either pressure head *h [L]* or moisture content θ *[L^3/L^3]* as the dependent variable, and the mixed form of them. The "h-based" form is written as [10]:

$$C(h)\frac{\partial h}{\partial t} = \nabla . K(h)\nabla h - \frac{\partial K}{\partial z} \quad (1)$$

Where *C(h)* is the specific moisture capacity function *[1/L]*, *K(h)* is the unsaturated hydraulic conductivity *[L/T]*, which can be written as $K(h)= kk_s$ in saturated and unsaturated regions, where k_s is the saturated conductivity and *k* is the relative permeability which equals one in the saturated zone [15].

To close Eq. 1 appropriate conditions are specified on the boundary for all time and within the flow region at the initial time. The Dirichlet boundary condition specifies the pressure head on some part of the boundary, whereas the Neumann condition specifies the flux on other part of the boundary. The initial condition prescribes the distribution of the pressure head and the saturation throughout the solution domain at the start of the solution history. Therefore, the initial and boundary conditions take the form [15]:

$$h(x, 0) = h_{ini} \quad (2)$$

$$h(x_b, t) = h_b \quad (3)$$

$$\frac{\partial h(x_b,t)}{\partial \bar{n}} = 0 \quad (4)$$

$$p = 0 \qquad on\ the\ seepage\ surface \quad (5)$$

Where h_{ini} is the initial water head, x_b the boundary nodes, h_b is the boundary water head, $\bar{n}$ is the outward normal vector along the boundary, and *p* is the pressure along the seepage surface which is an external boundary of the saturated zone. The solution of Eq. 1 yields the distribution of the soil-water pressure field in the domain. Thereafter the seepage free surface and paths in the dam can be determined.

3 Artificial neural network (ANN) model

ANN offers an effective approach for handling large amounts of dynamic, non-linear and noisy data, especially when the underlying physical relationships are not fully understood [16].

ANN is composed of a number of interconnected simple processing elements called neurons or nodes with the attractive attribute of information processing characteristics such as nonlinearity, parallelism, noise tolerance, and learning and generalization capability. Among the applied neural networks the feed forward neural network (FFNN) with back propagation (BP) algorithm are the most common used methods in solving various engineering problems [17]. FFNN technique consists of layers of parallel processing elements called neurons, with each layer being fully connected to the preceding layer by weights. Learning of these ANNs is generally accomplished by BP algorithm [18]. The objective of the

BP algorithm is to find the optimal weights, which would generate an output vector, as close as possible to the target values of the output vector, with the selected accuracy [19]. The explicit expression for an output value of a three layered FFBP is given by [3]:

$$\hat{y}_k = f_0\left[\sum_{j=1}^{M_N} W_{kj} \cdot f_h\left(\sum_{i=1}^{N_N} W_{ji}\, x_i + W_{jo}\right) + W_{ko}\right] \tag{6}$$

Where W_{ji} is a weight in the hidden layer connecting the ith neuron in the input layer and the jth neuron in the hidden layer, W_{jo} is the bias for the jth hidden layer neuron, f_h is the activation function of the hidden neuron, W_{kj} is a weight in the output layer connecting the jth neuron in the hidden layer and the kth neuron in the output layer, W_{ko} is the bias for the kth output neuron, f_0 is the activation function for the output neuron, x_i is the ith input variable for input layer, and $\hat{y}_k$, y are computed and observed output variables, respectively. N_N and M_M are the number of neurons in the input and hidden layers, respectively. The weights are different in the hidden and output layers, and their values can be changed during the process of the network training.

RBF networks were introduced into the neural network literature by Broomhead and Lowe [20]. The interpretation of the RBF method as an ANN consists of three layers: a layer of input neurons feeding the feature vectors into the network; a hidden layer of RBF neurons, calculating the outcome of the basis functions; and a layer of output neurons, calculating a linear combination of the basis function [21]. The main differences between FFBP and RBF networks are that in the latter the connections between the input and hidden layer are not weighted and that the transfer functions on the hidden layer are radially symmetric. Although the choice of the basis function is not crucial to the performance of the network, the most common one is the Gaussian, which was used in this study too. Figure 1 shows a schematic of an RBF type ANN with N inputs, L hidden layer neurons and M output layer neurons [22].

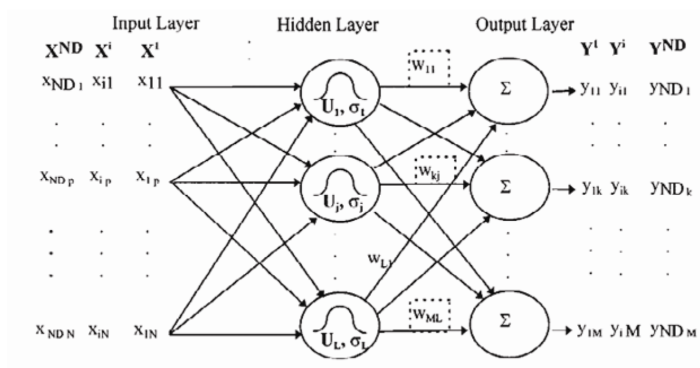


Figure 1. Schematic of a radial basis function network [22]

The proposed ANN modeling in this paper included two stages of single and integrated modeling. In the first step of single ANN modeling, input and target matrices for each piezometer using the observed time series of the upstream and downstream and piezometric water heads were arranged to predict the water head of each piezometer (i.e., the single ANN model was consisted of two input and one output neurons for each piezometer). In the second step, the arranged matrices were employed to train an ANN for each piezometer and the optimum number of neurons in the hidden layer and also training iteration number (epoch) which provided the best training results were determined. In the last step, the trained ANNs were verified using verification data set.

At the second stage in order to have a unique ANN, which is able to model all piezometers of the dam at different sections simultaneously, integrated ANN model was trained to predict the water heads of all piezometers placed in the dam core. For this purpose, two different ANN methods, the FFBP method and the RBF, were employed. The integrated ANN model was consisted of two input neurons including up and downstream water levels and the number of output neurons was set as the number of the dam's piezometers. Different values of training constant 'spread' were considered for RBF simulations, and the spread providing best performance criteria was selected. This integrated ANN was developed using training and verification data sets.

4 Finite element model (FEM)

One of the standard approximations which is applied to the spatial domain of Eq. 1 is the FEM. Although the FEM is a suitable and widely used numerical method for two-dimensional problems, it is not able to model transient seepage, and the time derivation can be approximated by a finite difference procedure [10]. In present study the spatial part of Eq. 1 has been solved by the Galerkin solution of the weighted residual method. Using integration by parts and Green-Gauss theorem, and considering boundary conditions, Eq. 1 can be re-written as follows [15]:

$$h = h_i N_j \tag{7}$$

$$D_{kj} h_j = 0 \tag{8}$$

$$D_{kj} = \sum_{e=1}^{m} \int_{\Omega_e} k_x \frac{\partial N_k}{\partial x}\frac{\partial N_j}{\partial x} + k_y \frac{\partial N_k}{\partial y}\frac{\partial N_j}{\partial y} \, d\Omega_e \tag{9}$$

Where N_j is the interpolation function, N_k is the weight function, and m is the number of elements.

5 Sattarkhan earthfill DAM and data

Sattarkhan earthfill dam is a reservoir dam placed in the East-Azarbaijan province, Iran, on the Aharchai River. The Ahar River basin is a sub-basin of the Aras watershed. The height of the dam is *59m* above the alluvial deposit layer and *78m* above the bed rock and its crest length is *340m*. The reservoir capacity (while the normal water level is *1451m* above the mean sea level) is *131.5 million m*^{3}.

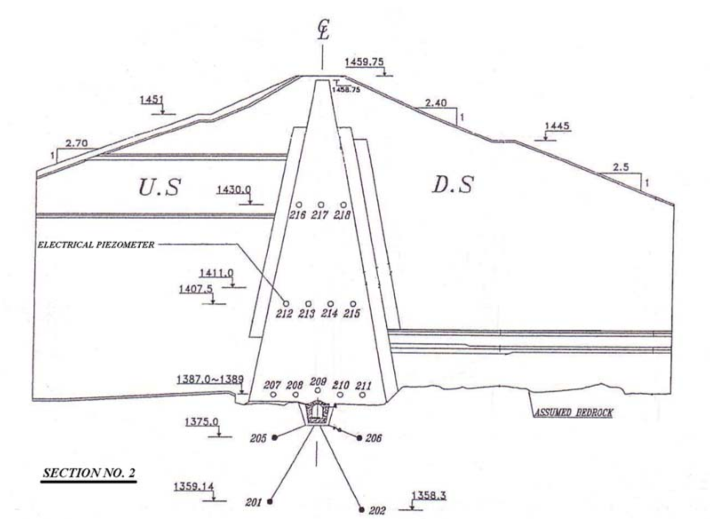


Figure 2. Piezometers' position of cross section No. 2

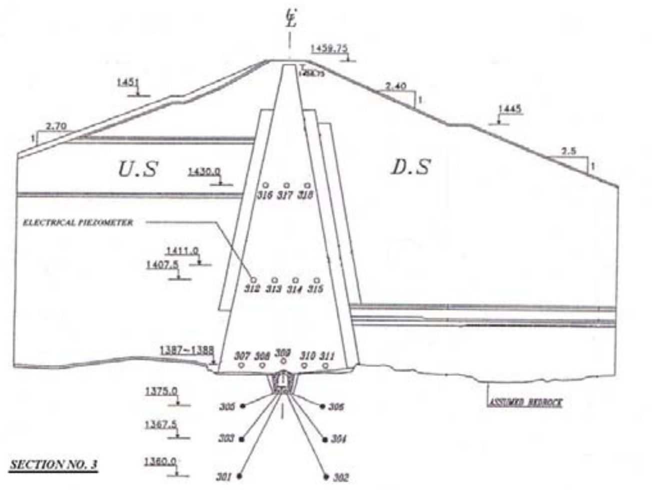


Figure 3. Piezometers' position of cross section No. 3

At the four cross sections of the dam several electrical piezometers have been placed; two cross sections on the middle part of the valley with maximum section area, and two cross sections on both sides of the dam. Three lines of electrical piezometers have been placed in the middle cross sections (sections No. 2 and 3). First line, in a short distance of the bed rock (at the elevation of *1387-1389 m*), consists of five electrical piezometers. Second line, placed in the middle of the cross section, consists of four electrical piezometers, and third line contains three electrical piezometers. Water levels in the piezometers have been monitored every 2 weeks for the period from 1999/1/4 to 2003/10/21; also daily water levels in the upstream of reservoir have been recorded for the dam. Figures 2 and 3, show the piezometers' positions of sections No. 2 and 3, respectively. Figure 4 presents the observed water levels in piezometers No. 211, 216, 315, 316 and the water levels of up and downstream of the dam for the considered period.

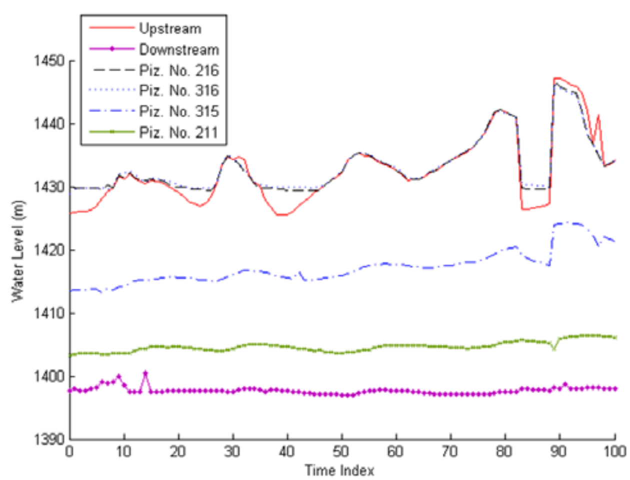


Figure 4. The observed water levels in the piezometers No. 211, 315, 316 and 216 along with the upstream and downstream water levels

6 Results and discussion

Since inappropriate ANN architecture may lead to under-fit, over-fit and computational overload, determining the best architecture of the ANN is the most important step of the modeling [23]. Considering pervious researches to obtain optimum

ANN structure, a three-layered Feed Forward Back Propagation (FFBP) network trained by Levenberg-Marquardt optimization algorithm was selected to develop single ANNs [3, 4, 19, 23-25]. Also a Tangent Sigmoid transfer function was used for hidden layer and a linear transfer function for the output layer according to Nourani and Ejlali [4]. Due to the nature of the Sigmoid function used in this algorithm, also to eliminate the dimension of the input and output variables, the raw data were scaled to fall between a range of *0* to *1* [25]. This kind of scaling tends to smooth the solution space and averages out some of the noise effects [26]. The following mapping is usually employed for this purpose [3]:

$$h_n = \frac{h_i - h_{min}}{h_{max} - h_{min}} \tag{10}$$

Where h_i is the actual value and h_n is the respective normalized value. h_{min} and h_{max} are the minimum and maximum of the used values, respectively.

At the first stage, a single ANN model was trained for each piezometer to predict the water level of the piezometer on the dam. These models were performed via trial- error process and the conditions in which the efficiency of the network and the reliability of the prediction can be improved are inquired. In addition to changing the number of neurons in the hidden layer, changing of training epoch has been investigated to get the optimum ANN. The developed models were evaluated according to the Mean Squared Error (*MSE*) and Determination Coefficient (R^2) criteria as follows [9], until getting the best structure:

$$MSE = \frac{\sum_{i=1}^{m}(h_i - \hat{h}_i)^2}{m} \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(h_i - \hat{h}_i)^2}{\sum_{i=1}^{m}(h_i - \bar{h})^2} \tag{12}$$

Where h_i, $\hat{h}_i$ and $\bar{h}$ are the observed value, computed value by the model, and average of the observed data set with m observations, respectively.

At the second stage, an integrated model was proposed for the whole dam body, which contained the data of all piezometers. In this approach, two different algorithms of ANN were employed, and the applicability of the RBF type ANN, which differs from the more widely used FFBP, was investigated.

Finally, in order to compare the obtained results of the both single and integrated ANN models, the results were compared with the results of the FEM physical-based method.

6.1 Single ANN modeling

At the first step of the ANN modeling, the input and output matrices were arranged. In this research the single ANN structure consisted of two input neurons, including the water levels on the upstream and downstream and the output neuron indicated water levels in the piezometers. For this purpose, the available data set was portioned into two sets for training and validation purposes. During training, the weights and bias values are adjusted based on the difference between ANN output and the target responses. This adjustment can be continued until a weight space is found, which results in the smallest overall prediction error. However, there is the danger of over-training (over-fitting) a network. This happens when the network parameters are too fine-tuned to the training data set [26]. To prevent this kind of overtraining, a validation process is accomplished. In this study, 80% of the data set was used for training and the rest of it, set aside for verification step.

At this stage, piezometers No. 211, 216, 315 and 316 have been simulated individually and the results of these models have been evaluated using *MSE* and R^2 criteria. Obviously the closer *MSE* to *0* and R^2 to *1*, the better would be the model. The available data used for each single ANN model development, comprised a total of 100 individual cases from 1999/1/4 to 2003/10/21, which were divided into two sets of 80 cases from 1999/1/4 to 2002/12/20 and 20 cases from 2003/1/6 to 2003/10/21 for training and validation steps, respectively. At the first step, regarding this arrangement of data sets, training and verification of single ANN model of piezometer No. 211 were carried out. The best performance of this model was done with a determination coefficient (R^2) of *0.6645* and *0.4293* for training and verification steps, respectively. As to the matter of this low performance, it can be said that due to the heterogeneity of data, the first 80 cases of it used for training step, did not consist of all ranges of the total data. Therefore, random selection of the training and validation data sets would help to improve the efficiency of the model. For this purpose, another model was trained and verified for piezometer No. 211, in which the data sets were randomly picked out. According to the results, evident improvement of the performed model can be seen. In the same way, ANN models for piezometers No. 216, 315 and 316 were developed. The optimal model structure and epoch number with its performance for each piezometer have been summarized in Table 1. As instance, the computed heads of piezometer No. 316 with the corresponding up and downstream and observed water levels for 11 randomly chosen cases of validation step are tabulated in Table 2. Figure 5 shows the scatter plots of the observed data and obtained results of the best performance of the ANN model for piezometer No. 211 in validation step. In Figure 6, the observed data time series for piezometer No. 216 with the output of the ANN model in both train and validation steps have been plotted, where a significant positive correlation can be seen. Figures 7 and 8 present the scatter diagram of the observed and predicted values of the best ANN model in training step, and time series of the measured and calculated values in verification step, both for piezometer No. 316, respectively. In Figure 9, time series of the measured data and obtained results of the training process for piezometer No. 315 have been compared.

Table 1. Performance of the optimal single ANN models

No. of Piz.	Model structure*	Epoch number	R^2		*MSE*
			Training	***Validation***	***(training)*****
211	2-7-1	160	0.8914	0.7984	4.845×10^{-5}
216	2-7-1	40	0.995	0.9835	1.246×10^{-5}
316	2-7-1	35	0.9983	0.9735	1.129×10^{-5}
315	2-5-1	80	0.9377	0.8688	2.229×10^{-5}

*The structure 2-7-1 denotes to the number of neurons in layers; i.e., 2,7,1 neurons in input , hidden and output layers, respectively; ***MSE* is calculated for normalized data

Table 2. Output of single ANN model of piezometer No. 316 in validation step

Upstream water level*	0.99731	0.99004	0.97799	0.9734	0.95338	0.8971	0.79231	0.88435	0.72259	0.72637	0.74012
Downstream water level*	0.021396	0.032493	0.0204	0.020998	0.020898	0.021994	0.022591	0.021994	0.021197	0.020599	0.019304
Observed water level*	0.96962	0.95787	0.95029	0.94691	0.89372	0.81981	0.79211	0.75924	0.72817	0.72817	0.73932
Computed water level*	0.97738	0.94827	0.9706	0.96648	0.94242	0.76899	0.68513	0.73996	0.70307	0.70657	0.71714

*Water levels have been normalized

Although the quality of the results in the training step in each piezometer's model is roughly comparable, the obtained results of the validation step intensely depend on the quality and selection of the data. Generally, it can be concluded that in each process of training step, by increasing the number of neurons in the hidden layer, the requisite epoch number will decrease. However, this fact could be seen until the definite number of epoch, and after it error rate could increase or maintain the same. Therefore, if the number of training epoch is few, the operation of training process would be done by the hidden layer units, and in contrast in the small amount of hidden layer neurons this task would be done by the many epochs of the Back Propagation Algorithm.

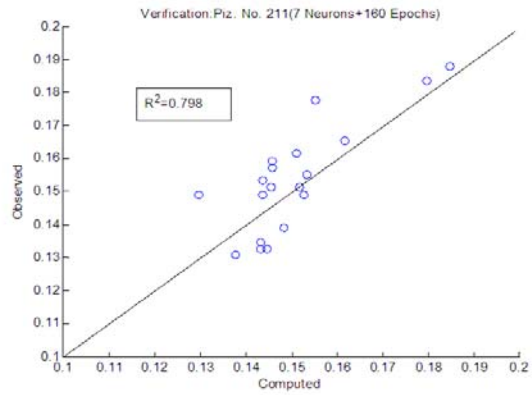


Figure 5. The scatter plots of the observed and computed water heads of piezometer No. 211 in verification step

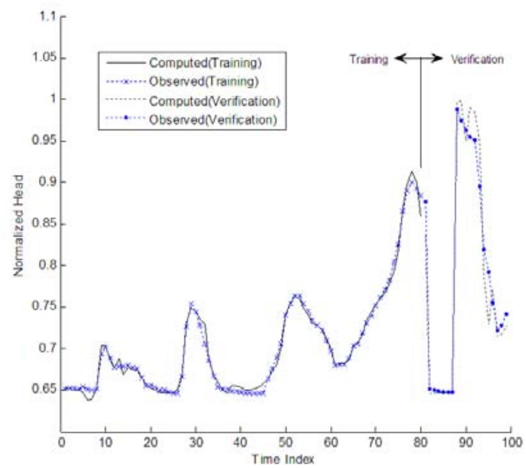


Figure 6. Time-series of the observed and computed water heads of piezometer No.216 for both training and verification steps.

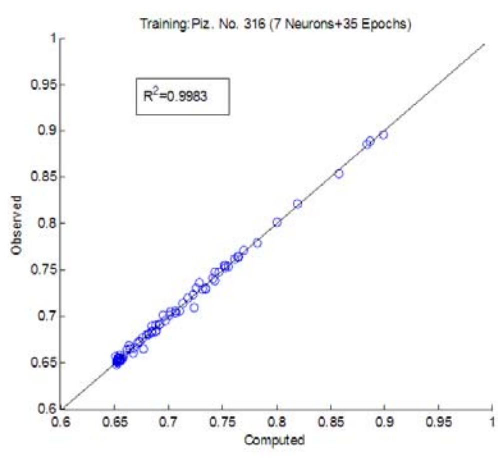


Figure 7. The scatter plots of the observed and predicted values in training step for piezometer No. 316

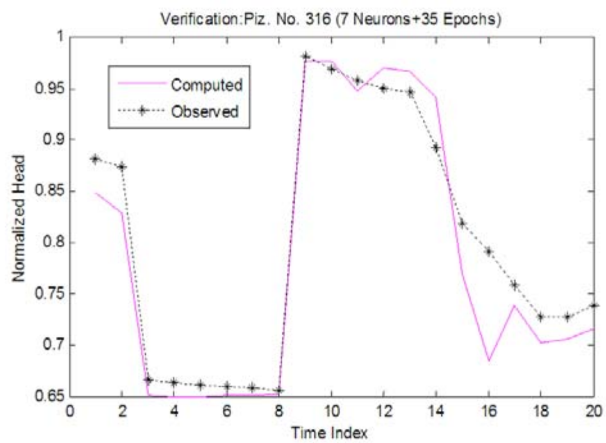


Figure 8. Time-series of the measured and calculated values in verification step for piezometer No. 316

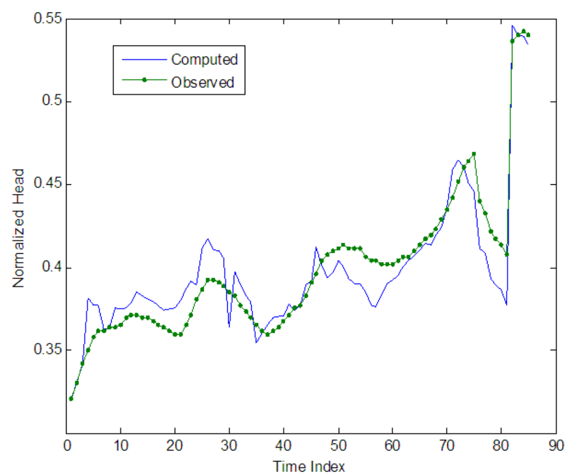


Figure 9. Time-series of the observed and computed water heads of piezometer No.315 for training step

As it can be deduced from the results of Table 1, all single ANN models have reliable performance but piezometer No. 211. This matter could be issued from the position in which each piezometer is placed; piezometers No. 216 and 316, both are placed at the uppermost level of the core, near the upstream, which are affected mostly by the variations of the upstream water level; consequently the models of these piezometers appear to fit the fluctuations of the upstream water level quite well. Whereas, piezometer No. 211 is placed at the lowest level of the cross section, near the downstream; it is far enough from the upstream to parallel with the fluctuations of the upstream water level immediately; on the other hand, due to soil friction these fluctuations would be disappeared through the dam; hence this piezometer is affected by the downstream rather than upstream water level, and the fluctuations of upstream water level do not have significant influence on the water level of this piezometer. Therefore, Adjusting the ANN model to the upstream water level parameter for this piezometer will need more trial and error process with more error percentage. Despite these three cases, piezometer No. 315 is placed at the middle of the cross section, which the variation of water level in this piezometer is relatively affected by the fluctuations of upstream water level; so the performance of this model is not as high as piezometers No. 216 and 316, nor is it as low as piezometer No. 211. Three-dimensional graphs of Figures 10 and 11 show the responses generated by the ANNs versus input variables for piezometers No. 211, 216 and 315, 316, respectively.

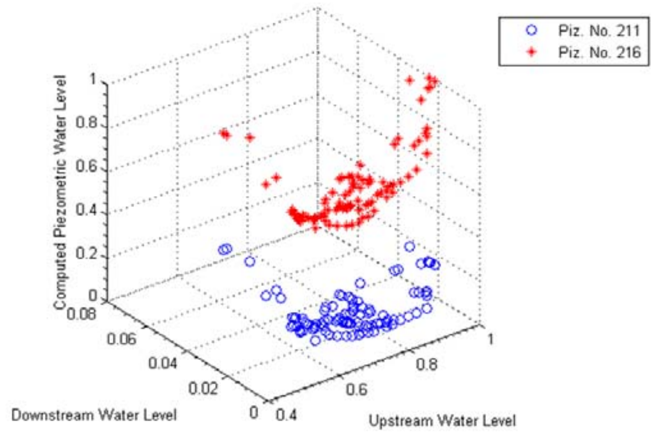


Figure 10. Three- dimensional graph of computed water heads of piezometers No. 211 and 216 vs. input variables (for normalized data)

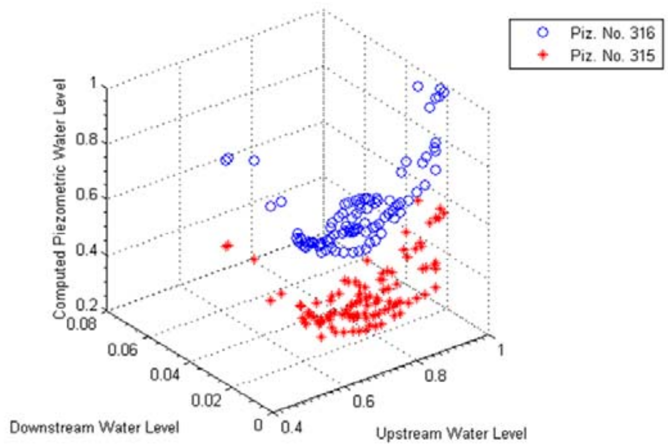


Figure 11. Three dimensional graph of computed water heads of piezometers No. 315 and 316 vs. input variables (for normalized data)

6.2 Integrated ANN modeling

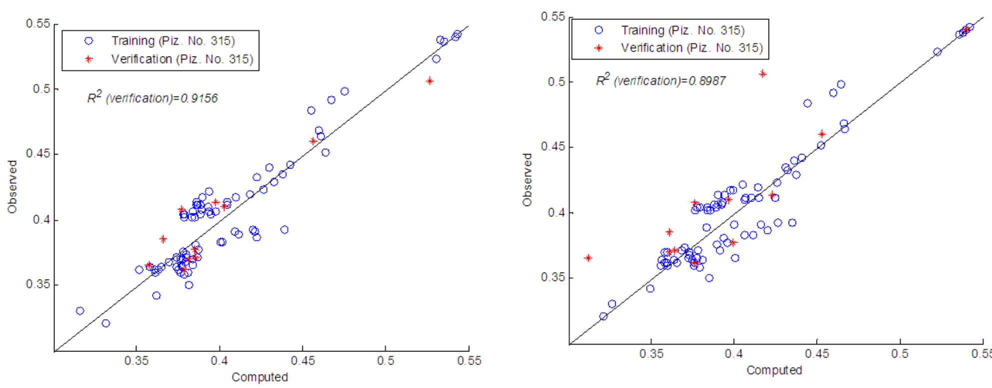
Accessibility and employment of the available three-dimensional software in the field of seepage modeling through earthfill dams is complicated in that many geometrical and physical data are needed, while sometimes such data are unreachable. As the second stage of this study, a suitable and useful solution was presented for modeling of seepage through earthfill dams. In this approach an integrated ANN model was trained using all piezometers data at all sections. In this way two algorithms, FFBP and RBF, were employed for ANN simulations. The ANN network structure consisted of three layers, i.e., input layer, hidden layer and output layer. The input layer of the integrated ANN contained two input neurons including up and downstream water levels, whereas the output layer neurons corresponded to the number of piezometers of the dam. In the recent study, these networks were trained and validated for the piezometers No. 211, 216, 315 and 316 placed in the sections of 2 and 3 (i.e., 4 output layer neurons). For FFBP, the number of neurons in the hidden layer and training iteration number (epoch) were determined after trying several network structures. In this experiment, various number of hidden layer neurons from 2 to 10, and epoch number from 10 to 160 were examined, and finally a network structure with 6 hidden layer neurons which was trained with 80 epoch number, provided the best performance criteria (i.e., lowest *MSE* and highest R^2, for the validation data). For RBF, the same structure with FFBP was employed.

Training parameter 'spread' was also decided by several trials with different values between *0* and *1*, and the spread value of *0.5* was found to be appropriate. For instance, scatter plots of the observed data and the output of the integrated FFBP and RBF networks for piezometers No. 216 (section No. 2) and 315 (section No. 3) are shown in Figures 12 and 13, respectively. The performance evaluation measures (i.e., *MSE* and R^2) between simulated and observed water levels in the piezometers No. 211, 216, 315 and 316, for the best performance of the FFBP and RBF networks are given in Table 3.

Table 3. Performance of the optimal integrated ANN model

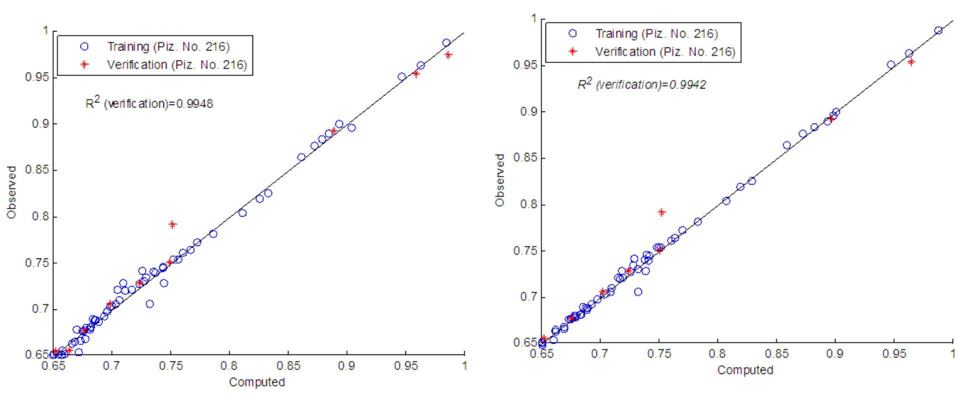
No. of Piz.	FFBP network				RBF network			
	R^2		$MSE\times10^3$*		R^2		$MSE\times10^3$*	
	Training	*Validation*	*Training*	*Validation*	*Training*	*Validation*	*Training*	*Validation*
211	0.8777	0.8703	0.0515	0.0807	0.8941	0.6699	0.0391	1.063
216	0.9966	0.9948	0.0471	0.1648	0.9984	0.9942	0.0219	0.4107
315	0.9371	0.9156	0.2917	0.3433	0.9393	0.8987	0.2819	0.1848
316	0.9967	0.9948	0.0416	0.1647	0.9986	0.9890	0.0178	0.2070

**MSE* is calculated for normalized data



(a) (b)

Figure 12. The scatter plots of the observed and predicted values in training and verification steps for piezometer No. 216, a) Integrated FFBP network, b) Integrated RBF network



(a) (b)

Figure 13. The scatter plots of the observed and predicted values in training and verification steps for piezometer No. 315, a) Integrated FFBP network, b) Integrated RBF network

Results of Table 3 reveal that integrated RBF and FFBP models provided relatively same results. However, employment of RBF method provided an extra advantage, so that in FFBP method, different performance criteria were obtained for different FFBP simulations for the same network due to the different number of training iterations. Therefore, several simulations were needed to achieve the best performance of FFBP. In contrast, the RBF could be developed with relative ease and with much less time, since estimations could be carried out with a unique simulation.

Next, in order to determine the efficiency of the integrated models, also to compare the obtained results of these models with single ANN models results, the model-predicted water levels for two arbitrary up and downstream water levels were drawn out and the error percentage of each case was calculated. As can be seen from the results shown in Table 4, although in some cases integrated FFBP network led to more error percentage, this amount is negligible and in most cases integrated RBF network performed even better than single ANN models. Furthermore, integrated models are included all piezometric data of the dam, so the conditions of a piezometer could affect the performance of other piezometer(s) in other section(s); moreover, easy training process of integrated ANN models, which ends in saving time, also the ability of three-dimensional modeling which just needs one training process (instead of training one model for each piezometer like single ANN model) makes this approach more convenient.

Table 4. Comparison of the integrated and single ANN models

No. of Piz.	Observed water level*	Integrated ANN				Single ANN	
		FFBP		RBF		FFBP	
		Computed water level*	Error (%)**	Computed water level*	Error (%)**	Computed water level*	Error (%)**
211	0.18774	0.18344	2.29	0.18785	-0.06	0.18673	0.54
	0.13473	0.14282	-6	0.13977	-3.74	0.14312	-6.23
216	0.72699	0.72408	0.4	0.72647	0.07	0.73072	-0.51
	0.89259	0.88924	0.37	0.89708	-0.5	0.90017	-0.85
315	0.39069	0.42106	-7.77	0.38333	1.88	0.41012	-4.97
	0.40603	0.38396	5.43	0.38797	4.44	0.3848	5.23
316	0.75546	0.75702	-0.2	0.75247	0.39	0.75295	0.33
	0.89611	0.86851	3.08	0.89771	-0.18	0.89877	-0.3

*Water levels have been normalized; ** Error percentages have been calculated for normalized results

6.3 Finite element model

To evaluate the results of proposed ANN models with the result of a common mathematical model which nowadays is widely used, seepage analysis through Sattarkhan dam was performed by the FEM, and the water levels obtained by this model were compared to the measured water levels in piezometers and results of the single and integrated ANNs. For this purpose sections No. 2 and 3 were analyzed. Generally in this modeling it was supposed that water movement in the body and foundation of dam is under Darcy's law. The cross sections No. 2 and 3 were divided into quadratic finite elements. Although the hydraulic conductivity of the dam was reported as $k_x=k_y= 10^{-7}\ m/s$ by the constructor, for more assurance the model parameter (i.e., conductivity) was calibrated using the observed water level in piezometer No. 315 for upstream and downstream water heads of *1446.695 m* and *1398.63 m*, respectively (analysis No. 1). This calibration was done with a determination coefficient (R^2) of *0.9975*. Thereafter, the predicted results of the model for other piezometers (i.e., piezometers No. 211, 216 and 316) were drawn out. To increase the reliability of modeling, another analysis was carried out for upstream and downstream water heads of *1442.214 m* and *1397.43 m*, respectively (analysis No. 2). The model results are presented in Table 5. FEM results show that except piezometer No. 315, which was employed for the calibration, the model performance for other piezometers is not satisfactory. In the case of piezometer No. 211, it seems possible that these results are due to the crack placed in the bed rock. This crack was discovered before constructions, and during constructions the grouting operation was performed to improve water-tightness and reinforce weak parts; it is difficult to accurately estimate the improvement brought about by grouting, but the FEM results reveal that maybe the injections had not been enough. A possible explanation for the results of the other piezometers might be that the dam body has not remained homogeneous over the time span.

Table 5. Results of the FEM model

No. of Piz.	No. of analysis	Observed water head (m)	Computed water head by FEM (m)
211	1	1406.11	1405.4
	2	1405.1	1404.8
216	1	1445.35	1444.6
	2	1442.15	1441
315	1	1424.22	1424.2
	2	1419.66	1419.5
316	1	1445.08	1444.6
	2	1441.98	1441

In order to compare the results of the single and integrated ANNs with the employed physical-based method (i.e., FEM), the estimated water levels in piezometers by the ANNs for different upstream water levels, which were employed by the numerical method, were drawn out. Then for each method the error percentage was calculated. As can be seen from Table 6, the physical-based model in all cases except piezometer No. 315 led to less accuracy in comparison with the single ANN models; this case is due to that during numerical modeling, developed model has been calibrated toward piezometer No. 315 and then the obtained results of the model for other piezometers were derived. By the way, the poor results of FEM reveal existence of some fundamental problems in the body and foundation of Sattarkhan earthfill dam, and the accurate results of ANN prove the reliability of this model as a powerful approximator. However, it is worth taking into consideration that ANN is a black box model in which there is no clear relationship between input and output variables; therefore there isn't any chance to come up with an explicit insight into available physical problems in a project. Generally it should be mentioned that numerical models based on physics, like FEM, perform with physical and field data whereas such data are not available at times, or somehow calculating conditions and assumptions are different with real situation, so model-predicted results will not agree with measured data. As an instance, in the case of an earthfill dam, due to problems in execution and limitations of constructions seepage condition is gradually changed, therefore obtained results of mathematical models often do not fit with measured data; in such situations employment of black box models like ANN, set up on the base of real time condition, daily monitoring and new training data, would lead to more satisfactory results. In other words, problems and defects of constructing and operating conditions are hidden in these models.

Table 6. Computed water level and error percentage for each method

No. of Piz.	Observed water level (m)	Integrated FFBP network		Integrated RBF network		Single ANN		FEM	
		Computed water level (m)	Error (%)*	Computed water level (m)	Error (%)*	Computed water level (m)	Error (%)*	Computed water level (m)	Erro r (%)*
211	1406.11	1405.653	5.012	1406.103	0.072	1406.103	0.121	1405.4	7.793
	1405.1	1404.998	1.264	1405.087	0.161	1405.136	-0.39	1404.8	3.703
216	1445.35	1445.357	-0.015	1445.34	0.02	1444.667	1.451	1444.6	1.551
	1442.15	1441.849	0.666	1442.242	-0.204	1442.88	-1.568	1441	2.547
315	1424.22	1424.26	-0.177	1424.21	0.007	1424.063	0.586	1424.28	0.073 5
	1419.66	1420.274	-0.027	1419.685	-0.14	1420.35	-3.032	1419.5	0.706
316	1445.08	1445.146	-1.66	1445.054	0.024	1444.6	-1	1444.6	0.998
	1441.98	1441.63	0.75	1442.047	-0.18	1442.12	-0.297	1441	2.179

7 Concluding remarks

In view of considering the importance of earthfill dam construction especially in developing countries, and multiplicity of constructed or under operation earthfill dams, accurate modeling of pore water pressure and appropriate analysis of seepage through earthfill dams could increase safety of the dam. In this paper several ANN models were employed to model pore water pressure and seepage through Sattarkhan earthfill dam. For this purpose, measured data of several piezometers at different sections of the dam were employed, and then a single model for each piezometer was presented. Next, integrated ANN models were developed to the whole dam. Moreover, the results of the ANN models were compared to a physical-based numerical model in which model equations were solved by the FEM. Generally the following conclusions can be drawn:

Due to governing a mathematical relationship between input and output of the system (Diffusion PDE), the efficiency of the ANN models would be high, if the quality of recorded data sets is approved; this fact can be obviously seen in the results.

By a thorough consideration of the obtained results it can be concluded that developed ANN models are not so sensitive to the training parameters such as the number of neurons in the hidden layer or epoch number, but the quality and selection of data sets are the factors that can influence the efficiency of the models.

Using updated real time data sets which can be measured after construction and operation of a dam for training ANN model enables this model to predict accurately, in spite of some shortcomings and deficiencies of construction.

The proposed integrated ANN, satisfactorily provided the modeling of the whole dam via only a unique network.

The results of the integrated model trained with two different networks (i.e., FFBP and RBF) reveal that the model based on the RBF network can predict piezometric heads with accuracy comparable with the FFBP method; moreover, the estimations by RBF method can be accomplished much faster than FFBP, which requires repetition to ensure optimality. The RBF type models have the superiority that they can be developed and implemented with much less time and effort compared with their FFBP counterparts.

It is suggested that sensitivity analysis to the several parameters which influence seepage and pore water pressure is investigated in future studies. For example the effect of downstream water level can be investigated and if the influence of it is negligible, it can be omitted from the modeling.

Furthermore, similar modeling can be performed to predict other important aspects of earthfill dam such as settlement and its variation at different points of the dam. . Employing other artificial intelligence tools such as Genetic Algorithm and Fuzzy Logic to improve the quality of presented models will also be worthwhile.

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