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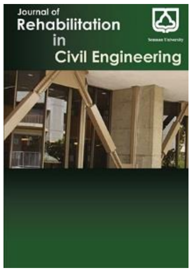

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Dam Seepage Prediction Using RBF and GFF Models of Artificial Neural Network; Case Study: Boukan Shahid Kazemi's Dam

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ABSTRACT

Dams have been always considered as the important infrastructures and their critical values measured. Hence, evaluation and avoidance of dams' destruction have a specific importance. In this study seepage of the embankmentof Boukan Shahid Kazemi's dam in Iran has been analyzed via RBF (radial basis function network) and GFF (Feed-Forward neural networks) models of Artificial Neural Network (ANN). RBF and GFF of ANN models were trained and verified using each piezometer's data and the water levels difference of the dam. To achieve this goal,based on the number of data and inputs,864piezometric data set were used, of which 80% (691 data) was used for the training and 20% (174 data) for the testing the network.The results showed good agreement between observed and predicted values and concluded the RBF model has high potential in estimating seepage with Levenberg Marquardt training and 4 hidden layers. Also the values of statistical parameters R^2 and RMSE were 0.81 and the 33.12.

1. Introduction

One of the ways to solve the water scarcity problem is to control surface waters. Dam construction and water storage are considered as one of the best methods to control water surface. The behavior of dams should be always evaluated and controlled due to the fact that their construction's cost are too high and the damage of their destruction is irrecoverable. The study of dam behaviourconsists of three periods; construction, first dewatering and the operation time.

For providing useful information about the possible problems of the embankment, earthquake and its effects on dam, pore pressure of the core, and the vertical and horizontal displacements should be studied in all three stages.

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To study dam behavior, numerical methods were used. Since these methods are usually difficult, time-consuming and require complex programming researchers were looking for easier ways with less time and cost [1].

Artificial neural networks which are modeled on biological neural networks can be helpful in solving problems such as the above problem. Now, these networks which are considered as intelligent systems, are used in different science including water engineering with a wide variety of constructions.

Generally, it can be said that in any given case which learning a linear or nonlinear mapping and a special space would be needed, these networks can ideally perform this conversion [1].

Recently, with the development of software programs, we can predict different phenomena with high accuracy. Artificial neural networks are one of the good and accurate predicting methods employed in different disciplines, including water resources engineering.

Ersayin examined the seepage of the dam embankment, specifically. In his study, after a comprehensive introduction of various types of dams and seepage phenomenon, this phenomenon was modeled using artificial neural networks (ANNs). In his thesis, Ersayin used a set of data including 125 piezometric data collected from the Jeziorsko earth fill dam in Poland to train and test his proposed model. Upstream and downstream water levels as inputs and water surface of piezometers were considered as output. The statistical parameters used in his study were consisted of; correlation coefficient (R^2), root mean square error (RMSE) and MAE. The values of these parameters for train data were 0.95, 0.232 and 0.205 respectively, and for test data were 0.93, 0.477 and 0.125 respectively. In his study, hidden layers and various activity functions were used to obtain the best results. Finally, the network with the sigmoid activity function and one hidden layers yielded the most accurate result [2].

Nourani et al. analyzed the piezometric height at the core of Sattarkhan embankment dam in Iran using artificial neural networks (ANNs). The ANNs with details of the three layer prediction with the Levenger-Marqurdt algorithm post-propagation trained the data. While for the integrated FFBP network, the number of hidden neurons was 6 and for the integrated RBF network the radius was considered 0.5, the hidden neurons for single network were 5 and 7. The results of their study showed a good adaptation between prediction and measured values. The correlation coefficient (R^2) for the single network was 0.798 and for the FFBF and RBF networks were 0.67 and 0.87, respectively. They concluded that the results of artificial neural networks are closer to reality, compared to the numerical methods which have been used in previous studies [3].

Pourkarimi et al. presented a new method for determining the seepage flow from the foundation and body of embankment dam based on data analysis methods. After studying Fileh-Khaseh embankment dam in Zanjan province in Iran, the seepage of embankment's soil was estimated by the finite element software called SEEP. In his study, a set of 96 data on effective parameters of seepage including permeability coefficient of the foundation and water heights behind the dam in allowable range were produced. Then, 65 and 31 data were used for training and testing the model respectively. The results showed that ANN provides an effective appliance for detecting patterns in data and accurate prediction of seepage from the foundation and body of Filleh-Khaseh dam. The statistical parameters used in this study were R^2, RMSE, MSE and MAE. The values of these parameters for the train data were 0.93, 43, 1870 and for the test data were 0.092, 17 and 1841 respectively [4].

Kamanbedast and Delvari Analyzed seepage and stability of earth dam using Ansys and Geo-Studio software.Therefore, result wore compared whit Geo studio Software result. Firstly, Dam were studied with using there analysis method, then seepage are predicated the seepage rate in Ansys, 18% is lower than Geo-Studio results. Results showed the significant difference of two software is related to safety factor and eventually it can be deducted that Ansys answer is more acceptable. Brifly, as a result, dam is at suitable situation according to the software results and Just vertical settlement at core zone should be studied more and perfectly [5]. Ebtehaj and Bonakdari (2013), Evaluated of Sediment Transport inSewer using Artificial Neural Network (ANNs). They reported in comparison with existing methods, the ANN showed acceptable results [6].

Aljeyri attempted to investigate soil dam behavior using Ansys. In this study, H was assumed that, none impervious layer behind layer are exist and downstream seepage is influenced by each change of two impervious layers which are concluded dams [7].

Shamsaie et al. studied the behavior of Mahabad dam using numerical methods. In their study, the status of Mahabad dam was analyzed for changes in seepage. After constructing the cutoff wall and grout curtain at foundation of dam, numerical simulation showed the seepage foundation of dam decreased to 0.05 that it ignorable [8].

Nourani and Babakhani predicted seepage from Sattarkhan dam using RBF model. The results of RBF model indicated this method has better accuracy and less computation in comparison with the finite difference method [9].

Naderpour et al. estimated the Shear Strength Capacity of Masonry Walls Improved with Fiber Reinforced Mortars (FRM) Using ANN-GMDH Approach. The results showed the proposed model (ANN-GMDH) has a correlation coefficient of 0.95, which represented the high efficiency of the model [10].

Jamal et al. predicted the amount of discharge to the clay core of embankment dams under unstable permeability conditions using ANN. In his study, finite element models were constructed and analyzed for non-saturated conditions. Then the results with input conditions were used to train the perceptron neural network model. The results of this research indicate the ability of ANN to accurately predict seepage of embankment dam in unsaturated condition [11].

Santillán et al. analyzed dam seepage by means of an artificial neural network model. Results showed artificial neural network models a powerful tool for predicting and understanding seepage phenomenon [12].

Naderpour et al. predicted the torsional strength of RC beams strengthened with FRP sheets by using neural network and reported it was possible to achieve a satisfactory result with less cost and time by training the artificial neural networks [13].

Ebtehaj et al. predicted sediment transport in sewers using an expert system with radial basis function neural network based on decision trees. The results of DT-RBF are compared with RBF and RBF particle swarm optimization (PSO), which uses PSO for RBF training. It appears that DT-RBF is more accurate R^2= 0.934, MARE = 0.103, RMSE = 0.527, SI = 0.13, BIAS = -0.071) than the two other RBF methods [14].

Naderpour et al. used artificial neural networks (ANNs) for compressive strength prediction of environmentally friendly concrete. The results showed that the ANNs were an efficient method to predict the compressive strength of ARC [15].

Given that the seepage of Shahid Kazemi Boukan dam has not investigated yet, in the present research, was investigated the power of the neural network in predicting the seepage and monitoring of Boukan dam body.

The following purposes were pursued:

- Comparison of RBF (radial basis function network) and GFF (Feed-Forward neural networks) models of ANN.

- Determine the best topology of ANN model (number of nodes and neurons, number of layers and appropriate training function).

2. Materials and Methods

2.1.Area of Study

In order to use artificial neural network (ANN) method to predict seepage value from dam body, ShahidKazemiBoukan dam located in Boukan city of west Azarbaijan province was selected. This dam was built on Zarrineh River in Azarbaijan province. The purposes of the construction of ShahidKazemi dam were to irrigate 85000 haof Miandoab plain lands, control of destructive floods, adjust the water level of the Zarrineh River, supply the drinking water of upstream and downstream cities and protect aquatic ecosystems. Zarrineh River basin is located between the geographical limits on the 32° 26 minute in the northern, also on the meridian 46° 32 minutes east of the Greenwich meridian [16].

The location of Shahid Kazemi dam is shown in Figure 1.

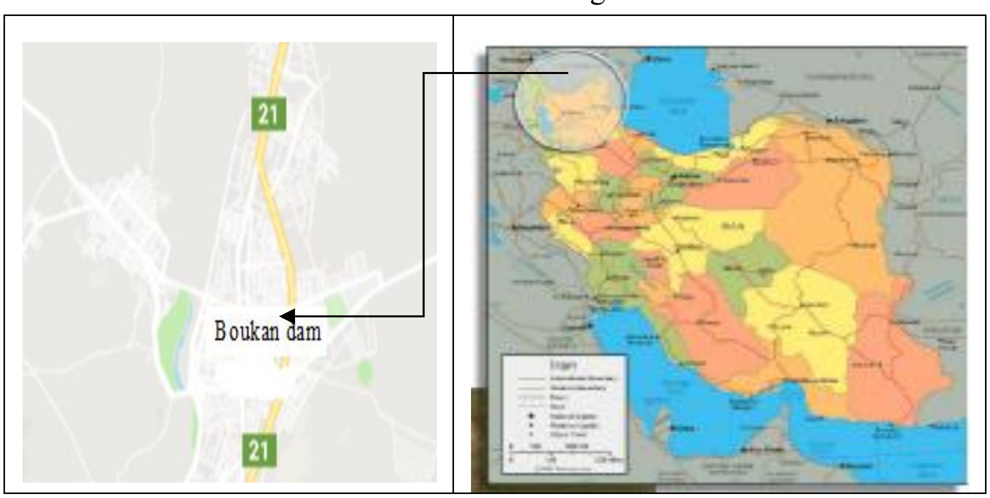

Fig. 1. ShahidKazemiBoukan dam position on the map

In Table 1, the technical characteristics of ShahidKazemiBoukan dam are given. This study is conducted using these characteristics.

Table 1. BoukanShahidKazemi dam technical characteristics.

Construction characteristics and Facilities	After Increasing the height of the dam	Before Increasing the height of the dam
Dam Body Type	Gravel with a Clay core	Gravel with a Silt-Clay core
Height of Foundation	52.5 m in 1995	50-174 m
Crest length	520 m	520 m
Crest Width	50 m	10 m
The Level of Dam Crest	1426.5 m	1424 m
Spillway Type	10 Radial Gates with 5 m Height	Free
Spillway Capacity	2300 m^3/s	4300 m^3/s
Water Level	1421 m	1416 m
Reservoir Volume in Normal Level	808 Mm^3	650 Mm^3
Dead volume	135.8 m^3	117.5 m^3

2.2. 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) or moisture content (θ)as the dependent variable, and the mixed form of them. The h-based" form is written as [3]:

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

Where C(h)is the specific moisture capacity function $[L^{-1}]$, K(h)is the unsaturated hydraulic conductivity $[LT^{-1}]$, 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. 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 [3]:

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

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

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

P= one the seepage surface

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.

2.3. GFF Model

2.3.1. Feed-Forward Neural Networks

Feed-forward networks have the following characteristics:

1. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence are called hidden layers.

2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed forward" from one layer to the next and this explains why these networks are called feed-forward networks.

3. There is no connection among perceptrons in the same layer.

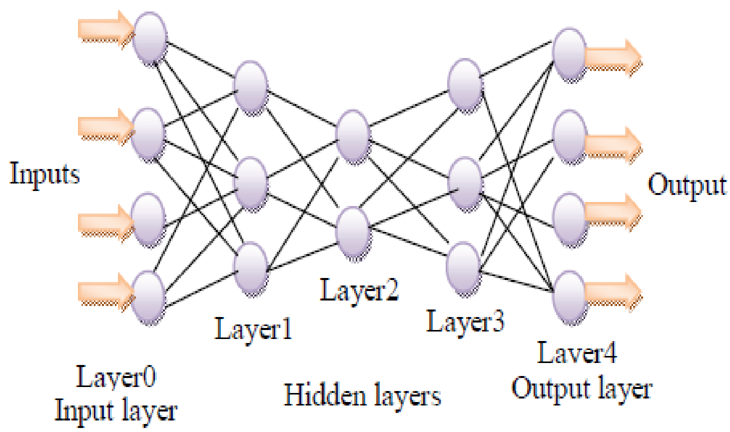

Fig. 2. Feed forward network.

The intended scenarios for activity function and training algorithm in the GFF network are exactly similar to MLP networks.

2.4. RBF (Radial Basis Function Network) Model

In the field of mathematical modeling, a radial basis function network is an artificial neural network that uses radial basis functions (RBF) as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many usages, including function approximation, time series prediction, classification, and system control. They were first formulated in a 1988 paper by Broom head and Lowe, both researchers at the Royal Signals and Radar establishment.

Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modeled as a vector of real numbers. The output of the network is then a scalar function of the input vector, and is given by where is the number of neurons in the hidden layer, is the center vector for neuron, and is the weight of neuron functions in the linear output neuron. Functions that depend only on the distance from a center vector are radially symmetric about that vector, hence the name radial basis function. In the basic form all inputs are connected to each hidden neuron. The norm is typically taken to be the Euclidean distance (although the Mahalanobis distance appears to perform better in general) and the radial basis function is commonly taken to be Gaussian. The Gaussian basis functions are local to the center vector in the sense that i.e. changing parameters of one neuron has only a small effect for input values that are far away from the center of that neuron. Given certain mild conditions on the shape of the activation function, RBF networks are universal approximators on a compact subset of [2]. This means that an RBF network with enough hidden neurons can approximate any continuous function on a closed, bounded set with arbitrary precision. The parameters are determined in a manner that optimizes the fit between the data.

2.4.1. Training

RBF networks are typically trained from pair of inputs and target values:

$$x(t), y(t), t = 1, \dots, T \tag{5}$$

by a two-step algorithm. In the first step, the center vectors C_i of the RBF functions in the hidden layer are chosen. This step can be performed in several ways; centers can be randomly sampled from some set of examples, or they can be determined using k-means clustering. Note that this step is unsupervised. A third back-propagation step can be performed to fine-tune all of the RBF net's parameters [1].

The second step simply fits a linear model with coefficients to the hidden layer's outputs with respect to some objective function. A common objective function, at least for regression/function estimation, is the least squares function:

$$K(w) \stackrel{\text{def}}{=} \sum_{t=1}^{T} K_t(w) \tag{6}$$

Where,

$$K_t(w) \stackrel{\text{def}}{=} [y(t) - \varphi(X(t), w)]^2 \tag{7}$$

The main structure of the RBF network consists of 3 layers, as in Fig. 3.

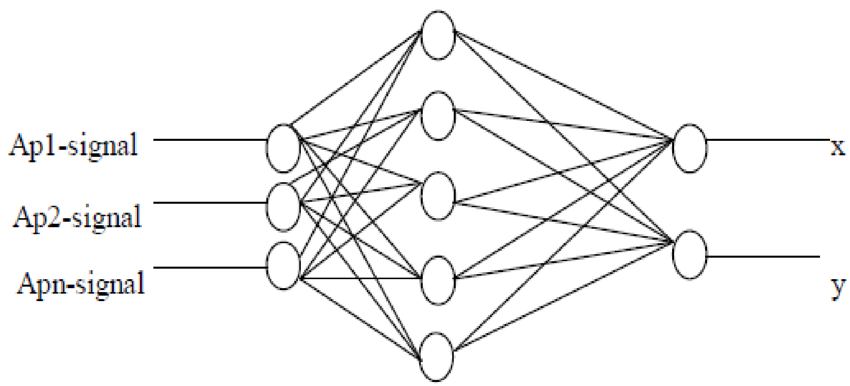

Fig. 3. Hidden layer (The weight associated with the cluster center and the output function are usually Gaussian).

2.4.2. Momentum Algorithm

Momentum algorithms in neural networks and the applications for solving linear systems are discussed. In this algorithm, we can consider the weight change law so that the weight change in the repetition of n depends on the size of the weight change in pervious repetition (equation 8):

$$\Delta W_{ji}(n) = \eta \delta_i X_{ji} + \alpha \Delta W_{ji}(n-1) \tag{8}$$

In which the amount of momentum α, like as $0 \leq \alpha \leq 1$.

2.4.3. Sigmoid Function

Sigmoid functions are often used in artificial neural networks to introduce nonlinearity in the model. A neural network element computes a linear combination of its input signals, and applies a sigmoid function to the result. Derivatives of the sigmoid function are usually employed in learning algorithms.

The non-linear transfer function, usually in the form of a sigmoid, is defined as follows:

$$f(s) = (1 + \exp(-s))^{-1} \tag{9}$$

y" output can be the result of the model or input of the next layer (in multilayer networks).

2.4.4. Levenberg–Marquardt Algorithm (LM)

In mathematics and computing, the Levenberg–Marquardt algorithm (LMA or just LM), also known as the damped least-squares (DLS) method, is used to solve non-linear least squares problems. These minimization problems arise especially in least squares curve fitting. The LMA is used in many software applications for solving generic curve fitting problems. However, as with many fitting algorithms, the LMA finds only a local minimum, which is not necessarily the global minimum. The LMA interpolates between the Gauss–Newton algorithm (GNA) and the method of gradient descent. The LMA is more robust than the GNA, which means that in many cases it finds a solution even if it starts very far off the final minimum. For well-behaved functions and reasonable starting parameters, the LMA tends to be a bit slower than the GNA. LMA can also be viewed as Gauss–Newton using a trust region approach. The algorithm was first published in 1944 by Kenneth Levenberg [17,18] while working at the Frankford Army Arsenal. It was rediscovered in 1963 by Donald Marquardt [7].

2.5. Datasets

For using data mining methods such as neural networks, Fuzzy models, programming genetics etc. the proper data set is required. Three attributes are required for each data set [19].

1) Reliablity, which means the data set should be real and accurate.

2) The numbers of data should be sufficeint according to the size and complexity of the problem.

3) Cover all aspects of the problem.

In this study, to measure the amount of seepage and water hole pressure of dam body, No. 4 electric piezometer was used. In order to evaluate the capability of 2 models of ANN, a 6 years monthly statistical data (2007 to 2013 years) was carried out for analysis. First, the relationship between the appropriateness of the variation in the water height of reservoir and the water hole pressure changes, deteriorated piezometer were identified and the data was discarded. The dataset used in this range consists of data collected over a period of 10 to 14 days and includes 80 different reading and a total 864 unique data, which is used in calculations.

In many references, divide data into training and testing, the two methods are 80 to 20 and 70 to 30 percent. The choice of each of these methods depends on the number of data and inputs, which is in this study, to train and test the proposed models, 80% (691 data) and 20% (174 data) of the dataset were used, respectively. This pair of data has been selected randomly from all possible historical couples by main training time continuity. The reason for random selection is to provide adequate training information for all events in the historical time series. Using the validation data, we can examine the effectiveness of trained model.

The relationship between the appropriateness of the variation in the water height of reservoir and the water hole pressure changes, deteriorated piezometer were identified and the data was discarded. Accordingly, the collected dataset was included 864 piezometric data. This collection includes information on the location of the piezometer (X, Y, Z), the piezometer readings and the water level behind the dam. In order to developing the model, the piezometer reading data was combined with the water height behind the dam and the input of the time interval ratio was considered as:

$$\text{Data Rate } (\alpha) = \frac{\text{Elevation } n_2 - \text{Elevation } n_1}{\Delta \text{ Data (Time}_2 - \text{Time}_1)} \quad (10)$$

Due to the large amount of data to train models, tried to divide the training data into categories 150, 300, 450, 600 and 864 to train the model training, so that, the minimum amount of data would lead to appropriate results. The input and output variables used along with statistical parameters in the ANN model are presented in two sets of training and test data in table 2.

Table 2. Statistical parameters related to training and testing.

Parameter	Statistic	Training data	Test data
X(m)	Max	56	56
	Mean	28.86	26.19
	Min	-34	-34
	Std Dev	24.47	28.88
Y(m)	Max	1400	1560
	Mean	1371	1524.67
	Min	1347	1500
	Std Dev	22.67	24.26
Z(m)	Max	320	320
	Mean	246.84	242.03
	Min	170	170
	Std Dev	74.99	74.98
Date Rate	Max	0.424	0.424
	Mean	-0.011	-0.016
	Min	-0.585	-0.585
	Std Dev	0.167	0.156
Elevation	Max	1406	1576.46
	Mean	1375	1548.46
	Min	1351	1520.69
	Std Dev	14.62	15.50
P (kPa)	Max	583.83	452.36

Communication weights and the constants between intermediate the inlet layer also the middle layer to the output for the optimal model selected with 6 neurons in the middle layer is shown in table 3 and 4. By using these coefficients and constants, by identifying data normalization and the transfer function used in network, one can simulate the neural network and use it to estimate piezometric pressure only with simple calculations.

Table 3. ANN model communication weights.

Hidden neurons	Connection weights					
	X (m)	Y(m)	Z(m)	Date Rate	Elevation	Output
1	-3.06	-2.21	-4.70	-3.37	-2.54	-0.04
2	7.28	-1.49	0.00	0.04	0.29	-0.35
3	-0.08	1.22	0.39	0.00	-0.11	-1.19
4	-2.94	-0.03	0.29	0.22	0.96	0.89
5	3.09	5.74	-4.57	-0.09	-0.74	-0.51
6	-2.95	-3.51	0.00	0.03	-0.78	-1.05

Table 4. Constants of the ANN model.

Bias							
Hidden neurons							Output
1	2	3	4	5	6		1
3.738	1.883	-0.360	-0.284	0.931	-1.558		-2.450

According to table 4, various statistical parameters consist of correlation coefficient (R2), root mean squared error (RMSE), average errors (Bias) and Dispersion indicators were used to evaluate the trained model. The results of this performance are shown in table 5.

Table 5. Statistical Parameters.

Statistical Parameter	Definition
Coefficient of determination	$R^2 = (1 - \frac{\sum_{i=1}^{n}(M_i - P_i)^2}{\sum_{i=1}^{n}(P_i - \overline{P}_i)^2}$
Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - M_i)^2}{n}}$
Scatter Index	$SI = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\frac{(P_i - M_i)^2}{\overline{M}}}$
Mean Bias Error	$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - M_i)$

Table 6. Evaluation ofproposed models by statistical parameters for various categories of training data.

Number of Data	R^2	RMSE(kPa)	Bias(kPa)	SI%
150	0.755	11.473	0.045	9.967
300	0.905	12.190	0.033	9.351
450	0.926	12.763	0.022	9.369
600	0.925	13.481	0.016	8.871
864	0.962	14.657	0.011	8.472

Also, according to the results, the correlation coefficient (R^2) increases from 0.9 (which is the appropriate indicator) as the data increases from 150 to 450. Hence, can be stated that the minimum data needed to train the models for presented and obtain the appropriate result is 300 data. However, given the 864 available training data and increase the power of model prediction, training was based on this number of data. After training the network and verifying it will be able to put out new data and provide an appropriate output. In Fig.4 the position of the No. 4 electric piezometer is shown schematically.

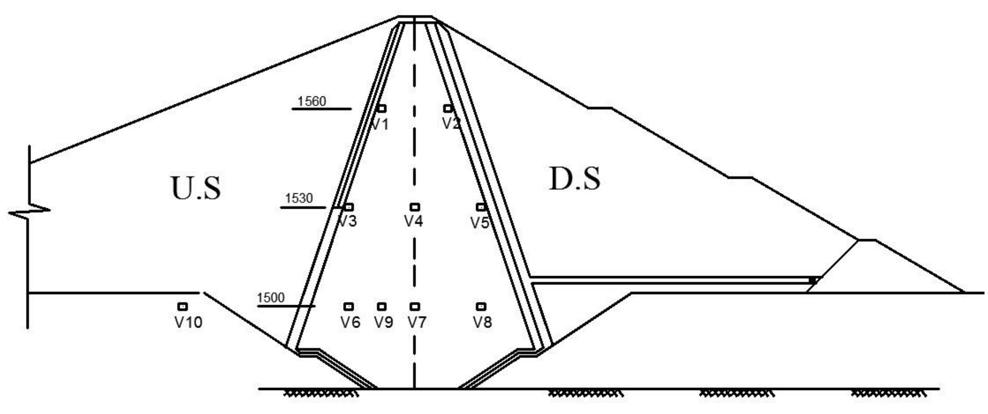

Fig.4. Position of Boukan Shahid Kazemi dam electric piezometers.

2.6. Evaluation Criteria

In order to compare the models with each other and evaluate them, we need indicators that can judge the function of the models in the entire datasets compared with the experimental results. In this study, correlation coefficient (R^2), mean absolute average error (MAE) and root mean square error (RMSE), NMSE, minimum and maximum absolute error were used serving this purpose.

3. Results and Discussion

3.1. Determining the best topology (number of training nodes and neurons, number of layers and appropriate function).

The purpose of determining the network topology is to determine the best number of nodes, the number of hidden layers, the training and testing functions and ultimately the type of network.

For this purpose, regression coefficient and error analysis were used.

In this section, the best chosen topology along with comparison graphs of observed and predicted values and the regression and error analysis tables for No.4 electric piezometer are presented.

In table 7, analysis of the error between the measured and predicted values which has been studied for No.4 electric piezometer is presented.

The best topology in this case is linear sigmoid tangent function with 1000 repetitions.

Table 7. Error Analysis between measured and predicted values of No. 4 electric piezometer.

Criterion	Values
MSE	6.982110
NMSE	1.587228
MAE	2.640323
Min Abs Error	3.9512691
Max Abs Error	0.101874
R^2	0.95844112

Figure 5, clearly illustrates the above mentioned.

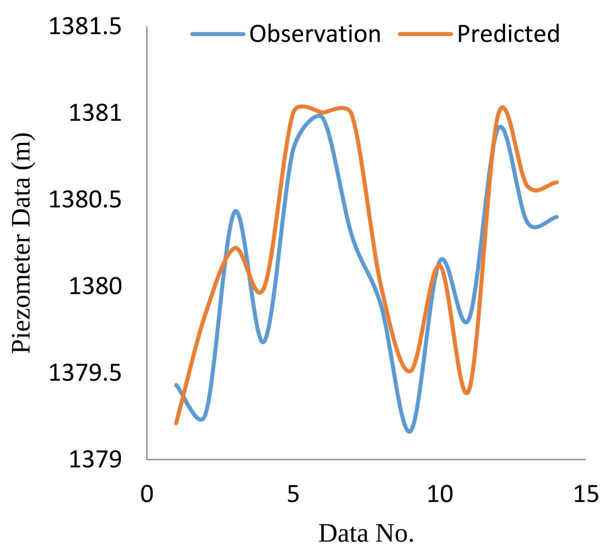

Fig. 5. Comparison between observed and predicted values of the No. 4 electric piezometer with the best ANN topology.

3.2. Determining the best hidden layer

An error analysis method was used to select the best hidden layer with different function. The layer with the lowest error is selected as the best layer. In this study, the network with the sigmoid activity function and one hidden layer yielded the most accurate result (table 8).

Table 8. Error Analysis between measured and predicted values of No. 4 electric piezometer, sigmoid function.

Values	Criterion		
MSE	1 hidden layer	2 hidden layer	3 hidden layer
	1.311258	3.982612	1.118929
NMSE	0.241968	0.254226	0.201178
MAE	0.947891	1.446697	0.829641
Min Abs Error	0.111467	0.028117	0.232968
Max Abs Error	2.293283	4.219126	2.232989
r	0.901897	0.871789	0.850914

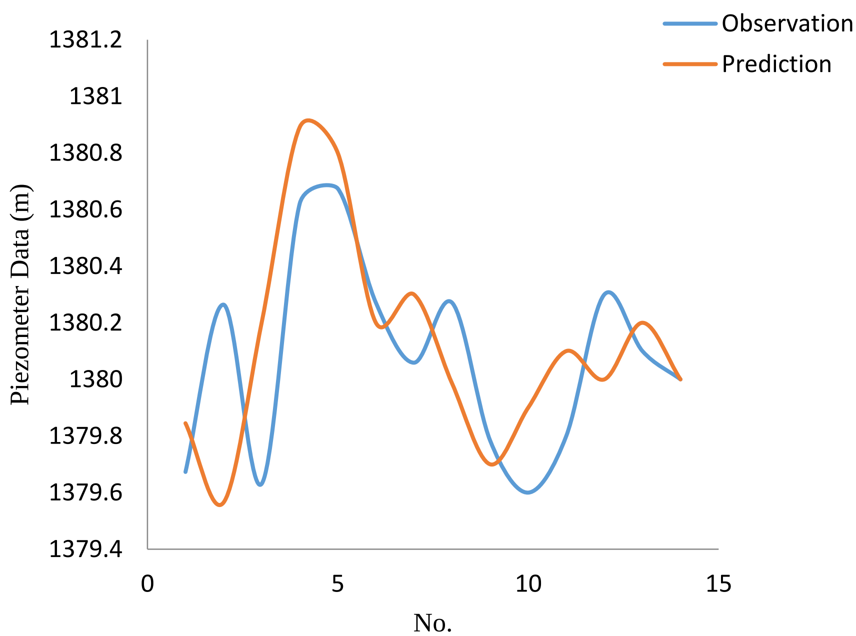

Fig. 6. Comparison of measured and predicted values of No. 4 electric piezometer, Linear sigmoid function with a hidden layer.

The results show the strength and accuracy of the ANN in predicting seepage from the dam body with a low predictive error and regression coefficient between the measured and predicted values more than 90%.

There were also different network topologies which are presented in table 8 ordered by their priorities.

Table 9. Error analysis of measured and predicted values for No. 4 electric piezometer.

Regression Coefficient	The Number of Training Nodes	The Number of Layer	The best Training function	Pizometer
0.9317	1000	1	Tangent Linear Sigmoid	Electric Piezometer
0.9309	5000	2	Linear Sigmoid	Electric Piezometer

3.3. Comparison of RBF and GFF Models in Predicting Seepage from Dam Body

The design of an ANN involves selecting the number of hidden layers and processor elements (neurons) for hidden layers, which is a trial and error process to obtain the best possible result for output.

3.3.1. Results from Training and Testing of ANN Model

In this study, water height parameters in reservoir were investigated as input variables in different networks. The output parameter in all networks was seepage from the dam body.

The number of 1000 cycles and the number of one hidden layer for the seepage parameter from the dam body were considered as appropriate ones.

The best results for each ANN models are presented in table 10.

Correlation of observed and predicted values with GFF and RBF models is shown in figures 7 and 8.

Table 10. Comparison of different networks in prediction of seepage from dam body.

Network Type	Transfer Function	Training Algorithm	Network Training Stage		Network Testing Stage	
			RMSE	R^2	RMSE	R^2
RBF	SigmoidAxon	momentum	0.038	0.79	33.12	0.88
GFF	SigmoidAxon	momentum	0.041	0.76	39.71	0.78

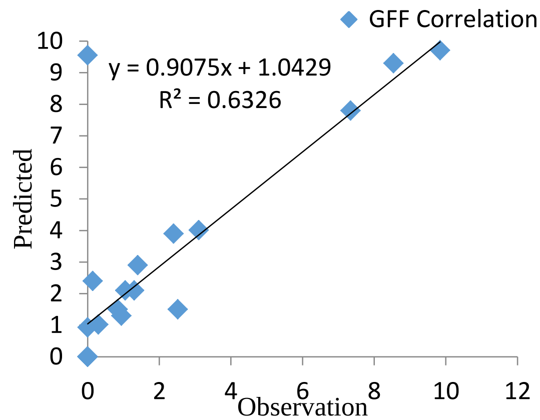

Fig.7. Correlation of observed and predicted values with GFF model.

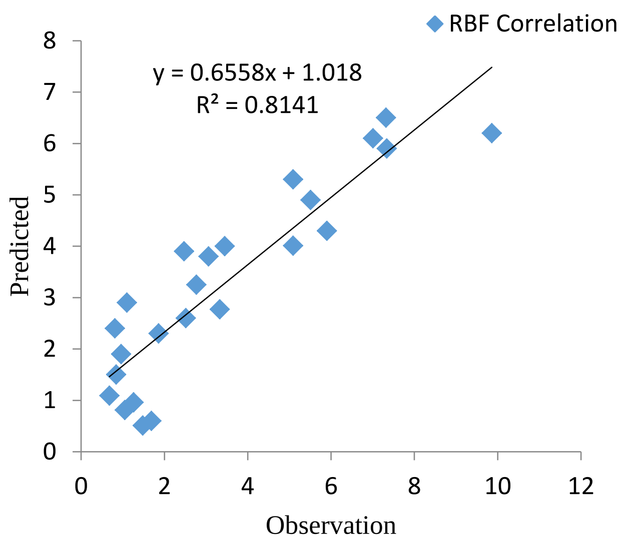

Fig.8. Correlation of observed and predicted values with RBF model.

As it is shown in the above figures, the RBF model has a better performance than the GFF model in predicting the seepage value from dam body.

According to the above diagrams, after comparing the results of RBF and GFF models, the RBF network (radial base function) with the discharge and reservoir water height parameters as the input is known as the best network.

The correlation coefficient obtained was 0.81 and the RMSE was 33.12.

3.4. Selecting the Best Model

Piezometer data (electric piezometer) was trained and tested by RBF and GFF neural network with different training algorithms, neurons and with 1 and 2 hidden layer. After applying different patterns and training the network, the best pattern was chosen from selected patterns.

Selecting criterion is the network that has the best training and provides satisfactory results.

Of course, in choosing a network, we need to be careful about occurrence of the preprocessing phenomenon, because in tests which the error approaches zero, network generalization will be unacceptable.

The results of this section for Boukan Shahid Kazemi dam are presented in table 11. After applying the test set to the selected networks, the generalization of the networks was examined and finally the network that showed the best generalization in the test setup, were considered as an optimal network for the existing data series from seepage of dam body.

According to the results presented in table 5, the GFF network with the Conjugate Gradient training and 8 hidden layers and RBF model with Levenberg-Marquardt and 4 hidden layers has got the best results. Also, in this study, the RBF model with Levenberg-Marquardt training was chosen as the best network according to R^2 and MSE.

Table 11. Selected test pattern among suggested patterns for Boukan Shahid Kazemi dam.

Verification Set R^2	Verification MSE	Test Set R^2	The Number of Second Hidden Layer Neurons	The Number of First Hidden Layer Neurons	Kind of Network Training	Type of Network
0.83	0.0976	0.874	–	4	Momentum	GFF
0.82	0.0825	0.873	10	8		
0.88	0.056	0.915	–	8	Conjugate Gradient	
0.86	0.06	0.869	8	5		
0.87	0.059	0.9	10	9		
0.87	0.057	0.965	–	2	Levenberg Marquardt	
0.86	0.063	0.98	4	2		
0.89	0.0518	0.9	–	5	Momentum	RBF
0.9	0.0464	0.898	–	6		
0.92	0.0389	0.896	–	8		
0.83	0.071	0.895	4	4		
0.91	0.0415	0.915	–	5	Conjugate Gradient	
0.92	0.034	0.9	–	10		
0.88	0.0478	0.926	8	5		
0.86	0.0565	0.91	5	6		
0.92	0.0437	0.999	–	4	Levenberg Marquardt	
0.95	0.0337	0.999	–	5		
0.88	0.055	0.998	5	5		
0.87	0.0748	1	9	7		

3.5. Comparison of optimization methods

In this study, the efficiency of the RBF (radial basis function network) model was compared with the results of the Nourani et. al. (2012) study, which investigated seepage from dam with ANN model. Comparison of RBF model with single network showed that the RBF model with the correlation coefficient (R^2) 0.81 gave better results, while the correlation coefficient (R^2) value of single network model is 0.798.

4. Conclusion

In this research, piezometric pressure was simulated in Boukan Shahid Kazemi'dam using artificial neural networks (ANNs) (Comparison between RBF and GFF models). This simulation was performed based on the dataset from electric piezometers (vibrating curvature) applied in the dam body. In this study, the accuracy of piezometers and their data has been checked before using those data.

Test result of suggested models of this paper showed that in finding the purpose of the problem, the introduced models perform successfully and operate in high speed. In this study, 1000 cycles for the seepage parameter of dam body was chosen as the appropriate one using trial and error technique. After running the models, the result showed that the artificial neural network RBF model (radial function) has better performance compare with the GFF model in predicting the seepage value of the dam. According to the obtained diagrams and after comparing the results of different networks, the radial base function (RBF) model with the discharge flow into the lake of dam and the height of water as inputs was known as the best network.

This network contained one hidden layer. The obtained R^2 was 0.81and the RMSE was 33.12. The results from running the proposed models in the MATLAB software have proved the capability of ANN in predicting the seepage from dam body.

Also, the results show the superiority of the RBF model compared with the other proposed model (GFF). The results indicate that RBF model provides very acceptable results for predicting seepage values from the dam body. Due to the differences in geometric and physical characteristics of embankment dam, in this study, such characteristics were not considered as inputs and only the seepage of Boukan Shahid Kazemi's dam was investigated.

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