Seepage Modeling via Hybrid Soft Computing Methods

Vahid Nourani and Elnaz Sharghi

Abstract—In this paper, several artificial intelligence (AI) models were employed to model seepage through Sattarkhan earth fill dam. For this purpose, measured data of several piezometers of the dam were employed, and then single models for each piezometer was presented based on two scenarios with different inputs. Next, ensemble models were developed to improve predicting performance. Afterwards, the results of the models were compared. The obtained results indicated that model ensemble led to a promising improvement in its performance for seepage modeling. Moreover, by comparison the both scenarios, it is concluded that in case of a failure of a piezometer, other piezometers can be used in modeling.

Keywords—Seepage, Earth Fill Dam Seepage, Ensemble, Artificial Intelligence, Artificial Neural Network, Support Vector Machine, Adaptive Neural Fuzzy Inference System, Sattarkhan Earth Fill Dam

I. Introduction

Since early days of civilization, capturing and storing water was an essential element to survival; for this purpose, dam construction on the rivers get common. Earth fill dams are the most common type of dams; because constraining of these dams is affordable and could be built on most foundations and earth fill dams in comparison to other types of dams are more economical. Like most of engineering structures, earth dams may fail due to faulty design, improper construction and poor maintenance practices, etc. The various causes of failure may be classified as seepage failure, hydraulic failure, structural failure. According to the failure of dams, 58% of the damage caused by seepage problems that take place in the dam body or foundation of this type of dams [1]. Seepage always occurs in the dams; however, if seepage is concentrated or uncontrolled beyond limits, it will lead to failure of the dam. Although physical-based and conceptual models are the main tools for investigating this problem, they have a number of practical limitations, including the need for large amounts of field data, and a detailed understanding of the underlying physical process [2].

Vahid Nourani and Elnaz Sharghi are with the Dept. of Water Resources Eng., Faculty of Civil Eng., University of Tabriz, Tabriz, Iran, nourani@tabrizu.ac.ir, elnaz_sharghi@yahoo.com

Due to these problems, use of black box models can be useful. Artificial Intelligence (AI) such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Adaptive Neural Fuzzy Inference System (ANFIS) are relatively new black box methods. Nowadays Artificial Intelligence, as a self-learning and self-adaptive function approximator, has shown great ability in modeling nonlinear time series and this method is widely used in hydrology and water resource studies. For instance, Tayfur et al. [3] developed a finite element method (FEM) and ANN model to simulate flow through Jeziorsko earth fill dam in Poland. Nourani et al. [4] analyzed Piezometric heads in the core of Sattarkhan earth fill dam in Iran via ANN model. Novakovic et al. [5] used a neuro - fuzzy model to predict the water level in piezometers of the Iron Gate 2 dam. Rankovic et al. [6] developed a support vector regression identification model for prediction of dam structural behavior.

One of the major developments in neural networks over the last decade is the model combining or ensemble modeling. By combining different models, different aspects of the underlying patterns may be captured. The concept of model combination was discussed and used in different works. for example, Shamseldin et al. [7] have examined 3 different combination methods in the context of flood forecasting. Zhang [8] proposed a hybrid neural-ARIMA model for time series forecasting.

In this paper ANN, SVM and ANFIS models employed for analysis of Sattarkhan dam seepage based on 2 scenarios with different inputs. Then ensemble models formed via outputs of the mentioned models for each scenario to improve predicting performance and the obtained results were compared.

II. Materials and Methods

A. Sattarkhan Earth Fill Dam

Sattarkhan earth fill dam is a reservoir dam that was constructed in Iran's East Azerbaijan Province on Ahar Chai River. The height of the dam is 78 m above the bed rock and its crest length is 340 m and volume of reservoir is 131.5 million m3 when the water level is at normal level. At the four cross sections of the dam several electrical piezometers have been placed. In this paper data of piezometers No. 207, 212, 216 and 217 are used. Fig. 1, shows the piezometers positions of section No. 2.

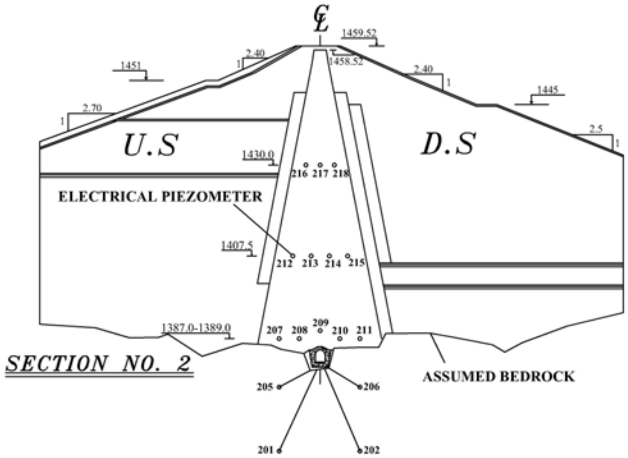

Fig. 1. Piezometers' position of cross section No. 2.

B. *Proposed Methodology*

In the proposed method in this study first ANN, SVM and ANFIS models are created and trained, based on two scenarios. Then ensemble models have been formed via outputs of the single models to improve predicting performance. In this methodology AI models were used for predicting seepage in time, but forecasting seepage could be useful as well.

1) First scenario was a Multi-Input and Single-Output (MISO) approach. In scenario 1, it was tried to model the piezometric heads using each piezometer's data, and also upstream level. Where the prediction of the piezometer's head was patterned as follows:

$$P_t^i = f_n(P_{t-1}^i, P_{t-2}^i, ..., P_{t-n}^i, h_t, h_{t-1}, ..., h_{t-m}) \qquad (1)$$

Where head of piezometer i in time t (P^i_t) is the function (f_n) of ith piezometer head in previous times (*t-1, t-2, ...*) up to lag time n and upstream level in time t (h_t) and previous times (*t-1, t-2, ...*) up to lag time m. The dominant lag times were determined through trial-error procedure. It was found that each piezometer's head in time t is mostly correlated with the piezometer's head in time t-1 and upstream level in time t.

2) In scenario 2, as another MISO modeling, 2 other piezometer's data and upstream level were employed to model each piezometer. In a way that head of piezometer i was related to sub-series of upstream level and two other piezometers:

$$P_t^i = f_n(P_{t-1}^j, ..., P_{t-n}^j, P_{t-1}^k, ..., P_{t-r}^k, h_t, h_{t-1}, ..., h_{t-m}) \quad (2)$$

Where P^j_{t-n} and P^k_{t-r} are sub-series of jth and kth piezometers up to lag time n and r, respectively. Correlation coefficient was employed here for identification of proper piezometers. In this scenario like scenario 1, the dominant lag times were determined through trial-error procedure. Thus, upstream level in time t and 2 other piezometer's data in time t, as input data were employed to create and train the models. This scenario can be a helpful approach when some of piezometers failed during operation, and thus other piezometers could be used in modeling.

C. *Feed Forward Neural Network (FFNN)*

The feedforward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, and there are no cycles or loops in the network. The FFNN is widely applied in hydrology and water resource studies as a forecasting tool. It has already been demonstrated that an FFNN model trained by the back-propagation (BP) algorithm with three layers is satisfactory for forecasting, predicting and simulating in any engineering problem [9,10]. The explicit expression for an output value of a three layered FFBP is given by [4]:

$$\hat{y}_k = f_0\left[\sum_{j=1}^{M_N} w_{kj}.f_h\left(\sum_{i=1}^{N_N} w_{ji}x_i + w_{j0}\right) + w_{k0}\right] \qquad (3)$$

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_N 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 [4].

D. *Adaptive Neural Fuzzy Inference System (ANFIS)*

ANFIS as a hybrid model is formed of a fuzzy system combined with a feed forward network. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. In the simplest way, a cooperative model can be considered as a preprocessor where in ANN learning mechanism determines the fuzzy inference system (FIS) membership functions or fuzzy rules from the training data [11]. Each fuzzy system contains three main parts, fuzzifier, fuzzy data base and defuzzifier. Fuzzy data base contains two main parts, fuzzy rule base, and inference engine. In fuzzy rule base, rules related to fuzzy propositions. Thereafter, analysis operation is applied by fuzzy inference engine. There are several fuzzy inference engines which can be employed for this goal, which Sugeno and Mamdani are the two of well-known ones [10,12]. Neuro-fuzzy simulation refers to the algorithm of applying different learning techniques produced in the neural network literature to fuzzy modeling or a fuzzy inference system (FIS) [13,14]. This is done by fuzzification of the input through membership functions, where a curved relationship maps the input value within the interval of [0–1]. The parameters associated with input as well as output membership functions are trained using a technique like back-propagation and/or least squares [14].

E. Support Vector Regression (SVR)

The support-vector network is a relatively new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high dimension feature space [15]. A version of a SVM for regression has been proposed in 1997 by Vapnik, Steven Golowich, and Alex Smola [16]. This method is called support vector regression. SVR is the most common application form of SVMs [17]. In SVR, the goal is to do a linear regression and then linear regression combines with a kernel and a non-linear regression obtain, according to the following equation [18]:

$$y = \sum_i (\alpha_i^+ - \alpha_j^-) k(x_i, x_j) + b \tag{4}$$

Where α_i^+ and α_j^- are Lagrange multipliers, $k(x_i, x_j)$ is the kernel function performing the non-linear mapping into feature space and b is bias term. One commonly used kernel function is the Gaussian Radial Basis Function (RBF) kernel, according to the following equation [19]:

$$k(x_1, x_2) = \exp(-\lambda \| x_1 - x_2 \|^2) \tag{5}$$

where the free parameter λ is the kernel parameter. Through this mapping on to a higher dimensional space, the training data can be approximated to a linear function [19].

F. Ensemble

It is well known that a combination of many different predictors can improve predictions. The basic idea of model combination in predicting is to use each model's unique features to capture different patterns in the data. Both theoretical and empirical findings suggest that combining different methods can be an efficient way to improve forecasting and predicting [8]. Most often the networks in the ensemble are trained individually and then their predictions are combined. This combination is usually done by simple averaging (in regression), but one can also use a weighted combination of the networks [20,21].

The ensemble consists of n models and the output of model i on input x is called $f_i(x)$. In simple ensemble model, combination is done by simple averaging, and the weighted ensemble average is denoted as following [21]:

$$\bar{f}(x) = \sum_i^n w_i f_i(x) \tag{6}$$

Where $f(x)$ is output of weighted ensemble model, $f_i(x)$ is output of ith single model (output of ANN, ANFIS and SVR) and w_i is the weight that is determined based on the determination coefficient (DC) of single models. It need to be mentioned that the weights should have positive value and the summation of them should be one. Nonlinear ensemble model is determined by ANN. A schematic diagram of the ensemble model is shown in Fig. 2.

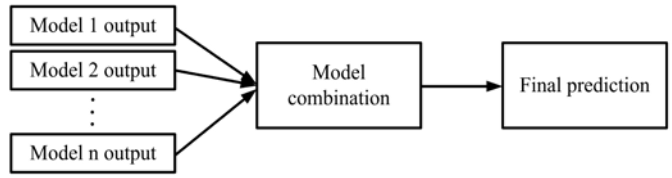

Fig. 2. Schematic of ensemble model.

G. Efficiency criteria

Two different criteria were used to measure the efficiency of the modeling; the determination coefficient (DC) and root mean square error (RMSE). They are calculated as [22]:

$$DC = 1 - \frac{\sum_{i=1}^{n} (o_{obs_i} - o_{com_i})^2}{\sum_{i=1}^{n} (o_{obs_i} - \bar{o}_{obs})^2} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (o_{obs_i} - o_{com_i})^2}{n}} \tag{8}$$

Where n, o_{obs}, $\bar{o}_{obs}$ and o_{com} are data number, observed data, averaged value of the observed data and calculated values, respectively.

III. RESULTS AND DISCUSSION

At first, the multi-layer perceptron (MLP) feed forward back propagation network created and trained by scaled conjugate gradient optimization algorithm for piezometers No. 207 and 217 by 70% of each piezometers datasets for scenario 1 and also a Tangent Sigmoid transfer function was used for hidden layer and the output layer. In addition to changing the number of neurons in the hidden layer, changing of training epoch has been investigated to get the optimum ANN. After that, efficiency of the models has been verified by the remaining 30% of datasets. In ANFIS modeling, Sugeno fuzzy inference system was considered and trained using hybrid optimization algorithm. ANFIS models were designed by Gaussian combination membership function for piezometer no. 207 and Triangular-shaped membership function for piezometer no. 217. To continue, SVR models were designed by RBF kernel for mentioned piezometers. In ANFIS and SVR models like ANN models, efficiency of the models has been verified and optimum models have been got too.

In scenario 2 correlation coefficient was applied to determine the dominant piezometers between piezometers of sec. 2 and piezometer no. 207 and 217. So piezometers no. 212 and 216 were employed for modeling of piezometer no. 207, and piezometers no. 207 and 216 were used for modeling piezometer no. 217. In scenario 2, ANN, ANFIS and SVR models, such as scenario 1 were designed. The results of ANN, ANFIS and SVR models have been summarized in Tables 1-3.

TABLE I. RESULTS OF ANN MODEL

Piezometer	Scenario	Network Structure [a]	Overall DC	Overall RMSE (m)
Piz. 207	Scenario 1	2-4-1	0.9535	0.7252
	Scenario 2	3-10-1	0.9671	0.6140
Piz. 217	Scenario 1	2-8-1	0.9121	0.6660
	Scenario 2	3-3-1	0.9495	0.5028

[a] The first, second and third numbers represent input, hidden and output neurons, respectively.

TABLE II. RESULTS OF ANFIS MODEL

Piezometer	Scenario	MF	Overall DC	Overall RMSE (m)
Piz. 207	Scenario 1	Gaussian	0.9566	0.7068
	Scenario 2	Gaussian	0.9637	0.6464
Piz. 217	Scenario 1	Triangular	0.9082	0.6776
	Scenario 2	Triangular	0.9449	0.5276

TABLE III. RESULTS OF SVR MODEL

Piezometer	Scenario	RBF-Kernel Parameter (γ)	Overall DC	Overall RMSE (m)
Piz. 207	Scenario 1	0.5	0.9502	0.7577
	Scenario 2	0.33	0.9507	0.7464
Piz. 217	Scenario 1	0.33	0.9170	0.6444
	Scenario 2	0.5	0.9468	0.5184

According to the results of two scenarios, in scenario 2 although the data of each piezometer have not been used in input variables, but performance of scenario 2 because of using synchronous data with targets and using of 2 piezometers for modeling, is better than scenario 1. The results of models show that each model has better ability in modeling of different scenarios and different piezometers. Thus, by combining different models, predicting performance can be improved over the single models. In the next step, results of models were used to create simple ensemble model, weighted ensemble model and nonlinear ensemble model to improve predicting performance for each scenario. In this step, ensemble models have been formed for scenario 1, based on four different combinations of models as follow:

Comb. 1: ANN, ANFIS

Comb. 2: ANN, SVR

Comb. 3: ANFIS, SVR

Comb. 4: ANN, ANFIS, SVR

Then according to the results of scenario 1, ensemble models for best combinations have been formed for scenario 2. Obtained results of both scenarios have been tabulated in Tables 4-6. Fig. 3 shows the Time-series of the observed and computed water heads of piezometer No.207 and 217 by ANN ensemble models for both training and verification steps.

TABLE IV. RESULTS OF SIMPLE ENSEMBLE MODEL

Piezometer	Scenario	Best comb.	Overall DC	Overall RMSE (m)
Piz. 207	Scenario 1	Comb. 1	0.9599	0.6731
	Scenario 2	Comb. 1	0.9677	0.6045
Piz. 217	Scenario 1	Comb. 2	0.9190	0.6366
	Scenario 2	Comb. 2	0.9495	0.5030

TABLE V. RESULTS OF WEIGHTED ENSEMBLE MODEL

Piezometer	Scenario	Best comb.	Overall DC	Overall RMSE (m)
Piz. 207	Scenario 1	Comb. 1	0.9599	0.6733
	Scenario 2	Comb. 1	0.9677	0.6044
Piz. 217	Scenario 1	Comb. 2	0.9190	0.6366
	Scenario 2	Comb. 2	0.9495	0.5029

TABLE VI. RESULTS OF NONLINEAR ENSEMBLE MODEL

Piezometer	Scenario	Best comb.	Overall DC	Overall RMSE (m)
Piz. 207	Scenario 1	Comb. 4	0.9661	0.6190
	Scenario 2	Comb. 4	0.9693	0.5889
Piz. 217	Scenario 1	Comb. 4	0.9236	0.6182
	Scenario 2	Comb. 4	0.9534	0.4828

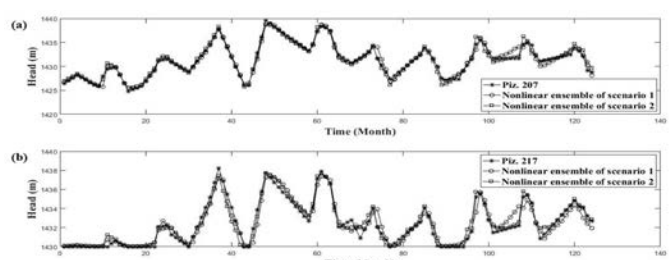

Fig. 3. Time-series of the observed and computed water heads by ANN ensemble models for both training and verification steps. (a) piezometer No.207; (b) piezometer No. 217.

The results of ensemble models indicated that almost all of the ensemble models produced better outcomes than single models. Each model has advantages and disadvantages but ensemble models because of using each component model's unique capability, simulate the phenomenon better than single models. As it can be seen from Table 2, the results of simple and weighted ensemble models are very close together, which may be because of the close results of the single models. On the other hand, the performance of the nonlinear ensemble is better than other ensembles; in nonlinear ensemble because of employing ANN, simulation of the nonlinear behavior of the phenomenon would be more accurate than other ensemble models.

IV. Conclusion

In this paper Sattarkhan dam piezometric heights have been analyzed via artificial neural network, support vector machine and adaptive neural fuzzy inference system model, based on two scenarios. Then ensemble models have been formed via outputs of the single models to improve predicting performance. Finally, the results were compared. Overall, the results of this study provide promising evidence for combining models. Ensemble models produced better approximation than the single models. By employing the ANN model in ensemble models, the developed models had a non-linear kernel so that they could simulate the non-linear behavior of the phenomenon more accurately than other linear ensemble models. Furthermore, the effect of using other piezometers in modeling performance was investigated. Results showed that in case of a failure of a piezometer, other piezometers can be used in modeling.

References

[1] L.M. Zhang, Y. Xu, J.S. Jia, "Analysis of earth dam failures: A database approach," Georisk, Vol. 3, pp. 184-189, September 2009.

[2] V. Nourani, A.H. Baghanam, F.D. Vousoughi, M.T. Alami, "Classification of groundwater level data using SOM to develop ANN-based forecasting model," Int. J. Soft. Comput. Eng., Vol. 2, pp. 464-469, March 2012.

[3] G. Tayfure, D. Swiatek, A. Wita, V.P. Singh, "Case study: finite element method and artificial neural network models for flow through Jeziorsko earthfill dam in Poland," J. Hydraul. Eng., Vol. 131, pp. 431–440, June 2005.

[4] V. Nourani, E. Sharghi, M.H. Aminfar, "Integrated ANN model for earthfill dams seepage analysis: Sattarkhan Dam in Iran," J. Artif. Intell. Res., Vol. 1, pp. 22-37, August 2012.

[5] A. Novaković, V. Ranković, N. Grujović, D. Divac, N. Milivojević, "Development of neuro-fuzzy model for dam seepage analysis," Annals of the faculty of engineering Hunedoara, Vol. 12, pp.133-136, April 2014.

[6] V. Ranković, N. Grujović, D. Divac, N. Milivojević, "Development of support vector regression identification model for prediction of dam structural behavior," Struct. Saf., Vol. 48, pp. 33-39, May 2014.

[7] A.Y. Shamseldin, K.M. O'Connor, G.C. Liang, "Methods for combining the outputs of different rainfall-runoff models," J. Hydrol., Vol. 197, pp. 203-229, October 1997.

[8] G.P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," Neurocomputing, Vol. 50, pp. 159–175, January 2003.

[9] K. Hornik, M. Stinchcombe, H. White, "Multilayer feedforward networks are universal approximators," Neural Netw., Vol. 2, pp. 359-366, December 1989.

[10] V. Nourani, Ö. Kisi, M. Komasi, "Two hybrid artificial intelligence approaches for modeling rainfall–runoff process," J. Hydrol., Vol. 402, pp. 41-59, May 2011.

[11] A. Abraham, "Adaptation of fuzzy inference system using neural learning," in Fuzzy systems engineering: theory and practice, N. Nedjah and LdeM. Mourelle, Eds. Berlin: Springer, 2005. pp. 53-83.

[12] J.Y. Lin, C.T. Cheng, Y.G. Sun, K. Chau, "Long-term prediction of discharges in Manwan hydropower using adaptive-network-based fuzzy inference systems models," Lect. Notes Comput. Sci., Vol. 3612, pp. 1152–1161, 2005.

[13] M. Brown, C.J. Harris, Neuro-fuzzy adaptive modelling and control, New Jersey: Prentice-Hall, 1994.

[14] T. Rajaee, S.A. Mirbagheri, M. Zounemat-Kermani, V. Nourani, "Daily suspended sediment concentration simulation using ANN and neuro-fuzzy models," Sci. Total Environ., Vol. 407, pp. 4916-4927, August 2009.

[15] C. Cortes, V. Vapnik, "Support-vector networks," Mach. Learn., Vol. 20, pp. 273-297, 1995.

[16] V. Vapnik, S.E. Golowich, A. Smola, "Support vector method for function approximation, regression estimation, and signal processing," Neural Information Processing Systems 9, pp. 281-287, September 1997.

[17] D. Basak, S. Pal, D.C. Patranabis, "Support vector regression," Neural Information Processing-Letters and Reviews, Vol. 11, pp. 203-224, October 2007.

[18] SR. Gunn, Support vector machines for classification and regression, Southampton: University of Southampton, 1998.

[19] Y. Liu, G. Pender, "A flood inundation modelling using v-support vector machine regression model," Eng. Appl. Artif. Intell., Vol. 46, pp. 223-231, November 2015.

[20] D.H. Wolpert, "Stacked generalization," Neural Netw., Vol. 5, pp. 241-259, December 1992.

[21] A. Krogh, J. Vedelsby, "Neural network ensembles, cross validation, and active learning," Advances in neural information processing systems 7, 231-238, May 1995.

[22] V. Nourani, A.H. Baghanam, J. Adamowski, M. Gebremichael, "Using self-organizing maps and wavelet transforms for space–time pre-processing of satellite precipitation and runoff data in neural network based rainfall–runoff modelling," J. Hydrol., Vol. 476, pp. 228-243, January 2013.