NEURAL NETWORK TO PREDICTION OF EARTHEN DAM PEAK BREACH OUTFLOW AND BREACH TIME

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There are a number of models have been developed and employed over the years to estimate the effects of a dam breach and the resultant flood. The embankment dams breach has many serious consequences such as financial damages, life losses, environmental problems, huge floods, sedimentation, ... So in order to decrease and control these events, many attempts and studies have been done on the base of breach analysis and the outflow hydrograph determination by Walder and O'Connor (1997), Froehlich(1995), Von Thun &Illette(1990) and some models have developed. These have included physical scale models and mathematical or computer models. Among the more widely used dam breach computer models over decades is the dam-break flood forecasting model (DAMBRK). DAMBRK is a physically based mathematical model to predict the breach characteristics (size, time of formation) and the discharge hydrograph emanating from a breached earthen dam is presented. The model was developed by the National Weather Service in mid-1970's and improved throughout the 1980's (Fread, 1977, 1988, 1992). DAMBRK simulates the outflow from a reservoir and through the downstream resulting from a developing breach in a dam. It is based on erosion, soil mechanic equations, hydraulic laws and sediment transportation. As such, the model is not one that can easily be employed this difficulty led to use other powerful methods.

In this study a new method has been developed for prediction peak breach outflow and breach time by Artificial Neural Networks (ANNs). Artificial Neural Networks (ANNs) are a form of artificial intelligence attempt to mimic the behavior of the human brain and nervous system. ANNs learn from data examples presented to them and use these data to adjust their weights in an attempt to capture the relationship between the model input variables and the corresponding outputs. Consequently, ANNs do not need any prior knowledge about the nature of the relationship between the input/outputs variables, which is one of the benefits that ANNs have compared with most empirical and statistical methods. The application of ANNs to forecast Breach parameters consisted of two steps. The first step was the training of the neural networks. In this study the back propagation multiplayer which exists in neural network toolbox of MATLAB software ver.6.5 was used.

For this purpose synthetic breach parameters of about 115 dams were developed by DAMBRK model and they were used to train and test the neural networks. The training set consisted of 92 cases, while the test set of 23 cases. For each hidden layer various architecture patterns were employed and for that architecture the best R value (correlation coefficient) was considered. Upon successful completion of the learning stage of the analysis, the verification of each specified architecture is investigated. Three separate models, listed in Table 1 were examined.

The neural network analysis for breach parameters assessment for three models are presented in this paper. The network architectures for these three models are given in Tables 2 and 3.

Table 1. Input parameter for models used

Model	Input Parameters
1	H_U, Q, RSA, Z_U, Z_D, Z_C, RCL
2	H_U, Q, RSA, RCL
3	H_U, Q, RSA

Table 2. A summary of network training and testing results for peak breach outflow forecasting

Qp	TRAIN			TEST			Architectures
	R	MAE	RMSE	R	MAE	RMSE	Layers
Model 1	0.992	0.012	0.022	0.909	0.019	0.027	(8-3-1)
Model 2	0.984	0.010	0.018	0.982	0.044	0.079	(4-13-1)
Model 3	0.968	0.014	0.026	0.986	0.034	0.062	(3-7-1)

Table 3. A summary of network training and testing results for breach time forecasting

t_f	TRAIN			TEST			Architectures
	R	MAE	RMSE	R	MAE	RMSE	Layers
Model 1	0.993	0.013	0.023	0.883	0.086	0.170	(7-1-1)
Model 2	0.946	0.041	0.063	0.655	0.083	0.143	(4-7-1)
Model 3	0.881	0.056	0.091	0.833	0.047	0.089	(3-5-1)

The performance of the network models is investigated by changing input parameters. The most efficient and global model for assessing dam breach potential and the most significant input parameters affecting dam breach are summarized. The most compatible structure for breach outflow prediction have 8 neurons in the first layer , 3 neurons in the middle layer and 1 neuron in the output layer(8-3-1 structure) with correlation coefficient 0.992,0.909 for training and testing respectively.

For breach time a 7-1-1 structure has correlation coefficient 0.993, 0.884 for training and testing respectively. Upon completion of the learning stage and verification stage successfully, a forecast or prediction study is investigated. To illustrate the application of the ANN results, a case study is presented. For forecast study Mollasadra earthen dam is located on the Koor reviver about 125 km northwest of Shiraz in Fars Province, south of Iran is selected. The dam is a zoned-earthfill structure with a structural height of 72 m. Comparisons between the artificial neural network results and dam DAMBRK model are made. The results indicate that neural networks are useful for predicting dam breach parameters.

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