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Simulation of soil stress in earth dams using artificial intelligence models and determination of effective features

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ABSTRACT: The general purpose of this paper is to select effective features and model soil stress in earth dams during construction. Five features, including fill level, duration of construction, reservoir level (impoundment), impounding rate and fill rate, were selected as hybrid model inputs. By performing hybrid algorithm and sensitivity analysis and feature selection method, fill level and duration of construction were recognized as the most effective features in modeling the total stress in selected cells, because concurrent mean square error values for the fill level and duration of construction in TPC25.1, TPC25.3 and TPC25.4 cells were 1.523, 2.747 and 0.750, respectively. In TPC25.2 cell, three features including fill level, duration of construction and impoundment level, had the greatest effect in modeling the total soil stress based on the mean square error value of 5.245. Comparison of the results of the ANN model with ANFIS and GEP showed that although the difference in the accuracy of the models is very small, all three models had acceptable results in the test step, the ANFIS model results indicated that the statistical error measures of R^2, RMSE, MAE and NS in TPC25.4 cell were 0.9955, 0.0227, 0.0185 and 0.9666, respectively. It showed that how much the input data are more scattered, the ANFIS model had more capability than ANN and GEP models to simulate the soil stress in the studied earth dam.

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1- Introduction

Instrumentation during the construction of earth dams is used to ensure safety, minimize construction costs and control construction methods for better measurement of committees [1]. Nowadays, the use of new methods such as artificial intelligence and meta-heuristic algorithms is very important in the analysis and evaluation of engineering and executive designs [2]. In this research, different parameters as inputs to artificial intelligence models for simulating the soil stress during the construction of earth dams were proposed and the superior model among the ANN, ANFIS and GEP models was identified based on statistical error measures.

2- Materials and methods

For the present study, the recorded data in Kaboudwal Dam, located in Golestan Province [3], were used during the dam construction.

2- 1- Hybrid particle swarm algorithm - artificial neural network

In this study, fill level (F) (m.a.s.l), reservoir water level (R) (m.a.s.l), duration of dam construction (T) (day), fill rate ((m.a.s.l)/day) and impounding rate ((m.a.s.l)/day) were selected as inputs, and vertical soil stress P (kPa) during the construction was considered as the output of the models. A meta-heuristic algorithm was combined with a nonlinear modeling method such as an artificial neural network and a hybrid algorithm that can simulate complex and nonlinear relationships well and has the capability to identify the effective features with appropriate accuracy. The data were randomly divided into two parts: training (70%) and test (30%) and the weighted average errors in all cells were used to calculate the model error as follows:

$$Error_f = 0.8 error_{tr} + 0.2 error_{te} \quad (1)$$

In which, $Error_f$، $error_{tr}$ and $error_{te}$ are total model error for different subsets of features, training data error, and testing data error, respectively.

2- 2- Modeling of total stress with ANN model

According to Table 3 and the values of statistical error measures in both training and test steps, the ANN model is superior in modeling the target variable (total stress). Comparison of ANN model with ANFIS and GEP Tables 3 and 4 show the values of statistical error measures for different soil stress models in the training and test steps. According to the statistical error measures for different models and considering the results of Tables 2 and 3 in different cells, although the differences in the accuracy of the models are very small, all three models have acceptable and satisfactory results.

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Table 1. Optimal values of PSO algorithm

Max Iteration	Number of Population (search agent)	Range partitions	Swarm Size	Cognition coefficient (c1)	Social Coefficient (c2)
1000	100	LB=0; UB=1	10	2	2

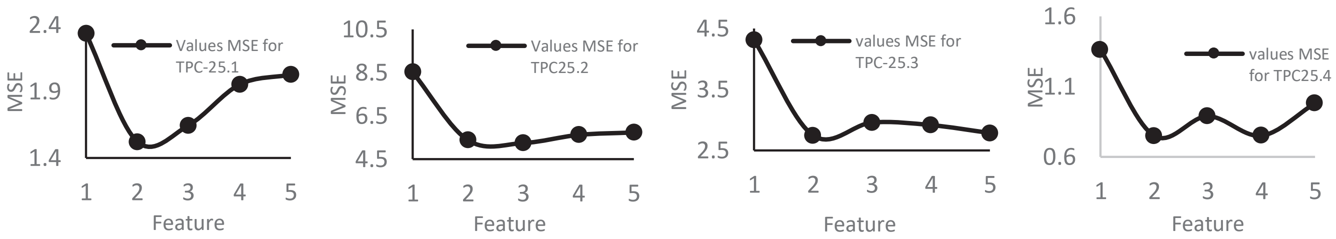

Fig. 1. Features values in the Features selection method for cells

Table 2. Statistical error measures in predicting soil stress, training and testing of ANN model

cell	inputs	raining					testing					Parameter
		GMER	NS	MAE	RMSE	R^2	GMER	NS	MAE	RMSE	R^2	
TPC25.1	T ،F	1.0008	0.7902	0.0081	0.0105	0.9980	1.0007	0.4725	0.0121	0.0206	0.9939	MLP 2-2-1
TPC25.2	T ،F ،R	1.0012	0.9433	0.0121	0.0168	0.9969	0.9809	0.6800	0.0137	0.0205	0.9960	MLP 3-3-1
TPC25.3	T ،F	1.0185	0.9061	0.0089	0.0127	0.9985	1.0071	0.6147	0.0096	0.0121	0.9979	MLP 2-2-1
TPC25.4	T ،F	1.0016	0.8969	0.0203	0.0286	0.9911	0.9924	0.7285	0.0189	0.0149	0.9921	MLP 2-2-1

In the above table, F is the fill level, R is the reservoir level and T is duration of construction.

3- Results and discussion

Feature selection using the PSO-ANN hybrid algorithm

Table 1 shows the optimal values of the parameters of the PSO algorithm. According to Figure 1, in TPC25.1, TPC25.3 and TPC25.4 cells, among the 5 mentioned features, two features, i.e. fill level and duration of construction, have the greatest effect in modeling the total soil stress. In TPC25.2 cell, three characteristics of fill level, duration of construction and reservoir level have the greatest effect on modeling total soil stress.

On the other hand, the genetic programming model has a comparative advantage over other models; because genetic programming is able to provide a relationship between model inputs and outputs. Table 4 shows the relationships for estimating soil stress (P) in the cross-section in which 25th cells have been installed.

4- Conclusion

Among the five features as inputs of the PSO-ANN hybrid model, fill level, duration of construction and reservoir level were the most effective features in modeling total stress in selected cells and impounding rate and fill rate has less effect on total stress modeling. Also, the error in the installed cells behind the filter and drainage layers is less than errors in other cells. The results of sensitivity analysis in the ANN model showed that the fill level and duration of construction with the highest sensitivity coefficient are the most important features in modeling the total stress in most cells. As an important result, the position of the installation of cells with respect to the filter and drainage layers, as well as the levels of cells installation, are effective in modeling the total soil stress and the selection of inputs as well.

Table 3. Statistical error measures for different cells in the training and testing stages of the ANFIS model

Model ANFIS	Training					testing					Parameter	
	GMER	NS	MAE	RMSE	R^2	GMER	NS	MAE	RMSE	R^2	MF Type	Number of membership functions
TPC25.1	1/0000	0.9859	0..0015	0.0023	0.9999	0.9996	0.96666	0.0059	0.0087	0.9980	Gauss2mf	3
TPC25.2	0.0010	0.9856	0.0032	0.0059	0.9997	0.0120	0.9668	0.0118	0.0229	0.9955	Gaussmf	4
TPC25.3	0.9998	0.9852	.0016	0.0024	0.9999	0.9926	0.9605	0.0109	0.0169	0.9972	psagmf	3
TPC25.4	0.0012	0.9857	0.0032	0.0045	0.9997	0.9911	0.9666	0.0185	0.0227	0.9955	Gaussmf	3

Table 4. Relationships obtained from each subtree to predict soil vertical stress for different cells

cell	Relationships derived from each subtree	R^2
TPC25.1	P = ((((F)-((T)^5))^3)/((1.0/(1.28))+ -4.23))+ (((((((T)^5)* (R))+ -0.91)^3)^2)/ 6.56)+ (F)	0.99
TPC25.2	P = (T)+ ((R)/-9.38)+ (((F)/-6.87)^2)	0.97
TPC25.3	P = (((((F)^4)- (T))^2)^2)+ ((((R)- (F))^5)^5)+ (F)	0.99
TPC25.4	P = ((F)-((R)^5))+ (((F)- (T))^4)+ ((R)^5)	0.98

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