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USE OF ARTIFICIAL NEURAL NETWORKS IN STABILITY CONTROL OF CANTILEVER RETAINING WALLS

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Abstract

Stability conditions effective on the design of the wall are safety factors of sliding, overturning and slope stability. Design of a cantilever retaining wall depends on great numbers of parameters such as soil properties and wall dimensions. In addition, design of the cantilever retaining wall must be satisfies stability conditions like safety factors of sliding, overturning and slope stability. It takes time to design wall considered all effective parameters with traditional methods. For this reason, some methods like artificial neural networks have been preferred due to reach the result in brief time, nowadays. In this study, algorithms of multi-layer artificial neural networks, generalized regression artificial neural networks and radial based artificial neural networks have been handled to investigate the model which provides to gain safety factors of sliding, overturning and slope stability. 1024 (4^5) different wall designs have been composed, for parameters of the length of base, the toe extension, the thickness of base, the angle of front face, the angle of internal friction which have four levels each of them. Training stage of artificial neural networks method has been completed by using this 1024 data set and testing stage of the method has been achieved for random 100 different wall designs. end of testing stage, safety factors of sliding, overturning and slope stability have been obtained for random 100 data set. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Determination Coefficient (R^2) of obtained safety factors according to developed models by using the artificial neural networks algorithms have been compared for three algorithms. The model improved by algorithms of multi-layer artificial neural networks and radial based artificial neural networks have proper R^2 value (0.99) when is compared the generalized regression artificial neural networks algorithm. This result show that improved model by means of Artificial Neural Networks can be used reliably and effectively in design of the cantilever retaining wall.

Keywords: Cantilever retaining wall; Artificial neural network; Mathematical model

1. Introduction

In geotechnical engineering, connecting two different soil levels each other with vertical load-bearing wall which is stand out against lateral soil pressures is a common problem. In solution of this problem, cantilever retaining walls is employed especially in case of absence of enough site area like construction of highway, railway and dock so on. Design of a retaining wall which depends on great numbers of parameters such as soil properties and wall dimensions must be satisfies stability conditions like safety factors of sliding, overturning and slope stability. In traditional design of retaining wall, trial-error method is used to ensure the stability conditions of wall. Analyzing stability conditions like safety factors of sliding, overturning and slope stability of wall is a time-consuming procedure when is used trial-error method (McCormac et al. 2015). Today, different methods come into prominence to determine safety factors of wall design in a shorter time. Artificial neural network (Hsu et. al 1995) method which is one of these different methods have been used commonly in solution of many engineering problems. Artificial neural networks method is method based on simulation of simple biological nervous system. Applications of ANN methods in geotechnical engineering have given in a literature study examined by Shahin (2001). Manjunath et al. (2012) have performed a study to obtain the optimum value of required tension reinforcement and area of concrete of cantilever retaining wall. In study presented by Alias et al (2015), stability conditions of reinforcement concrete cantilever retaining wall has been investigated by using height of the wall, angle of slope, and surcharge load as input parameters. For reinforced concrete (RC) walls with two different shapes, estimating of required concrete volume and amount of steel reinforcement has been investigated (Gokkus et al. 2018). In stage of training of this ANN method, the Artificial Bee Colony (ABC) algorithm has been employed for seven different retaining wall designs.

In this study, design of the cantilever retaining wall has been realized by using artificial neural network (ANN) and taken into consideration stability conditions of wall. Considered stability conditions are safety factors of sliding, overturning and slope stability. The length of base, the toe extension, thickness of base, angle of front face and angle of internal friction are taken input parameters for predicting of safety factors of sliding, overturning and slope stability.

2. Design of the Cantilever Retaining Wall

In analyses, cross section of the wall with parameters and acting load of the wall consideration in this study is given in Figure 1. All wall designs have been performed for the wall height, H=6m. Safety factor of slope stability has been determined according to Bishop method (Bishop 1955).

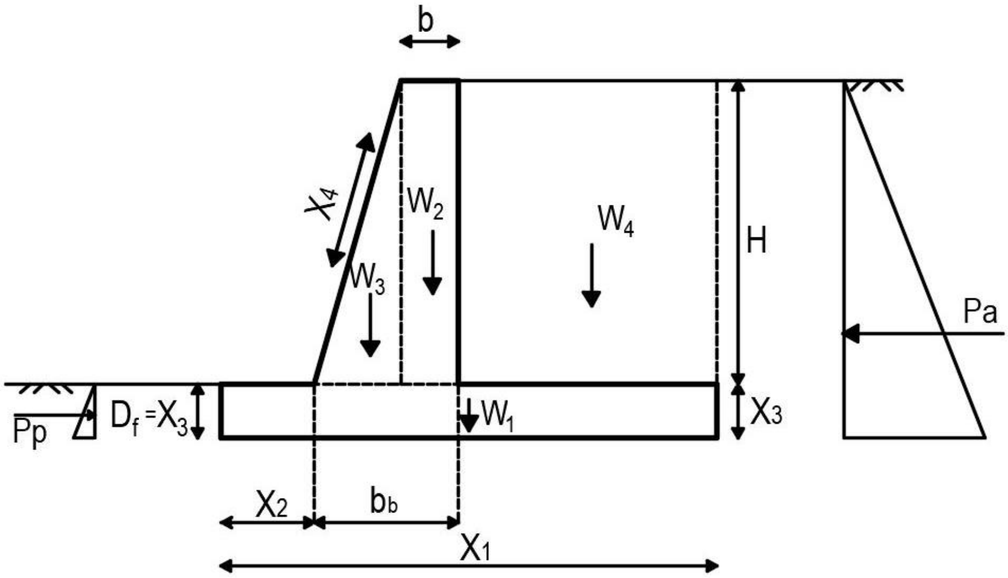

Figure 1. The cantilever retaining wall and acting load

While values of W1, W2 and W3 are corresponding to weight of wall, W4 is corresponding to weight of backfill. Values of the active soil pressure coefficient (Ka) and the passive soil pressure coefficient (Kp) which are used in determining of the active pressure (Pa) and the passive soil pressure (Pp) have been calculated according to Mazindrani Theory (Mazindrani 1997).

1024 different wall designs which contain all combinations (4^5) have been generated by using wall parameters and their levels are given in Table 1.

Table 1. The cantilever retaining wall parameters and levels

Parameter	Level 1	Level 2	Level 3	Level4
Length of base (X1)	0.25H	0.50H	0.75H	1.0H
Toe extension (X2)	0.15X1	0.30X1	0.45X1	0.60X1
Thickness of base (X3)	0.06H	0.09H	0.12H	0.15H
Angle of front face (X4)	0.00	0.01	0.02	0.04
Angle of internal friction (Ø)	20°	27°	34°	41°

The parameters with given value in Table 2 have been taken same for all wall designs modelled in GEO 5 computer program.

Table 2. Values of parameters in computer programs

Parameter	Value
Bottom thickness of the stem (b)	0.25m
Coefficient of friction between wall and soil (δ)	(2/3) Ø
Depth of foundation	X3
Unit volume weight of backfill (γ_{soil})	18 kN/m^3
Cohesion of backfill (c)	0 kN/m^2

To obtain all safety factors of sliding (Fsk), overturning (Fsd) and slope stability (Fst) of the wall, 1024 different wall designs have been analyzed in GEO5 geotechnics computer program. End of computer analyses, 1024 safety factors of sliding, overturning and slope stability have been gained for training stage of ANNs. 100 different wall designs which is differ from the given parameter levels in Table 1 have been composed for test stage of ANNs.

3. Artificial Neural Networks

Artificial neural networks are inspired by the human brain. In the modeling, the nerve cells (neurons) in the human brain are sampled. The studies that started in medical science have become a subject of interest in computer engineering, mathematics and civil engineering and have been used successfully in solving problems. ANN can quickly identify and perceive different structures in problem solving. It also has features such as forecasting. The ANN consists of 5 main elements. These; inputs (1), weights (2), colection function (3), activation function (4) and outputs (5).

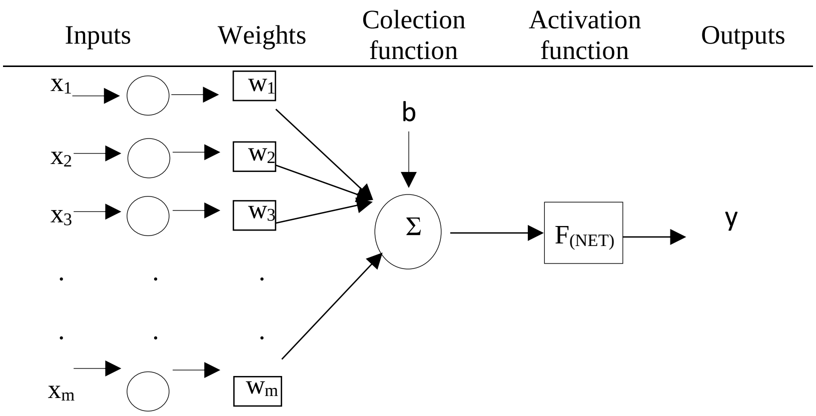

Figure 2. Structure of artificial neural network

In the Figure 2, inputs are shown with "x". Each of the input values is multiplied by the weights “wi”. Then, threshold b (bias) value is added to obtained information. Activation function is applied for the result value and “y” output value is obtained. The learning capability of the ANN is dependent on the optimal updating and adjustment of the weights. This process differs with the training algorithm. Error is found by comparing the system output with the values corresponding to the input from the training set. Different learning algorithms reduce the error value and try to approach the expected output. In this process the weights of the network are updated. Weights are renewed in each iteration and try to get closer to the expected output. What is the criterion to minimize the error is an externally defined value. If the target is reached with the input-output given in ANN, the weight value is not updated. Weights are kept constant. The time until the weight is updated to the desired state is called the training phase. After the network is trained, the network is tested by providing different inputs (different from phase of training). If it can give good results to these data, it means that the network problem is learned. To test this situation, the data should be divided into two groups as training set and test set. The training set is the data presented to the system for input and output data to enable the network to be trained. The test set is different from the training set which is not presented to the system before (the output is known but only inputs are presented to the system). There is no specific rule on how much of the data for the problem is the test set. However, it should be emphasized that the training set should cover the problem (Yılmaz 2017). Three different ANN methods were used in this study. These are Multi-later Artificial Neural Networks, Generalized Regression Artificial Neural Networks and Radial Based Artificial Neural Networks.

3.1. Multi-layer artificial neural networks

The function used to adjust the weights at MLANN is the Levenberg-Marquardt (LM) function (Marquardt 1963). LM function has been found to be more successful in many studies. The MLANN, the collection function is as in Equation 1.

$$NET_{tl} = \sum_{k=1}^{D} A_{kl} Ç_{tk} + \theta_l \tag{1}$$

θ_l bias constant, A_{kl} set of weights between input and intermediate layer, D size of input vector, $Ç_{tk}$ the output set of the input layer for example t.

3.2. Radial based artificial neural networks

The RBANN interlayer cell number can be adjusted and Radial Based Functions are used as an activation function. The output of the RBANN is achieved by passing the distance between the input vector and the intermediate layer through the weights and activation function (Cetinkaya 2011). The RBANN collection function is as in Equation 2.

$$o_j(t) = \sum_{i=1}^{k} w_{ji} \psi_{ji} \left(\left\| x^s - v_i \right\| \right) \tag{2}$$

Where x^s: s. the input vector of the observation, wji: i. with input j. radial-based function weight between artificial nerve cells, vi: i. artificial nerve cell center vector, Ψi: i. activation function. The Gaussian function is generally used as an activation function in the hidden layer (Kılıc 2015). Gaussian function was used in this study.

3.3. Generalized regression artificial neural networks

GRANN does not require an iterative training procedure (Specht 1991). Regression of the dependent variable y according to the independent variable x follows (Alp and Cigizoglu 2004);

$$y(x) = \frac{\sum_{k=1}^{N} y_k K(x, x_k)}{\sum_{k=1}^{N} K(x, x_k)} \tag{3}$$

Here, y(x)is the prediction value of input x, y_k is the activation weight for the pattern layer neuron k, $K(x,x_k)$ is the Radial basis function kernel (Gaussian kernel).

4. Data and Application

4.1. Data

In total there are 1024 input training data and 100 randomly selected test data. The fact that the coefficient of skewness between the data is low (<1) and the standard deviations are not high are important parameters that affect the accuracy of the modeling. Furthermore, the high number of training data affects the accuracy of the study. Generally, good learning at the training stage, depending on the number of data, results in the correct estimation of well-learned information during the testing phase. The safety numbers (Ø) and X1 (m) parameters (0.5-0.70) were found to be more correlated than the other parameters. Other statistical data are given in Table 3.

4.2. Application

In the study, three different safety numbers were modeled using MLANN, RBANN and GRANN methods (safety factors of sliding, overturning, slope stability). X1 (m), X2 (m), X3 (m), X4 (m) and Ø (°) data were used as input data. Five different input combinations were tested: (i) X1 (m); (ii) X1 (m), X2 (m); (iii) X1 (m), X2 (m), X3 (m); (iv) X1 (m), X2 (m), X3 (m), X4 (m); (v) X1 (m), X2 (m), X3 (m), X4 (m), Ø (°). In the study, the Root Mean Square Error RMSE, Mean Absolute Error MAE and the determination coefficient R^2 were used. RMSE and MAE, R^2 formulas can be expressed as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_p - F_o)^2} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|F_p - F_o\right| \tag{5}$$

$$R^2 = \left(\frac{Nx\left(\sum_{i=1}^{N}F_o x F_p\right)-\left(\sum_{i=1}^{N}F_o\right)x\left(\sum_{i=1}^{N}F\right)}{\sqrt{Nx(\sum_{i=1}^{N}F_o^{2})-\left(\sum_{i=1}^{N}F_o\right)^2 x\left(Nx\sum_{i=1}^{N}F_p^{\;2}\right)-\left(\sum_{i=1}^{N}F_p\right)^2}}\right)^2 \tag{6}$$

Table 3. Statistical information for ANN's modelling

Data Set	Parameters	Max	Min	Mean	S_x	C_{sx}
Training	X1 (m)	6.000	1.500	3.750	1.678	0.001
	X2(m)	3.600	0.225	1.406	0.933	0.824
	X3 (m)	0.900	0.360	0.630	0.201	0.001
	X4(%)	0.040	0.000	0.017	0.015	0.435
	Ø(°)	41.000	20.000	30.500	7.830	0.001
	Fs(sliding)	6.678	0.109	1.292	1.175	1.740
	Fs(overturning)	12.933	0.226	3.373	2.933	1.092
	Fs(slope stability)	2.910	0.700	1.525	0.522	0.420
Testing	X1 (m)	6.000	1.500	3.624	1.322	0.241
	X2(m)	3.540	0.285	1.429	0.767	0.773
	X3 (m)	0.890	0.380	0.643	0.152	0.020
	X4(%)	0.040	0.000	0.022	0.014	-0.340
	Ø(°)	41.000	20.000	29.510	6.073	0.100
	Fs(sliding)	3.516	0.175	0.988	0.664	1.396
	Fs(overturning)	9.246	0.428	2.749	2.017	1.094
	Fs(slope stability)	2.380	0.790	1.426	0.370	0.393

Here, F_p and F_o show the estimated and known safety numbers and N represents the number of data. The different hidden layer cell numbers were tried for the MLANN and the test phase was based on the value giving the least squared error. Table 4 shows the test results of MLANN for safety factors of sliding (Fsk), overturning (Fsd) and slope stability (Fst). There are also optimum hidden layer cell numbers. For example, (1,8,1); 1 shows a MLANN model with an input layer cell number, 8 intermediate cell number and 1 output layer cell number. As can be clearly seen from the table, the model obtained from the 5th combination gave lower values of RMSE and MAE and greater R^2 (0.99) values than the others. The worst result was obtained from the first combination.

In Figure 3-5, the values observed in the test phase of the MLANN and the observed values were compared on the graph and the scattering diagram. It is seen that the model results have almost all the observed values.

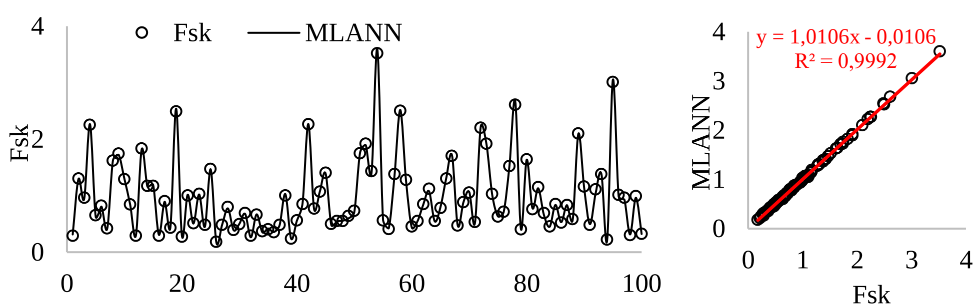

Figure 3. The number of Fsk safety values obtained from the MLANN in the observed and test phase

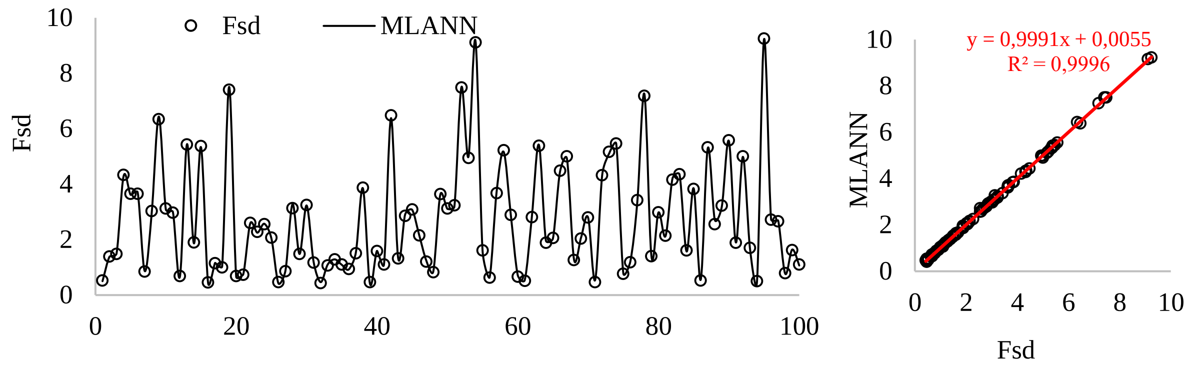

Figure 4. The number of Fsd safety values obtained from the MLANN in the observed and test phase

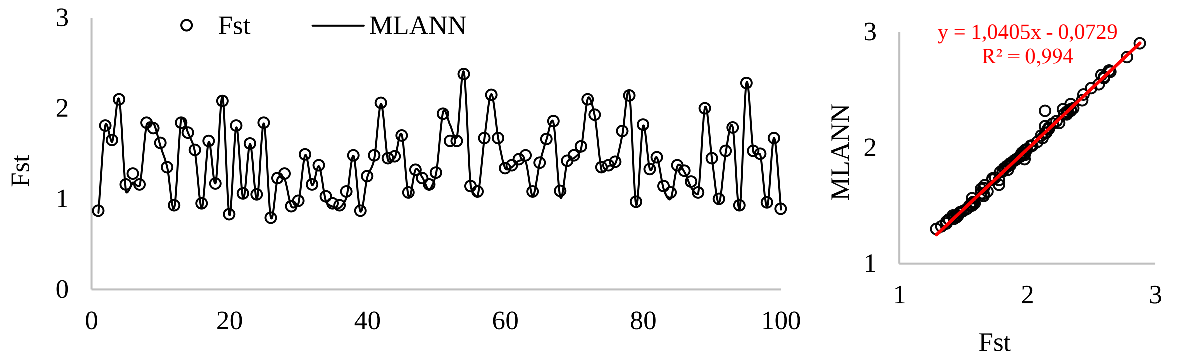

Figure 5. The number Fst of safety values obtained from the MLANN in the observed and test phase

Table 4. Errors in the testing phase of MLANN models

Safety Factors	Model	Input	Structure	RMSE	MAE	R^2
Fsk	(i)	X1	(1,8,1)	2.2135	1.6227	0.2839
	(ii)	X1, X2	(2,8,1)	0.6725	0.5633	0.2272
	(iii)	X1, X2, X3	(3,4,1)	0.6294	0.5058	0.2763
	(iv)	X1, X2, X3, X4	(4,2,1)	0.6261	0.5005	0.2788
	(v)	X1, X2, X3, X4,Ø(°)	(5,3,1)	0.0206	0.0153	0.9992
Fsd	(i)	X1	(1,11,1)	4.2366	3.2470	0.0813
	(ii)	X1, X2	(2,12,1)	1.2992	0.9419	0.7411
	(iii)	X1, X2, X3	(3,4,1)	0.8548	0.6109	0.8333
	(iv)	X1, X2, X3, X4	(4,4,1)	0.8542	0.6075	0.8324
	(v)	X1, X2, X3, X4,Ø(°)	(5,4,1)	0.0423	0.0323	0.9996
Fst	(i)	X1	(1,7,1)	0.8223	0.5943	0.0736
	(ii)	X1, X2	(2,10,1)	0.3483	0.2964	0.1408
	(iii)	X1, X2, X3	(3,5,1)	0.3614	0.3054	0.0941
	(iv)	X1, X2, X3, X4	(4,2,1)	0.3621	0.3057	0.0928
	(v)	X1, X2, X3, X4,Ø(°)	(5,2,1)	0.0366	0.0253	0.9940

The test results of RBANN are presented for safety factors of sliding (Fsk), overturning (Fsd) and slope stability (Fst) in Table 5. For each RBANN model, different hidden layer cell and spread counts were tried and the best results were selected. Here (1,5,0.1,1); 1 refers to the RBANN model with input cell number, 5 hidden layer cell number, 0.1 spread coefficient and 1 output layer cell number. It is seen that the 5-input model gives better predictions than the others.

Table 5. Errors in the testing phase of RBANN models

Safety Factors	Model	Input	Structure	RMSE	MAE	R²
Fsk	(i)	X1	(1,5,0.1,1)	0.6231	0.5120	0.2617
	(ii)	X1, X2	(2,17,0.5,1)	0.5927	0.4882	0.3358
	(iii)	X1, X2, X3	(3,5,1.1,1)	0.6166	0.5075	0.3331
	(iv)	X1, X2, X3, X4	(4,2,0.9,1)	0.6125	0.5029	0.3333
	(iv)	X1, X2, X3, X4, Ø (°)	(5,20,1.6,1)	0.0529	0.0415	0.9938
Fsd	(i)	X1	(1,5,0.1,1)	0.9753	0.6985	0.7897
	(ii)	X1, X2	(2,15,1,1,1)	0.9005	0.6472	0.8186
	(iii)	X1, X2, X3	(2,20,1,1,1)	0.8538	0.6068	0.8341
	(iv)	X1, X2, X3, X4	(4,13,2,1)	0.8628	0.6201	0.8317
	(iv)	X1, X2, X3, X4, Ø (°)	(5,19,1.6,1)	0.0516	0.0409	0.9994
Fst	(i)	X1	(1,5,0.1,1)	0.3564	0.3028	0.1057
	(ii)	X1, X2	(2,9,0.4,1)	0.6010	0.4914	0.3305
	(iii)	X1, X2, X3	(3,9,0.8,1)	0.3622	0.3058	0.0931
	(iv)	X1, X2, X3, X4	(4,6,0.8,1)	0.3614	0.3051	0.0969
	(iv)	X1, X2, X3, X4, Ø (°)	(5,20,1.6,1)	0.0219	0.0088	0.9966

The values observed in the RBANN test phase and the observed values are compared on the graph and the scattering diagram in Figure 6-8. Here, it is seen that the results of the model in general catch the observed values, but some peak values are less than the fact and lower values are more predictive than they are.

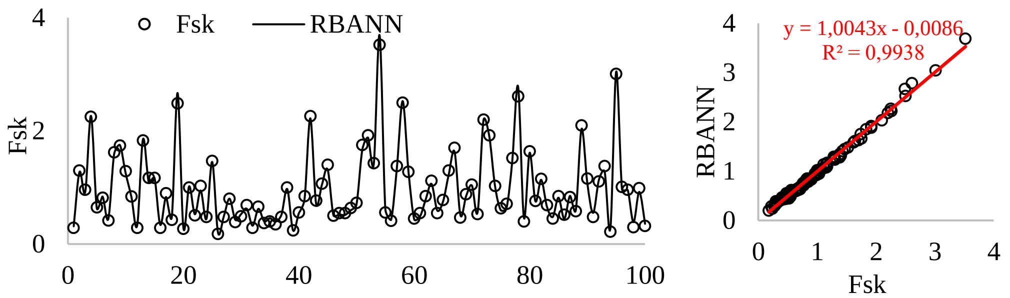

Figure 6. The number of Fsk safety values obtained from the RBANN in the observed and test phase

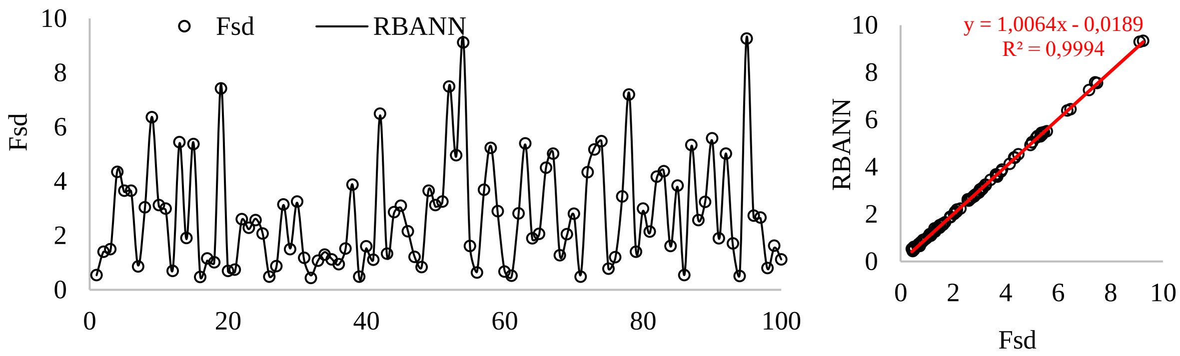

Figure 7. The number of Fsd safety values obtained from the RBANN in the observed and test phase

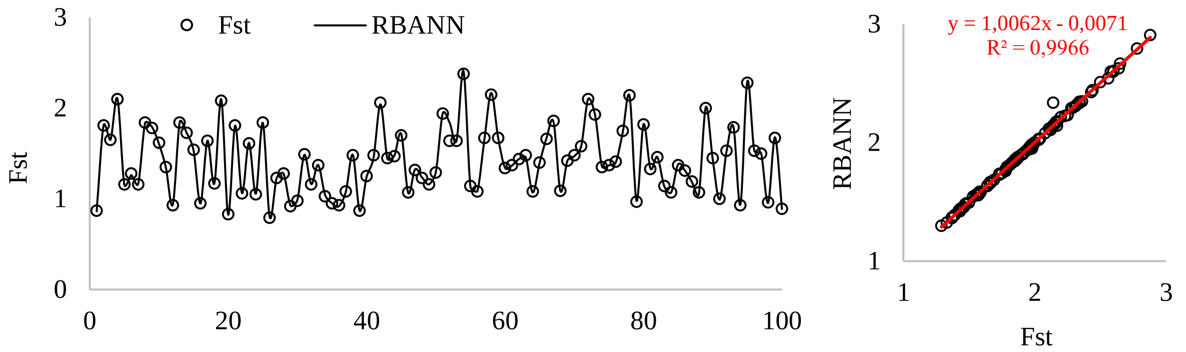

Figure 8. The number Fst of safety values obtained from the RBANN in the observed and test phase

Table 6 shows the test results of the GRYSA model for safety factors of sliding (Fsk), overturning (Fsd) and slope stability (Fst). In the fourth column, optimum spread coefficients obtained by trial and error are given. As can be clearly seen from the table, the best GRYSA model was obtained from the 5th combination as in the other models. The first model, which uses the first combination as input, yielded the worst results.

Table 6. Errors in the testing phase of GRANN models

Safety Factors	Model	Input	Structure	RMSE	MAE	R^2
Fsk	(i)	X1	0.07	0.6298	0.5206	0.2757
	(ii)	X1, X2	0.01	0.6153	0.4999	0.3169
	(iii)	X1, X2, X3	0.16	0.6307	0.5311	0.2467
	(iv)	X1, X2, X3, X4	0.16	0.6292	0.5284	0.2471
	(iv)	X1, X2, X3, X4, Ø (°)	0.1	**0.3384**	**0.2346**	**0.8552**
Fsd	(i)	X1	0.12	0.9783	0.7291	0.7901
	(ii)	X1, X2	0.11	0.9307	0.6993	0.8073
	(iii)	X1, X2, X3	0.1	0.8922	0.6619	0.8225
	(iv)	X1, X2, X3, X4	0.11	0.8893	0.6657	0.8205
	(iv)	X1, X2, X3, X4, Ø (°)	0.1	**0.2418**	**0.1802**	**0.9871**
Fst	(i)	X1	0.04	0.3548	0.3028	0.1219
	(ii)	X1, X2	0.04	0.3476	0.2943	0.1504
	(iii)	X1, X2, X3	0.09	0.3634	0.3080	0.0884
	(iv)	X1, X2, X3, X4	0.1	0.3633	0.3071	0.0859
	(iv)	X1, X2, X3, X4, Ø (°)	0.11	**0.0412**	**0.0309**	**0.9882**

In Figure 9-11, the values observed in the test phase of GRANN and the observed values were compared. Similar to RBANN, it was found that the model predicted some peaks and low values less than the fact. In addition, in the Fs estimation, the peak values are seen to be higher than the required ones, and the lower values are clearly seen from the graphs they predict.

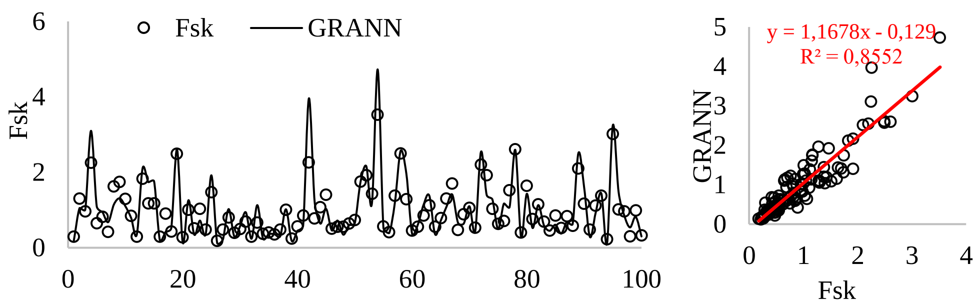

Figure 9. The number of Fsk safety values obtained from the GRANN in the observed and test phase

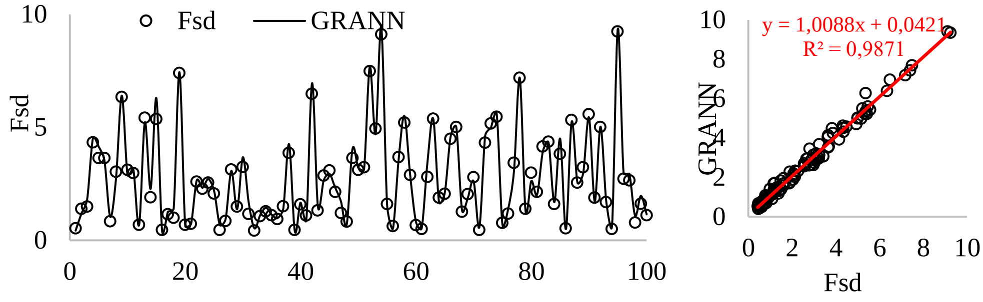

Figure 10. The number of Fsd safety values obtained from the GRANN in the observed and test phase

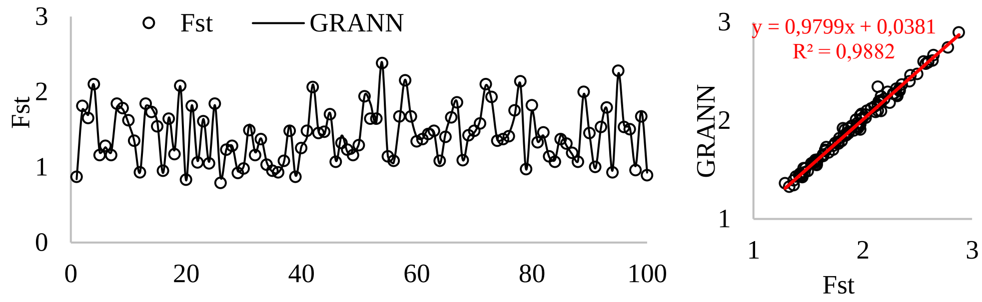

Figure 11. The number Fst of safety values obtained from the GRANN in the observed and test phase

When the Table 4-6 is compared, it is seen that RBANN and MLANN method predicts the safety numbers better than GRANN. The MLANN method was better modeled than the RBANN method. When the results of the training part are examined, the best modeling is observed in the same order (best MLANN, RBANN and worst GRANN). In Figures 3-11, it can be clearly seen from the weaving diagrams (assuming that equality is y = ax + b) that the MLANN model provides better estimates than others, and that the linear equality a and b coefficients are closer to 1 and 0 (i.e., 45° line). In addition, maximum R^2 value was obtained from the MLANN method.

5. Results

Problem of connecting two soil levels each other safely is common problem in geotechnical problem. In solution of this problem cantilever retaining walls have been employed to resist lateral soil loads. In design of cantilever retaining wall, it should be found wall dimensions which are satisfy stability of wall. Within the scope of the study, safety factors of sliding (Fsk), overturning (Fsd) and slope stability (Fst) were taken into consideration as stability conditions of wall. In the study, three different safety factors (Fsk, Fsd, Fst) were modeled by three different ANN methods (MLANN, RBANN, GRANN). X1, X2, X3, X4, Ø (°) variables were used as inputs to models. The model results were evaluated according to the criteria of RMSE, MAE and R^2. As a result of the comparison, it was seen that MLANN and RBANN models gave better estimates than GRANN. When the security numbers are evaluated among themselves;

- For safety factor of sliding (Fsk) is the model that gives the least error for the MLANN method. RMSE (0.0206), MAE (0.0153) and R^2 (0.9992).
- For safety factor of overturning (Fsd), the model that gives the least error is again MLANN method. RMSE (0.0423), MAE (0.0323) and R^2 (0.9996).
- For safety factor of slope stability (Fst), the least error is the model RBANN method. RMSE (0.0219), MAE (0.0088) and R^2 (0.9966).

In the study, only the cantilever retaining wall design data was used and the comparison of model performances using more data in future studies is important for the generalization of the study. Values of all safety factors were calculated by means of random design parameters used for testing phase in ANN method and were obtained realistic results. Obtained results show that ANN methods may be used effectively and successfully in solution of geotechnical engineering.

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References

Alias, R., Kasa, A. & Taha, M. R. (2015). Artificial Neural Networks Approach for Predicting the Stability of Cantilever RC Retaining Walls. *International Journal of Applied Engineering Research*, 10(10), 26005-26014.

Bishop, A. W. (1955). The Use of The Slip Circle in The Stability Analysis of Slopes. *Geotechnique*, 5(1), 7-17.

Cetinkaya C. (2011). Retina Görüntülerinde Radyal Tabanlı Fonksiyon Sinir Ağları İle Damar Tipik Noktalarının Tespit Edilmesi. *Master Thesis*, Ege University Department of International Computer, İzmir, 68p.

GEO5, Geotechnical Design Computer Program, fine software, https://www.finesoftware.eu.

Gokkus, U., Yildirim, M. S. & Yilmazoglu, A. (2018). Prediction of Concrete and Steel Materials Contained by Cantilever Retaining Wall by Modeling the Artificial Neural Networks. *Soft Computing in Civil Engineering,* 2(4), 47-61.

Hsu, K. L., Gupta, H. V. & Sorooshian, S. (1995). Artificial neural network modeling of the rainfall runoff process. *Water Resources Research*, 31(10), 2517-2530.

Marquardt D. (1963). An Algorithm for Least Squares Estimation of Non-Linear Parameters, *Journal of the Society for Industrial and Applied Mathematics*, 431–441.

Manjunath, K., Gowda, K. & Prasad, G. E. (2012). Optimization of Cantilever Earth Retaining Wall Using Artificial Neural Network. *Proceedings of National Conference on Innovations in Civil Engineering*, Paper No: T118.

Mazindrani, Z. H. & Ganjali, M. H. (1997). Lateral Earth Pressure Problem of Cohesive Backfill with Inclined Surface. *Journal of Geotechnical and Geoenvironmental Engineering*, 123(2), 110-112.

McCormac, J. C., Brown, R. H. (2015). Design of reinforced concrete. *John Wiley & Sons.*

Murat A, & Cigizoglu H.K. (2004). Farklı Yapay Sinir Ağı Metodları İle Yağış-Akış İlişkisinin Modellenmesi, *İtü Dergisi,* (3): 80-88.

Kılıc G. (2015). Yapay Sinir Ağları İle Yemekhane Günlük Talep Tahmini, Master Thesis, Pamukkale University, Computer Engineering Department, Denizli, p53.

Shahin, Mohamed A., Mark B. Jaksa, & Holger R. Maier. (2001). Artificial Neural Network Applications in Geotechnical Engineering. *Australian Geomechanics*, 36.1 49-62.

Specht, D.F. (1991). A General Regression Neural Network, *IEEE Transactions on Neural Networks,* 2(6): 568-576.

Yılmaz A. (2017). Yapay Zeka, KODLAB Yayınevi, p 373, İstanbul.