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Reliability Analysis Of Soil Slope Stability Using Ann, Anfis, Pso-Ann Soft Computing Techniques

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Abstract

Slope stability is an important concern while constructing any slope or constructing any structure on a soil slope. As soil is heterogeneous in nature due to the process of its formation, slope stability analysis cannot be done without considering the variability in the properties of soil. To consider soil variability, with time the research approach is shifting towards probabilistic approach. In the present paper to study soil slope stability, three soft computing techniques were used: Artificial Neural Network (ANN), Adaptive Network based Fuzzy Inference System (ANFIS), and Particle Swarm Optimization based Artificial Neural Network (PSO-ANN). Because three soil parameters, unit weight (ϒ), cohesion (c) and angle of shear resistance (φ), mostly determine the stability of a soil slope, they were employed as input variables for the models, and the factor of safety was used as an output. Models were examined using statistical criteria such as NS, RPD, RMSE, R^2, PI, GPI to assess performance. The output of the result showed that although all the models performed well, however, the model PSO-ANN out-performed among the above three models. As a result, PSO-ANN can be utilized to analyze multi-layered soil embankment slope stability as a robust soft computing technique.

Keyword: slope stability, probabilistic analysis, reliability, ANN, ANFIS, PSO-ANN.

1. Introduction

Slope stability of soil is a major factor for construction with the so illike embankments, open pits and dams. Soil being heterogeneous in nature due to the randomness in its formation leads to the uncertainty in its properties. Hence, to do any construction on or of soil all the variation in the properties of soil are need to be taken under consideration. Various methods are there to solve slope stability problems, e.g. Limit Equilibrium Method (LEM) and Strength Reduction Method, but these methods are deterministic in approach which may cause the slope design to be over conservative. Also, due to the error while performing the testing process and the due to the different soil depositions, leads to the variations in the testing data showed by Phoon [1]. For slope stability analysis, a probabilistic technique is employed to eliminate any potentially misleading results and to account for soil parameter variability. For the probabilistic approach, reliability analysis is performed, in which soil parameters that affect soil slope stability are employed as input variables for soft computing technique models, and the output response is studied by working through the models.

In past probabilistic approach using different methods is being used by many researchers, Christian et al.[2]showed the usage of field and laboratory data for the probabilistic approach and also showed the contribution of uncertainties in soil parameters for an embankment. Reliability approach for the multi layered embankment also incorporate the variability of soil properties shown by Liang et al. [3]. Cheng [4]used annealing method to determine the extreme limits of the variables on which slope failure depends so that the failure surface which is most critical can be found out with higher precision. Babu and Srivastava [5]done the reliability analysis on four selected earth dam section using response surface methodology with FOSM and calculated reliability index β. Researcher also used multi modal optimisation technique to locate multiple failure modes which is effective for both deterministic and probabilistic models [6].The ANN model was used to study small earth dams in both static and earthquake loading conditions, and the results showed that the model is capable of predicting factor of safety with reasonable accuracy.[7]. ANFIS model used by Karimi[8]to analyse the stability of site having filled material like sediment.After many critical evaluations, the researchers[9] found that the conventional analysis underestimate the variation in the parameters of soil properties but using reliability analysis the variation can be included. The goals of this research are to apply a probabilistic technique to perform soil slope stability reliability analysis by three soft computing models: ANN, ANFIS, and PSO-ANN. All of the models are also subjected to statistical testing and fitness parameters.

2. Theoretical background of soft computing models

2.1 PSO-ANN hybridisation

2.1.1 Particle Swarm Optimization (PSO)

PSO uses population search algorithm for computation. In this computational method there is grouping of particles into swarm and each solution of the optimization problem represented by a particle. In PSO the particles in search space of problem are provided with random velocity and positions and with this their function of objective are calculated. Results shows the estimation best level of each and every particle, which is defined as best position of each particles (P_{best}), and best position among them, the global best position (G_{best}) are found. Now by using the combination of P_{best} and G_{best}particles next movement and next position can be found. With the number of iterations, the particles optimum value for function can be found. Explanation of PSO is given by many researchers [10–13].

The N size and U dimension population is represented by $Z = [Z_1, Z_2, \ldots, Z_N]^T$, where T = transpose. Every particle Z_m is denoted as $Z_s = [Z_{s,1}, Z_{s,2}, \ldots, Z_{s,U}]$. Z's initial velocity is $V = [V_1, V_2, V_3, \ldots, V_s]$, and each subsequent velocity is $V_s = [V_{s,1}, V_{s,2}, \ldots, V_{s,U}]$, with s ranging from 1 to N.

$$V_{s,q}^{l+1} = w \times V_{s,q}^{l} + c_1 r_1 \left({P_{best}}_{s,q}^{l} - Z_{s,q}^{l} \right) + c_2 r_2 \left({G_{best}}_{q}^{l} - Z_{s,q}^{l} \right) \qquad (1)$$

$$Z_{s,q}^{l+1} = Z_{s,q}^{l} + V_{s,q}^{l+1} \qquad (2)$$

In above equation,${P_{best}}_{s,q}^{l}$ denotes best q^{th} of thes^{th} individual and${G_{best}}_{q}^{l}$ denotes q^{th} best of global. The $P_{best}$and G_{best} are calculated with updates as follows: -

At iteration l

$$\text{If } f\left(Z_s^{l+1}\right) < f\left({P_{best}}_s^{\,l}\right) \text{ then } {P_{best}}_s^{\,l+1} = Z_s^{l+1} \text{ else } {P_{best}}_s^{\,l+1} = {P_{best}}_s^{\,l} \quad (3)$$

$$\text{If } f\left(Z_s^{l+1}\right) < f\left({G_{best}}^{l}\right) \text{ then } {G_{best}}^{l+1} = Z_s^{l+1} \text{ else } {G_{best}}^{l+1} = {G_{best}}^{l} \quad (4)$$

2.1.2 Artificial neural network (ANN)

ANN relates the input and output datasets and works as model having black box. It consists of neurons which connects to inputs via weights and biases. An ANN is made up of three layers: an input layer, a hidden layer, and an output layer. The input layer is free of neurons, whereas hidden and output layers are made up of neurons. Figure 1 shows the outline of ANN having m inputs and single output. While the weights of neuron associated with i^{th} input of input layer and j^{th} neuron of hidden layer is w_{ij}, bias linked with $j^{th}$of the hidden part is b_j.

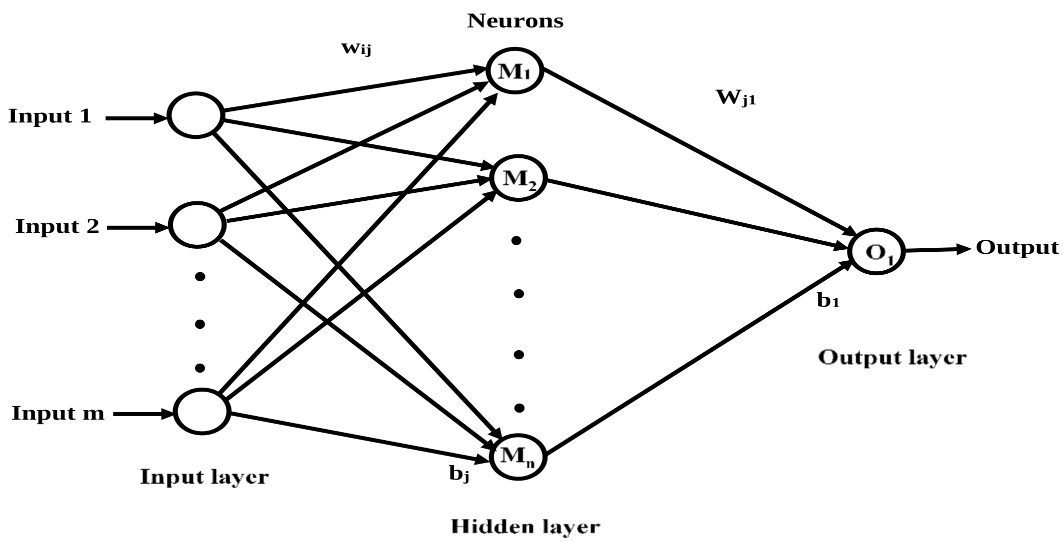


Figure 1. Layout of Artificial Neural Network (ANN) model

ANN model is trained input data set having the corresponding output set to get the bias and weights of the neurons. Weights and bias of the network are assigned by Training the network with the training data. In this study, training of the network to get correct weights and bias done with and without using PSO with the help of MATLAB 2015. Once training of the network is using training data, testing is done using testing data.

2.2 ANFIS

Modelling based on conventional tools is compatible not for the systems which are ill-defined and not certain in nature. For these types of system soft computing is very good in analysing. Soft computing technique consists of many methodologies with Nero-technology and Fuzzy logic. The neural network has an advantage of its self-adaptability and also its learning capability. And the fuzzy logic advantage is to take into account the uncertainties of the actual site condition using the fuzzy if-then rules. To integrate the benefits of both fuzzy systems and neural networks, the ANFIS [14] (Adaptive Network based Fuzzy Inference System) was developed.

2.2.1 Fuzzy If-Then rules and Fuzzy Inference Systems

IF M is true THEN N is true, [15]where M and N are fuzzy rules' labels, which is connected with membership functions which is appropriate for it, forms the If-Then rule. Because of the succinct structure of fuzzy if-then rules, they play a critical role in making decisions in uncertain systems.

Ex.: - If pressure is high, then volume decreases.

Linguistic variables [16] are pressure and volume, high is its value that is linked with membership functions.

Fuzzy if-then rules play a critical role in making decisions in uncertain systems because of their succinct structure. as shown in Figure 2.

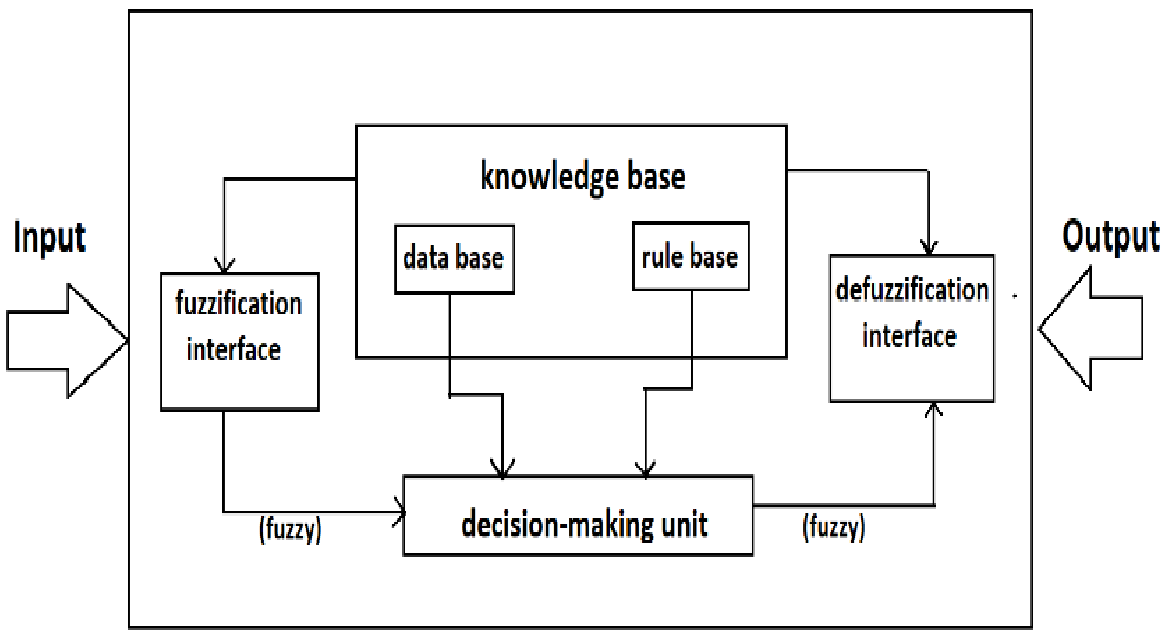


Figure 2. Fuzzy inference system

2.2.2 Adaptive networks

A network structure made up of nodes and directional links is known as an adaptive network. Using directional linkages, the nodes are connected or related to one another as shown in Figure 3. The nodes are adaptive in nature, which means that the output provided by them are dependent on linked parameters. To control the parameters of network learning rule [17] are applied such that the errors minimizes.

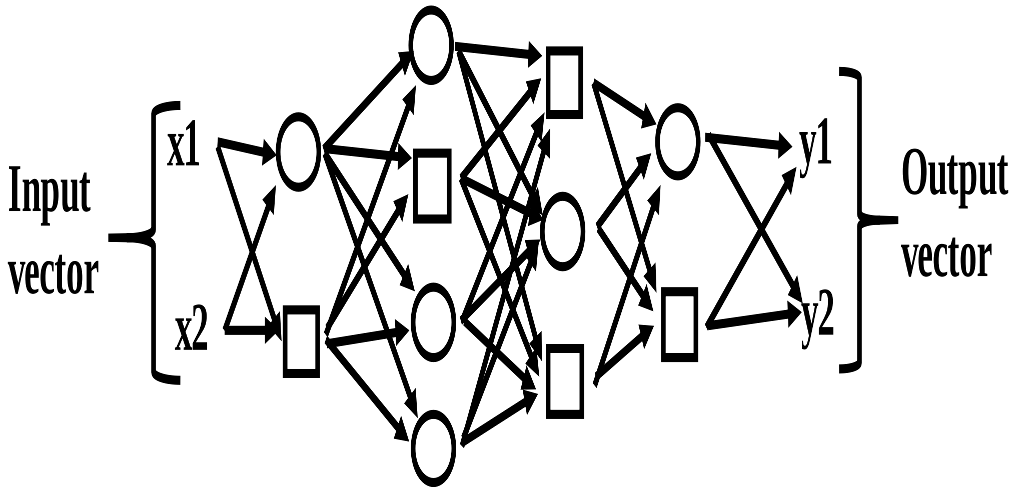


Figure 3. An adaptive network

3. Details of present analysis

In the present study, a 10m high embankment with side slope 1:2 on two 5m thick slightly stiffer bearing stratum described by Griffiths et al.[18] taken into consideration for our analysis. Details of embankment is shown in Figure 4.The change in soil properties is taken into account for unit weight (γ) and cohesion (c) when applying the probabilistic technique using reliability analysis. The coefficient of variation for unit weight was set at 0.03 for all three layers, while the coefficients of variation for cohesiveness (c) were set at 0.1, 0.1, and 0.15 for the three layers, respectively.

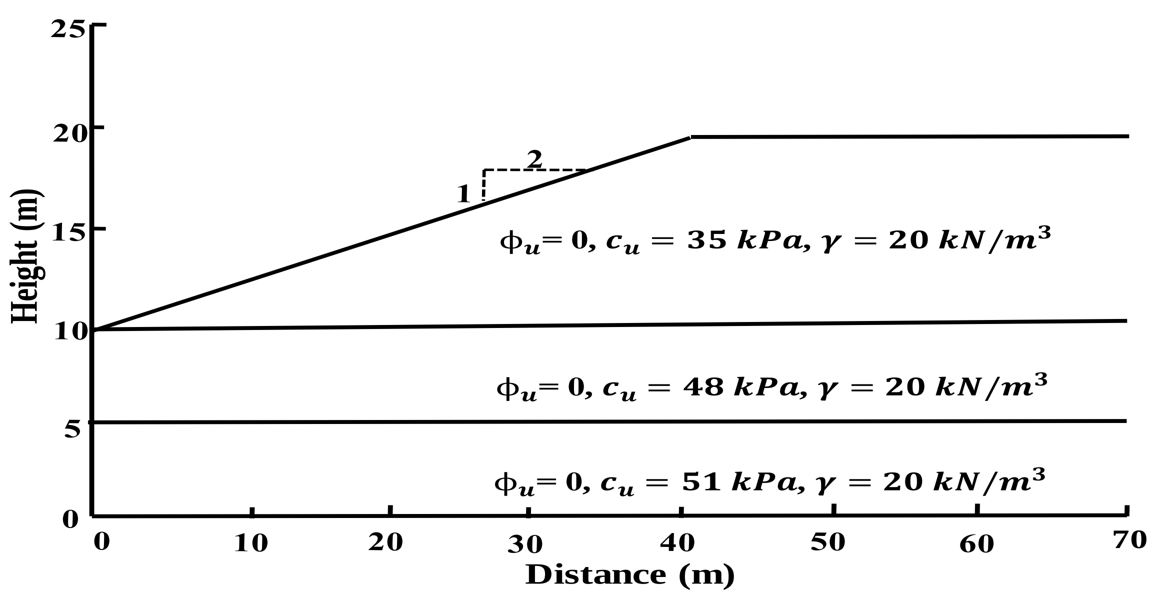


Figure 4. Section of typical multi-layered soil embankment[18]

Using the Geo Studio 2016 application, the Morgenstern-Price technique is utilised to calculate the slope stability factor of safety (F) in a multi-layered soil embankment. The safety factor (F) of a multi-layered soil embankment slope is determined by the soil variable parameters γ, c, and φ. These soil variable factors are used as input variables, and the stability analysis outcome is F of slope. The mean and coefficient of variation of these parameters γ andc are used toget 100 set of soil parameter data and then these data are applied for slope stability analysis using Geo Studio 2016 software to get the corresponding 100 data set of F. After that to use these data set for the training and testing purpose of models in MATLAB, it needs to be normalized as given by Eq.5.

$$X_{nor} = \frac{X - X_{min.}}{X_{max.} - X_{min.}} \tag{5}$$

Where,

$X_{nor} =$ normalised form of the parameter value

$X =$ actual value of parameter

$X_{min.} =$ minimum value of that parameter

$X_{max.} =$ maximum value of that parameter

The normalised form of actual data are taken as input values for the soft computing models and their corresponding predicted output by the models using MATLAB are obtained by training and testing the models. After training and testing the models, the actual Factor of Safety and the Factor of Safety values that soft computing models have delivered as output are analysed using various performance parameters and various statistical tests to find the most reliable model among ANN, ANFIS and PSO-ANN.

4. Performance parameters

The fitness and adequacy of the model are justified using various statistical approaches, e.g., Nash-Sutcliffe efficiency (NS) [9], Legate and McCabe's Index (LMI), Expanded uncertainty (U_{95})[9], Root Mean Square Error (RMSE) [19][20], Variance Account Factor (VAF), R^2 (Coefficient of determination) [21], t-statistic [22], Adj. R^2 (adjusted Coefficient of determination), Performance Index (PI) [23], Bias Factor [24], RSR [25], Normalized Mean Bias Error (NMBE) [26], MAPE (Mean Absolute Percentage Error) [27], Relative Percentage Difference (RPD) [19], Willmott's Index for agreement (WI), Mean Bias Error (MBE) and Mean Absolute Error (MAE) [28], Global Performance Indicator (GPI) [29] and Reliability Index (β) [30].

$$NS = 1 - \frac{\sum_{i=1}^{n}(d_i - y_i)^2}{\sum_{i=1}^{n}(d_i - d_{mean})^2} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i - y_i)^2} \tag{7}$$

$$VAF = \left(1 - \frac{var(d_i - y_i)}{var(d_i)}\right) \times 100 \tag{8}$$

$$R^2 = \frac{\sum_{i=1}^{n}(d_i - d_{mean})^2 - \sum_{i=1}^{n}(d_i - y_i)^2}{\sum_{i=1}^{n}(d_i - d_{mean})^2} \tag{9}$$

$$\mathrm{AdjR^2} = 1 - \frac{(\mathrm{n}-1)}{(\mathrm{n}-\mathrm{p}-1)}(1 - \mathrm{R^2}) \tag{10}$$

$$\mathrm{PI} = \mathrm{adj.R^2} + 0.01\mathrm{VAF} - \mathrm{RMSE} \tag{11}$$

$$\text{Bias Factor} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \frac{\mathrm{y_i}}{\mathrm{d_i}} \tag{12}$$

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{d_i} - \mathrm{d_{mean}})^2}} \tag{13}$$

$$\mathrm{NMBE}\ (\%) = \frac{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_i} - \mathrm{d_i})}{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\mathrm{d_i}} \times 100 \tag{14}$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left|\frac{\mathrm{d_i} - \mathrm{y_i}}{\mathrm{d_i}}\right| \tag{15}$$

$$\mathrm{RPD} = \frac{\mathrm{SD}}{\mathrm{RMSE}} \tag{16}$$

$$\mathrm{WI} = 1 - \left[\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{d_i} - \mathrm{y_i})^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}}(|\mathrm{y_i} - \mathrm{d_{mean}}| + |\mathrm{d_i} - \mathrm{d_{mean}}|)^2}\right] \tag{17}$$

$$\mathrm{MBE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{y_i} - \mathrm{d_i}) \tag{18}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{n}}|(\mathrm{y_i} - \mathrm{d_i})| \tag{19}$$

$$\mathrm{LMI} = 1 - \left[\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}|\mathrm{d_i} - \mathrm{y_i}|}{\sum_{\mathrm{i}=1}^{\mathrm{N}}|\mathrm{d_i} - \mathrm{d_{mean}}|}\right] \tag{20}$$

$$\mathrm{U_{95}} = 1.96 * (\mathrm{SD^2} + \mathrm{RMSE^2})^{1/2} \tag{21}$$

$$\text{t-stat} = \sqrt{\frac{(\mathrm{N}-1)\mathrm{MBE^2}}{\mathrm{RMSE^2} - \mathrm{MBE^2}}} \tag{22}$$

$$\mathrm{GPI} = \mathrm{MBE} \times \mathrm{RMSE} \times \mathrm{U_{95}} \times \mathrm{t_{stat}} \times (1 - \mathrm{R^2}) \tag{23}$$

$$\beta = \frac{\mu_{\mathrm{F}} - 1}{\sigma_{\mathrm{F}}} \tag{24}$$

Here, d_i represents the i^{th} observed value and y_i represents the i^{th} predicted value, d_{mean} represents the mean of the observed value, SD represents the standard deviation of the data, F data's mean value represented by μ_F, and F data's standard deviation represented by σ_F.

5. Results and Discussion

For using the probabilistic approach using the reliability analysis of multi-layered embankment slope stability on the under consideration section all the normalized values of parameters of soilused as input values for the models ANN, ANFIS and PSO-ANN for their training and testing and then the model output i.e. predicted values are analysed.

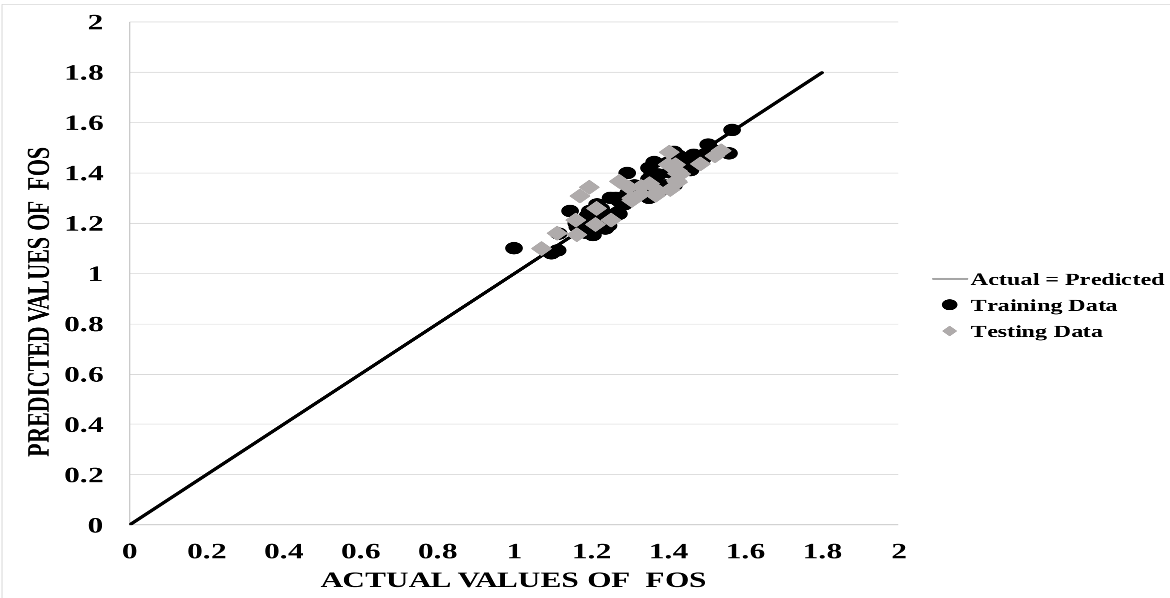


Figure 5.ANN model performance

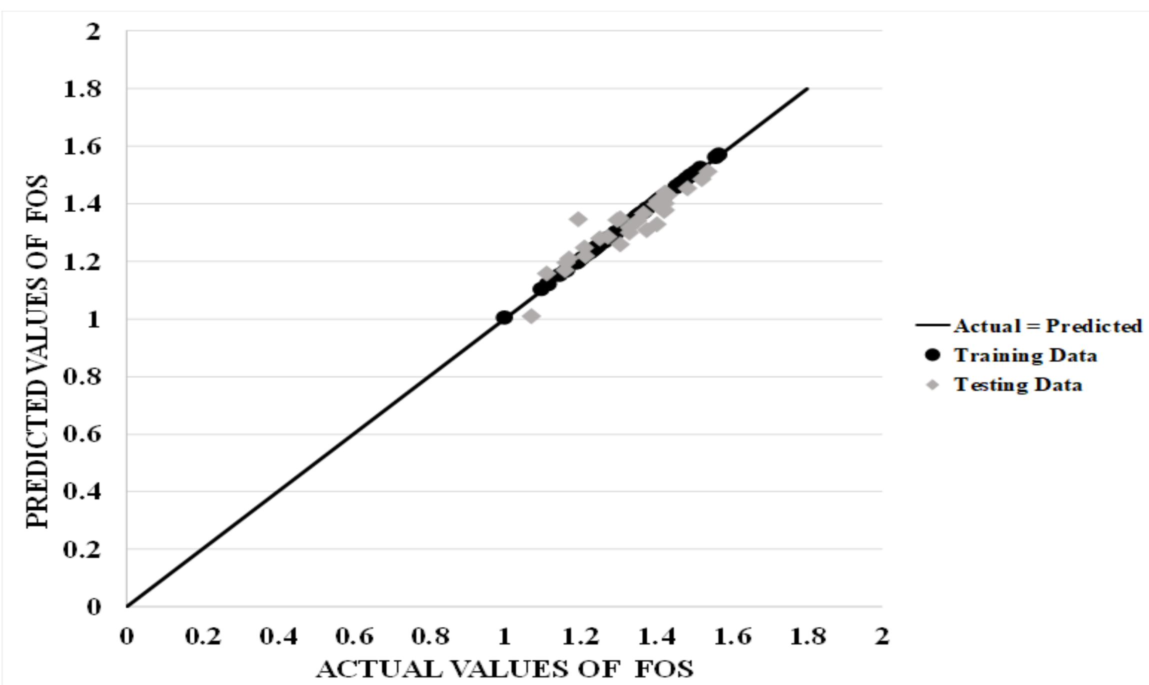


Figure 6.ANFIS model performance

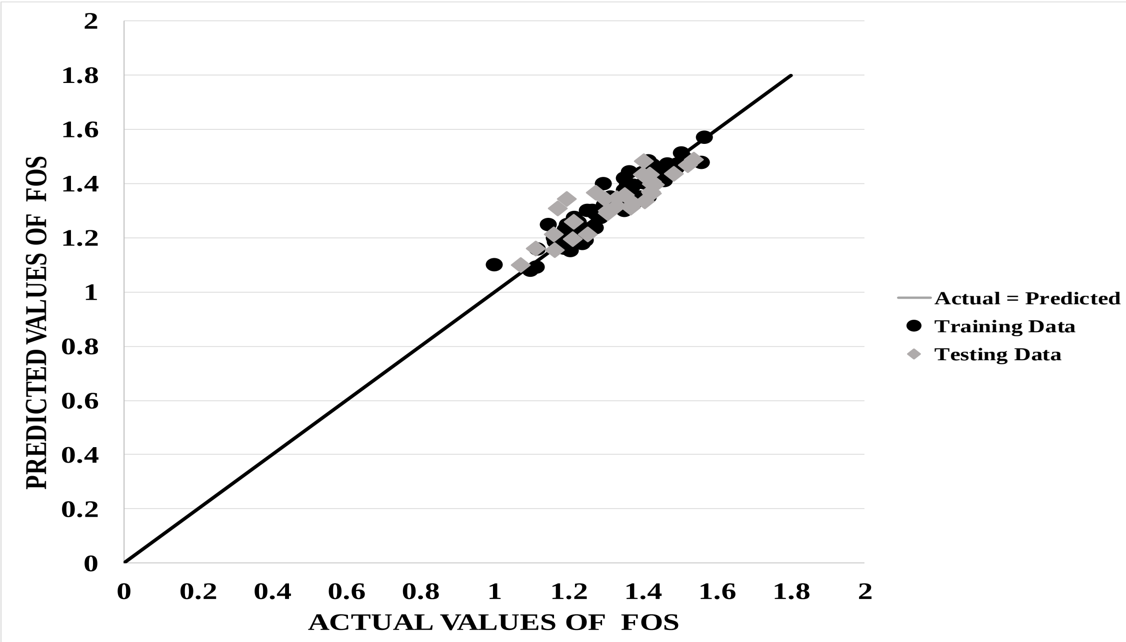


Figure 7.PSO-ANN model performance

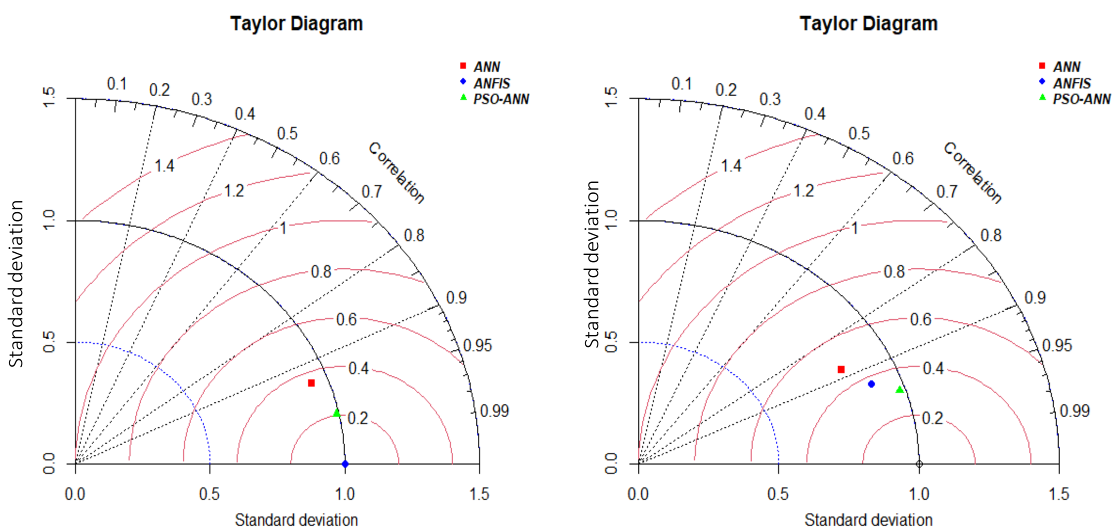
Figures 5, 6 and 7 indicate how the models performed during training and testing by plotting the actual and predicted values of the factor of safety of a multi-layered embankment slope. The plots show that the prediction of the ANN, ANFIS, PSO-ANN models are satisfactory i.e. the maximum no. of values of factor of safety are nearer along the line depicting actual equal to predicted, PSO-ANN model prediction performance is good when compared to other models.

Table 1. Performance parameters of ANN, ANFIS, PSO-ANN models

Parameters	ANN	ANFIS	PSO-ANN	Ideal Values
NS	0.7747	0.8286	0.9049	1.0
RMSE	0.0569	0.0443	0.0370	0.0
VAF	77.5391	82.9581	90.5051	100 %
R^2	0.7747	0.8286	0.9049	1.0
Adj. R^2	0.7487	0.8089	0.8939	1.0
PI	1.4672	1.5942	1.7620	> 1.0
Bias Factor	1.0048	1.0023	1.0018	1.0
RSR	0.4747	0.4139	0.3084	0.0
NMBE (%)	0.2437	0.2470	0.1127	0.0
MAPE	0.0350	0.0256	0.0210	0.0
RPD	2.1066	2.4158	3.2426	> 2.5
WI	0.9288	0.9610	0.9751	0.0-1.0
MAE	0.0456	0.0332	0.0281	0.0
MBE	0.0032	0.0033	0.0015	0.0
LMI	0.5473	0.6029	0.7207	1.0
U_{95}	0.2600	0.2270	0.2458	0.0

t-stat	0.3068	0.3988	0.2182	Smaller value
GPI	3.31E-07	2.25E-07	2.82E-08	Higher value
β	3.3710	3.1216	3.8052	>3

The performance of all the models are assessed using various parameters as given in Table 1. Table 1 demonstrates that the NS value for PSO-ANN is the closest to 1 of all the models., which indicates that predictive power of PSO-ANN is high among all. On comparing the models on the basis of RMSE and VAF, PSO-ANN is having the lesser prediction error that shows model performed better as compared to other models. The R^2 and Adj. R^2values for the PSO-ANN modelare the closest to 1 and also to each other amongst these three models, which depict that PSO-ANN soft computing model has taken most of the variability of soil parameter under consideration. PSO-ANN model is least biased from the actual and mean value and more accurate in prediction of factor of safety of stability of multi-layered soil embankment, according to the Bias factor, RSR, PI, MAPE, and NMBE values. RPD, WI, MAE, MBE and LMI values shows that PSO-ANN model predict with less error and high accuracy as compared to other two model. As per the values U_{95} and t-stat all models are performing good and GPI value shows PSO-ANN model is having higher accuracy compared to other two models. All three models, ANN, ANFIS, and PSO-ANN, have a reliability index (β) of 3 to 4, indicating that their performance is in the good category [30, 31].



(a) Training (b) Testing

Figure 8. Plot of the Taylor diagram for the models

Taylor diagram[32]depicts the models performance ,the diagram includes Standard deviation (SD),Correlation coefficient and RMSE as shown in Figure 8and all are taken together to get the most accurate model. According to the results, PSO-ANN shows more desirable performance indicates that, the actual value and predicted values for PSO-ANN model have a good agreement[33].

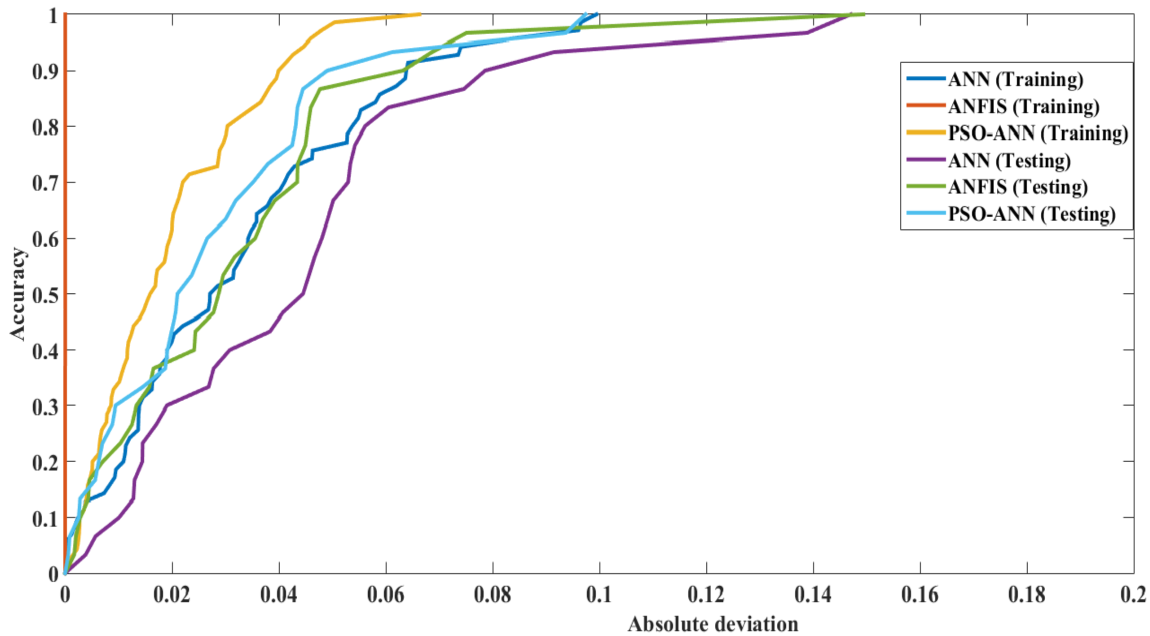


Figure 9.ROC curve plot for for ANN, ANFIS and PSO-ANN Model

Table 2. Area Under Curve (AUC) value for models of ROC curve

Models		**AUC**
ANN	**Training**	0.9683
ANFIS		0.9999
PSO-ANN		0.9814
ANN	**Testing**	0.9569
ANFIS		0.9693
PSO-ANN		0.9735

Figure 9 shows a ROC curve plot [34] for factor of safety (F) values of multi-layered soil embankment slope for the soft computing models ANN, ANFIS, and PSO-ANN during training and testing. Table 2 shows the AUC value of the ANN, ANFIS, and PSO-ANN models based on the ROC curve. In compared to the other two models, the PSO-ANN model has a higher classification accuracy based on AUC values.

Table 3. Mann–Whitney statistics of ANN, ANFIS and PSO-ANN models

M–W test statistics	**Training**			**Testing**		
	ANN	**ANFIS**	**PSO-ANN**	**ANN**	**ANFIS**	**PSO-ANN**
M–W U	2472	2536	2443	453	454	456
P	0.9286	0.6377	0.9954	0.9705	0.9752	0.992

In addition, Mann–Whitney U (M–W) test is also used to ensure that the models are homogeneous and that the acceptancy is acceptable [35]. As shown in Table 3, the P-values for all three models ANN, ANFIS, and PSO-ANN are greater than 0.05, indicating that they all support the null hypothesis, implying that they all follow the normal distribution trend. Among all the models, PSO-ANN follows the normal distribution trend the best.

Table 4.ANN, ANFIS, and PSO-ANN models are subjected to an A-D k-sample test.

A-D k-sample test	Training			Testing		
	ANN	ANFIS	PSO-ANN	ANN	ANFIS	PSO-ANN
AD	0.2200	0.2160	0.1460	0.4940	0.4653	0.4120
P	0.9876	0.9889	1	0.7630	0.8672	0.9852

Anderson-Darling (AD) statistical test is also used to evaluate which model's data is obtained from same distribution of probability which determines whether or not the model follows a normal distribution. P-value acquired from the Anderson-Darling (AD) test[36] shown in Table 4, all the models P value are greater than 0.05 which indicates that ANN, ANFIS and PSO-ANN all works as normal distribution, but PSO-ANN model follows the normal distribution trend closer among ANN, ANFIS and PSO-ANN models.

6. Conclusion

In this research, for the reliability analysis of multi-layered soil embankment slope stability, three modelling soft computing techniques, ANN, ANFIS, and PSO-ANN, were applied.On the basis of numerous performance parameters, all of the models were compared. The models' capacity of prediction factor of safety of multi-layered embankment slope for slope stability is good, according to the reliability index of all models. But on the basis of various performance parameters it was found that PSO-ANN outperformed among all three models which reveals a new technique of reliability analysis ofslope stability analysis of multi-layered soil embankment slope. Models were also analysed using two statistical tests Mann–Whitney U (M–W) and Anderson-Darling (AD) test and the results showed that models follow the normal distribution trend very closely. Taylor diagram and ROC curve showed the performance of models and among the models PSO-ANN outperformed.So, based on the findings, for slope stability studies, PSO-ANN can be used as a reliable soft computing reliability analysis technique for determining the factor of safety of a multi-layered soil embankment slope.

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