



# Probabilistic Stability Analysis of Earthen Slope Using ANN, PSO-ANN, GPR and GA-ANFIS Soft Computing Techniques

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**Abstract** In the present paper, reliability analysis is performed for soil slope stability on  $c$ - $\phi$  soil slope section using four different soft computing techniques ANN, PSO-ANN, GPR and GA-ANFIS. For performing reliability analysis, the coefficient of variation for cohesion, angle of shear resistance and unit weight is taken as 0.3, 0.2 and 0.03, mean value as 10 kPa, 30° and 20 kN/m<sup>3</sup>, respectively, was used to generate 100 datasets and factor of safety (FOS) of soil slope was calculated by Morgenstern-price method using the GeoStudio 2016 software. After the generation of the actual dataset for the factor of safety of soil slope stability, the dataset is divided into 70% and 30% of the training and testing, respectively, of the soft computing models (ANN, PSO-ANN, GPR and GA-ANFIS). Soft computing models were used to evaluate factor of safety while in training and testing. All of the models are analysed based on various fitness parameters, Taylor diagram and statistical Anderson Darling test to find the most reliable model for the slope stability analysis of  $c$ - $\phi$  soil slope section under study. From the results, it was found that all models performed well, but GA-ANFIS outperformed on comparison among the models i.e. GA-ANFIS model is having higher accuracy and lowest error for the prediction FOS of the soil slope stability.

**Keywords** Probabilistic analysis · Reliability analysis · ANN · PSO-ANN · GPR · GA-ANFIS

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## Introduction

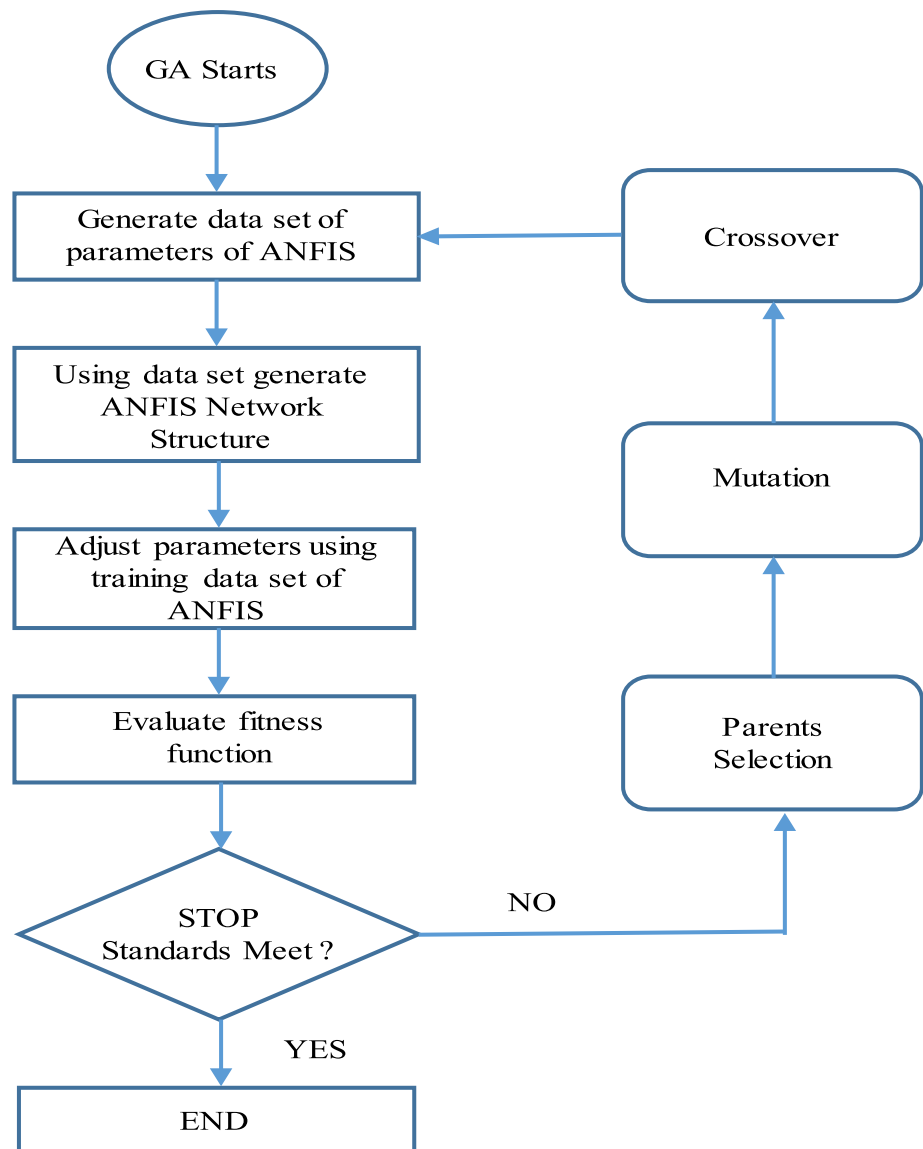
The stability of soil slopes is a significant issue nowadays since it affects the stability of many open pits, earth dams, and other structures built with soil [1]. On Earth, soil is a naturally occurring substance that exhibits a high degree of variability in its attributes as a result of the process of its evolution. This because of which, it is quite challenging to determine the attributes of soil with high accuracy. Despite the fact that there are many methods, such as the strength reduction method (SRM) and limit equilibrium method (LEM), that can be used to solve the problem of slope stability, one of the reasons for the failure in most of the cases occurs because these methods use deterministic approach. Testing data variability is also a result of the numerous errors, such as error while taking sample and test, as illustrated by Phoon [2]. Reliability analysis is taken in this study to analyse soil slopes in order to use the probabilistic technique in order to overcome these limitations. The soil factors on which stability of soil slope depends are used to develop multiple models for the reliability study, and the outputs provided by these models are examined for the determination of their applicability.

Many scholars in the past have adopted a probabilistic approach in their work. To demonstrate the uncertainty in the soil parameters of an embankment, researchers have performed probabilistic analysis using field and laboratory data sets [3]. Wang et al. [4] investigated post-slope failure utilising a probabilistic model random smoothed particle hydrodynamics. In past, multi-layer embankment was subjected to a reliability investigation by Liang et al. [5], which demonstrated the integration of soil property variability. Cheng [6] demonstrated how to use the annealing approach to quickly and precisely determine the critical failure surface. On a particular earth dam segment, Babu and

Srivastava [7] used response surface methodology (RSM) to conduct a reliability analysis. Using a variety of probabilistic models, different failure modes were found by means of the multi-modal soft computing models [8]. Earthen dam's structure was analysed for safety using an artificial neural network (ANN) soft computing model in both static problem and dynamic problem, and the model performed well at predicting the slope safety factor [9]. For the reliability investigation of infinite slope, Kumar et al. [10] used a variety of probabilistic methods, including multivariate adaptive regression spline (MARS) and adaptive network-based Fuzzy inference system (ANFIS), findings indicate that the models are working good. Samui et al. [11] built a Gaussian process regression (GPR) model in conjunction with an MPMR model to estimate the suction caisson's uplift capacity. Gao et al. [12] constructed a soft computing model GPR

for the prediction of fragmentation of rock in mines. After evaluating past critical studies, it was found out that variability in the soil characteristic parameters is not generally taken into account by standard methods of soil slope stability analysis. In the current study, our aim is to determining the reliability of soil slope stability integrating artificial neural network (ANN), particle swarm optimisation ANN (PSO-ANN), Gaussian process regression (GPR) and genetic algorithm based adaptive network-based fuzzy inference system (GA-ANFIS) soft computing models using first order reliability method (FORM). Additionally, the reliability of these models' analyses of soil slope stability is also tested using various assessment parameters.

**Fig. 1** Scheme of a GA-ANFIS



### Theoretical Background of Models

#### Gaussian Process Regression (GPR)

According to Grbić et al. [13], Gaussian process (GP) is a soft computing model which uses continuous data group for the analysis. This approach can be used to solve issues involving both classification and regression [14]. GPR’s mean and covariance [15] are used to define it. Since the mean function represents the function’s central tendency, it is typically set to zero. The covariance function contains the function’s structure that is required for the solution of the problem that we have identified. In this study, FOS is a function of  $Y, \phi$  and  $c$ .

GPR follows Eq. 1 for its working.

$$y_i = f(x_i) + \epsilon \tag{1}$$

where,  $\epsilon$  is Gaussian noise.

$x = [Y, \phi, c]$  and  $y = [\text{FOS}]$  in the current analysis.

For finding output based on the new input, the following relation is provided:

$$\begin{pmatrix} y \\ y_{N+1} \end{pmatrix} \sim \mathcal{N}(0, K_{N+1}) \tag{2}$$

where  $y_{N+1}$  is target and  $x_{N+1}$  is new input.

$y_{N+1}$  follows the Gaussian distribution and  $K_{N+1}$  related to different parameters using Eq. 3.

$$K_{N+1} = \begin{bmatrix} [K] & [k(x_{N+1})] \\ [k(x_{N+1})]^T & [k_1(x_{N+1})] \end{bmatrix} \tag{3}$$

In this study, training inputs and test input is given by  $k(x_{N+1})$ , train and test input auto-covariance is expressed as  $K$  and  $k_1(x_{N+1})$ . The covariance function used to create the GPR model is the radial basis function.

#### Genetic Algorithm (GA)

Genetic algorithm (GA) is an part of evolutionary algorithms’ population-based probabilistic algorithms and also one of the metaheuristic algorithms [16]. Similar to other EAs, GA uses selection, crossover, and mutation as its main operators. Evolutionary theory serves as the foundation for the class of computational models known as genetic algorithms [17–19]. These algorithms add recombination operators for getting critical values while encoding a suggested answers based on data structure that resembles a chromosome. Chromosomes are selected at random and are used for a genetic algorithm development. The reproduction

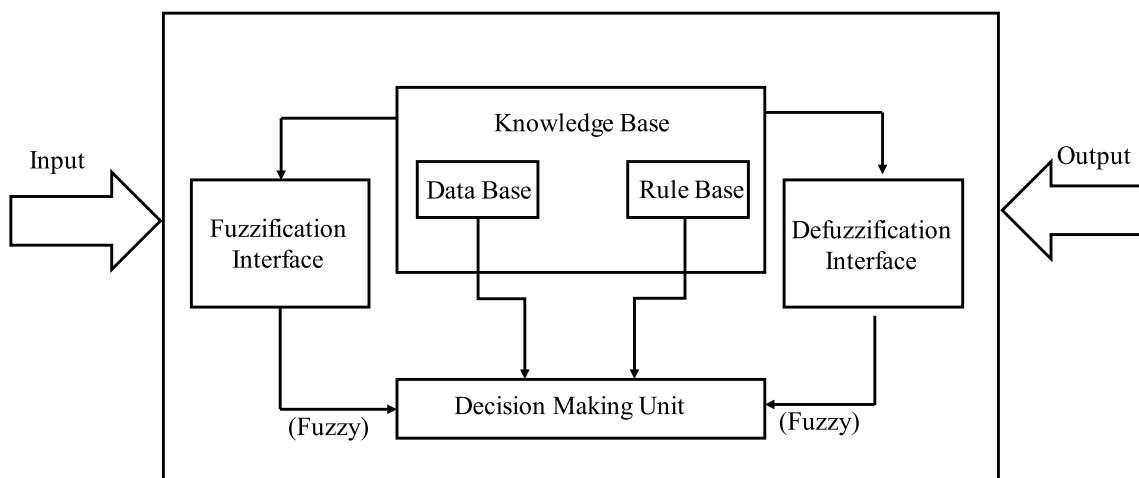
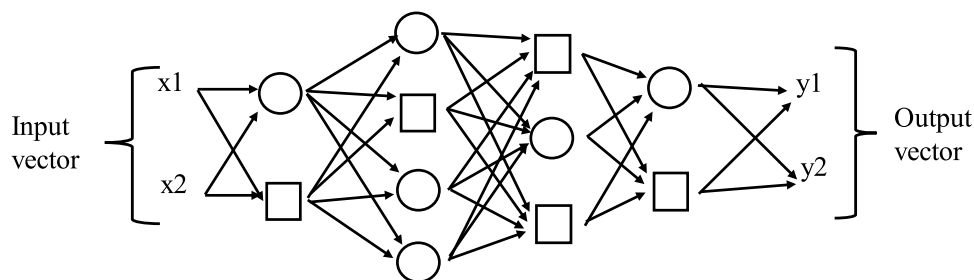


Fig. 2 Inference system of fuzzy logic

Fig. 3 Adaptive network diagram



opportunities are then allocated and these structures appraised so that the chromosomes having best solution will have more chances to reproduce than who will provide a subpar result.

Steps involved in GA process [20]: (a) initialisation, (b) operators in GA, and (c) evaluation.

- (a) **Initialisation:** The initial dataset for the starting candidate is randomly generated. Each of the solution, denoted by chromosome in GA, is associated with set of variable values, which is binary values taken in current study.
- (b) **Operators in GA:**
  - (i) **Selection:** Solutions, also known as parents, are sorted by selection operator having max. survival, like Darwin’s selection theory and transferred to next level.
  - (ii) **Crossover:** The operator switches two people (parents) to produce new people (child) for the next generation. In this case, the GA model employs the scattering method, in which a random string of binary values is initially created, the bits (gens) with one parent are then chosen from the first, and the other bits are chosen from the other lot.
  - (iii) **Mutation:** This crucial tool randomly modifies the information stored into GA’s chromosomes. To prevent the set of rules from converging to neighbourhood optima, it is needed to modify the population’s diversity and boost the search potential of the quest scheme through mutation.

- (c) **Evaluation:** This function is used for finding right fit for every people. The following procedure includes the fitness function with the aim to optimise the problem.

In GA-ANFIS model in the first, the dataset is provided to the ANFIS model and after that the GA works for initialisation, operation through operators, and then, the evaluation of the dataset to predict the most accurate factor of safety for the considered slope section. Figure 1 shows the working of GA-ANFIS soft computing model.

**ANFIS**

Traditional modelling techniques are incompatible with systems that are not in proper procedure and are indeterminate. Soft computing analysing systems are good for interpreting the system of this nature. Neural technology and fuzzy logic are among the numerous techniques that comprise the ability to adopt various systems. The neural network for these types of system has the ability of learning and self-adaptation. In addition, fuzzy logic’s use of fuzzy if–then rules allows it to account for uncertainties in the actual site conditions. ANFIS (adaptive network-based fuzzy inference system) was designed to incorporate benefits of neural networks and if–then rules of fuzzy systems.[21].

**Fuzzy Logic Systems**

The definition of the if–then rule is as follows: When M and N are the labels for fuzzy rules and their respective membership functions, then IF M is correct THEN N is also correct

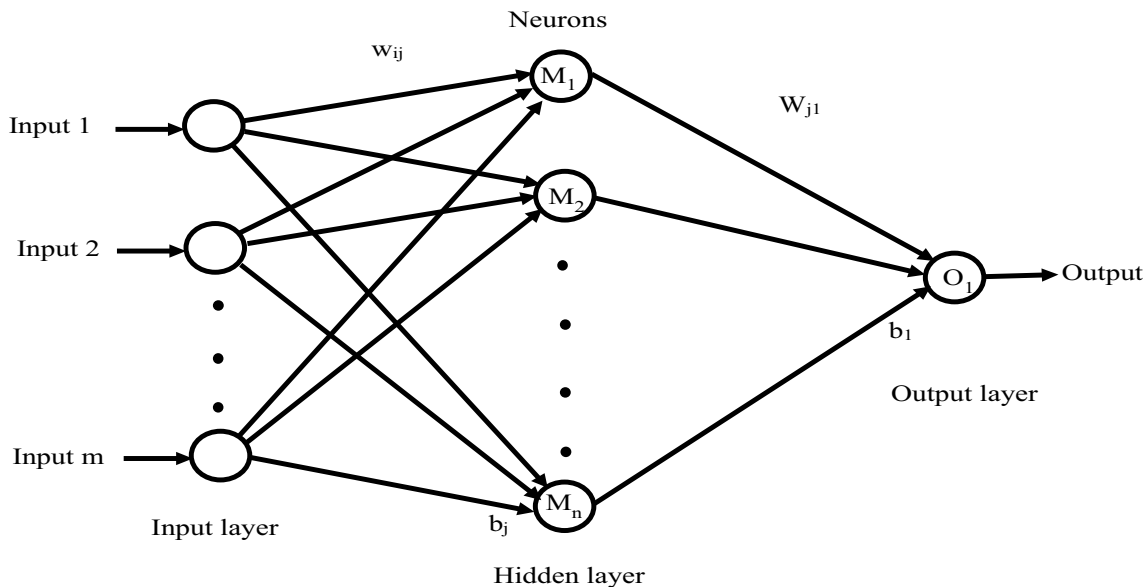
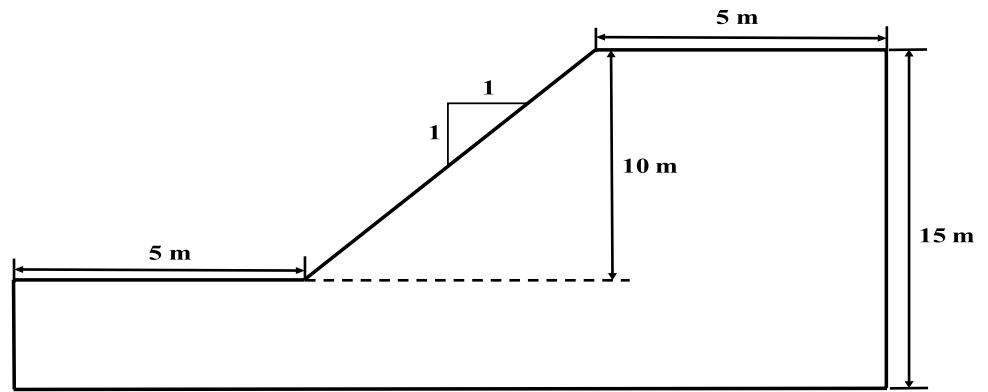


Fig. 4 Functional flow diagram of the ANN

**Fig. 5** Typical c-φ soil slope section



**Table 1** Statistical properties of soil parameters [30]

| Parameter                                   | Coefficient of variation (COV) | Mean value           | References |
|---|--------------------------------|----------------------|------------|
| Cohesion (c)                                | 0.3                            | 10 kPa               | Cho [30]   |
| Angle of shear resistance (φ <sup>0</sup> ) | 0.2                            | 30°                  | Cho [30]   |
| Unit weight (γ)                             | 0.03                           | 20 kN/m <sup>3</sup> | Cho [30]   |

[22]. As shown in Fig. 2, fuzzy if-then rules are crucial for making decisions under conditions of uncertainty due to their clear structure.

### Adaptive Networks

It is a part of ANFIS soft computing model which is having nodes and these nodes are linked to one another as shown in Fig. 3. The network learning rule's [23] control parameters are implemented to ensure that errors are minimised. The nodes of the network are of adaptive nature i.e. output that they provide is reliant on connected factors.

### Particle Swarm Optimisation-based Artificial Neural Network

#### Particle Swarm Optimisation (PSO)

PSO computes, using a population search technique. Each optimisation issue solution is represented by a particle in this computational technique, which groups particles into swarms. The estimated best level for each and every particle is shown in the results. This is known as the best position for all particle ( $P_{best}$ ), and the overall best position is known as  $G_{best}$ . The next movement and location can now be determined by combining  $P_{best}$  and  $G_{best}$  particles. The particle's ideal value for function can be discovered by counting iterations.

The  $N$  size population is represented by  $Z = [Z_1, Z_2, \dots, Z_N]^T$ . Every particle  $Z_m$  is defined as  $Z_s = [Z_{s,1}, Z_{s,2}, Z_{s,3}, Z_{s,4}, \dots, Z_{s,U}]$ . The starting velocity of  $Z$  is  $V = [V_1, V_2, \dots, V_s]$  and every velocity is  $V_s = [V_{s,1}, V_{s,2}, V_{s,3}, V_{s,4}, \dots, V_{s,U}]$ , where  $s$  varies from 1 to  $N$ .

$$V_{s,q}^{l+1} = w \times V_{s,q}^l + c_1 r_1 (P_{best,s,q}^l - Z_{s,q}^l) + c_2 r_2 (G_{best,q}^l - Z_{s,q}^l) \tag{4}$$

$$Z_{s,q}^{l+1} = Z_{s,q}^l + V_{s,q}^{l+1} \tag{5}$$

In above equation,  $P_{best,s,q}^l$  denotes best  $q^{th}$  of the  $s^{th}$  individual and  $G_{best,q}^l$  denotes  $q^{th}$  best of global.  $w$  denotes inertia weight parameter and,  $r_1$  and  $r_2$  as +ve acceleration that is influence on the  $p_{best,s}$  position. The  $P_{best}$  and  $G_{best}$  are calculated with updates as follows:

At iteration 1

$$\text{If } f(Z_s^{l+1}) < f(P_{best,s}^l) \text{ then } P_{best,s}^{l+1} = Z_s^{l+1} \text{ else } P_{best,s}^{l+1} = P_{best,s}^l \tag{6}$$

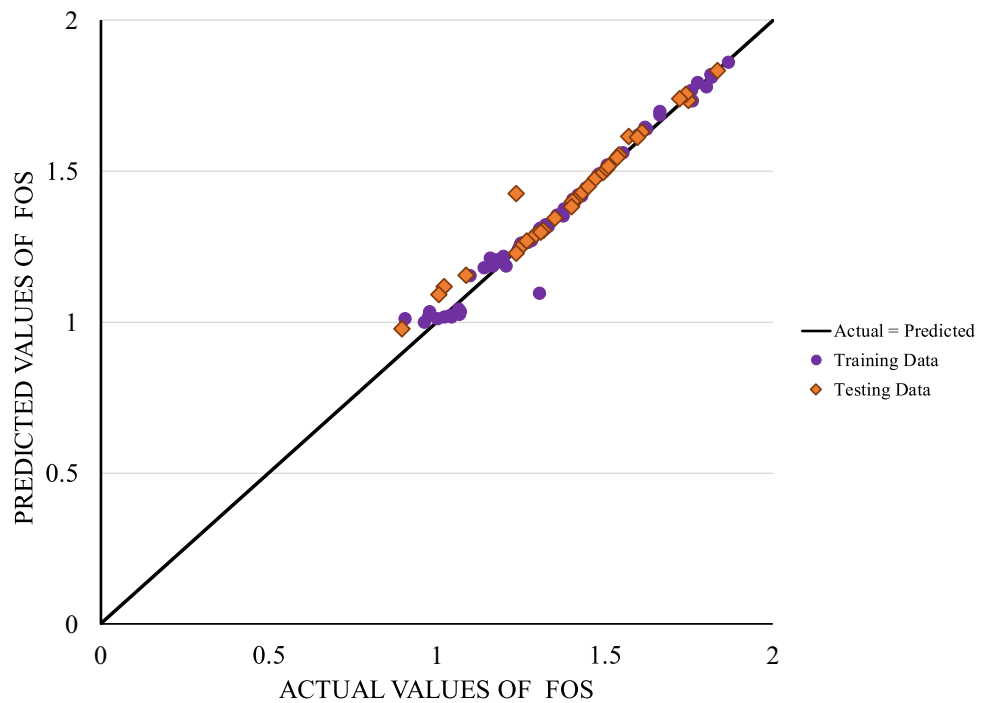
$$\text{If } f(Z_s^{l+1}) < f(G_{best}^l) \text{ then } G_{best}^{l+1} = Z_s^{l+1} \text{ else } G_{best}^{l+1} = G_{best}^l \tag{7}$$

PSO has been explained and used in many research works [24–26].

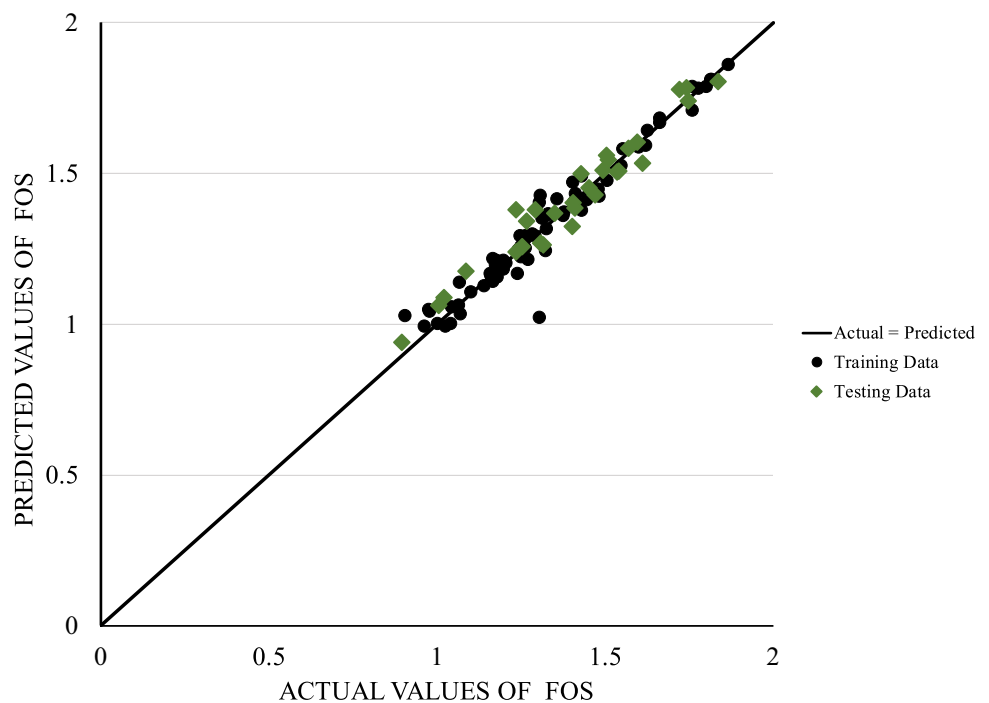
#### Artificial Neural Network (ANN)

ANN functions as a model with a black box that connects the input and output datasets. It is made up of neurons that are connected to inputs by biases and weights [27–29]. The three layers that make up an ANN are the input layer, the hidden layer, and the output layer. The hidden and output layers both contain neurons; however, the input layer does not. Figure 4 depicts the general layout of an ANN with  $m$  numbers of inputs and having one output. The neurons' weight linked to the  $i^{th}$  input of the input layer and the  $j^{th}$  neuron of the hidden layer is called  $w_{ij}$ , and the bias connected to the  $j^{th}$  of the part is called  $b_j$ , respectively.

**Fig. 6** Model's performance for training and testing dataset of ANN



**Fig. 7** Model's performance for training and testing dataset of PSO-ANN



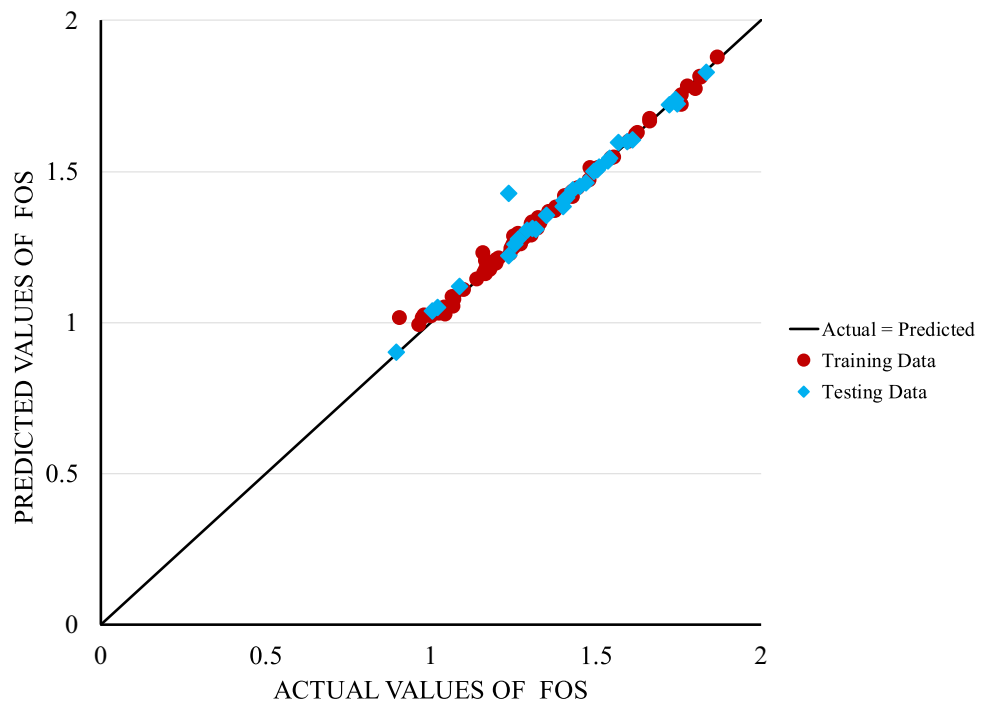
To determine the bias and weights of the neurons, an ANN model uses trained input datasets and corresponding output sets. With the aid of MATLAB 2015, the network was trained in this study to obtain accurate weights and bias both with and without the use of PSO. For the PSO-ANN model, first PSO optimises the dataset, and after the optimisation, the dataset was transferred for the ANN model run for the

prediction of the factor of safety (FOS) for the considered slope section.

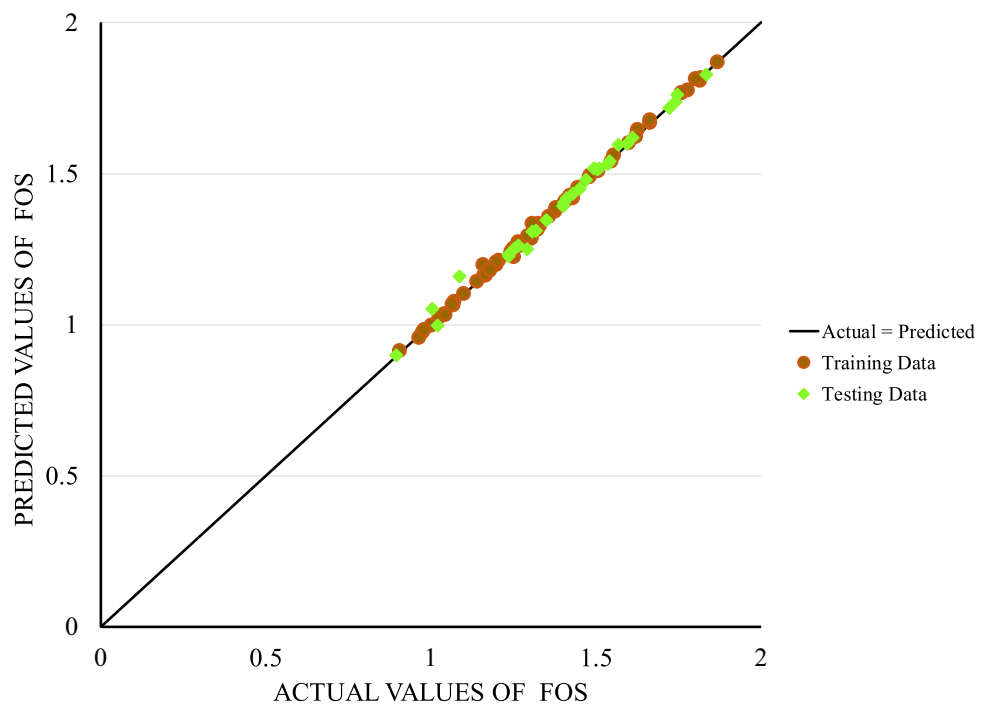
*Model Development*

Our reliability investigation of soil slope stability utilising ANN, PSO-ANN, GPR, and GA-ANFIS soft computing

**Fig. 8** Model's performance for training and testing dataset of GPR



**Fig. 9** Model's performance for training and testing dataset of GA-ANFIS



models was conducted in this research work employing a 15-m high  $c-\phi$  soil slope having a side slope of 1:1, as provided as an example by Cho [30]. Figure 5 depicts the  $c-\phi$  soil slope in detail. The variation in soil parameters,  $c$ ,  $\phi^\circ$  and  $\gamma$  is taken into account in the probabilistic analysis. Table 1 summarises the statistical properties of soil parameters for the considered slope section [30].

Using the GeoStudio 2016 programme, the Morgenstern-price technique is applied to calculate the factor of safety (FOS) of the  $c-\phi$  type of soil slope.  $c$ ,  $\phi^\circ$  and  $\gamma$  are the three parameters taken as input variables, and the FOS of the slope is obtained as a response. By the help of GeoStudio 2016 software, the allowable range of  $c$ ,  $\phi^\circ$  and  $\gamma$  is used to obtain 100 datasets of corresponding factor of safety (FOS). ANN,

**Table 2** Assessment parameters of ANN, PSO-ANN, GPR and GA-ANFIS models

| Parameters          | ANN       | PSO-ANN   | GPR       | GA-ANFIS  | Ideal values  |
|---------------------|-----------|-----------|-----------|-----------|---------------|
| NS                  | 0.9525    | 0.9406    | 0.9711    | 0.9918    | 1.0           |
| RMSE                | 0.0486    | 0.0543    | 0.0379    | 0.0202    | 0.0           |
| VAF                 | 96.1072   | 94.5584   | 97.3137   | 99.2145   | 100%          |
| R <sup>2</sup>      | 0.9525    | 0.9406    | 0.9711    | 0.9918    | 1.0           |
| Adj. R <sup>2</sup> | 0.9471    | 0.9338    | 0.9678    | 0.9909    | 1.0           |
| PI                  | 1.8596    | 1.8250    | 1.9030    | 1.9629    | > 1.0         |
| Bias Factor         | 1.0181    | 1.0142    | 1.0088    | 1.0033    | 1.0           |
| RSR                 | 0.2178    | 0.2437    | 0.1700    | 0.0904    | 0.0           |
| NMBE (%)            | 1.4630    | 1.1155    | 0.7170    | 0.2822    | 0.0           |
| MAPE                | 0.0220    | 0.0331    | 0.0128    | 0.0094    | 0.0           |
| RPD                 | 4.5904    | 4.1039    | 5.8812    | 11.0615   | > 2.5         |
| WI                  | 0.9871    | 0.9840    | 0.9924    | 0.9979    | 0.0–1.0       |
| MAE                 | 0.0261    | 0.0435    | 0.0161    | 0.0117    | 0.0           |
| MBE                 | 0.0206    | 0.0157    | 0.0101    | 0.0040    | 0.0           |
| LMI                 | 0.8519    | 0.7525    | 0.9087    | 0.9332    | 1.0           |
| U <sub>95</sub>     | 0.4474    | 0.4500    | 0.4434    | 0.4389    | 0.0           |
| t-stat              | 2.5206    | 1.6255    | 1.4870    | 1.0825    | Smaller value |
| GPI                 | 5.356E-05 | 3.707E-05 | 7.298E-06 | 3.111E-04 | Higher value  |
| β                   | 2.08      | 2.03      | 3.23      | 3.52      | Higher value  |

PSO-ANN, GPR and GA-ANFIS models must be standardised in accordance with Eq. 8 in order to use these datasets in MATLAB.

$$X_{\text{nor}} = \frac{X - X_{\text{min.}}}{X_{\text{max.}} - X_{\text{min.}}} \quad (8)$$

where,

$X_{\text{nor}}$  = normalised value

$X$  = value

$X_{\text{min.}}$  = min. of range

$X_{\text{max.}}$  = max. of range

The normalised dataset is fed into the models as input, and the associated predicted output of the models is obtained. The dataset of FOS obtained from the GeoStudio 2016 is the actual dataset and the output which is obtained from four soft computing models is the predicted dataset. In order to compare and determine which models are the best at making predictions, the actual and predicted FOS values that are derived from models are put to the test using a variety of fitness factors.

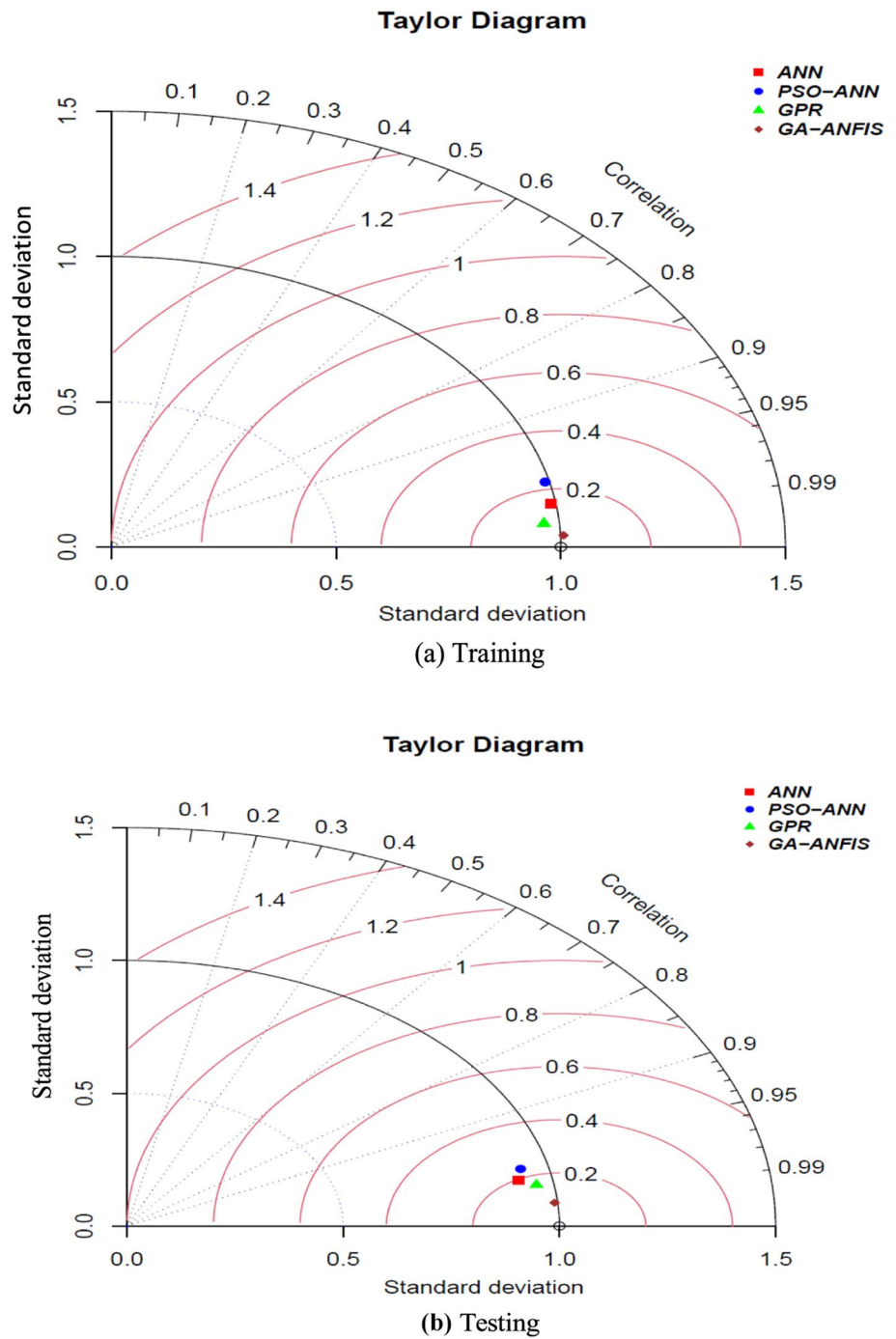
## Results and Discussion

The four soft computing models ANN, PSO-ANN, GPR, and GA-ANFIS were used for a reliability analysis using first-order reliability method (FOSM) of the slope stability for the analysis of  $c$ - $\phi$  soil section under consideration. The dataset of FOS obtained from the GeoStudio 2016 is the actual dataset and the output which is obtained from four soft computing models is the predicted dataset. The data were normalised, divided into training and test sets and used as input and output for each model. Graph of actual versus predicted factor of safety of slope stability for both the stage of training and testing of the ANN, PSO-ANN, GPR and GA-ANFIS models is shown in Figs. 6, 7, 8 and 9, respectively. All values from the training and testing sets of model are relatively close along the line showing actual factor of safety equal to predicted factor of safety, but when the models are compared among the four models, GA-ANFIS model performs well because the results of GA-ANFIS are closest aligned along the actual equals to predicted line.

All the four soft computing models are analysed using various assessment parameters Nash–Sutcliffe efficiency (NS)[31], root mean square error (RMSE)[32], relative percentage difference (RPD) [33], R<sup>2</sup> (coefficient of determination) [1], performance Index (PI) [34], bias factor [35], variance account factor (VAF), RSR, normalised mean bias error (NMBE), MAPE (mean absolute percentage error) [36], Willmott's index for agreement (WI), mean bias error (MBE) and mean absolute error (MAE), Legate and McCabe's index (LMI)[37, 38], expanded uncertainty (U<sub>95</sub>)



**Fig. 10** Taylor diagram **a** training, **b** testing plotted for ANN, PSO-ANN, GPR and GA-ANFIS model

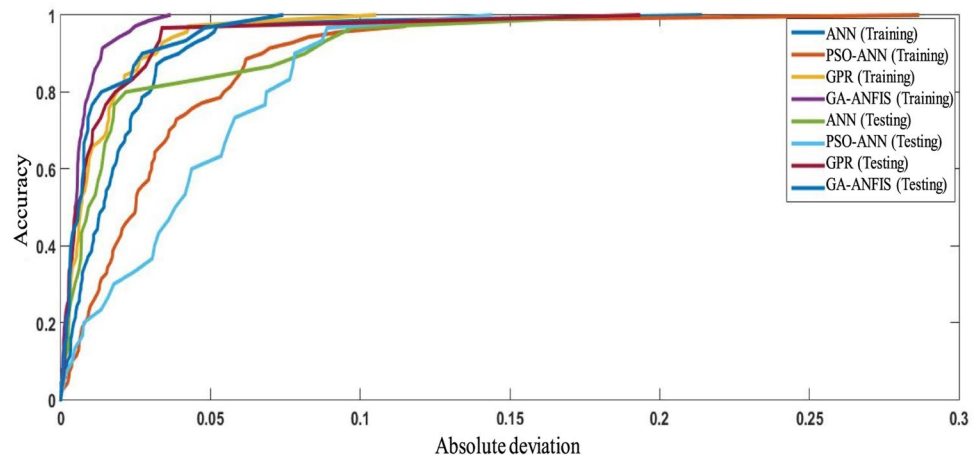


[39, 40], *t*-statistic [41], reliability index ( $\beta$ ) [42] and global performance indicator (GPI) [43] are used as mentioned in Table 2.

The assessment parameters for the four models ANN, PSO-ANN, GPR and GA-ANFIS are listed in Table 2. As obtained the NS value is close to 1 for each model, which demonstrates the excellent predictive capacity of all models. The RMSE and VAF values demonstrate that, in comparison with other models, the GA-ANFIS model performed well in prediction of FOS since it has the lowest error while

predicting the FOS among the four models. GA-ANFIS model's  $R^2$  and Adj.  $R^2$  data are almost equal and also the values are closer to 1 when compared to other models, this indicates that the GA-ANFIS has included the variability in soil attributes into account. The GA-ANFIS model has a high level of prediction capability and with least amount of biasness, according to comparisons of the models on the basis of MAPE, PI, RSR, bias factor and NMBE (%) parameters. The values for MAE, LMI, MBE and WI for four models demonstrate how smaller the models diverge from the

**Fig. 11** ROC curve plot for four soft computing models



**Table 3** AUC value of ROC curve for four soft computing models

|          | Models   | Area under curve (AUC) |
|----------|----------|------------------------|
| Training | ANN      | 0.9809                 |
|          | PSO-ANN  | 0.9675                 |
|          | GPR      | 0.9878                 |
|          | GA-ANFIS | 0.9936                 |
| Testing  | ANN      | 0.9771                 |
|          | PSO-ANN  | 0.9589                 |
|          | GPR      | 0.9871                 |
|          | GA-ANFIS | 0.9893                 |

actual values. According to the RPD value of soft computing models, the GA-ANFIS is the most accurate of the four (Table 2). All of the models, including ANN, PSO-ANN, GPR and GA-ANFIS, did well because the *t*-stat and  $U_{95}$  values were quite low. Given that the GPI value for the GA-ANFIS model is the lowest of the four models, it is highly accurate in forecasting the FOS of soil slope. The  $\beta$  values for ANN, PSO-ANN, GPR and GA-ANFIS are presented in Table 2. The performance of the models is comparable, as indicated by the reliability index ( $\beta$ ) value of all four soft computing models [42, 44].

A Taylor diagram [45] is a statistical graphic used to determine the most accurate soft computing model which is having the following parameters to represent: standard deviation (SD), RMSE and correlation coefficient in the

diagram. In Fig. 10, Taylor curves combine SD, RMSE and correlation coefficient to determine the most precise model for the prediction of FOS. According to the plot of the training Taylor diagram (Fig. 10), the GA-ANFIS soft computing model represents the most precise model for the prediction of FOS in comparison with the other three models. In conclusion, it demonstrates that the actual and predicted results of the GA-ANFIS soft computing model are in good agreement.

Figure 11 presents the ROC (receiver operating characteristic) curve plot for the ANN, PSO-ANN, GPR, and GA-ANFIS soft computing models [46]. Table 3 displays the AUC (area under curve) values for all four soft computing models. Area under curve values from Table 3 show that the GA-ANFIS soft computing technique has the highest value of area under the curve among the four techniques, which indicates that it is having the highest classification accuracy.

A statistical test known as Anderson–Darling (A–D) was developed by Anderson and Darling in 1952 to determine if the model observes the trend of normal distribution or not [47]. For all the models ANN, PSO-ANN, GPR, and GA-ANFIS, the test yields *P*-values (given in Table 4), which are obtained to be greater than 0.05, demonstrating that all four models behave normally. The GA-ANFIS model observes the trend of normal distribution trend the closest out of the four.

**Table 4** A–D k-sample test results of ANN, PSO-ANN, GPR and GA-ANFIS

| A–D k-sample test | Training |         |        |          | Testing |         |        |          |
|-------------------|----------|---------|--------|----------|---------|---------|--------|----------|
|                   | ANN      | PSO-ANN | GPR    | GA-ANFIS | ANN     | PSO-ANN | GPR    | GA-ANFIS |
| AD                | 0.1025   | 0.1960  | 0.0997 | 0.0714   | 0.1350  | 0.1520  | 0.1250 | 0.1090   |
| P                 | 1        | 0.9940  | 1      | 1        | 1       | 0.9997  | 1      | 1        |

## Conclusions

In this article, the ANN, PSO-ANN, GPR and GA-ANFIS soft computing models were taken as a tool to study reliability analysis of soil slope stability. On the basis of numerous performance assessment parameters and Taylor curves, all the four models were thoroughly evaluated and compared, based on which it was found that GA-ANFIS model outperformed having some testing outputs as  $NS = 0.9918$ ,  $RMSE = 0.0202$ ,  $VAF = 99.2145\%$ ,  $Bias\ Factor = 1.0033$ ,  $PI = 1.9629$ ,  $R^2 = 0.9918$ ,  $GPI = 3.1E-04$ ,  $U_{95} = 0.4389$ ,  $t\text{-stat} = 1.0825$  and  $\beta = 3.52$ . According to the ROC curve results, the GA-ANFIS model had the highest area under the curve (AUC) value, which was then followed by the GPR, ANN and PSO-ANN models. The Anderson–Darling (A–D) statistical test revealed that the GA-ANFIS model had the trend that was most similar to that of a normal distribution. The results conclude that GA-ANFIS model is better model with higher accuracy and lowest error for the prediction FOS of the soil slope stability and also, it can be a part of the portfolio of predicting tools utilised by the practitioners.

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**Data Availability** Data will be made available on request.

## Declarations

**Conflict of interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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