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The Feasibility of Three Prediction Techniques of the Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System, and Hybrid Particle Swarm Optimization for Assessing the Safety Factor of Cohesive Slopes

Hossein Moayedi [1,2], Dieu Tien Bui [3,4,*], Mesut Gör [5], Biswajeet Pradhan [6,7] and Abolfazl Jaafari [8]

1. Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam; hossein.moayedi@tdtu.edu.vn
2. Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam
3. Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam
4. Geographic Information System Group, Department of Business and IT, University of South-Eastern Norway, N-3800 Bø i Telemark, Norway
5. Department of Civil Engineering, Division of Geotechnical Engineering, Firat University, 23119 Elâzığ, Turkey
6. Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering and IT, University of Technology Sydney, Sydney, NSW 2007, Australia
7. Department of Energy and Mineral Resources Engineering, Choongmu-gwan, Sejong University, 209 Neungdong-ro Gwangjin-gu, Seoul 05006, Korea
8. Research Institute of Forests and Rangelands, Agricultural Research, Education, and Extension Organization (AREEO), P.O. Box 64414-356, Tehran, Iran

* Correspondence: buitiendieu@duytan.edu.vn; Tel.: +47-966-77-678

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Abstract: In this paper, a neuro particle-based optimization of the artificial neural network (ANN) is investigated for slope stability calculation. The results are also compared to another artificial intelligence technique of a conventional ANN and adaptive neuro-fuzzy inference system (ANFIS) training solutions. The database used with 504 training datasets (e.g., a range of 80%) and testing dataset consists of 126 items (e.g., 20% of the whole dataset). Moreover, variables of the ANN method (for example, nodes number for each hidden layer) and the algorithm of PSO-like swarm size and inertia weight are improved by utilizing a total of 28 (i.e., for the PSO-ANN) trial and error approaches. The key properties were fed as input, which were utilized via the analysis of OptumG2 finite element modelling (FEM), containing undrained cohesion stability of the baseline soil (C_u), angle of the original slope (β), and setback distance ratio (b/B) where the target is selected factor of safety. The estimated data for datasets of ANN, ANFIS, and PSO-ANN models were examined based on three determined statistical indexes. Namely, root mean square error (RMSE) and the coefficient of determination (R^2). After accomplishing the analysis of sensitivity, considering 72 trials and errors of the neurons number, the optimized architecture of $4 \times 6 \times 1$ was determined to the structure of the ANN model. As an outcome, the employed methods presented excellent efficiency, but based on the ranking method, the PSO-ANN approach might have slightly better efficiency in comparison to the algorithms of ANN and ANFIS. According to statistics, for the proper structure of PSO-ANN, the indexes of R^2 and RMSE values of 0.9996, and 0.0123, as well as 0.9994 and 0.0157, were calculated for the training and testing networks. Nevertheless, having the ANN model with six neurons for each hidden layer was formulized for further practical use. This study demonstrates the efficiency of the proposed neuro model of PSO-ANN in estimating the factor of safety compared to other conventional techniques.

Keywords: machine learning; particle swarm optimization; hybrid techniques; slope failure

1. Introduction

In most engineering problems such as stability of slopes, many parameters need to be taken into account (e.g., soil stiffness, soil-interface interaction parameters, etc.) [1–3]. Most conventional approaches are very complicated, an in most cases, not considered reliable solutions (e.g., consisting nonlinear finite element model or finite difference method analysis consideration). In fact, in most cases, traditional solutions require heavy experimental equipment too. Up to now, the developed solutions explained how a particular slope (for example height, slope angle, soil characteristics, and so on) affects the above infrastructures but did not present a general solution in the case of other slope conditions. In this regard, the applied stresses on the slope, along with its distance from the crest of slope, are known as an essential factor that affects the stability of the slope [4–6]. The slope stability (e.g., subjected to vertical stresses or seismic loading) is demonstrated as a function of different key parameters that are called initial ground properties (e.g., soil elastic modulus (E), internal friction angle (φ) which for the cohesive slope is equal to zero, unit weight (γ), undrained cohesion strength (C_u) which for the sandy slope is considered to zero, Poisson's ratio (v)).

Particle swarm algorithm (PSO) provides an excellent population-based stochastic model (for example, start with specified population size), which may be utilized to set the biases and weights of an artificial neural network (ANN) to optimize its network efficiency. Several works like Nguyen et al. [7], Moayedi et al. [8], and Moayedi et al. [9] used hybrid PSO-ANN predictive approaches for dissolving complex engineering issues. However, none of them provided a proper structure for the problem of slope stability failure. Li and Wang [10] investigated the prediction of steel plate temperature using the PSO-ANN algorithm. The result revealed that the new PSO-ANN model estimated predicated speed, plate temperature, and precision of control with reasonable accuracy. Song et al. [11] used PSO-ANN successfully to find rock parameter identification surrounding tunnels. Alnaqi et al. [12] explored the possibility of the PSO-ANN model in order to estimate structure federate photovoltaic/thermal method via ANN, and also hybrid PSO models. The outputs of this work indicate that the method of PSO-ANN is capable of predicting efficient energy of the structure integrated photovoltaic/thermal apparatus with higher precision than the traditional ANN method. Moayedi et al. [9] assessed the feasibility of the surficial settlement prediction using the PSO-ANN model. The obtained results from their investigation proved that the combination of PSO-ANN could enhance the prediction reliability, since a higher degree of agreement was obtained in comparison with the conventional ANN techniques. Moayedi and Hayati [13] emphasized that the PSO-ANN model may be used to estimate the final bearing capacity concerning rock-socketed piles. Therefore, a database including 132 piles was collated from the project of Klang Valley Mass Rapid Transit, Malaysia. However, it has been recommended that the new PSO-ANN model should be used in the preliminary stages of pile design.

In general, understanding the factor of safety of homogeneous undrained slope is the main parameter in scheme most civil engineering planes, as the stability of these slopes directly impacts both short as well as high-rise structures. Various factors like soil properties of elements are used in the structure, foundation flexibility, soil condition, geological condition, and type of the soil (e.g., cohesionless or cohesive, or both as different soil layers) influence horizontal displacement of every node and result in changing the initial slope geometry. Moayedi et al. [14], Raftari et al. [15], and Jiao et al. [16] investigated and suggested formulas to calculate a reliable estimation of the factor of safety of slopes. However, in real-world examples, all of these rules are not sufficiently accurate because they did not take the most influential input layers into account. Recently, ANN-based solutions are vastly proposed for supporting the prediction of a factor of safety of homogeneous undrained slope (e.g., Pourghasemi et al. [17], Moayedi and Armaghani [18], and Moayedi et al. [19]). In this study, to predict the minimum factor of safety subjected to an external vertical stress (e.g., high-rise building next to the slope crest), 48 distinct ANN approaches (6 iterations along with 10 distinct number of neurons) and also 29 hybrid PSO-ANN algorithms (for example, PSO helping the ANN to predict better results) are provided. While the constructed models are evaluated, their main factors such as a number of swarm sizes, acceleration coefficients, and inertia weight of the models are optimized by taking advantage of a set of trial and error prediction approaches. The introduced hybrid PSO-ANN approaches that are introduced in this paper are not widely utilized in civil engineering usages. Reviewing the literature, there is almost no work that has assessed the utilization of the hybrid neuro particle-based optimization of artificial neural network (PSO-ANN)-based learning approaches to predict the factor of safety after the slope is subjected to heavy vertical stress from structures near the slope's crest. Therefore, in this research, the basic objective was to investigate the possibility of an optimal hybrid ANN method, along with algorithms of PSO for estimating a parameter of the safety of cohesive slopes contained to external forces. Note that the results of this assessment are provided as a chain of design solution charts that may simply be utilized as a fast solution for practical engineering proposes.

2. Data Collection and Methodology

2.1. Data Collection

To calculate the factor of safety of the slopes (i.e., that is subjected to the vertical stresses exerted from a shallow footing), a total of 630 plane strain finite element limit equilibrium analysis (FELE) were simulated on a pure cohesive slope (e.g., having a strip footing on top with model width equal to 1.0 m) (as shown in Figure 1) were conducted. To analyze the slopes, an individual layer of cohesive soil (with a change in cohesion strength) was utilized. As to make the problem more applicable, a particular shallow footing type was considered on the slope crest. A commercial FELE-based software called OptumG2 was used to calculate the effects of subjected stresses on the slope, along with other practical factors which generally impact the slope stability. OptumG2 was selected since it is a user-friendly and intuitive geotechnical finite element modelling (FEM) software [20]. The influential factors and an instance of result from OptumG2 were demonstrated in Figure 2 graphically. Note that as the footing properties and slope height were not varied through the input database, they were not considered as influential parameters. Therefore, footing flexibility and its material properties were not considered as part of the database used in this study.

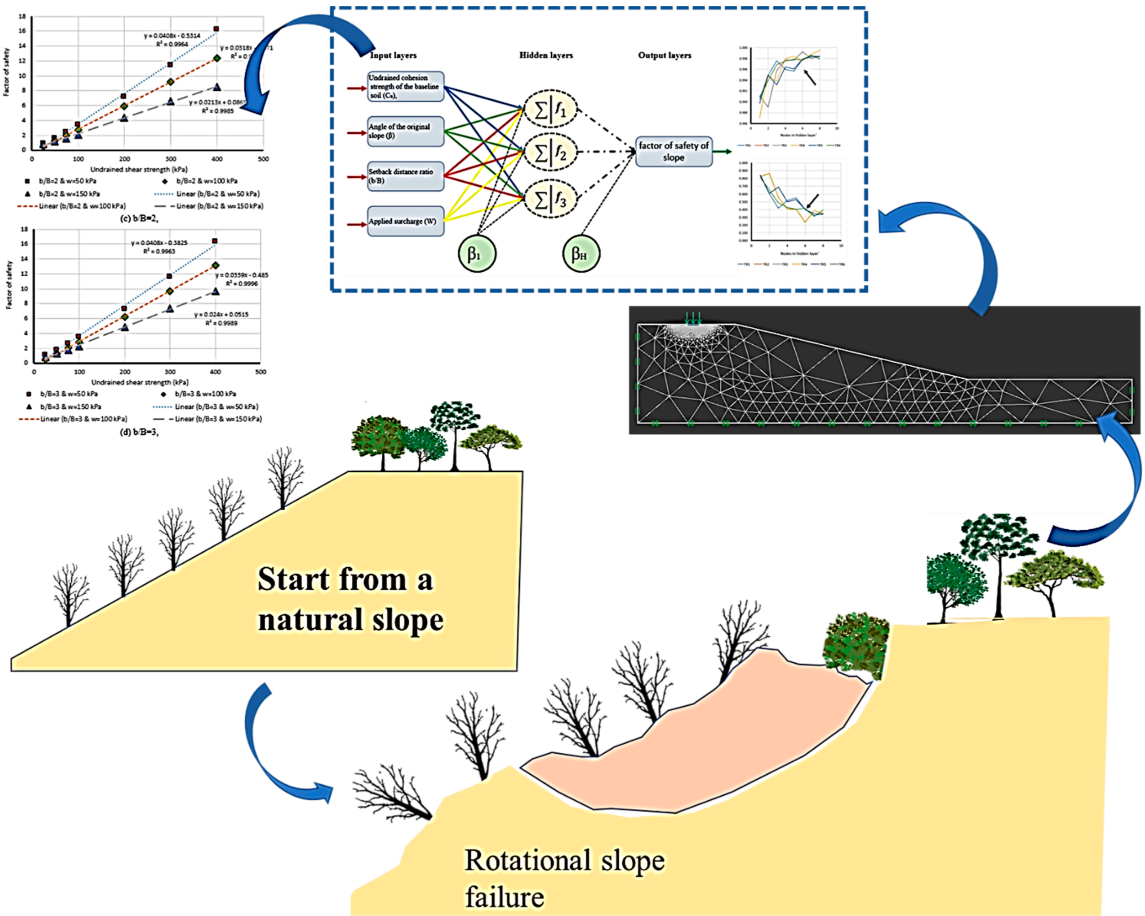
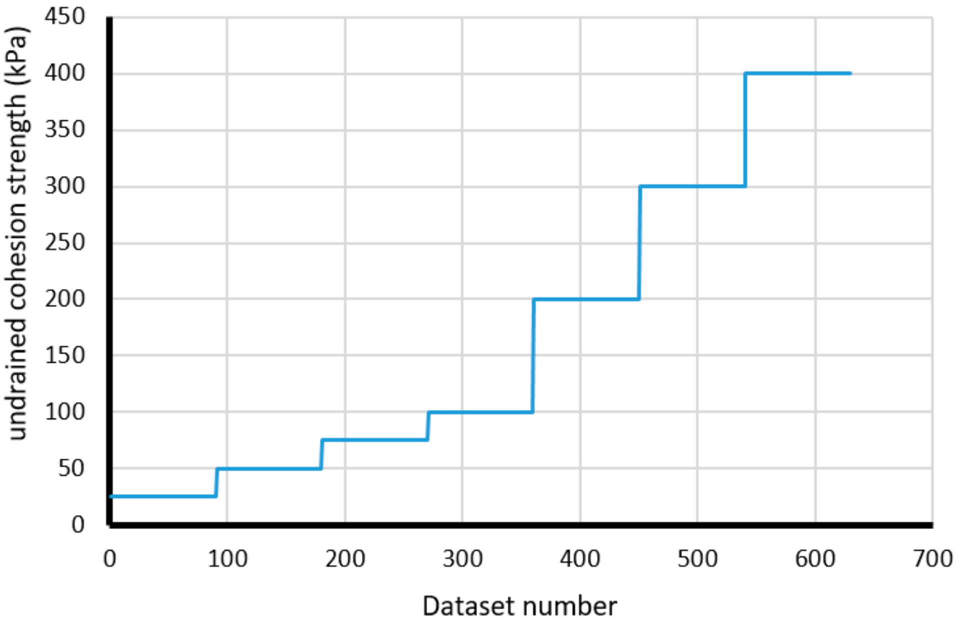
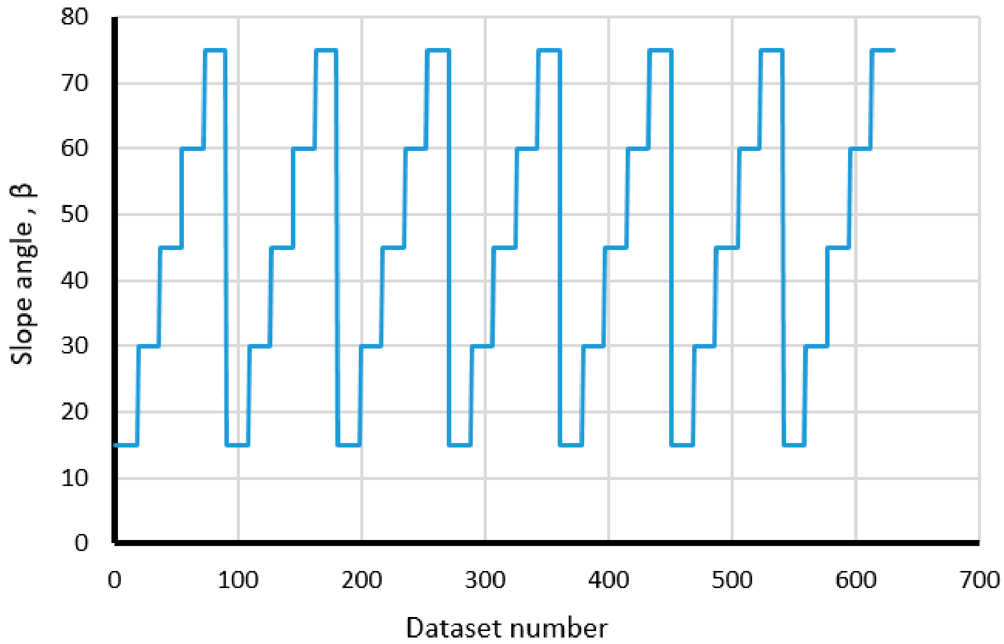


Figure 1. A schematic view of the data collection and analysis procedure used in this study (single cohesive slope).



(**a**)

Figure 2. *Cont.*



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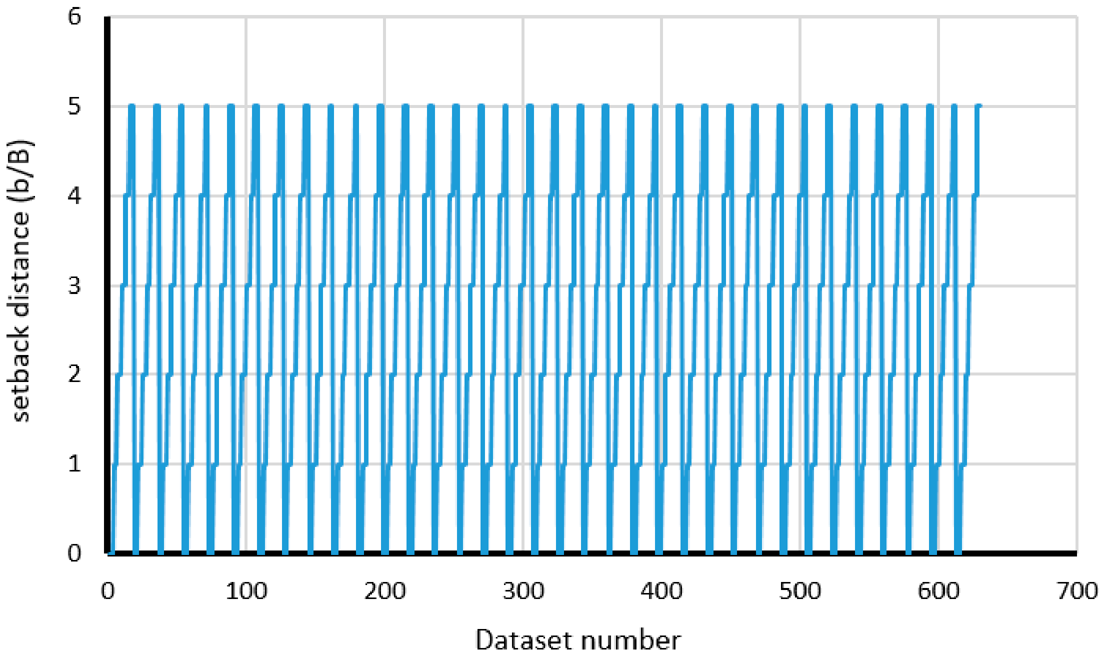

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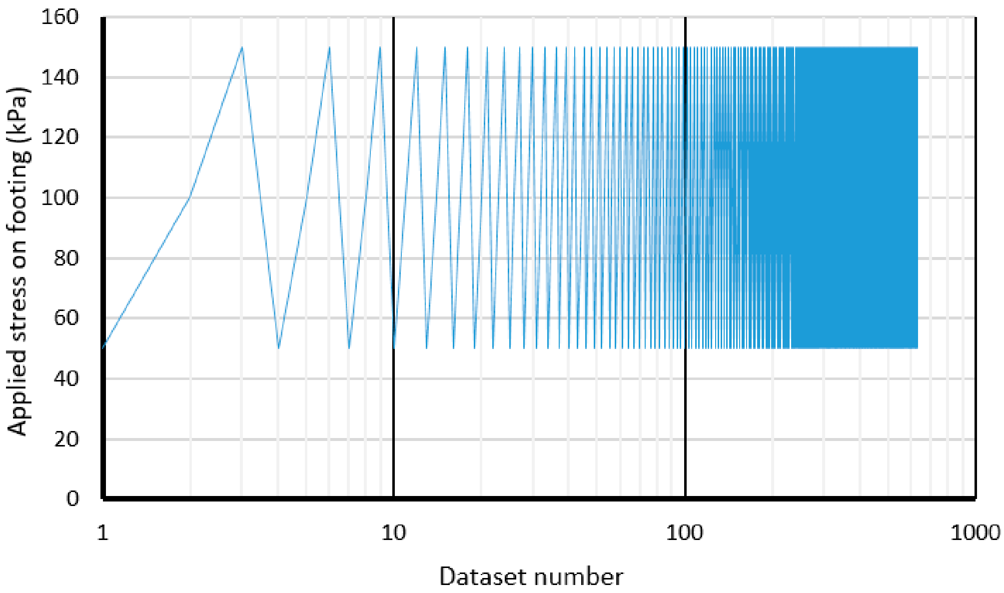
Figure 2. *Cont.*



(**d**)

Figure 2. Graphical figure of the input information range against the numbers of data for (**a**) C_u, (**b**) angle of the slope from the baseline, β, (**c**) Setback ratio (b/B), and (**d**) vertical stress on top of the slope.

2.2. Methodology

2.2.1. Artificial intelligence Implementation

Artificial neural network (ANN): The algorithm of ANN was firstly developed by McCulloch and Pitts [21]. However, Hebb [22] was the first person who proposed this approach. Generally, there are various rules in the case of the ANN model that are provided based on observations as well as the hypothesis of neuro-physiologic nature. The expansion of complex, non-linear, and also pure mathematical-based solutions have been widely investigated according to the biologic neuron. These works have provided various optimal network learning methods (for example, Moayedi et al. [19], Gao et al. [23], and Gao et al. [24]). The ANN learning approaches, utilized to find the links in a specific training database, were investigated by Ahmadi et al. [25], Wang [26], Gao et al. [27], and Gao et al. [28]). The ANN in a network can estimate results according to a training approach that is, according to the dataset, applied for training [29]. The suggested networks approximate the values for unknown results. It is important to note that the primary concern in these works is how they can estimate the unknown outcomes, which may call it an aim that requires to be obtained using the trained network. To assess the method verification (for example, comparison among the favorite target, as well as the output of output network), calculation method of the error was assumed according to a comparison among the predicted result and exact data. An example of the proposed 4 (input) × 3 (nodes in the first hidden layer) × 1 (output) neural network structure (e.g., the example) is shown in Figure 3.

Particle swarm optimization (PSO): The particle swarm optimization approach that facilities the ANN to provide a more trustworthy outcome was considered by Huang and Dun [30]. Figure 4 presents the details about an algorithm of PSO. These investigations were studied concerning the major effective factors in the algorithm of PSO. They showed that the four major parameters in the algorithm of PSO were: (a) Population number, (b) private learning factor (which is denoted with C_1 and the key learning coefficient determined by C_2), and (c) inertial weight (I_w). Note that the PSO-ANN method is well described in other investigations like Alsarraf et al. [31] and Moayedi et al. [32]. The PSO-ANN method begins with installing the initialization particle set and keeps selecting the particles with new adjustment of a location to each particle (for instance, providing an initial bias and also weight). The Pseudo-Code for the PSO algorithm is presented in Figure 5.

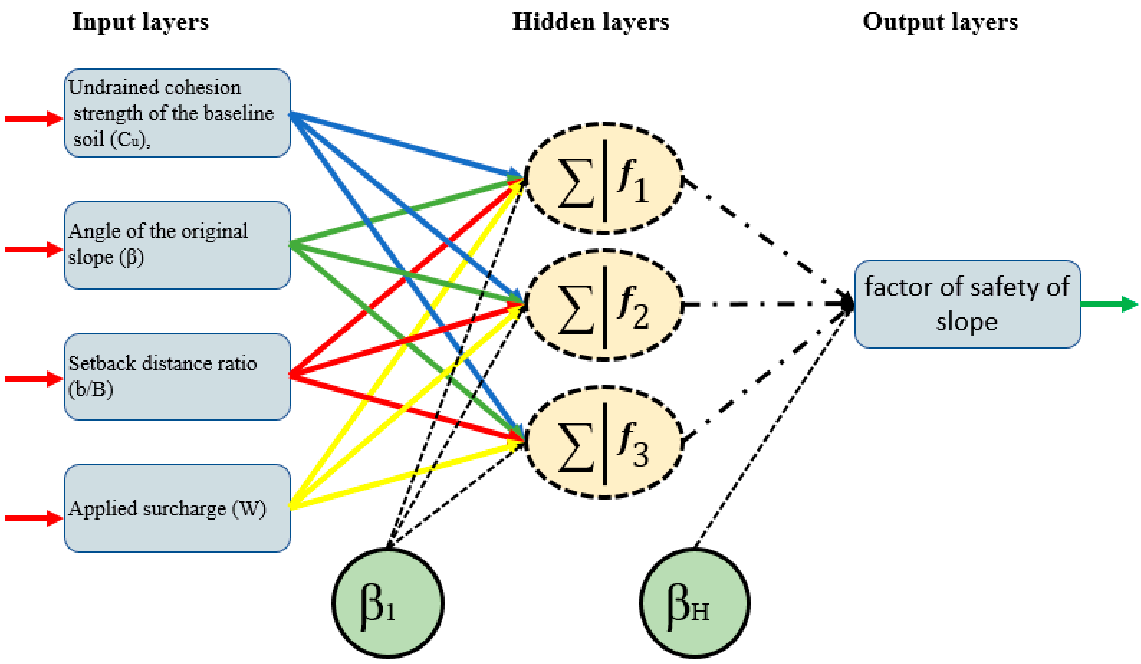


Figure 3. An example of the proposed 4 (input) × 3 (nodes in the first hidden layer) × 1 (output) neural network structure.

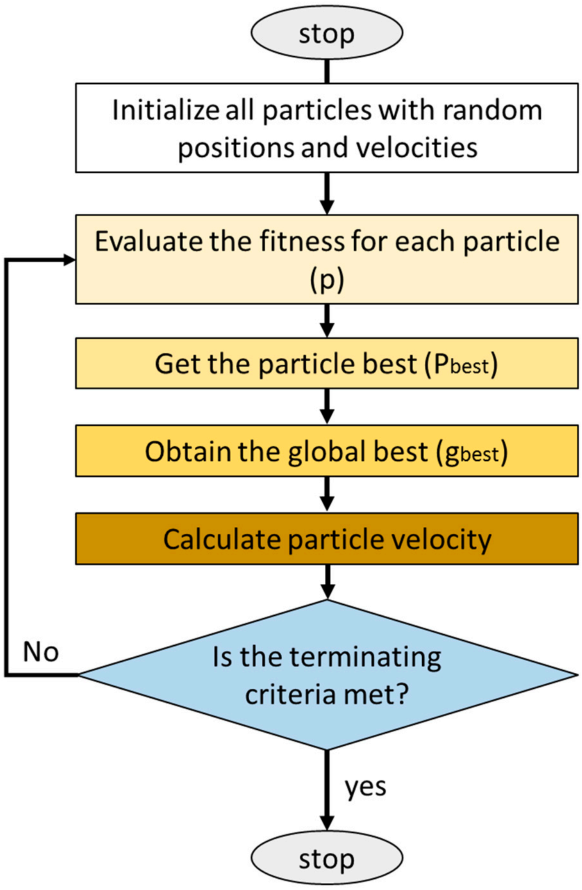


Figure 4. The initial algorithm of PSO (after Phuong-Thao et al. [33]).

```
P = Particle_Initialization();
For i=1 to it_max
  For each particle p in P do
    fp = f(p);
    If fp is better than f(pBest)
        pBest = p;
    end
  end
  gBest = best p in P;
  For each particle p in P do
     v = v + c1*rand*(pBest – p) + c2*rand*(gBest – p);
     p = p + v;
  end
end
```

Figure 5. The Pseudo-Code for the PSO algorithm.

Adaptive neuro-fuzzy inference system (ANFIS): ANFIS is a hybrid ANN, along with a fuzzy inference system (FIS), that has the benefits of both approaches [34,35]. In the structure of the ANFIS, ANN adapts fuzzy orders from among input information, and the factors of fuzzy membership functions have sets pending the abovementioned process. This hybrid approach may create a relationship among inputs and outputs according to human knowledge by considering input information and output data, along with utilizing a hybrid learning approach. ANFIS has been known as a multi-layer feedforward network that is combined of five classes. In ANFIS, each class algorithm structure includes various nodes, demonstrated using the function of the node. The learning approach of ANFIS is properly investigated in the studies performed by Jang [36] and Thomas et al. [37]. Figure 6 shows the structure of ANFIS, as well as its learning approach.

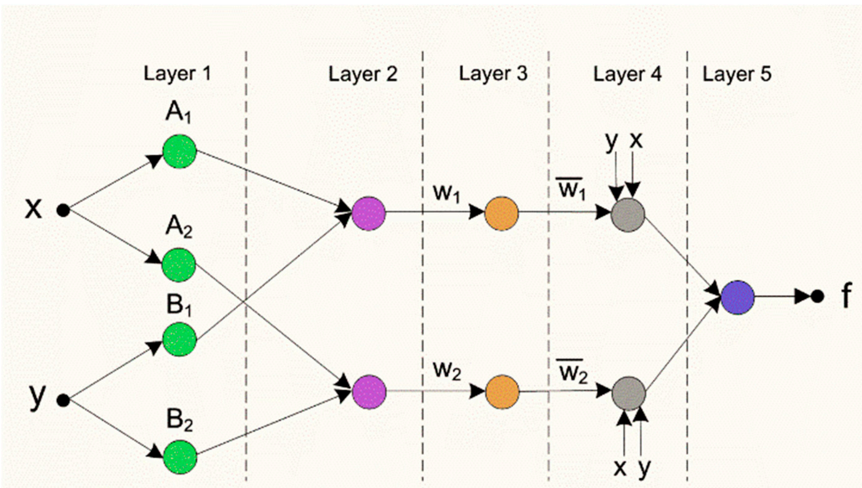


Figure 6. ANFIS structure.

2.2.2. Model Development for Estimation of a Factor of Safety

An appropriate estimation approximation, which is implemented by the models of the hybrid technique of PSO-ANN, needs to be evaluated from various stages like: (a) normalization or data pre-processing, as well as information processing; (b) choosing a proper hybrid approach; and eventually, (c) discovering a proper hybrid construction to expand the model. An appropriate hybrid structure can be obtained through a set of trial and error methods using major varying factors of the hybrid model. The utilized database is made by four main inputs that are the three effective factors. The database includes undrained cohesion stability of the baseline soil (C_u), angle of the original slope (β), applied surcharge (w), and setback distance ratio (b/B) where the target is selected factor of safety. Table 1 shows the abovementioned data as an example. Note that these values are derived from the OptumG2 simulation and, as illustrated, the four effective parameters.

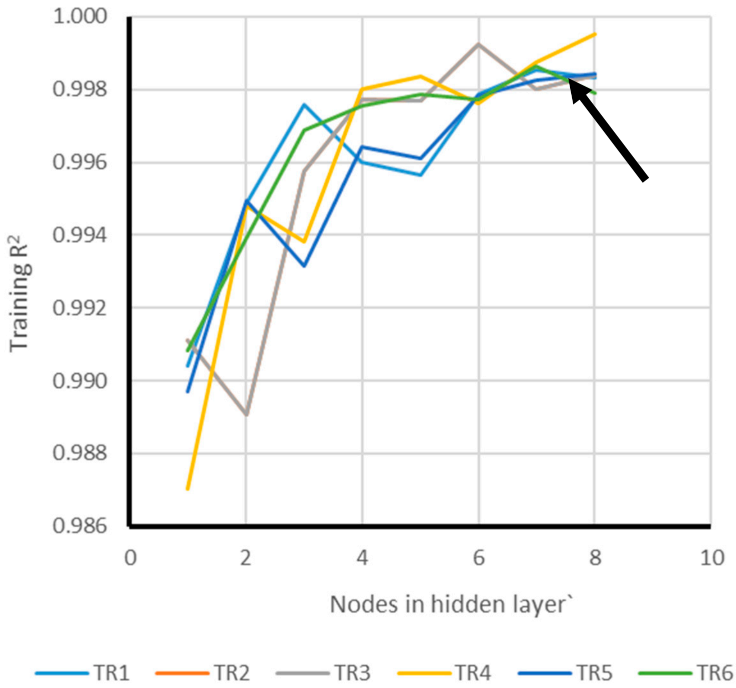
Table 1. Databases includes input layers and output used for the trained network.

Model Number	Inputs				Output	Model Number	Inputs				Output
	C_u (kN/m^2)	β (°)	b/B (-)	W (kN/m^2)	Safety Factor		C_u (kN/m^2)	β (°)	b/B (-)	W (kN/m^2)	Safety Factor
1	25	15	0	50	1.872	570	400	30	3	150	14.06
2	25	15	0	100	1.196	571	400	30	4	50	23.24
3	25	15	0	150	0.8154	572	400	30	4	100	19.63
4	25	15	1	50	1.852	573	400	30	4	150	14.11
5	25	15	1	100	1.324	574	400	30	5	50	22.82
6	25	15	1	150	0.8981	575	400	30	5	100	19.63
7	25	15	2	50	1.834	576	400	30	5	150	14.07
8	25	15	2	100	1.354	577	400	45	0	50	22
9	25	15	2	150	0.9133	578	400	45	0	100	13.76
10	25	15	3	50	1.824	579	400	45	0	150	9.387
11	25	15	3	100	1.356	580	400	45	1	50	21.32
12	25	15	3	150	0.9169	581	400	45	1	100	16.36
13	25	15	4	50	1.825	582	400	45	1	150	11.94
14	25	15	4	100	1.356	583	400	45	2	50	21.11
15	25	15	4	150	0.9171	584	400	45	2	100	16.52
16	25	15	5	50	1.832	585	400	45	2	150	13.08
17	25	15	5	100	1.357	586	400	45	3	50	21.16
18	25	15	5	150	0.9179	587	400	45	3	100	16.85
19	25	30	0	50	1.597	588	400	45	3	150	13.49
20	25	30	0	100	1.035	589	400	45	4	50	21.47

2.2.3. Network Structure Optimization

In order to determine the optimized architecture for the selection of the predictive network of ANN (to certify the capability of the ANN algorithm for estimating the results reliably), six distinct randomly chosen training and testing databases (for example, each iteration utilized a novel training and testing databases) were used to suggest the best intelligent method. Based on similar studies mentioned before, about 80% of the FEM result (504 databases) is randomly chosen for the training, along with 126 databases utilized for testing the expanded approaches. The ANN algorithm has to prepare in its proper architecture for optimizing the PSO-ANN estimating model. The optimization process of the ANN can be performed in preference to the PSO-ANN. This is because of the fact that the PSO always produces its outcomes based on the ANN results. The optimization of the ANN may be performed in the case of the nodes or neurons number. The hidden layer number may be chosen more than one that enhances the complication of the final result. In this work, an offered learning method from the Levenberg–Marquardt training back-dissemination (trainlm) as a neural network-based function that is sometimes selected to train the network of the ANN. Accordingly, 48 trainlm models were produced. In this regard, the predictive outputs of the networks and their efficiencies were investigated to discover their most appropriate efficiencies.

It should be noted that a network prediction output, along with the lower values of RMSE and higher values of R^2, were used for suggesting a proper outcome. A novel color intensity rating approach (known as CER) was utilized by using the total ranking system (or TRS). As seen in Figures 7 and 8, the RMSE as well as R^2 (as a network performance) outcomes varied according to the hidden nodes number in each layer. According to the calculated result, the best ANN architecture was $4 \times 6 \times 1$. Looking for the negligible variation at the network efficiency, as well as to possess a structure with a simpler network, the optimal structure ($4 \times 8 \times 1$) can be decreased to the $4 \times 6 \times 1$ (four input layers, six neurons at one single hidden along with output layers). Therefore, as for the optimal ANN in the present article, the neurons number in one hidden layer is selected to be equal to six. The outcomes of the ANN modeling utilized for the hybrid PSO-ANN. Therefore, the appropriate structure in terms of the ANN model before being forwarded for the algorithm of PSO is found to be $4 \times 6 \times 1$.



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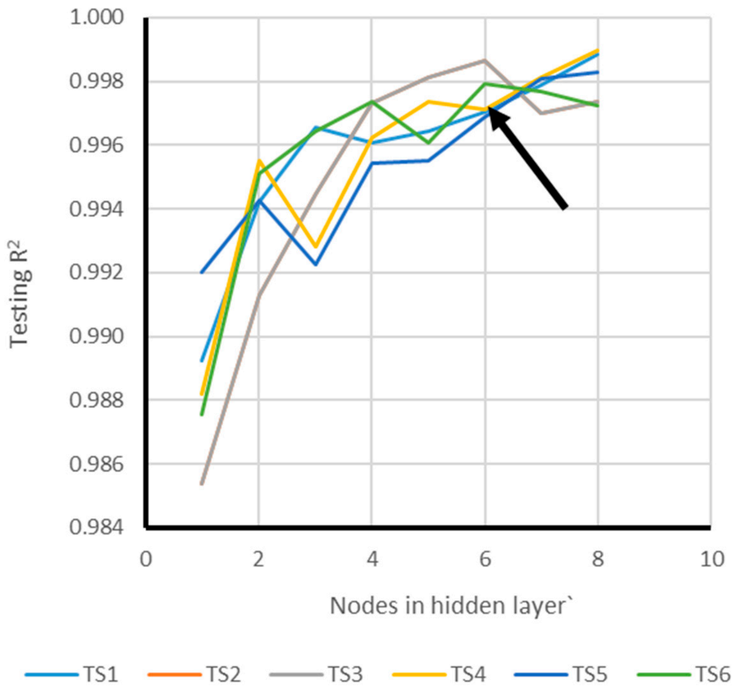
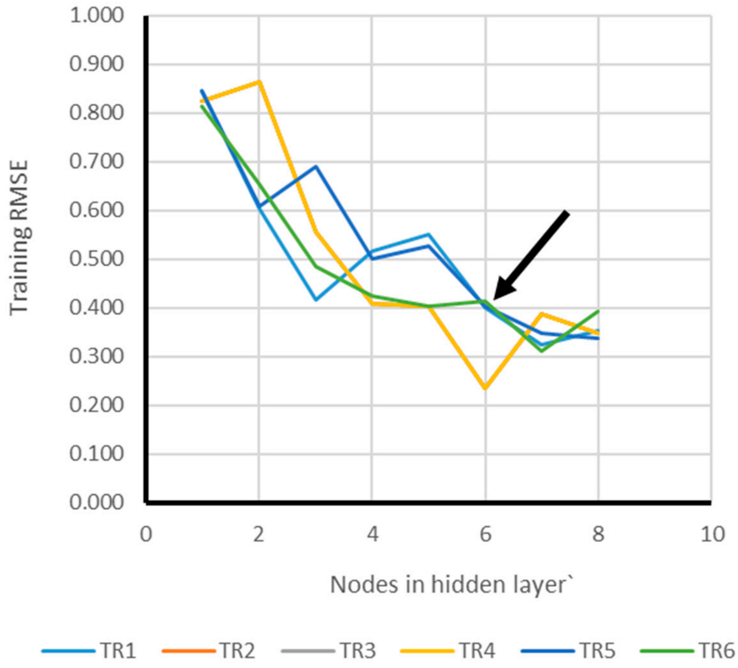


(**b**)

Figure 7. The R^2 sensitivity evaluation of various suggested ANNs on neurons number in each hidden layer. (**a**) R2 performance for the training dataset, (**b**) R2 performance for the testing dataset.



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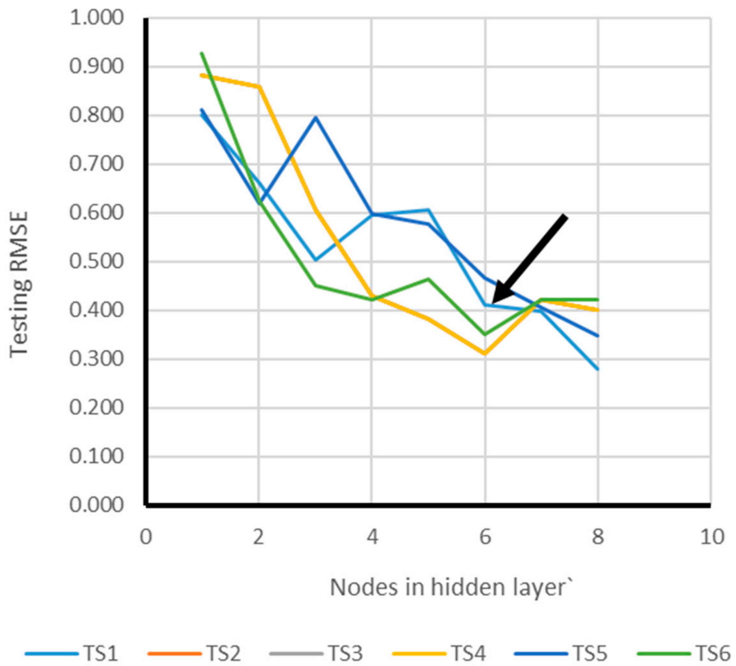


(**b**)

Figure 8. The RMSE sensitivity evaluation of various suggested ANNs on neurons number in each hidden layer. (**a**) RMSE performance for the training dataset, (**b**) RMSE performance for the testing dataset.

3. Results and Discussion

The base target of the current study was assessing the consistency of a cohesive slope by using three intelligent methods of ANN, ANFIS, and hybrid neuro PSO-ANN methods. The significant factor in predicting the factor of safety was considered as the output of the networks. In this way, four effective parameters were recognized as the input dataset: (i) The setback distance (b/B), (ii) the slope angle (β), (iii) the undrained cohesion strength, and (iv) the vertical load on the slope (F_y). Similar to former research, the database was divided, randomly, into two sections—training and testing the approaches, to a ratio between 80 and 20 percentages, respectively. These ratios are properly described in similar works (e.g., Dieu Tien et al. [38] and Moayedi et al. [32]). To assess the most suitable approximation networks, we compared the improved models with each other.

3.1. Neuro PSO-ANN Optimization

For measuring the credibility of the suggested PSO-ANN approach, a wide number of FELE simulations were suggested. For the structure of the optimal estimation network, the calculated outcomes from each method were evaluated and also compared where the influence of important factors was investigated. Different statistical indices were utilized in order to classify the results (for example, targets against calculated from the constructed network) to predict the strength of each approach. These CRS and TRS classifying methods were performed based on the result of various statistical indicators (R^2 and RMSE). Figures 9–11 show the efficiency outcomes for various values of population sizes—C_1, C_2, and I_W, respectively. Additionally, we inferred that the model of PSO-ANN, along with a number of swarm size (400), C_1 and C_2 (i.e., acceleration constants) equal to 0.67 and 3.33, respectively, and inertia weight of about 0.8, present the best predictive model of PSO-ANN. Outcomes from the suggested predictive networks are presented for datasets of training and testing approaches, according to the achieved results (for example, measured from FELE simulations, as well as estimated from the whole three suggested artificial intelligent models). Hence, the abovementioned models possess satisfactory estimation outcomes to estimate the factor of safety. The model of hybrid PSO-ANN can be prepared as a highly acceptable predictive network (for example, preparing higher accuracy in comparison to measured values) in the estimation of the factor of safety. Accordingly, in all predictive approaches, the learning method was great (for example, showed a high R^2 rate and a low RMSE rate), which can be obviously observed from the high-efficiency outcomes of the training and testing networks. According to the R^2 and RMSE approaches, respectively, the values of 0.9996, and 0.0123, as well as 0.9994, and 0.0157, were obtained. For the best structure of the ANN-based model, both the R^2 as well as the RMSE for the databases of training and testing were 0.999, and 0.236, and 0.998, and 0.313, respectively. Note that an excellent level of precision can be determined in the network results, particularly for the testing dataset. From all of the suggested models, the predictive model PSO-ANN presented higher efficiency results in the case of all statistical indexes (for example RMSE and R^2). Figures 9–11 show training and testing outcomes of the ANN, along with six neurons, ANFIS, and the predictive models of PSO-ANN, in estimating the factor of safety.

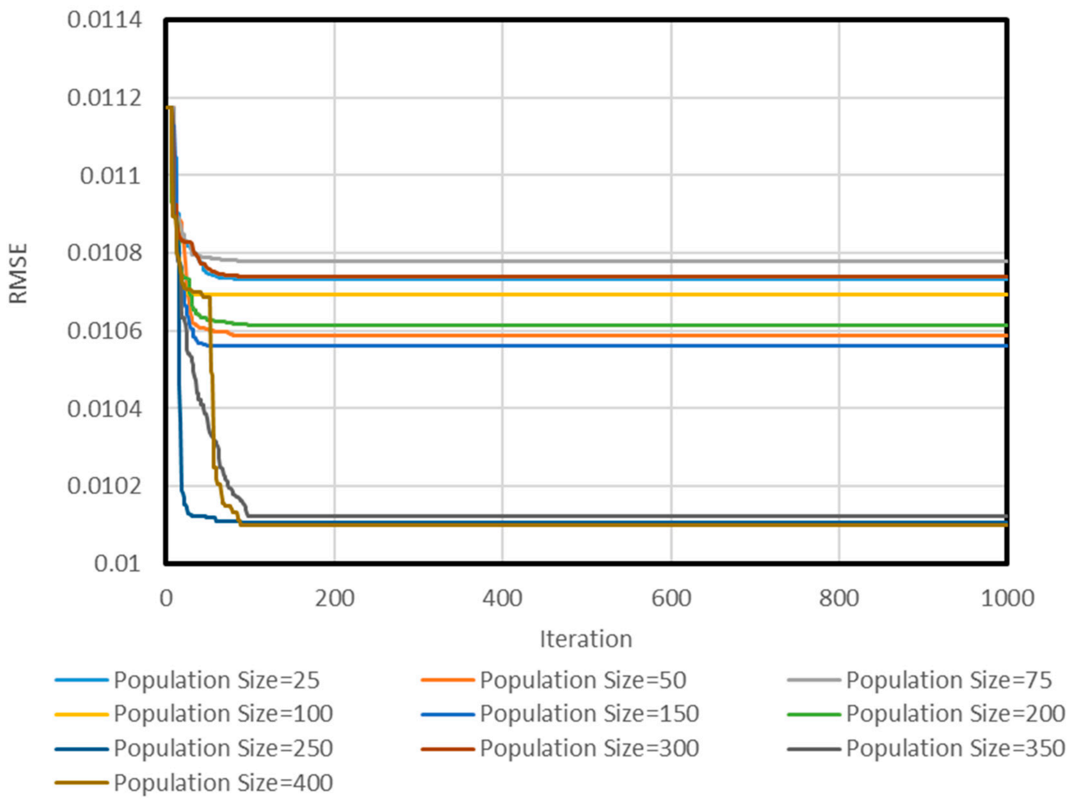


Figure 9. Efficiency results for various population sizes.

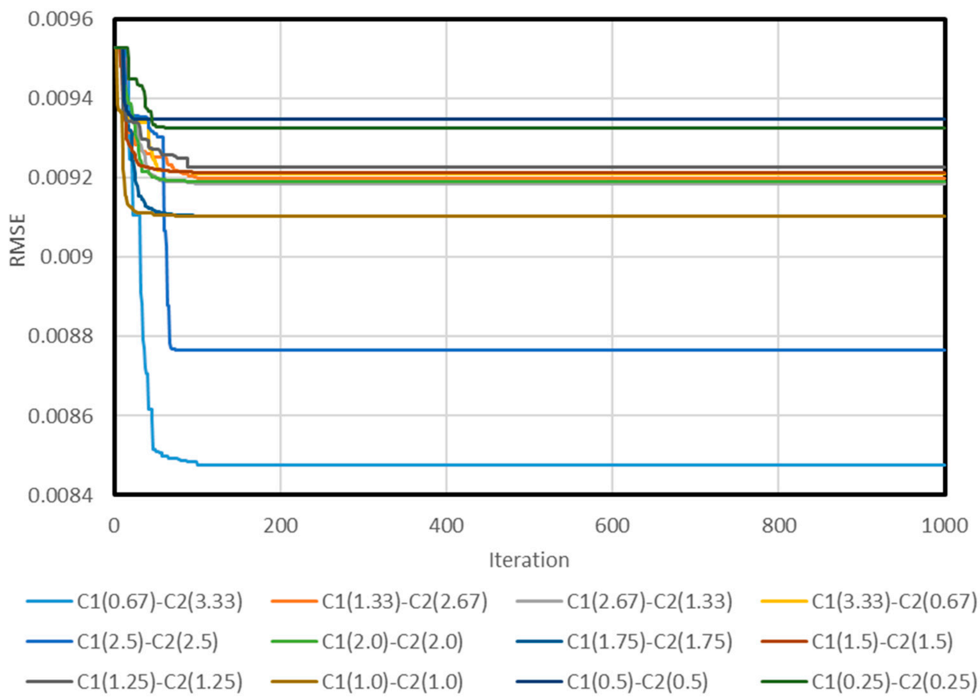


Figure 10. Efficiency results for various personal learning coefficients (C_1), as well as global learning coefficient and C_2 amounts.

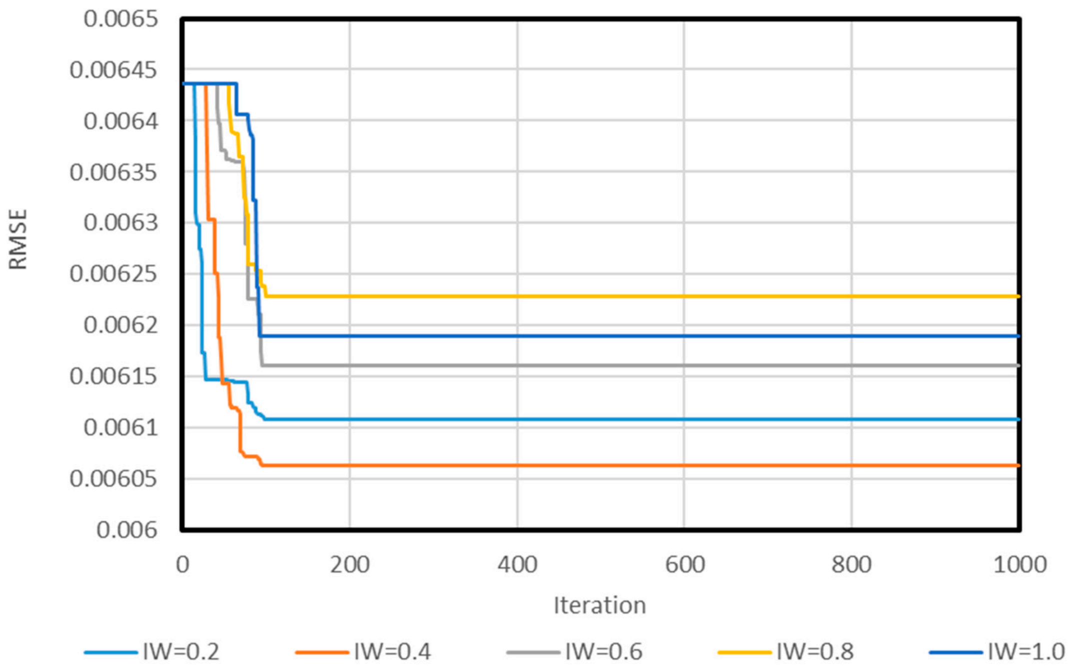
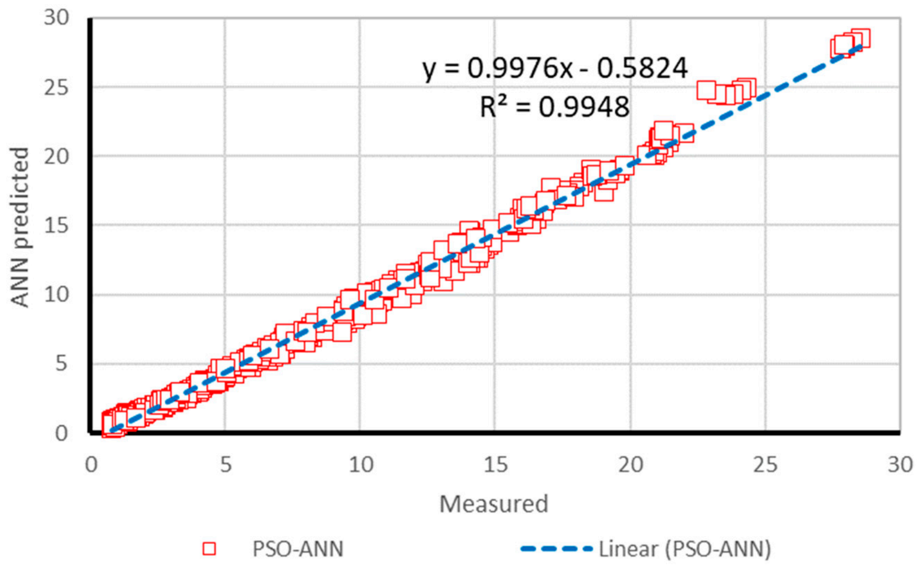


Figure 11. Efficiency results for various inertia weight amounts.

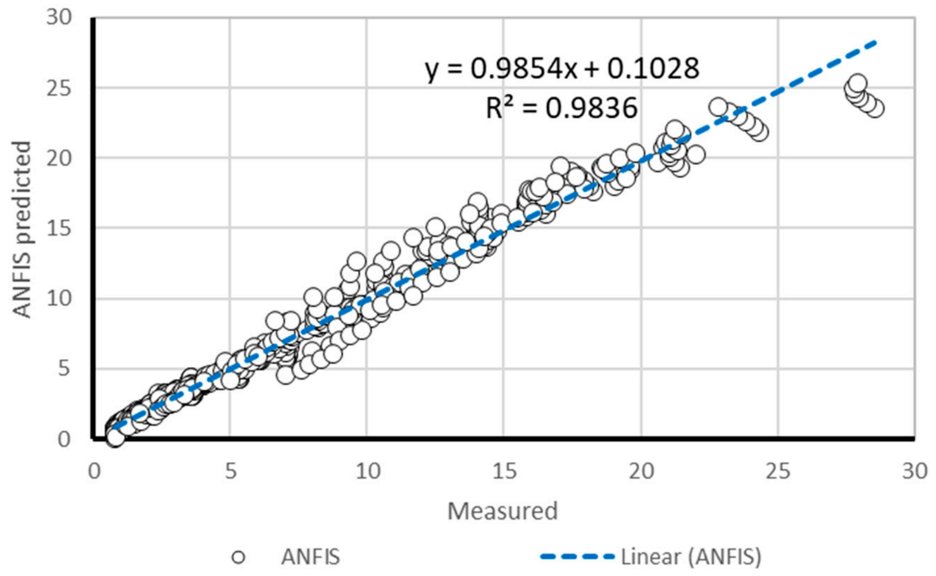
3.2. Model Assessment

In this way, the obtained outcomes of the proposed models of ANN, ANFIS, and neuro PSO-ANN are shown in Figure 12a–c, respectively. The design solution charts based on the proposed hybrid PSO-ANN predictive network for β = 15° (Figure 13), β = 30° (Figure S1), β = 45° (Figure S2), β = 60° (Figure S3), and β = 75° (Figure S4). Noting that the Figures S1–S4 are provided as Supplementary Materials. These design solution charts are varied according to the applied vertical stresses on the shallow footings that are placed on the slope with a particular setback distance (b/B). In these graphs, other critical factors on the slope stability such as slope angle (β) and undrained cohesion strength (C_u) of the cohesive soils are taken into consideration. Note that different setback distance ratio (b/B ratio between 0 to 5) was used.

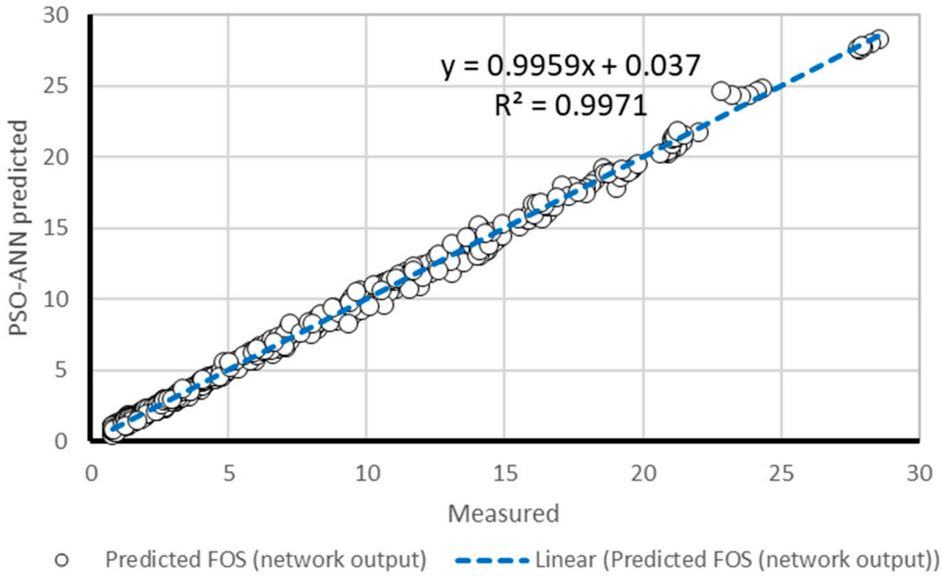


(**a**) ANN model in predicting factor of safety (ANN with six nodes).

Figure 12. *Cont.*

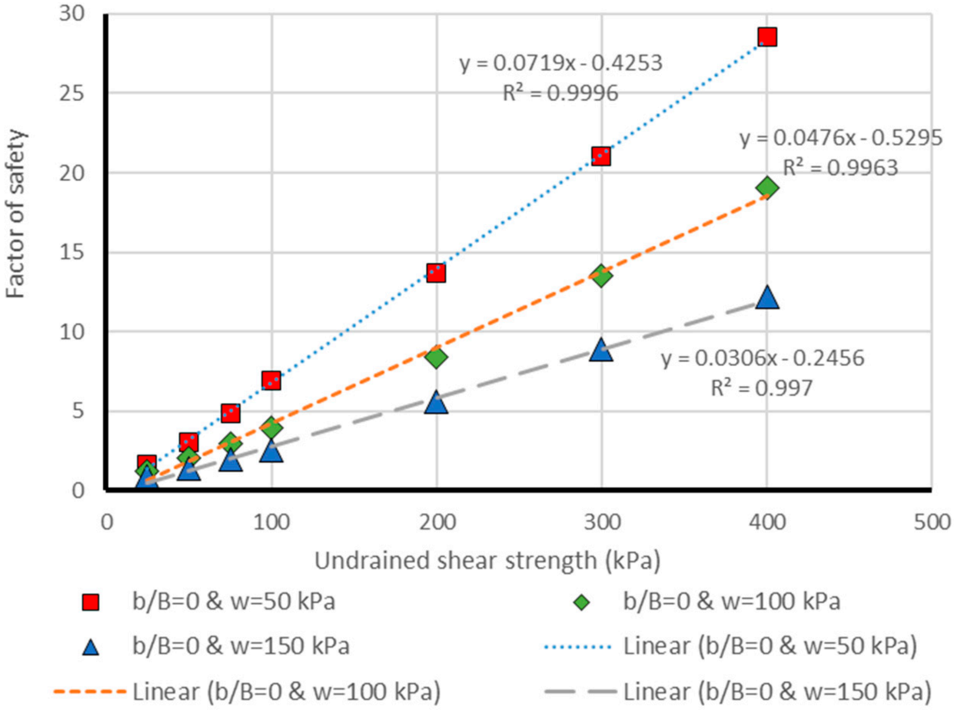


(**b**) ANFIS model in predicting factor of safety.

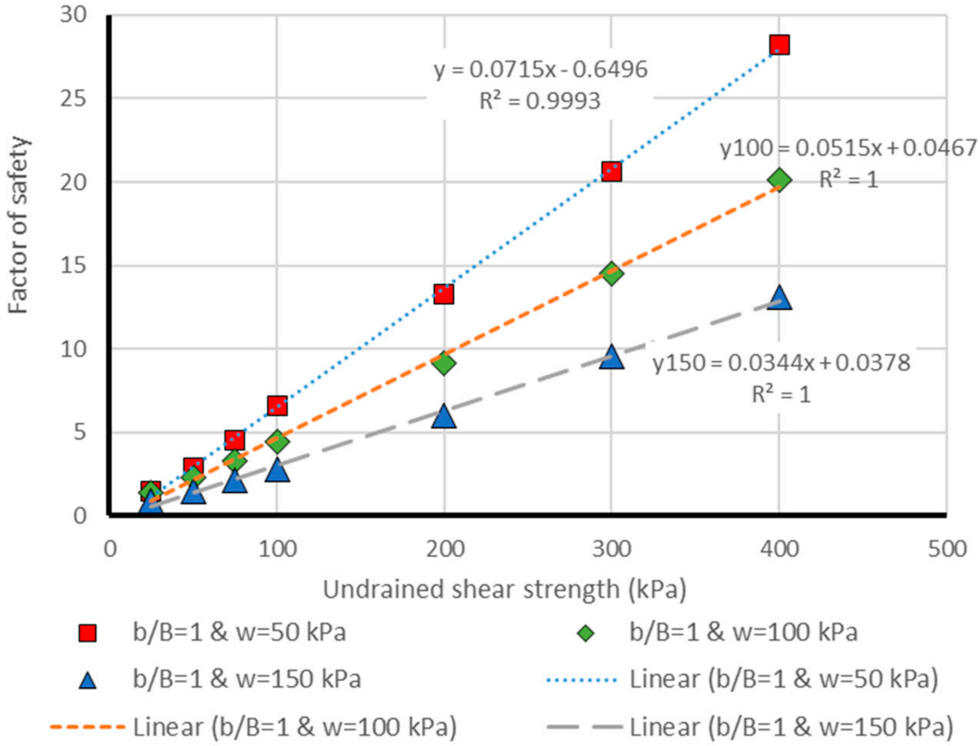


(**c**) PSO-ANN.

Figure 12. Training and testing outcomes of suggested approaches for predicting factor of safety for (**a**) ANN with six nodes, (**b**) ANFIS, and (**c**) PSO-ANN.

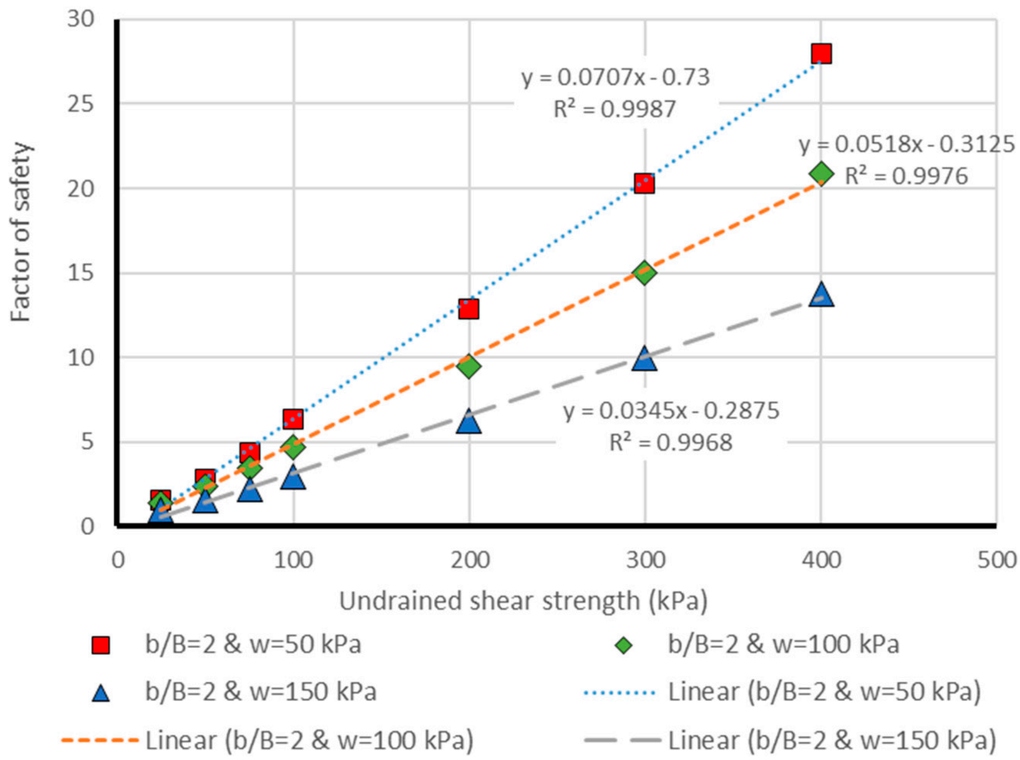


(**a**) b/B = 0.

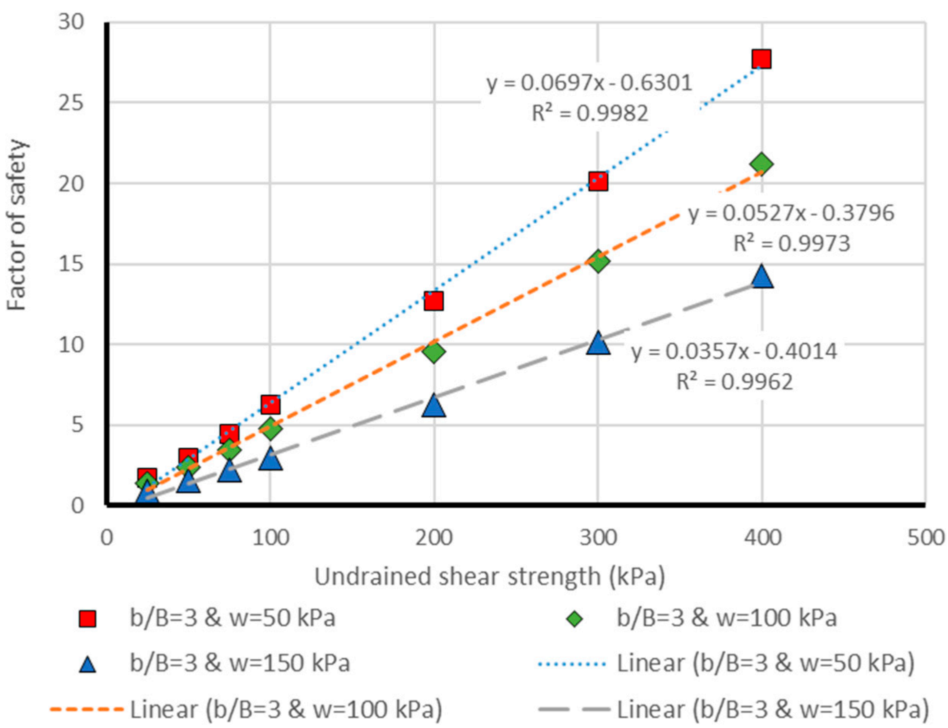


(**b**) b/B = 1.

Figure 13. *Cont.*

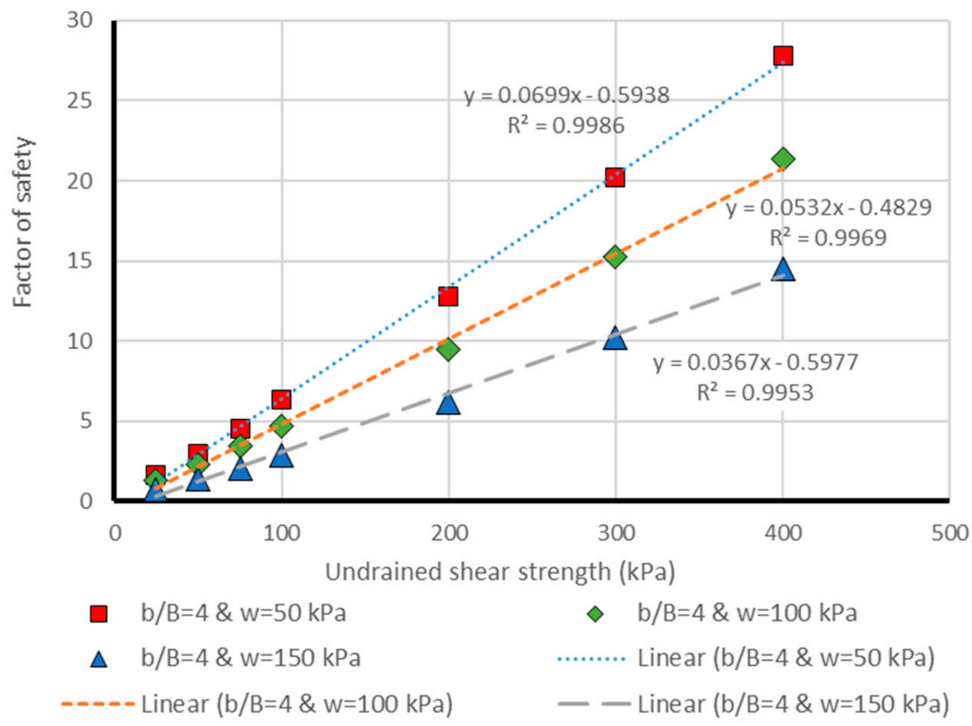


(**c**) b/B = 2.

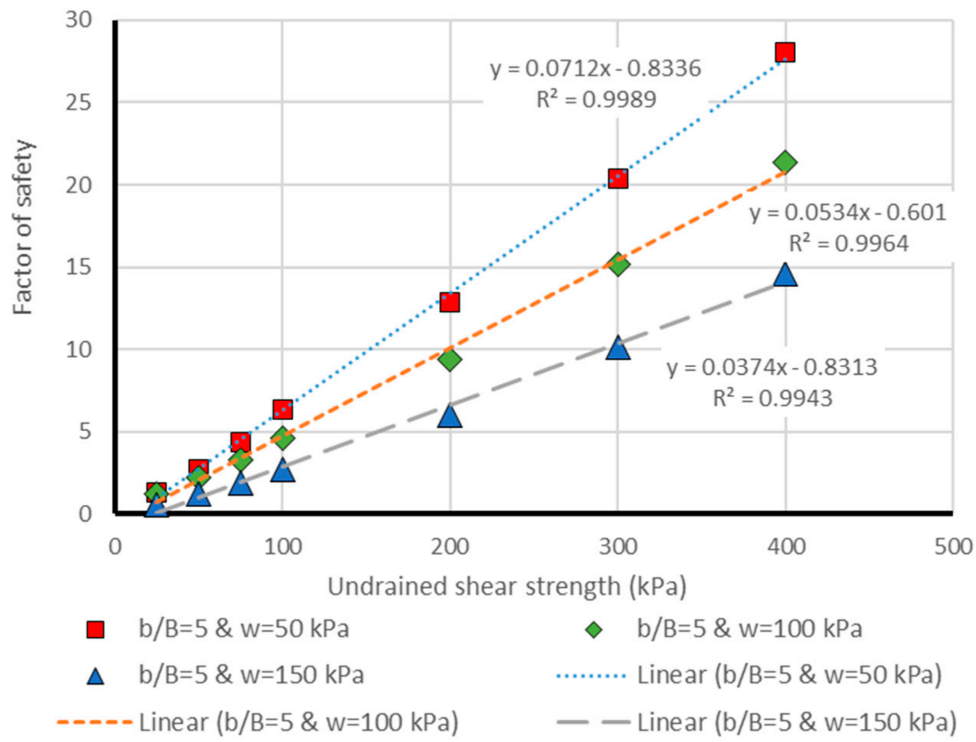


(**d**) b/B = 3.

Figure 13. *Cont.*



(**e**) b/B = 4.



(**f**) b/B = 5.

Figure 13. PSO-ANN solution charts for β = 15°; (**a**) b/B = 0, (**b**) b/B = 1, (**c**) b/B = 2, (**d**) b/B = 3, (**e**) b/B = 4, and (**f**) b/B = 5,

4. Conclusions

In this study, three predictive networks in their optimized structures were proposed. In fact, the basic aim of the present study was to propose a proper predictive approach in order to estimate the factor of safety of a single layer pure cohesive slope subjected to vertical stresses. The vertical stresses were applied considering strip footing with a particular setback ratio. The slopes were also built with different geometry parameters. Therefore, data gathered by a big number of finite element limit equilibrium analysis (FELE) were employed as the input layer. After analyzing the predicted networks obtained from the three proposed models' artificial neural network, adaptive neuro-fuzzy inference system, and also a hybrid model of PSO-ANN, an explanation on the constructed dataset and network modeling methods is presented. The results of each technique analyzed were then compared with other approaches. In the optimal predictive model of PSO-ANN, namely the R^2 as well as the RMSE in the case of the training and testing databases were 0.9996 and 0.0123 as well as 0.9994 and 0.0157, respectively—that is, more in their R^2 and lower in their RMSEs amounts in comparison with two other suggested approaches in this paper. It is important to note that our approach is suitable for implementation on reconfigurable system-like field-programmable gate array (FPGA).

Supplementary Materials: The following are available online at http://www.mdpi.com/2220-9964/8/9/391/s1, Figure S1: PSO-ANN solution charts for the $\beta = 30°$. Figure S2: PSO-ANN solution charts for the $\beta = 45°$. Figure S3: PSO-ANN solution charts for the $\beta = 60°$. Figure S4: PSO-ANN solution charts for the $\beta = 75°$.

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References

1. Pei, H.; Zhang, S.; Borana, L.; Zhao, Y.; Yin, J. Slope stability analysis based on real-time displacement measurements. *Measurement* **2019**, *131*, 686–693. [CrossRef]
2. Jellali, B.; Frikha, W. Constrained particle swarm optimization algorithm applied to slope stability. *Int. J. Geomech.* **2017**, *17*, 06017022. [CrossRef]
3. Binh Thai, P.; Manh Duc, N.; Kien-Trinh Thi, B.; Prakash, I.; Chapi, K.; Dieu Tien, B. A novel artificial intelligence approach based on multi-layer perceptron neural network and biogeography-based optimization for predicting coefficient of consolidation of soil. *Catena* **2019**, *173*, 302–311.
4. Youssef, A.M.; Pradhan, B.; Al-Harthi, S.G. Assessment of rock slope stability and structurally controlled failures along Samma escarpment road, Asir Region (Saudi Arabia). *Arab. J. Geosci.* **2015**, *8*, 6835–6852. [CrossRef]
5. Binh Thai, P.; Dieu Tien, B.; Prakash, I. Bagging based support vector machines for spatial prediction of landslides. *Environ. Earth Sci.* **2018**, *77*, 146.
6. Binh Thai, P.; Prakash, I.; Dieu Tien, B. Spatial prediction of landslides using a hybrid machine learning approach based on random subspace and classification and regression trees. *Geomorphology* **2018**, *303*, 256–270.
7. Nguyen, H.; Bui, X.-N.; Tran, Q.-H.; Le, T.-Q.; Do, N.-H. Evaluating and predicting blast-induced ground vibration in open-cast mine using ANN: A case study in Vietnam. *SN Appl. Sci.* **2019**, *1*, 125. [CrossRef]
8. Moayedi, H.; Mosallanezhad, M.; Safuan, A.R.A.; Amizah, W.J.W.; Muazu, M.A. A systematic review and meta-analysis of artificial neural network application in geotechnical engineering: Theory and applications. *Neural Comput. Appl.* **2019**, *31*, 1–24. [CrossRef]
9. Moayedi, H.; Mosallanezhad, M.; Mehrabi, M.; Safuan, A.R.A.; Biswajeet, P. Modification of landslide susceptibility mapping using optimized PSO-ANN technique. *Eng. Comput.* **2019**, *35*, 967–984. [CrossRef]

10. Li, J.; Wang, J. Research of steel plate temperature prediction based on the improved PSO-ANN algorithm for roller hearth normalizing furnace. In Proceedings of the 2010 8th World Congress on Intelligent Control and Automation (WCICA), Jinan, China, 7–9 July 2010; pp. 2464–2469.
11. Song, Z.P.; Ren, S.B.; Guo, Z.C. The tunnel surrounding rock parameters identification method based on PSO-ANN. In *Advances in Structural Engineering, Pts 1–3*; Zhou, X.J., Ed.; Trans Tech Publications Ltd.: Durnten-Zurich, Switzerland, 2011; Volume 94–96, pp. 637–640.
12. Alnaqi, A.A.; Moayedi, H.; Shahsavar, A.; Nguyen, T.K. Prediction of energetic performance of a building integrated photovoltaic/thermal system thorough artificial neural network and hybrid particle swarm optimization models. *Energy Convers. Manag.* **2019**, *183*, 137–148. [CrossRef]
13. Moayedi, H.; Hayati, S. Applicability of a CPT-based neural network solution in predicting load-settlement responses of bored pile. *Int. J. Geomech.* **2018**, *18*, 06018009. [CrossRef]
14. Moayedi, H.; Huat, B.; Kazemian, S.; Asadi, A. Optimization of shear behavior of reinforcement through the reinforced slope. *Electron. J. Geotech. Eng.* **2010**, *15*, 93–104.
15. Raftari, M.; Kassim, K.A.; Rashid, A.S.A.; Moayedi, H. Settlement of shallow foundations near reinforced slopes. *Electron. J. Geotech. Eng.* **2013**, *18*, 797–808.
16. Jiao, J.J.; Wang, X.S.; Nandy, S. Confined groundwater zone and slope instability in weathered igneous rocks in Hong Kong. *Eng. Geol.* **2005**, *80*, 71–92. [CrossRef]
17. Pourghasemi, H.R.; Moradi, H.R.; Aghda, S.M.F.; Gokceoglu, C.; Pradhan, B. GIS-based landslide susceptibility mapping with probabilistic likelihood ratio and spatial multi-criteria evaluation models (North of Tehran, Iran). *Arab. J. Geosci.* **2014**, *7*, 1857–1878. [CrossRef]
18. Moayedi, H.; Armaghani, D.J. Optimizing an ANN model with ICA for estimating bearing capacity of driven pile in cohesionless soil. *Eng. Comput.* **2017**, *34*, 347–356. [CrossRef]
19. Moayedi, H.; Mosallanezhad, M.; Nazir, R. Evaluation of maintained load test (MLT) and pile driving analyzer (PDA) in measuring bearing capacity of driven reinforced concrete piles. *Soil Mech. Found. Eng.* **2017**, *54*, 150–154. [CrossRef]
20. Krabbenhoft, K.; Lyamin, A.; Krabbenhoft, J. Optum Computational Engineering (OptumG2). Computer Software. 2015. Available online: https://www.optumce.com (accessed on 15 June 2016).
21. McCulloch, W.S.; Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* **1943**, *5*, 115–133. [CrossRef]
22. Hebb, D. *The Organization of Behavior: A Neurophysiological Approach*; Wiley: Hoboken, NJ, USA, 1949.
23. Gao, W.; Guirao, J.L.G.; Abdel-Aty, M.; Xi, W. An independent set degree condition for fractional critical deleted graphs. *Discret. Contin. Dyn. Syst. S* **2019**, *12*, 877–886. [CrossRef]
24. Gao, W.; Guirao, J.L.G.; Basavanagoud, B.; Wu, J. Partial multi-dividing ontology learning algorithm. *Inf. Sci.* **2018**, *467*, 35–58. [CrossRef]
25. Ahmadi, M.A.; Ebadi, M.; Shokrollahi, A.; Majidi, S.M.J. Evolving artificial neural network and imperialist competitive algorithm for prediction oil flow rate of the reservoir. *Appl. Soft Comput.* **2013**, *13*, 1085–1098. [CrossRef]
26. Wang, S.-C. Artificial neural network. In *Interdisciplinary Computing in Java Programming*; Springer: New York, NY, USA, 2003; pp. 81–100.
27. Gao, W.; Moayedi, H.; Shahsavar, A. The feasibility of genetic programming and ANFIS in prediction energetic performance of a building integrated photovoltaic thermal (BIPVT) system. *Sol. Energy* **2019**, *183*, 293–305. [CrossRef]
28. Gao, W.; Wu, H.; Siddiqui, M.K.; Baig, A.Q. Study of biological networks using graph theory. *Saudi J. Biol. Sci.* **2018**, *25*, 1212–1219. [CrossRef] [PubMed]
29. Moayedi, H.; Hayati, S. Artificial intelligence design charts for predicting friction capacity of driven pile in clay. *Neural Comput. Appl.* **2018**, *31*, 1–17. [CrossRef]
30. Huang, C.-L.; Dun, J.-F. A distributed PSO–SVM hybrid system with feature selection and parameter optimization. *Appl. Soft Comput.* **2008**, *8*, 1381–1391. [CrossRef]
31. Alsarraf, J.; Moayedi, H.; Rashid, A.S.A.; Muazu, M.A.; Shahsavar, A. Application of PSO–ANN modelling for predicting the exergetic performance of a building integrated photovoltaic/thermal system. *Eng. Comput.* **2019**, 1–14. [CrossRef]
32. Moayedi, H.; Raftari, M.; Sharifi, A.; Jusoh, W.A.W.; Rashid, A.S.A. Optimization of ANFIS with GA and PSO estimating α ratio in driven piles. *Eng. Comput.* **2019**, *36*, 1–12. [CrossRef]

33. Phuong-Thao, T.N.; Nhat-Duc, H.; Pradhan, B.; Quang Khanh, N.; Xuan Truong, T.; Quang Minh, N.; Viet Nghia, N.; Samui, P.; Bui, D.T. A novel hybrid swarm optimized multilayer neural network for spatial prediction of flash floods in tropical areas using sentinel-1 SAR imagery and geospatial data. *Sensors* **2018**, *18*, 3704.
34. Jang, J.-S.R.; Sun, C.-T. Neuro-fuzzy modeling and control. *Proc. IEEE* **1995**, *83*, 378–406. [CrossRef]
35. Jang, J.-S.R.; Sun, C.-T.; Mizutani, E. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*; Prentice Hall: Upper Saddle River, NJ, USA, 1997.
36. Jang, S.R. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
37. Thomas, S.; Pillai, G.N.; Pal, K.; Jagtap, P. Prediction of ground motion parameters using randomized ANFIS (RANFIS). *Appl. Soft Comput.* **2016**, *40*, 624–634. [CrossRef]
38. Dieu Tien, B.; Khosravi, K.; Li, S.; Shahabi, H.; Panahi, M.; Singh, V.P.; Chapi, K.; Shirzadi, A.; Panahi, S.; Chen, W.; et al. New hybrids of ANFIS with several optimization algorithms for flood susceptibility modeling. *Water* **2018**, *10*, 1210. [CrossRef]