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Assessing Dynamic Conditions of the Retaining Wall: Developing Two Hybrid Intelligent Models

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Abstract: The precise estimation and forecast of the safety factor (SF) in civil engineering applications is considered as an important issue to reduce engineering risk. The present research investigates new artificial intelligence (AI) techniques for the prediction of SF values of retaining walls, as important and resistant structures for ground forces. These structures have complicated performances in dynamic conditions. Consequently, more than 8000 designs of these structures were dynamically evaluated. Two AI models, namely the imperialist competitive algorithm (ICA)-artificial neural network (ANN), and the genetic algorithm (GA)-ANN were used for the forecasting of SF values. In order to design intelligent models, parameters i.e., the wall thickness, stone density, wall height, soil density, and internal soil friction angle were examined under different dynamic conditions and assigned as inputs to predict SF of retaining walls. Various models of these systems were constructed and compared with each other to obtain the best one. Results of models indicated that although both hybrid models are able to predict SF values with a high accuracy and they can be introduced as new models in the field, the retaining wall performance could be properly predicted in dynamic conditions using the ICA-ANN model. Under these conditions, a combination of engineering design and artificial intelligence techniques can be used to control and secure retaining walls in dynamic conditions.

Keywords: retaining wall; hybrid model; genetic algorithm-artificial neural network (GA-ANN); imperialist competitive algorithm-artificial neural network (ICA-ANN); dynamic conditions; safety factor

1. Introduction

Investigation of the retaining walls (RWs) behavior under dynamic conditions was originally done in the studies of Mononobe and Matsuo [1], and Okabe [2]. Afterwards, several cases of numerical and experimental research have been conducted to introduce a method/approach for rational design of RWs under dynamic condition. All relevant studies of active earth pressures can be grouped into three categories i.e., experimental, numerical and analytical. One of the important techniques in field of lateral earth pressure under seismic loading is the Mononobe-Okabe (M-O) method, which has been carried out by Mylonakis et al. [3]. In their studies, a closed-form stress plasticity solution was suggested for gravitational and earthquake-induced earth pressures on RWs. Results of the conducted shake table tests using centrifuge by Nakumara [4] and Al-Atik and Sitar [5] showed that the obtained earth pressure values during shaking are lower than those obtained by the M-O suggested method. Several walls with backfills situations of liquefiable, saturated, cohesion less were considered and used as material for centrifuge dynamic excitation tests in the study conducted by Dewoolkar et al. [6]. They found that in the walls with saturated backfill, excess pore pressure generation is the most influential factor on the seismic lateral earth pressure. In another study, a series of RWs constructed by dry medium dense sand under dynamic situation were modeled using finite difference code FLAC in the study carried out by Green and Ebeling [7]. They found that the seismic earth pressure results are in agreement with M-O technique, nevertheless, accelerations increased and seismic earth pressures were larger than the values estimated by the M-O approach. In order to approve the assumptions of Veletsos and Younan's analytical solution and to describe its range values, a research study was done by Psarropoulos et al. [8] using the numerical approach i.e., the commercial finite-element package ABAQUS. The versatility of the numerical methods, finite-element and finite-difference, permitted the treatment of more realistic situations that are not amenable to the analytical solution, including the heterogeneity of the retained soil, and translational flexibility of the wall foundation. In another study, Ostadan [9] tried to identify the characteristics of the lateral seismic soil pressure on RWs considering various analyses of soil-structure-interaction. Based on the conducted analyses, Ostadan [9] developed a technique to estimate the maximum seismic soil pressures in order to construct walls resting on firm foundation material and mentioned that the obtained results are better than those suggested in the study conducted by Wood [10]. It seems that most of the previous related research is based on empirical and numerical techniques for the design of RWs. Since there are some other new available techniques such as artificial intelligence (AI), the authors of this study decided to design the safety factor (SF) of the RW developing new hybrid AI methods.

Artificial neural network (ANN) is considered to be an AI technique that is able to forecast almost all problems in science and engineering fields [11–21]. However, they have several limitations which discussed and introduced in previous research [22–24]. As stated in several references [25–27], the use of efficient optimization algorithms (OAs) can overcome these limitations. Various optimization algorithms such as the genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC), and imperialist competitive algorithm (ICA) can be used to solve continuous and non-continuous problems. Due to the high ability of the global search for these OAs, weights and deviations of an ANN can be determined to improve its performance forecast. The above-mentioned hybrid models have been widely-used to solve nonlinear and complex engineering problems [28–33].

In the present study, two hybrid intelligent models, namely, ICA-ANN and GA-ANN, were utilized and implemented to forecast SF of RWs under dynamic conditions. These two models used the most effective factors of ICA and GA to create a proper relationship for prediction of the SF values. The hybrid models are less applicable in engineering and still have not been used in the SF forecast of RWs under dynamic conditions. The present study provides explanations in terms of databases after introducing applicable intelligent methods. Afterwards, modeling procedures were explained in detail and finally, the best predictive model was selected for forecasting the SF values.

2. Methodology

2.1. Artificial Neural Network

The data transfer procedure in the human brain is simulated as an estimated function called the artificial neural network (ANN). The ANN can be used even for complex and nonlinear relationships between input variables, predictors and network output [34,35]. Many types of ANN have been proposed and implemented; and among them, the multilayer feedforward ANN is considered to be a popular one. This method includes hidden nodes (neurons) that connect multi-layers with similar connection weights [36,37]. ANNs should be trained with some learning algorithms to achieve the most accurate results. The backpropagation algorithm (BP) is the most famous learning algorithm which can reduce the system error between optimal and estimated values [38,39]. The hidden node results for design of the transfer function (which is often the sigmoid function) are determined at the net input of the hidden node. The error is calculated by comparing optimal and estimated results. The error must be lower than the defined error for systems such as the root mean square error of approximation (RMSEA) to finish the process, otherwise the connection weights are corrected to achieve a better result (lower error). Figure 1 presents the BP-ANN algorithm structure with one hidden layer.

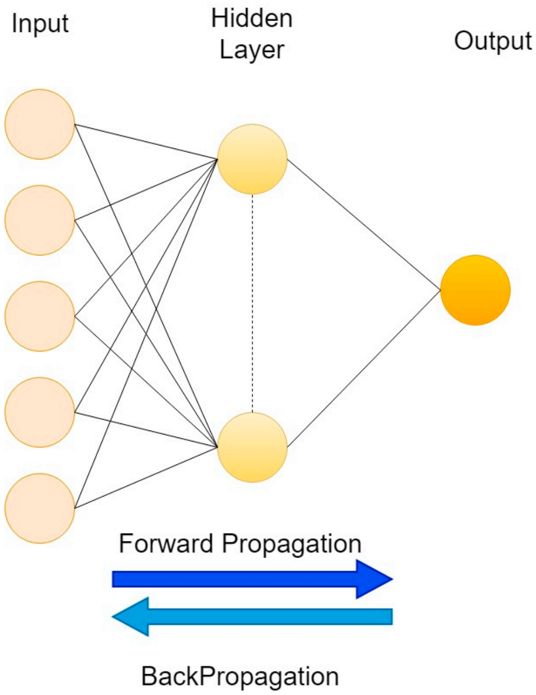

Figure 1. Typical structure of backpropagation algorithm-artificial neural network (BP-ANN) algorithm.

2.2. Genetic Algorithm

Holland [40] developed a technique for optimization aims called the genetic algorithm (GA). GA is strongly influenced by the evolution of biological species and the natural selection mechanism. This technique uses the objective function evaluation in all decision variables for processing. Since the GA is a probabilistic method, there is no need for specific data for action guidance [41]. Contractually, individuals within the population are called volunteering solutions who slowly gain their desired solutions over time. The numbers zero and one are chromosomes that form a linear strip, indicating a solution for each volunteer. Generation is the population size made for applied solutions by the optimization process in each repetition. These basic genetic operators or the reproduction, crossover, and mutation are used for the creation of the next generation in the GA. The procedure for selecting the best chromosomes is defined according to their graded values by taking into account the provided standard for fit as a reproduction operator. This operator directly transfers selected chromosomes to the next generation. The second operator is the crossover operator in which certain segments of individuals (parents) merge into each other and create new ones. There are several ways to apply re-crossover such as a single point crossover and two-point crossover. However, the random single point and two-point crossover are selected in the crossover procedure. The first offspring is created by crossover of the left side of the first parent gene with the opposite side of the second parent gene, but the second offspring is created by a reoccurrence of this process in the reverse order [42]. A random replacement occurs in chromosome elements of the mutation operator. Details of the GA background are available in other studies [41,42]. Figure 2 shows a real structure of GA combined with ANN.

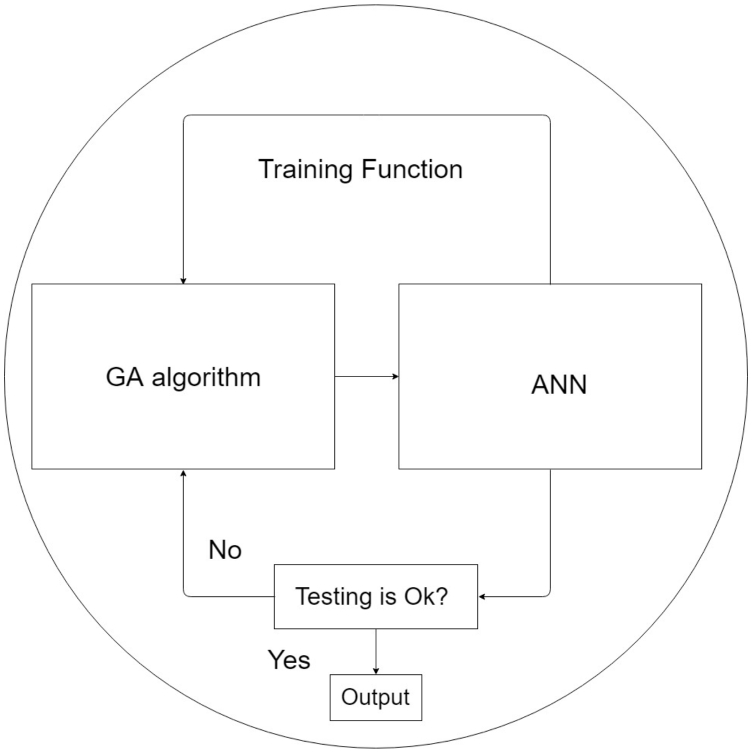

Figure 2. A view of genetic algorithm-artificial neural network (GA-ANN) algorithm.

2.3. Imperialist Competitive Algorithm

The imperialist competitive algorithm (ICA) was proposed by Atashpaz-Gargari and Lucas [43] according to the global search population which can be applied for optimization problems [43]. This algorithm searches a randomly primitive population of the same countries compared with other evolutionary algorithms. Afterwards, the countries with the minimum cost or system error compared to others are selected as imperialists (Nimp) and other countries are considered as their colonies (Ncol). Depending on how much primitive power the imperialists have, they acquire colonial ownership. Primary power is the function of normalized colonial costs. In ICA, imperialists who are more powerful (with the lowest cost/error) will be in possession of more colonies. ICA consists of three operators, namely absorption, revolution, and competition. In the first operator, colonies are attracted to imperialists. On the other hand, the revolution can lead to sudden changes in the ownership of countries. During the absorption and revolution, a colony has the potential to reach to the governance that is better than its colonial governance. Hence, it can obtain the ownership of that empire. During the competition, the imperialists seek to find an increasing number of colonies; and empires seek to seize the ownership of another colony of empires. Based on the power factor, each empire has a chance to at least own a colony of the weakest empire. Consequently, the empires which are weaker than others gradually fall and the stronger ones increase their powers in this competition. This process continues until the strongest empire remains and the rest of them fall, or the criterion of ending the process is essentially fulfilled (such as reaching a desired error or the highest number of failures) and this can be defined by users. Remember that the number of failures in the ICA is conceptually comparable to the number of iterations and generations in swarm optimization and genetic algorithms respectively. However, it is worth noting that the present study did not provide any mathematical formulation of the ICA. See other studies [44,45] for more information about this subject. Figure 3 presents a flowchart for the description of ICA.

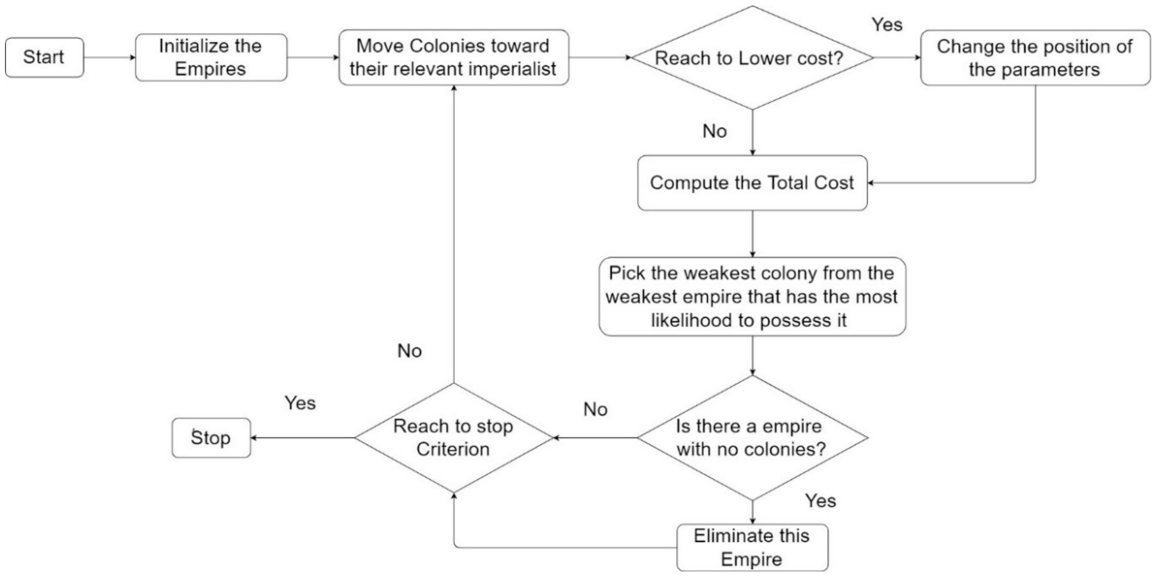

Figure 3. Structure of the imperialist competitive algorithm (ICA) algorithm.

2.4. Hybrid Models

In engineering applications, there are many studies on increasing the performance of ANN models using the OAs such as ABC, PSO, GA and ICA [46–49]. Due to the inability of the BP to find an exact global minimum, the ANN model may not lead to desirable results. Nevertheless, it is likely that the ANN model disconnects at a local minimum, while the adjusted OAs by weights and deviations of ANN can resolve this problem of ANN. In the present study, two methods of hybrid systems called the ICA-ANN and GA-ANN were built for forecasting the SFs of RWs under various dynamic conditions. In these models, ICA and GA were looking for the global minimum, and then the ANN uses it to achieve the best performance prediction.

3. Modeling of Retaining Walls and the Established Database

To obtain the suitable datasets for SF analysis, the modeling procedure was conducted in several steps. The process consisted of introducing boundary conditions, model dimensions, material properties and seismic motion. Mononobe's method utilizing visual basic language was applied to obtain SF values in this research. Many homogenous soils such as sand, gravel-sand and gravel behind the retaining masonry wall (in terms of material, γ = 17, 17.50, 18, 18.5 and 19 ton/m^3) with various conditions were modeled to obtain SF in the study. Retaining wall with heights of 3, 4, 5, 6, 7, 8, 9 and 10 m, were considered and designed. All the models were located on the bedrock with respect to the rigid behavior. In addition, wall widths of 0.5, 0.6, 0.7 and 0.8 m were assumed for all the models. Moreover, the range of gravity for stone mixed cement were assumed, including 20 ton/m^3, 24 ton/m^3 and 28 ton/m^3. Figure 4 shows a schematic view of RWs considered in modeling process of this study. It can be seen that both angles β and i are zero. The Mohr–Coulomb (MC) failure criterion is considered for the analysis in this study. Cohesions of 0 kPa for granular soil and internal friction angles of 30°, 35°, 40°, and 45° were applied in the analyses process. Granular soil was used to avoid the pure water pressure behind the walls. It should be noted that the earthquake motion effect plays an important role in controlling failure of the RWs. Figure 5 shows the distribution of active pressure for static and dynamic conditions and body forces for soil and stone blocks. As mentioned by Kramer [50], peak ground acceleration (PGA) is a measure of earthquake acceleration on the ground. To obtain various values of SF, the amplitudes of PGA were considered to be 0.1 g, 0.2 g, 0.3 g, 0.4 g and 0.5 g for the horizontal direction and it was set as zero for the vertical direction. As noted earlier, SF values were simulated under different conditions for a number of 8000 simulation models. The overall description of different designing parameters for retaining walls under various conditions is shown in Table 1.

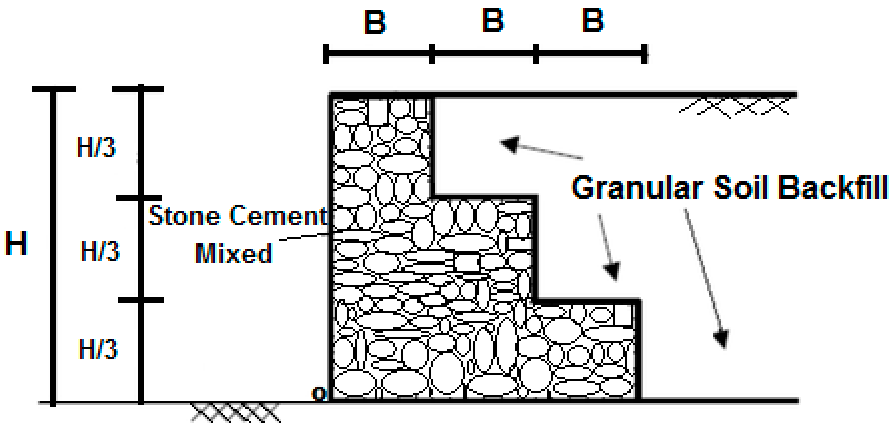

Figure 4. Dimension model for gravity masonry retaining wall.

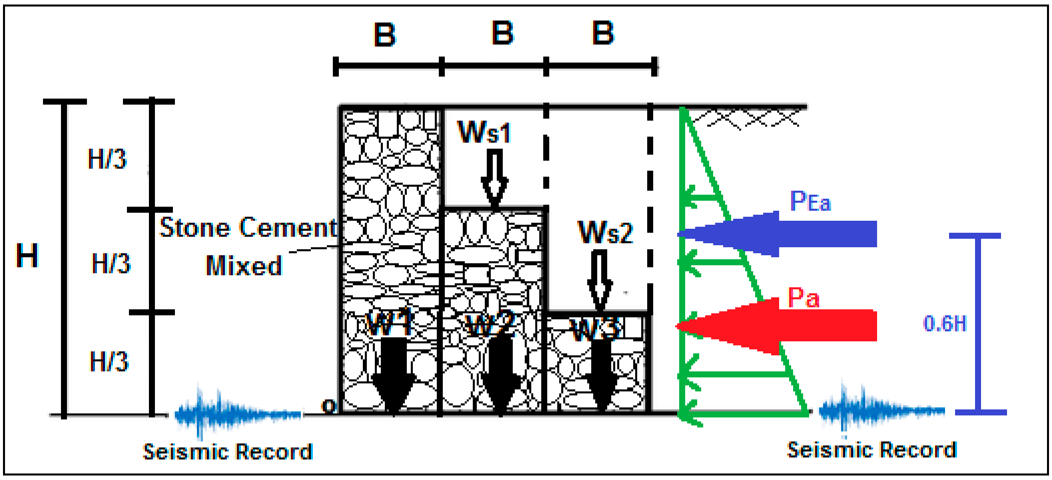

Figure 5. Distribution of active force for static and dynamic conditions with body forces for soil and Stone blocks.

Table 1. General description of the used database.

Input/Output Variable	Category	Unit	Min	Average	Max
Wall height (H)	Input	m	3	6.5	10
Wall width (B)	Input	m	0.5	0.65	0.8
Internal friction angles	Input	Degree	30	37.5	45
Soil density	Input	Kg/m^3	1700	1800	1900
Rock density	Input	Kg/m^3	2000	2426.67	2800
peak ground acceleration (PGA)	Input	g	0.1	0.3	0.5
Factor of Safety (FOS)	Output	-	0.027	0.568	6.476

4. Results and Discussion

This section provides the description of implemented hybrid models i.e., ICA-ANN and GA-ANN in order to forecast SF values of the RWs. Parameters affecting the ICA and GA are introduced and designed in order to achieve a proper level of accuracy.

4.1. Imperialist Competitive Algorithm-Artificial Neural Network (ICA-ANN)

Important parameters/coefficients of the ICA-ANN model should be examined for its achievement. Before examining ICA parameters, using a trial and error process, it was found that a 6 × 12 × 1 architecture (or an ANN with 6 inputs,12 neurons in a hidden layer and one output) yields better results compared to other built models. Therefore, this structure was used for all hybrid intelligent systems in the present study. As noted earlier, $N_{country}$, N_{decade} and N_{imp} are considered as the most important parameters in designing ICA. To assess N_{imp}, many models were implemented using various quantities of N_{imp} i.e., 5, 10, 15, 20, 25 and 30. In these models, $N_{country}$ = 300 and N_{decade} = 100 were considered. Results of this parametric study indicated that N_{imp} = 20 gives a higher functional capacity for the system. To choose the best value of N_{decade}, as shown in Figure 6, different models were built with various numbers of $N_{country}$ i.e., 25, 50, 75, 100, 150, 200, 250, 300, 350 and 400 and their results are presented based on the root mean square error (RMSE). The results indicated that the RMSE values do not change until the amount of N_{decade} arrived at 600. In the last step of modeling, different numbers of countries were considered using N_{imp} = 5 and N_{decade} = 500; and their ICA-ANN models were created. These models were evaluated based on their performance indices (PIs), the coefficient of determination (R^2) and the RMSE. The changes of the PIs for two sections of training and testing of ICA-ANN models are presented in Figures 7 and 8, respectively.

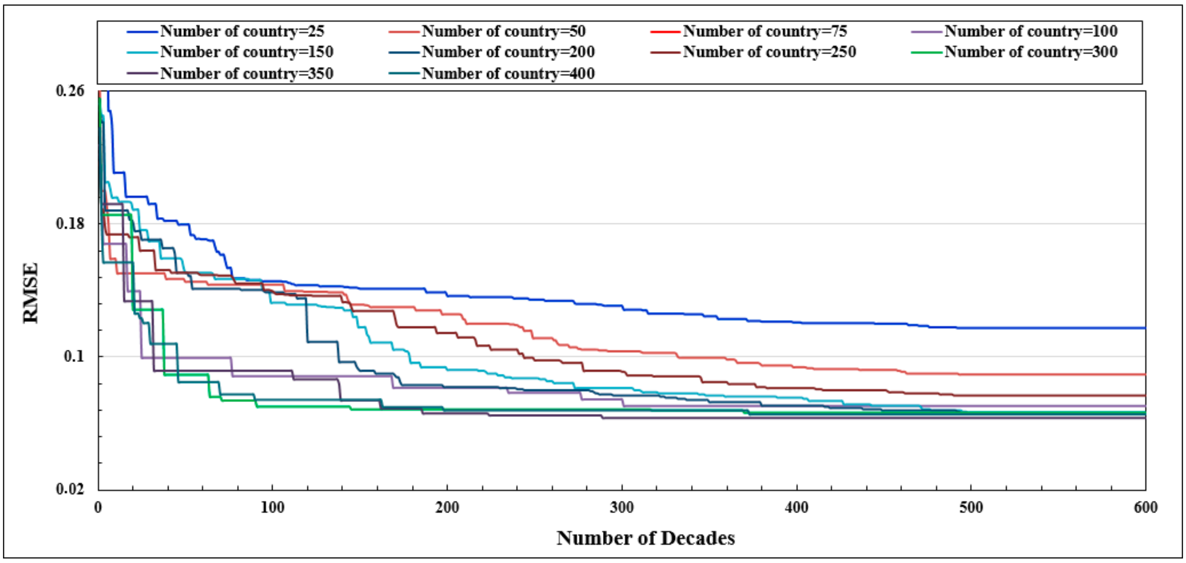

Figure 6. Performance of ICA-ANN models with different Ncountry values.

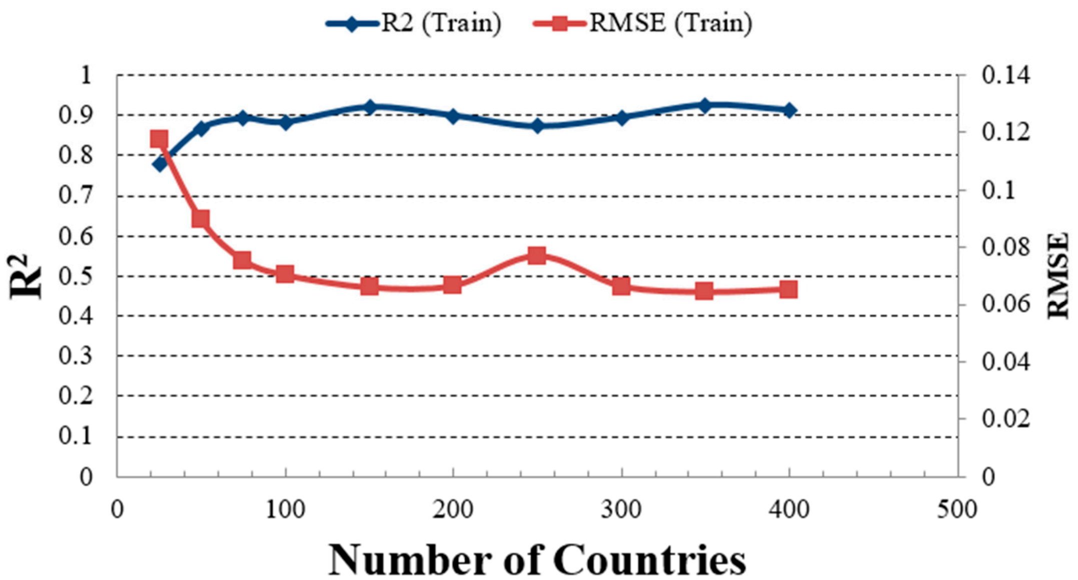

Figure 7. Performance indices (PIs) Changes for training section.

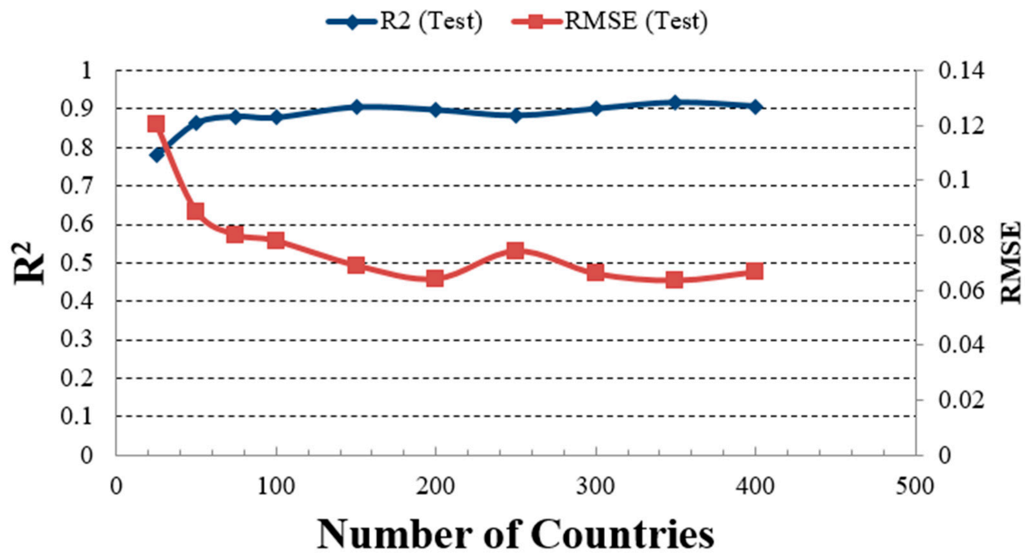

Figure 8. PIs Changes for testing section.

The proposed ranking technique by Zurlo et al. [51], was used to select the best hybrid model in the present study. The full version of this technique is available in the original research [51]. Based on this method, a rank was assigned to each PI in its group (train and test). For instance, values of 0.7782, 0.8676, 0.8917, 0.8832, 0.9194, 0.8987, 0.8724, 0.8944, 0.9248 and 0.9120 were respectively obtained for R^2 datasets of the training group of models 1 to 10; and then values of 1, 2, 5, 4, 9, 7, 3, 6, 10 and 8 were respectively considered as their ranks (see Table 2). The method was also performed for the obtained results of RMSE. The sums of R^2 and RMSE rank values for the training and testing groups were obtained and assigned as the total rank of each model. On this basis, Model 9 ($N_{country}$ = 350) with a total score of 40 was selected as the best ICA-ANN model. The performance evaluation of the best results of ICA-ANN is described later for the prediction of SF values. For design of the models, 80% and 20% of dataset were assigned to training and testing sections, respectively. In this study, the authors decided to utilize a technique of classification namely the color intensity ranking (CIR) suggested by Koopialipoor et al. [33] for each row of Table 2. According to this method, intensity of the color increases by increasing the rank values and similarly, it decreases by decreasing the rank values. For instance, model number 9 receives an intense red in the last column of Table 2. More explanations regarding the CIR can be found in the original study [33]. It should be noted that the same results were achieved using a ranking system. However, the CTR technique can be considered as a simpler way to select and classify the best models.

Table 2. Ranking and color intensity ranking (CIR) systems to select the best imperialist competitive algorithm-artificial neural network (ICA-ANN) model.

Model	Number of Countries	Training		Testing		Training Rate		Testing Rate		Total Rank
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	25	0.7782	0.1175	0.7799	0.1204	1	1	1	1	4
2	50	0.8676	0.0896	0.8628	0.0887	2	2	2	2	8
3	75	0.8917	0.0755	0.8802	0.0801	5	4	4	3	16
4	100	0.8832	0.0703	0.8773	0.0779	4	5	3	4	16
5	150	0.9194	0.066	0.904	0.069	9	8	8	6	31
6	200	0.8987	0.0666	0.897	0.0641	7	6	6	9	28
7	250	0.8724	0.0770	0.8826	0.0742	3	3	5	5	16
8	300	0.8944	0.0664	0.9001	0.0659	6	7	7	8	28
9	350	0.9248	0.0644	0.9163	0.0635	10	10	10	10	40
10	400	0.9120	0.0654	0.9064	0.0666	8	9	9	7	32

4.2. Genetic Algorithm-Artificial Neural Network (GA-ANN)

As explained earlier, the GA has a higher effect on the ANN performance [52]. The most effective GA parameters, which are used to build hybrid GA-ANN models, should be selected/determined. The probabilities of mutation and reproduction percentage were assigned at 25% and 9% respectively. A single point was used with 70 percent of probability for the crossover. The maximum number of generations (G_{max}) should be identified and used in the next step. A parametric study was examined to determine the impact of G_{max} on the network performance using different number of population sizes. As shown in Figure 9, 600 generations were considered as the stopping criterion, and RMSE results were obtained to determine the optimal number of generations. Based on Figure 9, RMSE values for all population sizes are constant after generation number of 500. Therefore, the optimal number of generations was considered to be 500 for designing GA-ANN models. Figures 10 and 11 show the R^2 and RMSE results of model constructed in Figure 9 for training and testing datasets, respectively. As the final step of GA-ANN modeling, a set of hybrid GA-ANN models were built to assess the best population size considering different sizes of 50, 100, 150, 200, 250, 300, 350 and 400 (see Table 3). Similar to ICA-ANN part, both ranking and CIR techniques were applied on the results of this table. As a result, the population size of 400 with total rank of 40 and ability to get intense red (model number 10) is selected as the best GA-ANN model in forecasting FS values of RWs. The results of this model will be discussed in the following section.

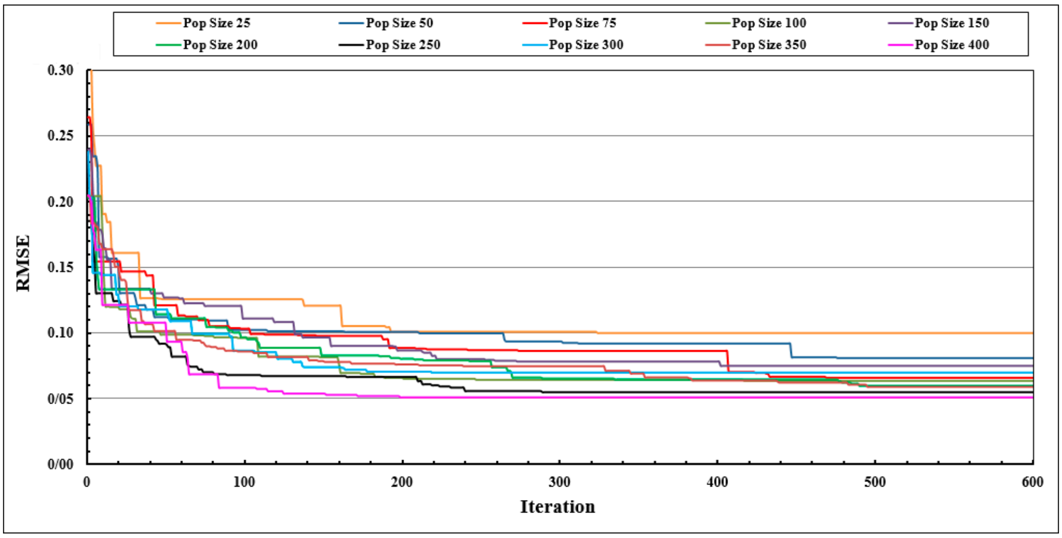

Figure 9. ICA-ANN models with different population sizes.

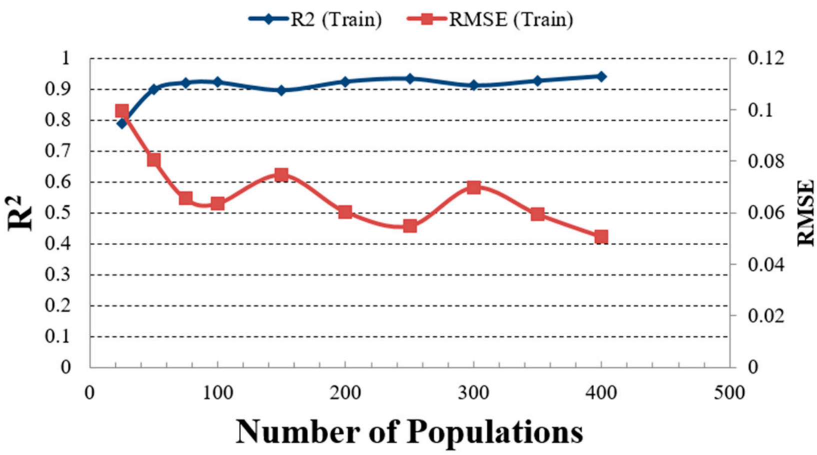

Figure 10. PIs changes for training section of GA-ANN models.

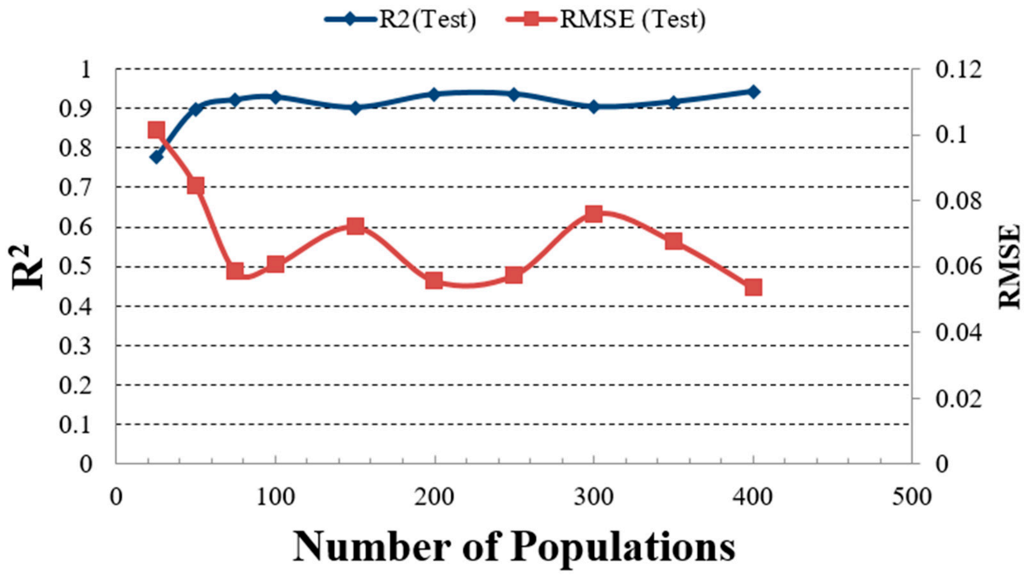

Figure 11. PIs changes for testing section of GA-ANN models.

Table 3. Ranking and CIR systems to select the best GA-ANN model.

Model	Number of Population	Training		Testing		Training Rate		Testing Rate		Total Rank
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	25	0.7881	0.0994	0.7764	0.1014	1	1	1	1	4
2	50	0.8979	0.0805	0.8977	0.0846	3	2	2	2	9
3	75	0.9206	0.0655	0.9207	0.0586	5	5	6	7	23
4	100	0.9218	0.0636	0.9275	0.0605	6	6	7	6	25
5	150	0.8966	0.0747	0.9015	0.0721	2	3	3	4	12
6	200	0.9242	0.0604	0.9344	0.0557	7	7	8	9	31
7	250	0.9336	0.055	0.9351	0.0574	9	9	9	8	35
8	300	0.9117	0.0699	0.9035	0.076	4	4	4	3	15
9	350	0.9268	0.0595	0.9157	0.0677	8	8	5	5	26
10	400	0.9418	0.0507	0.9415	0.0536	10	10	10	10	40

4.3. Performance of Models for Dynamic Conditions

In this section, we examined the performance of the proposed intelligent models to forecast SF of RWs under dynamic conditions. As noted earlier, various parameters were used to design the RWs with different ranges. The impact of these parameters was investigated on intelligent models, and then the best models were used to forecast SF values. Figure 12 illustrates 100 data (out of the database used in this study) which was randomly selected as real SF values together with the predicted ones by ICA-ANN and GA-ANN techniques. As can be seen, the results obtained by GA-ANN (black line) are closer to real values (blue line) in most of cases compared to another developed hybrid intelligent system. Therefore, the GA-ANN model can implement more effectively for SF values of RWs. Results of GA-ANN models for both training and testing datasets are shown in Figure 13. Based on these results, a high accuracy level can be obtained by the developed GA-ANN and this model can be suggested as an accurate one in the field of RW design.

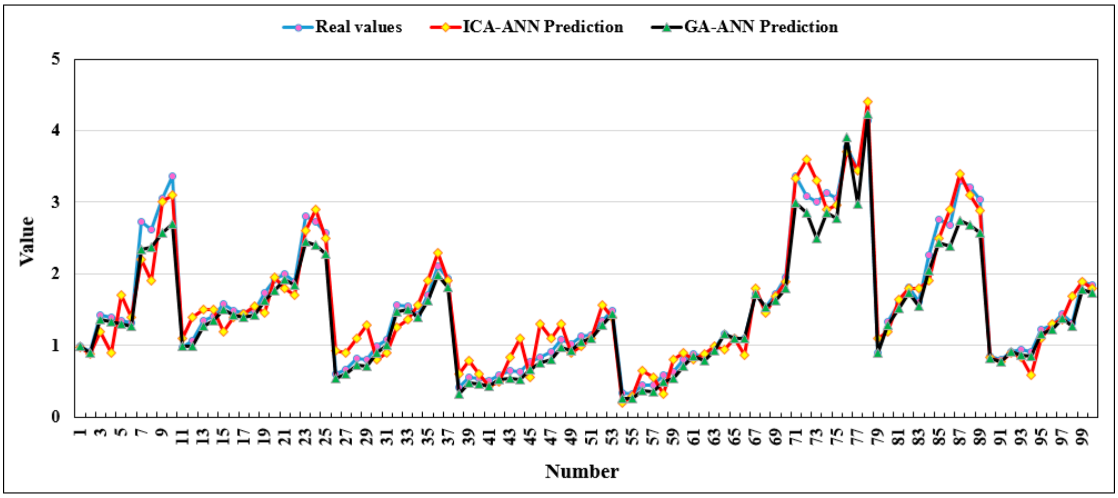

Figure 12. Comparison of real and predicted 100 number of data which was selected randomly in design of SF of the RWs.

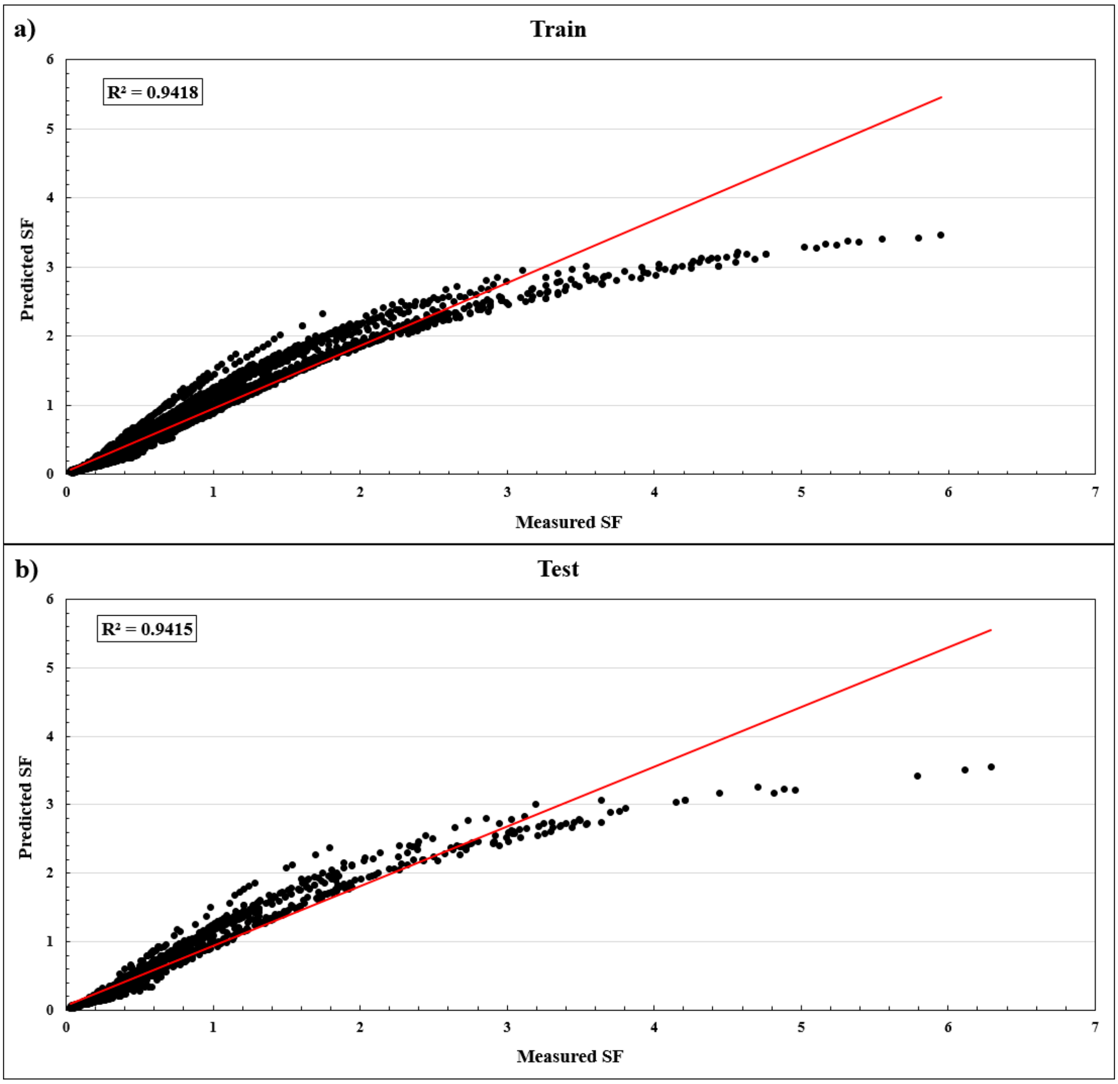

Figure 13. Results of the best predictive model (GA-ANN) in estimating SF values of RWs (**a**) Train, (**b**) Test.

5. Conclusions

In the present research, 8000 models of RWs under dynamic loads were designed and their SF values were obtained. In these models, effective parameters on stability of RWs i.e., wall height, wall width, internal friction angle of soil, soil density, rock density and peak ground acceleration, were considered for designing RWs. Then, the same parameters were used as model inputs in 2 hybrid models namely, ICA-ANN and GA-ANN for the prediction of SFs. Using these intelligent networks, new models were developed for evaluating the retaining wall in dynamic conditions. In hybrid intelligent modeling, effective parameters on performance of ICA and GA were determined using several parametric studies. The statistical indices, R^2 and RMSE, were used to evaluate the performance of intelligent networks. The performance of each network was obtained in different conditions using these indices and the best hybrid model was selected based on both simple ranking and CIR techniques. As a result, the GA-ANN model provided a higher degree of accuracy for designing RWs under dynamic conditions compared to the ICA-ANN model. Results of (0.9248 and 0.9163) and (0.0644 and 0.0635) for R^2 and RMSE of training and testing respectively were obtained for ICA-ANN model, while these values were (0.9418 and 0.9415) and (0.0507 and 0.0536) for the GA-ANN model. This showed that higher performance prediction of SF values is possible when the GA-ANN model is applied and developed. Under the mentioned conditions, the GA-ANN technique can be used to control risks induced by the failure of RWs.

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References

1. Mononobe, N. On determination of earth pressure during earthquake. In Proceedings of the World Engineering Congress, Tokyo, Japan, 30 October–11 November 1929; pp. 177–185.
2. Okabe, S. General theory of earth pressure. *J. Jpn. Soc. Civ. Eng.* **1926**, *12*, 23–45.
3. Mylonakis, G.; Kloukinas, P.; Papantonopoulos, C. An alternative to the Mononobe–Okabe equations for seismic earth pressures. *Soil Dyn. Earthq. Eng.* **2007**, *27*, 957–969. [CrossRef]
4. Nakamura, S. Reexamination of Mononobe-Okabe theory of gravity retaining walls using centrifuge model tests. *Soils Found.* **2006**, *46*, 135–146. [CrossRef]
5. Al Atik, L.; Sitar, N. *Experimental and Analytical Study of the Seismic Performance of Retaining Structures*; Pacific Earthquake Engineering Research Center: Berkeley, CA, USA, 2009.
6. Dewoolkar, M.M.; Ko, H.Y.; Pak, R.Y.S. Seismic behavior of cantilever retaining walls with liquefiable backfills. *J. Geotech. Geoenviron. Eng.* **2001**, *127*, 424–435. [CrossRef]
7. Green, R.A.; Ebeling, R.M. *Seismic Analysis of Cantilever Retaining Walls, Phase I*; Civil & Environmental Engineering Department University of Michigan: Ann Arbor, MI, USA, 2002.
8. Psarropoulos, P.N.; Klonaris, G.; Gazetas, G. Seismic earth pressures on rigid and flexible retaining walls. *Soil Dyn. Earthq. Eng.* **2005**, *25*, 795–809. [CrossRef]
9. Ostadan, F. Seismic soil pressure for building walls: An updated approach. *Soil Dyn. Earthq. Eng.* **2005**, *25*, 785–793. [CrossRef]
10. Wood, J.H. *Earthquake-Induced Soil Pressures on Structures*; California Institute of Technology: Pasadena, CA, USA, 1973.
11. Hasanipanah, M.; Armaghani, D.J.; Amnieh, H.B.; Koopialipoor, M.; Arab, H. A Risk-Based Technique to Analyze Flyrock Results Through Rock Engineering System. *Geotech. Geol. Eng.* **2018**, *36*, 2247–2260. [CrossRef]

12. Koopialipoor, M.; Nikouei, S.S.; Marto, A.; Fahimifar, A.; Armaghani, D.J.; Mohamad, E.T. Predicting tunnel boring machine performance through a new model based on the group method of data handling. *Bull. Eng. Geol. Environ.* **2018**. [CrossRef]
13. Liao, X.; Khandelwal, M.; Yang, H.; Koopialipoor, M.; Murlidhar, B.R. Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques. *Eng. Comput.* **2019**. [CrossRef]
14. Asteris, P.G.; Nozhati, S.; Nikoo, M.; Cavaleri, L.; Nikoo, M. Krill herd algorithm-based neural network in structural seismic reliability evaluation. *Mech. Adv. Mater. Struct.* **2018**. [CrossRef]
15. Asteris, P.G.; Plevris, V. Anisotropic masonry failure criterion using artificial neural networks. *Neural Comput. Appl.* **2017**, *28*, 2207–2229. [CrossRef]
16. Asteris, P.G.; Tsaris, A.K.; Cavaleri, L.; Repapis, C.C.; Papalou, A.; Di Trapani, F.; Karypidis, D.F. Prediction of the fundamental period of infilled RC frame structures using artificial neural networks. *Comput. Intell. Neurosci.* **2016**, 20. [CrossRef]
17. Hautamäki, V.; Siniscalchi, S.M.; Behravan, H.; Salerno, V.M.; Kukanov, I. Boosting universal speech attributes classification with deep neural network for foreign accent characterization. In Proceedings of the Sixteenth Annual Conference of the International Speech Communication Association, Dresden, Germany, 6–10 September 2015.
18. Barone, A.V.M.; Helcl, J.; Sennrich, R.; Haddow, B.; Birch, A. Deep architectures for neural machine translation. *arXiv*, 2017; arXiv:1707.07631. Available online: http://www.aclweb.org/anthology/W17-4710(accessed on 12 March 2019).
19. Salerno, V.M.; Rabbeni, G. An Extreme Learning Machine Approach to Effective Energy Disaggregation. *Electronics* **2018**, *7*, 235. [CrossRef]
20. Koopialipoor, M.; Fahimifar, A.; Ghaleini, E.N.; Momenzadeh, M.; Armaghani, D.J. Development of a new hybrid ANN for solving a geotechnical problem related to tunnel boring machine performance. *Eng. Comput.* **2019**. [CrossRef]
21. Zhou, J.; Aghili, N.; Ghaleini, E.N.; Bui, D.T.; Tahir, M.M.; Koopialipoor, M. A Monte Carlo simulation approach for effective assessment of flyrock based on intelligent system of neural network. *Eng. Comput.* **2019**. [CrossRef]
22. Armaghani, D.J.; Mahdiyar, A.; Hasanipanah, M.; Faradonbeh, R.S.; Khandelwal, M.; Amnieh, H.B. Risk Assessment and Prediction of Flyrock Distance by Combined Multiple Regression Analysis and Monte Carlo Simulation of Quarry Blasting. *Rock Mech. Rock Eng.* **2016**, *49*, 1–11. [CrossRef]
23. Hajihassani, M.; Jahed Armaghani, D.; Marto, A.; Tonnizam Mohamad, E. Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. *Bull. Eng. Geol. Environ.* **2015**, *74*, 873–886. [CrossRef]
24. Koopialipoor, M.; Ghaleini, E.N.; Tootoonchi, H.; Armaghani, D.J.; Haghighi, M.; Hedayat, A. Developing a new intelligent technique to predict overbreak in tunnels using an artificial bee colony-based ANN. *Environ. Earth Sci.* **2019**, *78*, 165. [CrossRef]
25. Gordan, B.; Jahed Armaghani, D.; Hajihassani, M.; Monjezi, M. Prediction of seismic slope stability through combination of particle swarm optimization and neural network. *Eng. Comput.* **2015**, *32*, 85–97. [CrossRef]
26. Hajihassani, M.; Jahed Armaghani, D.; Monjezi, M.; Mohamad, E.T.; Marto, A. Blast-induced air and ground vibration prediction: A particle swarm optimization-based artificial neural network approach. *Environ. Earth Sci.* **2015**, 74. [CrossRef]
27. Khandelwal, M.; Armaghani, D.J. Prediction of Drillability of Rocks with Strength Properties Using a Hybrid GA-ANN Technique. *Geotech. Geol. Eng.* **2016**, *34*, 605–620. [CrossRef]
28. Momeni, E.; Jahed Armaghani, D.; Hajihassani, M.; Mohd Amin, M.F. Prediction of uniaxial compressive strength of rock samples using hybrid particle swarm optimization-based artificial neural networks. *Meas. J. Int. Meas. Confed.* **2015**, *60*, 50–63. [CrossRef]
29. Mohamad, E.T.; Faradonbeh, R.S.; Armaghani, D.J.; Monjezi, M.; Majid, M.Z.A. An optimized ANN model based on genetic algorithm for predicting ripping production. *Neural Comput. Appl.* **2017**, *28*, 393–406. [CrossRef]
30. Jahed Armaghani, D.; Hajihassani, M.; Marto, A.; Faradonbeh, R.S.; Mohamad, E.T. Prediction of blast-induced air overpressure: A hybrid AI-based predictive model. *Environ. Monit. Assess.* **2015**, *187*, 666. [CrossRef]

31. Zhou, J.; Nekouie, A.; Arslan, C.A.; Pham, B.T.; Hasanipanah, M. Novel approach for forecasting the blast-induced AOp using a hybrid fuzzy system and firefly algorithm. *Eng. Comput.* **2019**. [CrossRef]
32. Zhou, J.; Li, E.; Wang, M.; Chen, X.; Shi, X.; Jiang, L. Feasibility of Stochastic Gradient Boosting Approach for Evaluating Seismic Liquefaction Potential Based on SPT and CPT Case Histories. *J. Perform Constr. Fac.* **2019**, *33*, 04019024. [CrossRef]
33. Koopialipoor, M.; Armaghani, D.J.; Hedayat, A.; Marto, A.; Gordan, B. Applying various hybrid intelligent systems to evaluate and predict slope stability under static and dynamic conditions. *Soft Comput.* **2018**. [CrossRef]
34. Garrett, J.H. Where and why artificial neural networks are applicable in civil engineering. *J. Comput. Civ. Eng.* **1994**, *8*, 129–130. [CrossRef]
35. Koopialipoor, M.; Armaghani, D.J.; Haghighi, M.; Ghaleini, E.N. A neuro-genetic predictive model to approximate overbreak induced by drilling and blasting operation in tunnels. *Bull. Eng. Geol. Environ.* **2017**. [CrossRef]
36. Simpson, P.K. *Artificial Neural System—Foundation, Paradigm, Application and Implementations*; Pergamon: New York, NY, USA, 1990.
37. Koopialipoor, M.; Murlidhar, B.R.; Hedayat, A.; Armaghani, D.J.; Gordan, B.; Mohamad, E.T. The use of new intelligent techniques in designing retaining walls. *Eng. Comput.* **2019**. [CrossRef]
38. Dreyfus, G. *Neural Networks: Methodology and Applications*; Springer: Berlin/Heidelberg, Germany, 2005.
39. Koopialipoor, M.; Ghaleini, E.N.; Haghighi, M.; Kanagarajan, S.; Maarefvand, P.; Mohamad, E.T. Overbreak prediction and optimization in tunnel using neural network and bee colony techniques. *Eng. Comput.* **2018**. [CrossRef]
40. Holland, J.H. Genetic algorithms. *Sci. Am.* **1992**, *267*, 66–73. [CrossRef]
41. Koopialipoor, M.; Fallah, A.; Armaghani, D.J.; Azizi, A.; Mohamad, E.T. Three hybrid intelligent models in estimating flyrock distance resulting from blasting. *Eng. Comput.* **2018**. [CrossRef]
42. Momeni, E.; Nazir, R.; Armaghani, D.J.; Maizir, H. Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. *Measurement* **2014**, *57*, 122–131. [CrossRef]
43. Atashpaz-Gargari, E.; Lucas, C. Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2007, Singapore, 25–28 September 2007; pp. 4661–4667.
44. Armaghani, D.J.; Hasanipanah, M.; Amnieh, H.B.; Mohamad, E.T. Feasibility of ICA in approximating ground vibration resulting from mine blasting. *Neural Comput. Appl.* **2018**, *29*, 457–465. [CrossRef]
45. Armaghani, D.J.; Hasanipanah, M.; Mohamad, E.T. A combination of the ICA-ANN model to predict air-overpressure resulting from blasting. *Eng. Comput.* **2016**, *32*, 155–171. [CrossRef]
46. Ghaleini, E.N.; Koopialipoor, M.; Momenzadeh, M.; Sarafraz, M.E.; Mohamad, E.T.; Gordan, B. A combination of artificial bee colony and neural network for approximating the safety factor of retaining walls. *Eng. Comput.* **2018**. [CrossRef]
47. Gordan, B.; Koopialipoor, M.; Clementking, A.; Tootoonchi, H.; Mohamad, E.T. Estimating and optimizing safety factors of retaining wall through neural network and bee colony techniques. *Eng. Comput.* **2018**. [CrossRef]
48. Zhao, Y.; Noorbakhsh, A.; Koopialipoor, M.; Azizi, A.; Tahir, M.M. A new methodology for optimization and prediction of rate of penetration during drilling operations. *Eng. Comput.* **2019**. [CrossRef]
49. Jahed Armaghani, D.; Hajihassani, M.; Monjezi, M.; Mohamad, E.T.; Marto, A.; Moghaddam, M.R. Application of two intelligent systems in predicting environmental impacts of quarry blasting. *Arab. J. Geosci.* **2015**, *8*, 9647–9665. [CrossRef]
50. Kramer, S.L. Geotechnical Earthquake Engineering. In *Prentice–Hall International Series in Civil Engineering and Engineering Mechanics*; Prentice-Hall: Upper Saddle River, NI, USA, 1996.
51. Zorlu, K.; Gokceoglu, C.; Ocakoglu, F.; Nefeslioglu, H.A.; Acikalin, S. Prediction of uniaxial compressive strength of sandstones using petrography-based models. *Eng. Geol.* **2008**, *96*, 141–158. [CrossRef]
52. Lee, Y.; Oh, S.H.; Kim, M.W. The effect of initial weights on premature saturation in back-propagation learning. In Proceedings of the IJCNN-91-Seattle International Joint Conference on Neural Networks, Seattle, WA, USA, 8–12 July 1991; pp. 765–770.