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REVIEW ARTICLE

A systematic review and meta-analysis of artificial neural network application in geotechnical engineering: theory and applications

Hossein Moayedi[1,2] · Mansour Mosallanezhad[3] · Ahmad Safuan A. Rashid[4,5] · Wan Amizah Wan Jusoh[6] · Mohammed Abdullahi Muazu[7]

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Abstract

Artificial neural network (ANN) aimed to simulate the behavior of the nervous system as well as the human brain. Neural network models are mathematical computing systems inspired by the biological neural network in which try to constitute animal brains. ANNs recently extended, presented, and applied by many research scholars in the area of geotechnical engineering. After a comprehensive review of the published studies, there is a shortage of classification of study and research regarding systematic literature review about these approaches. A review of the literature reveals that artificial neural networks is well established in modeling retaining walls deflection, excavation, soil behavior, earth retaining structures, site characterization, pile bearing capacity (both skin friction and end-bearing) prediction, settlement of structures, liquefaction assessment, slope stability, landslide susceptibility mapping, and classification of soils. Therefore, the present study aimed to provide a systematic review of methodologies and applications with recent ANN developments in the subject of geotechnical engineering. Regarding this, a major database of the web of science has been selected. Furthermore, meta-analysis and systematic method which called PRISMA has been used. In this regard, the selected papers were classified according to the technique and method used, the year of publication, the authors, journals and conference names, research objectives, results and findings, and lastly solution and modeling. The outcome of the presented review will contribute to the knowledge of civil and/or geotechnical designers/practitioners in managing information in order to solve most types of geotechnical engineering problems. The methods discussed here help the geotechnical practitioner to be familiar with the limitations and strengths of ANN compared with alternative conventional mathematical modeling methods.

Keywords PRISMA · ANN · Soft computing · Geotechnical engineering

1 Introduction

Because of a large number of complicated problems in most engineering applications, engineers depend on computational intelligence as well as soft computing analysis instead of following huge complicated calculations [1, 2]. In engineering problems, much sophisticated statistical analysis and mathematical modeling are introduced in order to solve engineering problems [3–5]. Challenges associated with the reliable engineering design solution and development of technology complicated the geotechnical engineering environment even more [6, 7]. Certainly, investigating the engineering properties of rock and soil masses show uncertain and varied behavior due to their imprecise and complex natures. On the other hand, many other materials in the field of civil engineering (e.g., steel, timber, and concrete) show far more homogeneity and isotropy. The artificial neural networks (ANNs), based on the sophisticated mathematical models and advanced software tools, can help to assess all the reliable choices available with respect to a predefined project outcome [8, 9]. The ANN, however, need to be used along with one optimization algorithm to reduce the rate of error especially

Corresponding author at Ton Duc Thang University, Ho Chi Minh City, Vietnam.

✉ Ahmad Safuan A. Rashid
http://civil.utm.my/ahmadsafuan/

Hossein Moayedi
hossein.moayedi@tdtu.edu.vn

Extended author information available on the last page of the article

in complex problems such as compressed sensing [10]. ANN offers the required tools for geotechnical engineers, working in large consultant companies, to make a fast and in most cases better decisions to improve the quality of their performance and to reduce risks [11]. Numerous researchers have discussed the operation and structure of ANNs (e.g., Wang [12], Choobbasti et al. [13], Gandomi and Alavi [14], Mukhlisin et al. [15], Lian et al. [16], Salsani et al. [17], Bahrami et al. [18], Mert [19], Moayedi and Rezaei [20]). As an alternative and effective approach, which has been proved to have a degree of success and reliability [21], is mainly based on the data alone to define the parameters and structure of the model [8]. The ANN was used in numerous academic subjects and projects, such as risk assessment [22, 23], health and medical [24], image processing [25, 26], mathematics [27–30], early warnings related to geotechnical problems [31], geosciences and remote sensing [32], business and management [33], civil engineering [14, 34–36] and particularly to the geotechnical engineering as the main concern for this study [32, 37].

In recent years some scholars have successfully attempted to generate, extend and present the new utility determining tools and approaches, as well as ANNs methods and techniques into the field of civil engineering. This interesting topic has been reviewed several times by researchers such as Flood and Kartam [38], Flood and Kartam [39], Adeli [3], Lu et al. [40], Lazarevska et al. [34] and Li and Hao [41]. Indeed, the use of ANNs method in the geotechnical engineering problems, as the first multi-criteria assessment method, was presented in the early 1990s by Bolt [42]. Different subjects have been studied using the ANNs method such as faults modeling [42], underground openings [43], braced excavation [44], pile integrity testing [45], pile bearing capacity [20, 46–56], predicting geotechnical parameters [1, 57–59], modeling tunnel boring machine (TBM) performance [60], kinematic soil pile interaction response parameters [61], slope stability [62]. There are very few research studies that classified and reviewed the ANNs application for these approaches in various areas such as; principles and understanding of NNs in civil engineering [3], shallow foundations [63], pile foundations [64], corrosion monitoring [65]. Various approaches have been suggested regarding the previous findings on the ANN application in geotechnical engineering. However, the conducted surveys were limited to specific subjects such as pile foundation [66], shallow foundation [63] or general subject of geotechnical engineering [8] and did not keep up with the new challenges and changing situation in the field of geotechnical engineering. Thus, the authors think that there is an absence of a systematic review from the recently published studies performed in the highlighted area. Also, the authors believe that there is a great demand for a comprehensive review paper, combining the available methods as well as current studies.

2 Literature review and distribution of the papers

Since the early 1900s, and up to the date of writing this paper, there are more than 4000 research scholar articles in the field of geotechnical engineering which indexed in the web of science (WOS). Distribution of papers published in the considered area, based on the source title, is presented in Table 1. In this regard, when the search narrows to the application of ANNs in the subject of geotechnical engineering only 152 articles, with a very limited number of source title, remained. Distribution of papers, based on the source title, in the use of ANN-based models in geotechnical engineering, is tabulated in Table 2. Figure 1 shows the subject of ANN application in the field of geotechnical engineering based on both total publications by year and sum of times cited by year. It can be seen that the number

Table 1 Distribution of papers in the subject of geotechnical engineering based on the source title

Number	Name of journal	*N*	%
1	P I Civil Eng-Geotech	293	7.31
2	J Geotech Geoenvironj Geotech Geoenviron	203	5.07
3	Engineering Geology	201	5.02
4	Canadian Geotechnical Journal	119	2.97
5	Soils and Foundations	113	2.82
6	Computers and Geotechnics	97	2.42
7	Geotechnique	91	2.27
8	Int J Geomech	70	1.75
9	Geotechnical Testing Journal	63	1.57
10	Soil Dyn Earthq Eng	61	1.52
11	Environmental Geotechnics	56	1.40
12	B Eng Geol Environ	55	1.37
13	J Mater Civil Eng	54	1.35
14	Rock and Soil Mechanics	51	1.27
15	Int J Numer Anal Metint J Numer Anal Met	50	1.25
16	Environmental Earth Sciences	43	1.07
17	Geotechnical and Geological Engineering	42	1.05
18	Arabian Journal of Geosciences	40	1.00
19	Int J Phys Model Geoint J Phys Model Geo	39	0.97
20	Q J Eng Geol Hydrogen	38	0.95
21	Tunn Undergr Sp Tech	38	0.95
22	P I Civil Eng-Ground Improvement	37	0.92
23	P I Civil Eng-Civil Engineering	36	0.90
24	Bautechnik	35	0.87
25	Applied Clay Science	33	0.82

Table 2 Distribution of papers in the subject of ANN application in geotechnical engineering based on the source title

Number	Name of journal	*N*	%
1	Computers and Geotechnics	12	7.90
2	Arabian Journal of Geosciences	6	3.95
3	Geotechnical and Geological Engineering	5	3.29
4	Neural Computing Applications	5	3.29
5	Engineering with Computers	4	2.63
6	Environmental Earth Sciences	4	2.63
7	Int J Numer Anal Met	4	2.63
8	J Comput Civil Eng	4	2.63
9	Scientia Iranica	4	2.63
10	Soils and Foundations	4	2.63
11	Engineering Computations	3	1.97
12	Engineering Geology	3	1.97
13	Geomechanics and Engineering	3	1.97
14	Measurement	3	1.97
15	Natural Hazards	3	1.97
16	Acta Geotechnica	2	1.32
17	Advances in Engineering Software	2	1.32
18	Canadian Geotechnical Journal	2	1.32
19	Computer-Aided Civil and Infrastructure Engineering	2	1.32
20	Computers Geosciences	2	1.32
21	Disaster Advances	2	1.32
22	Environmental Geology	2	1.32
23	Expert Systems with Applications	2	1.32
24	Geoscience Frontiers	2	1.32
25	Geotechnique	2	1.32

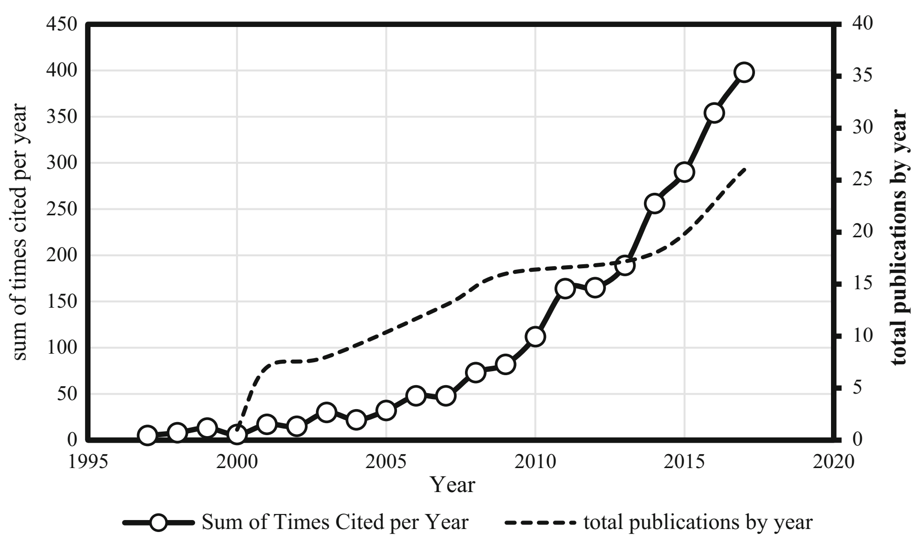


Fig. 1 The subject of ANN application in geotechnical engineering based on total publications by year and sum of times cited by year

of publications has increased sharply from one publication in the year 2000 to twenty-two publications in the Year 2017. ANN-based methods have been applied increasingly as an effective methods in most geotechnical engineering subjects, including: tunneling [67, 68], mathematical constitutive modeling [69], underground openings [70, 71], geo-material properties [72, 73], bearing capacity of pile [20, 53, 64]; slope stability [47, 74–79]; liquefaction [80, 81], earth retaining structures [82, 83], soil swelling [84, 85], classification of soils [86, 87] and site characterization [88, 89]. Indeed, the fundamentals of modern ANN and hybrid ANN methods were developed (in some cases generated) in the 2000s and 1960s. The research and development of ANN methods increased between 2010 and 2017, but as presented in Fig. 1, it seems that the exponential (here means rapid increase) growth of this process continued. ANN application in pile bearing capacity prediction (both skin friction and end-bearing capacities), modeling soil behavior, earth retaining structures and excavations, site characterization, liquefaction, slope stability, and classification of soils are reviewed in this section. To make readers familiar with the geotechnical interest of research scholar authors listed the journals that mostly publish on the subject of geotechnical engineering (see Table 1). On the other hand, the distribution of papers in the subject of ANN application in geotechnical engineering according to the source title (see Table 2) is illustrated.

2.1 ANN application in modeling soil behavior

AttohOkine and Fekpe [90] employed adaptive NNs to model strength properties of local lateritic soils. They compared the results from generalized adaptive NNs (GANN) with some of the traditional back-propagation NN (BPNN) approaches for modeling the in situ soil strength properties based on raw California bearing ratio (CBR) data. Their results showed the GANN seems to be more effective. Zhu et al. [91] used recurrent NN (RNN) to model shearing characteristics of residual soil. The network was able to determine volumetric strains during shearing courses and abrupt changes in axial. Pal [92] modeled seismic liquefaction potential using a support vector machine (SVM). In this study, the data were collected from several field tests such as standard penetration test (SPT value) and cone penetration test (CPT) and utilized to assess the liquefaction potential using the SVM-based classification approach. The author concluded that the complex relationship between the liquefaction potential and different soil parameters can effectively be presented using the SVM. Pala et al. [93] employed the ANNs to analyses the dynamic soil-structure interaction of buildings. They used the back-propagation (BP) algorithm. The results showed that the solution time is quite fast and the analysis and modeling stages are minimized. The NNs has shown excellent performance for the solution of soil-structure interaction problems.

Nazzal and Tatari [94] and Park et al. [95] used genetic algorithms and ANN, respectively, to propose a practical model and predict the resilient modulus of subgrade soils. They concluded that the ANN-based predictive models work as a simple and reliable mathematical tool. Groholski and Hashash [96] developed of a framework for extracting dynamic soil performance and pore water pressure response from field data collected in downhole array test (after ASTM D7400). To represent pore water pressure generation during cyclic loading they introduced an ANN-based constitutive model. As a result, the successful presentation of the established model is well demonstrated. Distribution of the papers in the subject of ANN application in soil behavior according to publication years, research areas of their publication and source title is listed in Table 3.

2.2 ANN application in pile capacity prediction

Different techniques of ANN, along with experimental experiments, applied in other studies such as Moayedi and Rezaei [20] and Mosallanezhad and Moayedi [53], Nazir et al. [97] and Moayedi [98] to predict pile bearing capacity, pile settlement, pile skin friction and/or pile end-bearing capacity. One of the most basic researches on the pile is provided by Chan et al. [99]. They have released a training dataset using back-propagation neural network to develop a prediction model for the evaluation of the skin friction as well as end-bearing capacity in piles. After comparison between the generated networks, they generate more reliable outputs than a pile driving. In this regard, Ismail and Jeng [100] established a HON-PILE model (high-order neural network model) in order to model the load-settlement behavior of piles. Indeed, a total number of 121 research scholar articles on the applicability of ANNs on the pile bearing capacity (both lateral and axial) were indexed in the WOS (see Table 4). It can be seen that almost 86% of the publications are listed in the category of "engineering geology," "engineering civil" and "geosciences multidisciplinary."

2.3 ANN application in earth retaining structures

Research on the earth retaining structures has been always one of the main interests between the geotechnical engineers. Countries such as Peoples R China (20.743%), USA (12.384%), England (6.502%), Japan (5.882%), France (5.623%), Italy (4.664%), Canada (4.025%) provided the most published articles on the subject of retiming structures in the WOS. However, when it comes to the ANN applicability, there are very few studies on the applicability of the neural network on the estimation of retaining structures behaviors. Studies such as Li et al. [101] and Chen and Wang [102] worked on the deformation prediction of the pile-anchor retaining structure. Li et al. [101] investigated on the application of neural network to predict displacement of deep foundation pit retaining structure. Their research indicated that the soft computing method is a useful and valid method for prediction of deformation in the foundation pit. Similarly, Chen and Wang [102] used ANN to predict the deformation characteristics of pile-

Table 3 Distribution of the papers in the subject of ANN application in geotechnical engineering based on the publication years, research areas of their publication and source title

Number	Publication years			Research areas			Source title		
	Publication years	*n*	%	Name of research areas	*N*	%	Name of source title	*N*	%
1	2016	35	10.87	Engineering	190	59.01	Computers and Geotechnics	12	3.73
2	2011	29	9.01	Geology	76	23.60	Neural Computing Applications	9	2.80
3	2015	29	9.01	Computer Science	72	22.36	Int J Numeri Anal Met	8	2.48
4	2017	29	9.01	Environmental Sciences Ecology	27	8.39	Int J Geomech	7	2.17
5	2014	27	8.39	Water Resources	25	7.76	Canadian Geotechnical Journal	5	1.55
6	2012	22	6.83	Mechanics	24	7.45	Engineering Applications of Artificial Intelligence	5	1.55
7	2013	19	5.90	Agriculture	22	6.83	Engineering Geology	5	1.55
8	2010	17	5.28	Materials Science	19	5.90	Remote Sensing of Environment	5	1.55
9	2008	15	4.66	Remote Sensing	17	5.28	Soils and Foundations	5	1.55
10	2009	15	4.66	Construction Building Technology	11	3.42	Computers and Electronics in Agriculture	4	1.24
11	2006	12	3.73	Imaging Science Photographic Technology	11	3.42	Engineering Computations	4	1.24
12	2002	11	3.42	Mathematics	11	3.42	Environmental Earth Sciences	4	1.24
13	2005	9	2.80	Science Technology Other Topics	8	2.48	Expert Systems with Applications	4	1.24
14	2007	8	2.48	Automation Control Systems	7	2.17	Journal of Civil Engineering and Management	4	1.24
15	2018	8	2.48	Chemistry	7	2.17	J Geotech Geoenvironj Geotech Geoenviron	4	1.24
16	2004	7	2.17	Geochemistry Geophysics	6	1.86	Journal of Rock Mechanics and Geotechnical Engineering	4	1.24
17	1998	6	1.86	Transportation	6	1.86	Applied Soft Computing	3	0.93
18	2003	6	1.86	Energy Fuels	5	1.55	Arabian Journal of Geosciences	3	0.93
19	2001	5	1.55	Physics	5	1.55	Geomechanics And Engineering	3	0.93
20	1999	4	1.24	Thermodynamics	5	1.55	Journal of Adhesion Science and Technology	3	0.93
21	1995	3	0.93	Operations Research Management Science	4	1.24	J Mater Civil Eng	3	0.93
22	2000	3	0.93	Physical Geography	4	1.24	KSCE Journal of Civil Engineering	3	0.93
23	1997	2	0.62	Marine Freshwater Biology	3	0.93	Remote Sensing	3	0.93
24				Meteorology Atmospheric Sciences	3	0.93	Soil Dyn Earthq Eng	3	0.93
25				Electrochemistry	2	0.62	Tunn Undergr Sp Tech	3	0.93

anchor structure (one of the established retaining system) in deep foundation pit. Distribution of the papers on the applicability of the ANNs in earth retaining structures as well as excavation according to the source title is tabulated in Table 5.

The ANN was also used to formalize and synthesize data derived from FE modeling studies. Up to the date of writing this article, there are 48 research scholars indexed in the WOS on the use of the neural network on excavations. In general, the input parameters used in the provided models were the wall stiffness, the soil layer thickness/excavation width ratio, excavation width, soil unit weight, soil undrained shear strength, the height of excavation, and undrained soil modulus/shear strength ratio [103, 104]. The maximum wall deflection was selected as the only output. For instance in braced excavation and in soft clay Goh et al. [44] established an ANN model to estimate maximum wall deflections (normally in the top of the wall). The results produced high accuracy with coefficients of correlation equivalent to 0.984 and 0.967 for the training and testing datasets, respectively.

Table 4 Distribution of the papers on the applicability of the ANNs in pile capacity based on the research areas

Number	Research areas	*N* (from 121)	% of 121
1	Engineering Geological	40	33.06
2	Engineering Civil	38	31.41
3	Geosciences Multidisciplinary	31	25.62
4	Computer Science Interdisciplinary Applications	23	19.01
5	Computer Science Artificial Intelligence	14	11.57
6	Construction Building Technology	9	7.44
7	Engineering Ocean	9	7.44
8	Engineering Mechanical	8	6.61
9	Materials Science Multidisciplinary	8	6.61
10	Mechanics	8	6.61

Table 5 Distribution of the papers on the applicability of the ANNs in earth retaining structures as well as excavation based on the source title

Number	Source title	Record count	% of 48
1	Computers and Geotechnics	5	10.42
2	Tunneling and Underground Space Technology	4	8.33
3	Applied Mechanics and Materials	3	6.25
4	Automation in Construction	2	4.17
5	J Comput Civil Engj Comput Civil Eng	2	4.17
6	J Geotech Geoenviron	2	4.17
10	Advanced Materials Research	1	2.08
11	AIP Conference Proceedings	1	2.08
12	Canadian Geotechnical Journal	1	2.08
13	Computing In Civil Engineering	1	2.08
14	Engineering Geology	1	2.08

Kwon and Wilson [105] used NNs to explore the impact of a deep excavation on other adjacent excavations. They applied NNs to investigate the influence of each parameter and the deformation increase on the deformation variation derived from extensometer measurements. Jan et al. [106] also investigated the use of ANN prediction model in the deep excavation. To collect the required data for training and verification, eighteen different case histories of deep excavations, with a minimum of four and maximum of seven excavation (construction) stages, were selected. The results of simulation show that not only the ANN can determine the maximum deflection of the diaphragm wall but also it can predict the location and the magnitude which the maximum deformations occur. Chua and Goh [107] used Bayesian NNs to determine wall deformation behavior in a deep excavation. It is found that the trained model could be used as a reliable and simple prediction tool. They could calculate the maximum wall deformation. Huang et al. [108] investigated the ANN-based reliability analysis for deep excavation. Chern et al. [109] applied a neural network to predict successfully lateral wall deflection in the top–down excavation. Yu et al. [110] used ANNs in artificial intelligent prediction model in order to calculate shallow settlement adjacent to the excavation of a foundation pit.

2.4 ANN application in site characterization

In all geotechnical engineering problems, site characterization is known as an important step that needs to be considered. It is essential to explore the subsurface before doing any project analysis. Many researchers such as Huang and Siller [111], Yilmaz et al. [112], Garcia-Fernandez and Jimenez [113], Orhan et al. [114], Kim et al. [115], Cao et al. [116], Wang [117], Aladejare and Wang [118] and Roy and Jakka [119] worked on this subject. Several researchers also applied ANNs to improve the estimation of the site characterization. For example, in order to represent the data obtained from borehole Huang and Siller [111] developed a fuzzy set-based model which uses to infer the subsurface profile. Bagtzoglou and Hossain [88] used RBFN for hydrologic inversion. The RBFN was used as a reliable method in the context of site characterization. In this regard, Samui and Sitharam [120] employed a relevance vector machine and least-square (LS) SVM based on corrected SPT data in order to estimate site characterization. Samui and Sitharam [121] modeled site characterization using ANN and Kriging. An extensive number of data (2700 field SPT values) were collected from SPTs in 3D subsurface of Bangalore, India.

2.5 ANN application in liquefaction

Soil liquefaction defined as a phenomenon whereby a partially or fully saturated soil (in most cases sands) substantially loses stiffness and strength in response to a specifically applied stress. In this regard, the applied stresses usually are induced by earthquake shaking causing the soil to behave like a liquid (with no shear strength). The liquefaction often leads to extensive damage and very high defamation to most infrastructures. The reason behind such large deformation is that the soil will lose its basic shear strength due to an increase in the pore pressure. Indeed, the soil liquefaction is introduced as one of the multicriteria tasks to assess in geotechnical earthquake engineering. Many experts stated that the assessment of soil liquefaction, due to a lot of variables, is the most complicated phenomena in geotechnical engineering [122–126]. Table 6 presents the distribution of the papers on the applicability of the ANNs in liquefaction evaluation. As one of the earliest researches on the use of ANN in liquefaction assessment, Goh [127] used ANN to solve the complex relationship between different soil parameters and seismic loading applied in order to explore liquefaction potential. The network model was trained using 13 case recorded real-world earthquakes. The study included eight input variables (SPT value, the mean grain size, the fines content, the earthquake magnitude, the equivalent dynamic shear stress, the total and effective stress, and the maximum horizontal acceleration at ground surface) and only one output variable. The output was assigned a no liquefaction (binary value of 0) and, for sites with extensive or moderate liquefaction potential (value of 1). The results gained by the proposed neural network model were compared with the conventional mathematical method that further developed by Seed et al. [128]. In comparison with the success rate of 84% from the method presented by Seed et al. [128], the study revealed that the ANN model gave reliable predictions in 95% of cases. Goh [129], Juang et al. [130], Liu et al. [131] and Chern and Lee [81] used ANN to evaluate liquefaction resistance based on raw CPT data. The results from the neural network showed a minimum success rate of 94%, which is acceptable in comparison with previous evaluation method presented by Shibata and Teparaksa [132] with a success rate of 84%. Wang and Rahman [133] presented a neural network-based model for liquefaction phenomena caused by horizontal ground

Table 6 Distribution of the papers on the applicability of the ANNs in liquefaction assessment based on the source title

Number	Source title	Record count	% of 160
1	Soil Dyn Earthq Eng	14	8.75
2	Computers and Geotechnics	6	3.75
3	J Geotech Geoenvironj Geotech Geoenviron	6	3.75
4	Int J Numer Anal Met	5	3.13
5	Canadian Geotechnical Journal	4	2.50
6	Environmental Earth Sciences	4	2.50
7	Journal of Geotechnical Engineering Asce	4	2.50
8	Natural Hazards	4	2.50
9	B Eng Geol Environ	3	1.88
10	Geotechnical and Geological Engineering	3	1.88
11	Int J Geomech	3	1.88
12	Int. Offshore and Polar Engineering Conference Proceedings	3	1.88
13	Journal of Marine Science and Technology Taiwan	3	1.88
14	Ieee Int. Joint Conf. On Nn Proce. Vols 1 10	2	1.25
15	Computers Geosciences	2	1.25
16	Earthquake Engineering and Engineering Vibration	2	1.25
17	Engineering Applications of Artificial Intelligence	2	1.25
18	Engineering Computations	2	1.25
19	Engineering Geology	2	1.25
20	European Journal of Environmental and Civil Engineering	2	1.25
21	Expert Systems with Applications	2	1.25
22	Geotechnical Special Publication	2	1.25
23	Ieee Int. Joint Conference on NNS	2	1.25
24	Int. Journal of Civil Engineering	2	1.25
25	Journal of Coastal Research	2	1.25

displacement. Young-Su and Byung-Tak [134] used ANNs to predict liquefaction resistance of sands. Hsu et al. [135] applied ANN to model liquefaction resistance. In their study, a total of 217 sets of shear wave velocity data, 31 from Taiwan after 1999 and 186 from the previous reports and studies, were collected and synthesized. Zhang et al. [136] evaluated soil liquefaction based on multivariate adaptive regression splines and capacity energy concept.

On the other hand, many others also investigated the use of SVM method in landslide assessment. For instance, Pal [92] employed SVM-based modeling to assess liquefaction potential induced by seismic loading. The data were collected from actual SPT and CPT field data. In fact, SVMs can provide better performance and required few user-defined parameters in comparison with the ANN approach. Similarly, Goh and Goh [137] explored the use of SVM in geotechnical engineering with the main focus on seismic liquefaction data. They trained and tested the SVM model based on a relatively large data set comprising 226 field records of CPT measurements and liquefaction performance. The results of classification showed that the overall success rate for the entire data set is 98%.

2.6 ANN application in slope stability

The slope stability analysis has been always a big challenge for geotechnical engineers. This is of course because of a wide variety of variables affecting the slope stability. Indeed, for most civil engineers working with software (i.e., include many details and variables) is not usually acceptable. Researchers such as Lu and Rosenbaum [138], Li and Liu [139], Liu et al. [140], Zhang et al. [36], Aghajani et al. [141], Rahul et al. [142], Gordan et al. [143], Kostic et al. [11] and Li et al. [144] studied on the subject of ANN application in slope stability. In their approaches, the input parameters were horizontal profile, gradient, location, height, vertical profile, soil texture, geological origin, the direction of slopes, depth of weathering, vegetation, maximum precipitation hour, and maximum daily precipitation. The slope failure potential was taken as the main output. Table 7 presents the distribution of the papers on the applicability of the ANNs in slope stability based on the source title.

Most practical applications prove that the estimation of slope stability analysis using ANN is achievable. In this regard, a well-trained neural network learning system reveals an extremely fast convergence, a better generalization and a high degree of accuracy for the slope stability problems. Lu and Rosenbaum [138] employed Grey and ANNs systems for the prediction of slope stability. Li and Liu [139] used AI forecast procedures for the slope stability. Liu et al. [140] applied a fast robust NN model called Extreme Learning Machine (ELM) to find a solution for the prediction of slope stability problems. After comparing several ANN techniques, the results prove that, in most of the common slope stability analysis, the ELM act as a helpful way to the genetic algorithm and the GRNN-based models. Gordan et al. [143] combined Particle Swarm Optimization (PSO) and neural network to predict slope stability induced by seismic loading. Kostic et al. [11] developed a model for prediction slope stability based on the ANNs. In this regard, they employed multilayer feed-forward network. The obtained results indicated a high level of statistical reliability.

2.7 ANN application in landslides assessment

The use of ANN in landslide susceptibility mapping is indeed well established. Perhaps the most well-known applicability of the ANN is in the subject of landslides [16, 35]. Indeed, the use of ANNs method in the landslide hazard mapping problems, as one of the multicriteria evaluation method, was introduced in the late 1990s by Yamagami et al. [145], Cai et al. [146] and Kobayashi et al. [147]. Different subjects have been studied using the ANNs method in landslide such as risk assessment [148], susceptibility analysis [149, 150], prediction [151, 152], earthquake-induced/triggering [153, 154], susceptibility mapping by geographical information system [155, 156]. Figure 2 shows the applicability of the NN in the subject of landslide based on both total publications by year and sum of times cited by year (Fig. 2). It can be seen that the number of publications has increased sharply from 10 publications in the year 2005 to 85 publications in the year 2016. Similarly, the number of citations per year raised to 3200 citations per year. This is showing that the subject is still one of the main interests of the researchers. Table 8 presents the distribution of the papers on the applicability of the ANNs in landslide assessment.

3 Research methodology

For the presented review study a new technique called PRISMA method, proposed by Moher et al. [157] was used. It is important to note that the PRISMA statement has two different parts; (1) systematic reviews and (2) meta-analysis. This method is well described in Shamseer et al. [158] and Mardani et al. [159]. Systematic reviews found out about research topics in order to provide summaries from the objectives and what has been written in the literature [157]. Generally, the systematic review part tries to present a full overview of research scholars performed on a specific subject (here it was applicability of ANNs in geotechnical engineering) until the present date. However, when it comes to the meta-analysis part, it offers main

Table 7 Distribution of the papers on the applicability of the ANNs in the subject of slope stability based on the source title

Number	Name of source titles	Record count	% of 299
1	Engineering Geology	14	4.68
2	Environmental Earth Sciences	13	4.35
3	Natural Hazards	12	4.01
4	Computers and Geotechnics	8	2.68
5	Lecture Notes in Computer Science	8	2.68
6	Applied Mechanics and Materials	6	2.01
7	Neurocomputing	6	2.01
8	Neural Networks	5	1.67
9	Advanced Materials Research	4	1.34
10	Arabian Journal of Geosciences	4	1.34
11	Eng Geol Environ	4	1.34
12	Asian Journal of Control	3	1.00
13	Computers Geosciences	3	1.00
14	Earth Surface Processes and Landforms	3	1.00
15	Geomorphology	3	1.00
16	IEEE Transactions on NN.	3	1.00
17	IEEE Transactions on NN. and Learning Systems	3	1.00
18	J Comput Civil Eng.	3	1.00
19	Landslides	3	1.00
20	Mathematical Problems in Engineering	3	1.00
21	Physical Review E	3	1.00
22	Rock and Soil Mechanics	3	1.00
23	Applied Ocean Research	2	0.67
24	Applied Soft Computing	2	0.67
25	Carpathian Journal of Earth and Environmental Sciences	2	0.67

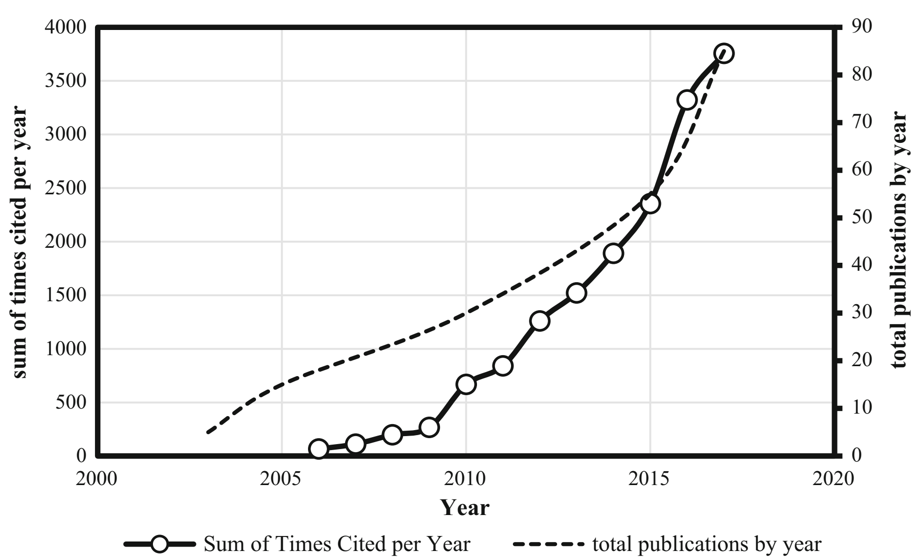


Fig. 2 The subject of ANN application in landslide assessment based on total publications by year and sum of times cited by year

findings of statistical approach from previously published works. The main objective of the PRISMA method is to assist practitioners and researchers in finding a complete, simple, and clear literature review [158, 160]. There are many good examples of previous studies which used the PRISMA method in various fields. In overall they intend to present a comprehensive review of the most recent published articles as a literature review [158, 160, 161]. In our review study, we considered three main steps (1) search in articles indexed in WOS, (2) selection of the eligible

Table 8 Distribution of the papers on the applicability of the ANNs in landslide assessment based on the journal of their publications, authors, research areas

No.	Research areas of their publication	Record count	% of 992	No.	Source title	Record count	% of 992	No.	Authors of their publication	Record count	% of 992
1	Geosciences	675	68.04	1	Environmental Earth Sciences	85	8.57	1	Pradhan B	55	5.54
2	Water Resources	281	28.33	2	Natural Hazards	84	8.47	2	Lee S	50	5.04
3	Environmental Sciences	207	20.87	3	Geomorphology	78	7.86	3	Pourghasemi Hr	26	2.62
4	Engineering Geological	189	19.05	4	Landslides	62	6.25	4	Chen W	25	2.52
5	Meteorology Atmospheric Sciences	153	15.42	5	Eng. Geology	45	4.54	5	Gokceoglu C	23	2.32
6	Geography Physical	141	14.21	6	Nat Hazard Earth Sys	31	3.13	6	Bui Dt	19	1.92
7	Remote Sensing	98	9.88	7	Arabian Journal of Geosciences	26	2.62	7	Hong Hy	16	1.61
8	Engineering Environmental	46	4.64	8	Environmental Geology	23	2.32	8	Oh Hj	14	1.41
9	Computer Science Interdisciplinary Applications	42	4.23	9	B Eng Geol Environ	22	2.22	9	Wang Qq	14	1.41
10	Imaging Science Photographic Technology	37	3.73	10	Computers Geosciences	22	2.22	10	Bai Sb	13	1.31
11	Engineering Civil	33	3.33	11	Catena	21	2.12	11	Li Wp	13	1.31
12	Computer Science Information Systems	30	3.02	12	Journal of Mountain Science	19	1.92	12	Wang J	13	1.31
13	Geography	30	3.02	13	Geomatics Natural Hazards Risk	17	1.71	13	Nefeslioglu Ha	12	1.21
14	Engineering Electrical Electronic	29	2.92	14	Eng. Geo. For Soc. And Ter. Vol 2	16	1.61	14	Reichenbach P	12	1.21
15	Soil Science	27	2.72	15	Ieee Int. Sympo. On Geo. And Remote Sensing	11	1.11	15	Xu C	12	1.21
16	Geology	26	2.62	16	Journal of The Geological Society Of India	11	1.11	16	Akgun A	11	1.11
17	Geochemistry Geophysics	19	1.92	17	Int. Journal of Remote Sensing	10	1.01	17	Chacon J	11	1.11
18	Computer Science Theory Methods	13	1.31	18	Int. Archives of The Photogrammetry Remote Sensing And Spatial Information Sciences	9	0.91	18	Irigaray C	11	1.11
19	Computer Science Artificial Intelligence	12	1.21	19	Int. Journal of Geo Information	8	0.81	19	Rossi M	11	1.11
20	Materials Science Multidisciplinary	12	1.21	20	Rendiconti Online Societa Geologica Italiana	8	0.81	20	Niu Rq	10	1.01
21	Multidisciplinary Sciences	11	1.11	21	Carpathian Journal of Earth And Environmental Sciences	7	0.71	21	Wu Yl	10	1.01
22	Mathematics Interdisciplinary Applications	10	1.01	22	Disaster Advances	7	0.71	22	Dhital Mr	9	0.91
23	Environmental Studies	9	0.91	23	Geocarto Int.	7	0.71	23	Ercanoglu M	9	0.91
24	Engineering Mechanical	8	0.81	24	Geosciences Journal	7	0.71	24	Park Hj	9	0.91
25	Engineering Multidisciplinary	8	0.81	25	IOP Conference Series Earth and Environmental Science	7	0.71	25	Pham Bt	9	0.91

published articles, and (3) extraction of datasets and summarizing the data [159].

4 Literature search

The database of WOS was used to provide a systematic review of applications and methodologies of ANN-based models in the subject of geotechnical engineering. The most recent published papers were found based on the searching several keywords such as bearing capacity, pile, retaining structures, excavation, site characterization, liquefaction, liquefaction susceptibility, slope stability, landslides and different ANN-based model approaches use in the field of geotechnical engineering. We have chosen those articles from the literature which were published between 2010 and 2018. In this regard, and according to our strategy search, a total of 734 scholarly papers were extracted. In the next step, and after a double check, we duplicated articles with repeated information. As a result, 108 papers were selected (see Fig. 3). Then, to remove the duplicated articles from the selected list, we eliminated 22 records due to duplicates. In the end, screened papers were selected based on different structures of the papers such as titles, keywords, topics, abstracts, and studies that were unrelated to the topic of this review were removed.

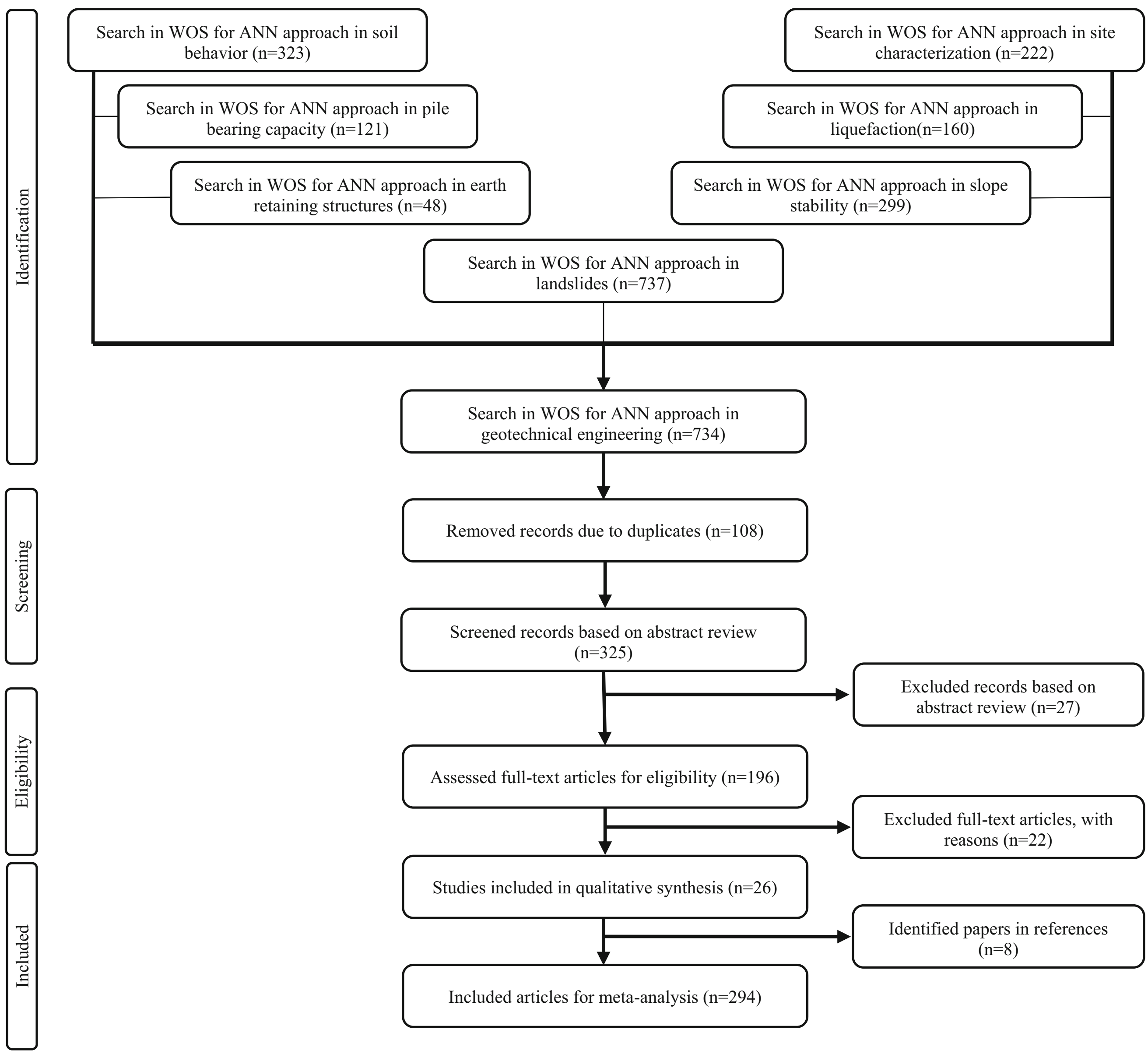


Fig. 3 Flowchart of the study in regard to the (i) identification, (ii) screening, (iii) eligibility, and (iv) included of articles

Table 9 Distribution of papers in the subject of ANN applicability in the field of geotechnical engineering based on the research areas

Number	Research areas	*N*	%
1	Engineering Geological	56	36.60
2	Engineering Civil	39	25.49
3	Geosciences Multidisciplinary	38	24.84
4	Computer Science Interdisciplinary Applications	26	16.99
5	Engineering Multidisciplinary	16	10.46
6	Computer Science Artificial Intelligence	15	9.80
7	Materials Science Multidisciplinary	12	7.84
8	Mathematics Interdisciplinary Applications	8	5.23
9	Mechanics	8	5.23
10	Water Resources	8	5.23
11	Environ. Science	7	4.58
12	Eng. Mechanical	6	3.92
13	Geochemistry Geophysics	6	3.92
14	Construction Building Technology	5	3.27
15	Engineering Electrical Electronic	5	3.27
16	Eng. Environ.	4	2.61
17	Computer Science Information Systems	3	1.96
18	Engineering Industrial	3	1.96
19	Mining Mineral Processing	3	1.96
20	Operations Research Management Science	3	1.96

Table 10 Distribution of papers in the subject of ANN applicability in the field of geotechnical engineering based on the source title

Number	Name of journal title	*N*	%
1	Computers and Geotechnics	9	5.88
2	Applied Mechanics and Materials	6	3.92
3	Arabian Journal of Geosciences	5	3.27
4	Environmental Earth Sciences	4	2.61
5	Neural Computing Applications	4	2.61
6	Proceedings and Monographs In Engineering Water And Earth Sciences	4	2.61
7	Advanced Materials Research	3	1.96
8	Engineering Computations	3	1.96
9	Engineering with Computers	3	1.96
10	Geomechanics And Engineering	3	1.96
11	Geotechnical and Geological Engineering	3	1.96
12	Scientia Iranica	3	1.96
13	Soils and Foundations	3	1.96
14	Advances in Engineering Software	2	1.31
15	Expert Systems with Applications	2	1.31
16	Geoscience Frontiers	2	1.31
17	Int. Journal of Civil Engineering	2	1.31
18	J Comput Civil Eng	2	1.31
19	Measurement	2	1.31
20	Natural Hazards	2	1.31

4.1 ANN

The ANN is known as a tool to model the multicriteria and complex systems involved in approximation problems. The theoretical background of the ANN is comprehensively discussed by Hill et al. [162], and Wang [12]. Tables 9 and 10 are listed the distribution of papers in the subject of ANN applicability in the field of geotechnical engineering based on the research areas and source title, respectively. A typical structure of most neural network-based models

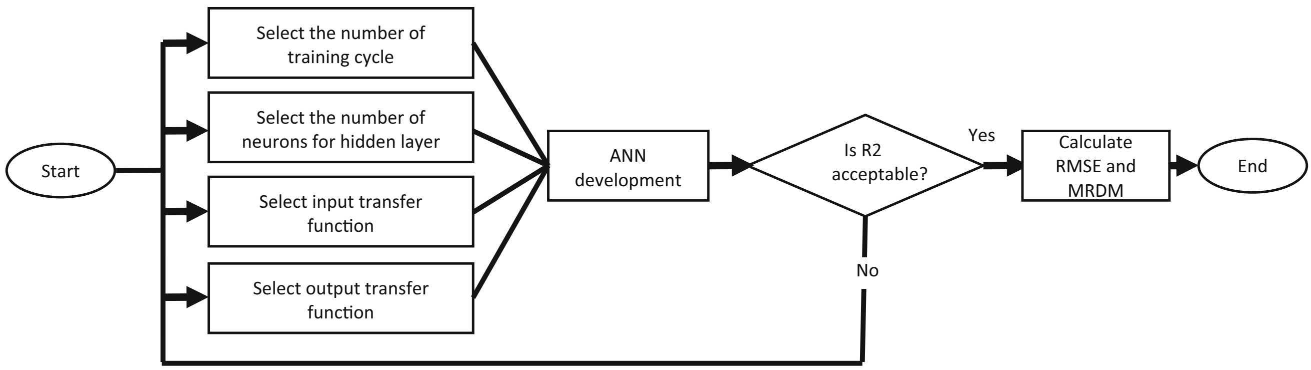
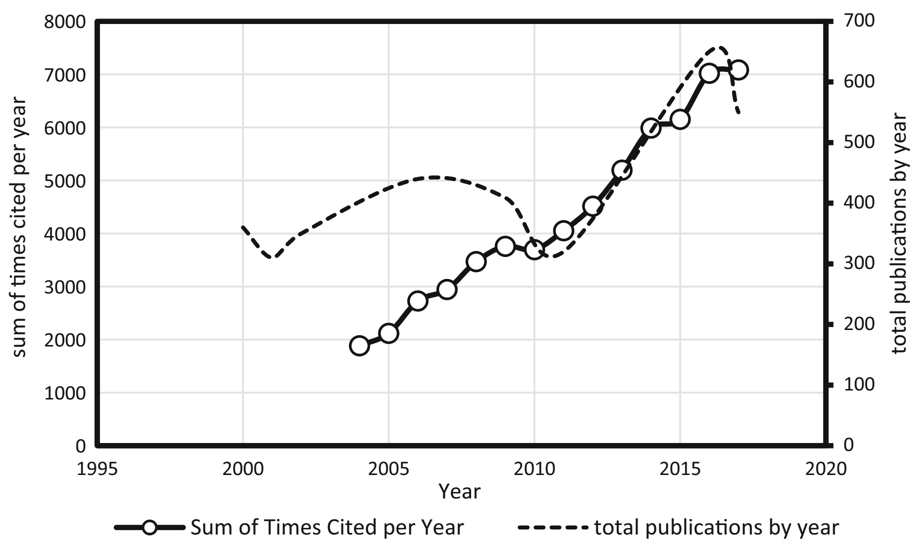


Fig. 4 A general flowchart for the ANN models [163]

Fig. 5 FFNN method used in the scholar papers between 1999 and 2017



consists of a number of nodes (or processing elements, PEs), that are typically arranged in form of several layers: one or more hidden layers, an output layer and an input layer [8]. A general flowchart for the ANN models is shown in Fig. 4.

4.2 FFNN

FFNN is a simple NN model used for modeling numerous nonlinear phenomena [164, 165]. As established by Hornik [164] it is a standard multilayer FFNN which are able to give a prediction value, in a very specific and satisfying sense, to any measurable function. One interesting capability of FFNN method is to pre-mapping the input data before sending it to the hidden layer for further processing. The selected data set for the training the network is firstly multiplied by W_h (a specific weight matrix). The results will later be added to a bias vector (b_h). As in the final step, a transfer function will be applied (e.g., during the data processing in the hidden layer). In fact, the process of network training is a modification of the introduced weight matrixes and bias vectors. This is because the outcome of the trained network needs to be minimized (the distance between both training data and network results). The increase in the number of neurons and layers, for instance, to get a better result, is not desirable. This is because such an increase can lead to a more complex network which later produces problems in both convergence and training of the networks. In this regard, the FFNN method is well described in the literature. For instance, several good examples of using the FFNN technique in the subject of geotechnical engineering are in Han et al. [166], Uncuoglu et al. [167], Lian et al. [168] and Protopapadakis et al. [169]. The FFNN method has been very popular among the researchers. Figure 5 shows the recent use of FFNN method in the scholar papers between 1999 and 2017. In this regard, the total publications by year increased to about 550 publications (indexed in the web of science only) and the summation of times cited by year.

4.3 RBFN

RBFN is another widely used MLP network. The RBFN is also well recommended because of its less time consuming during the training of the networks. The structure of an RBFN is like a single layer feed-forward network as shown in Fig. 6. The structure of the RBFN and its application in the subject of geotechnical engineering is well described in Mustafa et al. [170], Shu and Gong [171], Kang et al. [172] and Moayedi and Hayati [74]. The only difference is that in this function (e.g., in all the hidden layers) a radial basis (also called radbas) function is used in comparison with the FFNN function which it was a sigmoid function. The RBFN can simply be defined as Eq. (1).

$$\text{radbas}(x) = \exp\left(-x^2\right) \tag{1}$$

The RBFN method has been employed successfully in various research areas. Distribution of papers in the subject of RBFN applicability based on the research areas is tabulated in Table 11. However, the use of RBFN in the field of geotechnical engineering is still remained unknown. In recent years, there are very few studies use RBFN in the field of geotechnical engineering; modeling free-surface seepage flow [173], reliability analysis [174], predicting rock mass deformation modulus [175], three-dimensional simulations of tensile cracks [176], reliability analysis of geotechnical engineering [177], groutability prediction of permeation grouting [178, 179].

4.4 GRNN

GRNN includes four separate layers: the first layer is the input layer where the data will be introduced to the network and prepared for the training. The second layer is the pattern layer which follows a specific pattern function. Thirdly, it is the summation layer and finally, the results are generated from the output layer. The use of GRNN has been widely used in the subject of civil engineering and more particularly in the field of geotechnical engineering. Many researchers such as Ibric et al. [180], Pal and Deswal [181], Jiang et al. [182], Goorani and Hamidi [183] and Rajesh and Choudhury [184] used the GRNN through their studies. In this regard, the structure and application of GRNN are also well discussed in Cigizoglu and Alp [185] and Li et al. [186]. In training the neural network, linear activation and RBFN are used in both output and hidden layers. Each pattern layer unit is associated with the two different neurons in the summation layer (called D and S summation neurons). D summation neuron is used to calculate un-weighted outputs of pattern neurons, while S summation neuron computes the sum of weighted responses of the pattern layer [187].

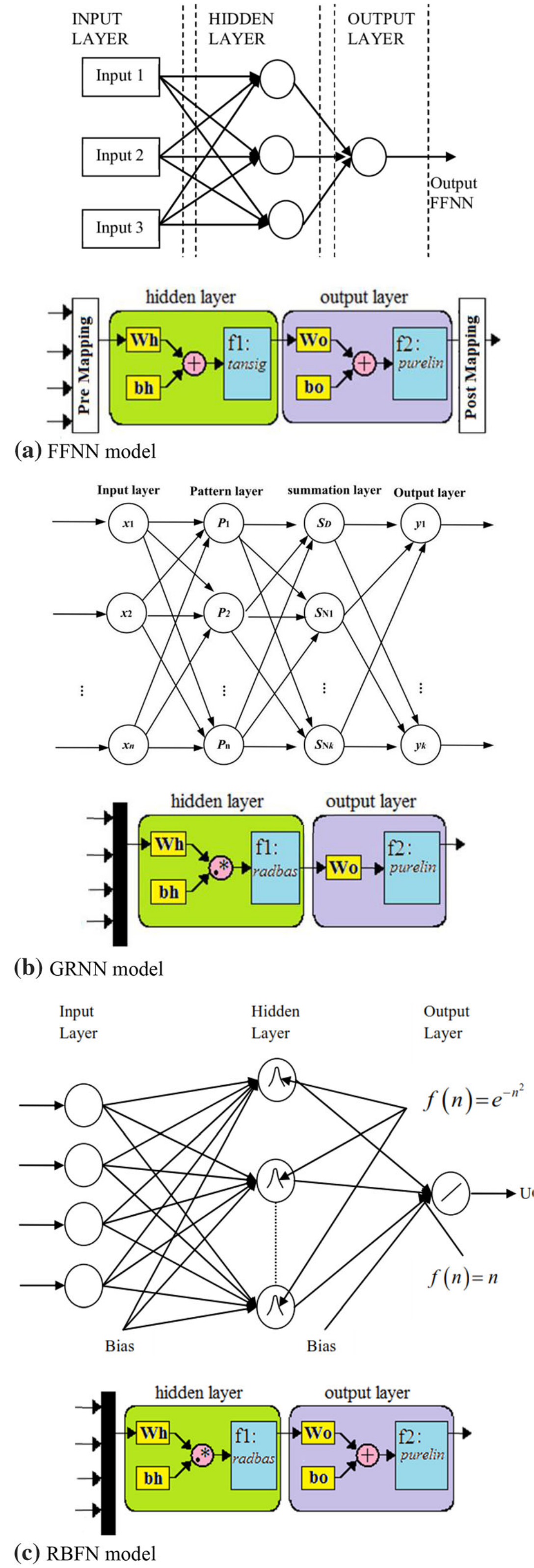


Fig. 6 The structure of **a** FFNN, **b** GRNN and **c** RBFN models

Table 11 Distribution of papers in the subject of RBFN applicability based on the research areas

Number	Name of research areas	*N*	%
1	Engineering	1933	45.14
2	Computer Science	1836	42.88
3	Mathematics	911	21.28
4	Automation Control Systems	380	8.87
5	Mechanics	231	5.40
6	Physics	227	5.30
7	Telecommunications	168	3.92
8	Materials Science	152	3.55
9	Chemistry	136	3.18
10	Instruments Instrumentation	122	2.85
11	Imaging Science Photographic Technology	119	2.78
12	Neurosciences Neurology	119	2.78
13	Optics	117	2.73
14	Operations Research Management Science	102	2.38
15	Science Technology Other Topics	69	1.61
16	Robotics	68	1.59
17	Energy Fuels	61	1.43
18	Mathematical Computational Biology	58	1.36
19	Radiology Nuclear Medicine Medical Imaging	55	1.28
20	Acoustics	47	1.10
21	Environmental Sciences Ecology	47	1.10
22	Geology	44	1.03
23	Water Resources	41	0.96
24	Remote Sensing	40	0.93
25	Thermodynamics	40	0.93

$$Y_i' = \frac{\sum_{i=1}^{n} y_i \cdot \exp -D(x, x_i)}{\sum_{i=1}^{n} \exp -D(x, x_i)} \quad (2)$$

The term D is Gaussian function and it is defined in Eq. (3):

$$D(x, x_i) = \sum_{k=1}^{m} \left(\frac{x_i - x_{ik}}{\sigma} \right)^2 \quad (3)$$

where n the training pattern's number, m the number of elements applied in the input vector, y_i the weight connection (connection between the ith neuron in the pattern layer and the neuron in the S summation), D the defined Gaussian function, x_k and x_{ik} are the jth elements of x and x_i, respectively.

A search in the topic of GRNN shows a total number of 1771 articles in different research areas. Distribution of research scholar papers in the subject of GRNN applicability based on the research areas is listed in Table 12. However, similar to the RBFN, the applicability of the GRNN method in the field of civil engineering is still considered a new topic. There are only a few studies that use the GRNN in the field of geotechnical engineering; compressive strength analysis of reinforced soil [188], slope stability inference [36, 140], lateral load bearing capacity modeling of piles [189], determination of ultimate bearing capacity of concrete driven piles in sand [190], expansive soil characterization [191] and three-dimensional site characterization [89].

4.5 Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is one of the strong learning systems for prediction of complex functions. ANFIS was first proposed by Jang and Sun [192]. Among fuzzy inference systems, it is one of the most commonly used training systems. In fact, ANFIS uses a Takagi–Sugeno fuzzy inference system (FIS). The structure and procedure of the ANFIS are presented and discussed by Jang [193]. General use of ANFIS in geotechnical engineering is well described in other studies such as Cabalar et al. [194]. However, the most common use of ANFIS is in the subject of landslide susceptibility mapping [195, 196], through landslide risk management [197, 198], rock-cutting trencher [199], constitutive modeling [200], prediction of uniaxial strength of rocks [201], liquefaction prediction [202], swelling potential [203], and permeability estimation [204].

Table 12 Distribution of papers in the subject of GRNN applicability based on the research areas

Number	Name of research areas	N	%
1	Computer Science	693	39.13
2	Engineering	675	38.11
3	Environmental Sciences Ecology	130	7.34
4	Mathematics	112	6.32
5	Water Resources	107	6.04
6	Geology	90	5.08
7	Automation Control Systems	85	4.80
8	Energy Fuels	83	4.69
9	Chemistry	82	4.63
10	Materials Science	81	4.57
11	Operations Research Management Science	76	4.29
12	Physics	53	2.99
13	Neurosciences Neurology	50	2.82
14	Science Technology Other Topics	48	2.71
15	Agriculture	46	2.60
16	Imaging Science Photographic Technology	46	2.60
17	Telecommunications	45	2.54
18	Meteorology Atmospheric Sciences	39	2.20
19	Business Economics	33	1.86
20	Instruments Instrumentation	33	1.86

4.6 Imperialist competitive algorithm (ICA)

The imperialist competitive algorithm function (also called ICA) is a global method of search population-based that was firstly proposed by Atashpaz-Gargari and Lucas [205] an followed by many other researchers such as Ahmadi et al. [206], Marto et al. [207], Mosallanezhad and Moayedi [53] and Moayedi and Armaghani [50]. The ICA has been used in many optimization problems. This is because it involves a procedure similar to many other evolutionary algorithms such as those used by Thangavelautham et al. [208], Manouchehrian et al. [209], Lian et al. [210] and Gandomi and Kashani [211]. The imperialist competitive algorithm begins with a candidate solution (or initial population), which, along with the imperialist competitive algorithm itself, consists of many countries [205]. In this step, all countries are separated into two main categories (shown in Fig. 7): (1) some of the best countries which called imperialists) and (2) the remaining countries which called colonies. In order to make an empire, first, the colonies required to be distributed through the best countries (called here imperialists or stronger countries). The distribution of the colonies is according to the relative strength of the countries in which the stronger countries could get a higher number of colonies. This competition will continue as the empires intend to expand their territories and control over more colonies. At the end of the competition algorithm (as mentioned by title imperialist competitive algorithm), the stronger empires expanded their power by taking control of weaker colonies. The process is like variables with higher relevancy could impact more on the output layer. Once a predefined stopping criterion is satisfied, the process will stop. A more detailed description of the designed steps in the imperialist competitive algorithm alone is discussed the literature by researchers such as Ghorbani and Jokar [212], and Al Dossary and Nasrabadi [213]. An overview of the imperialist competitive algorithm is depicted in Fig. 8.

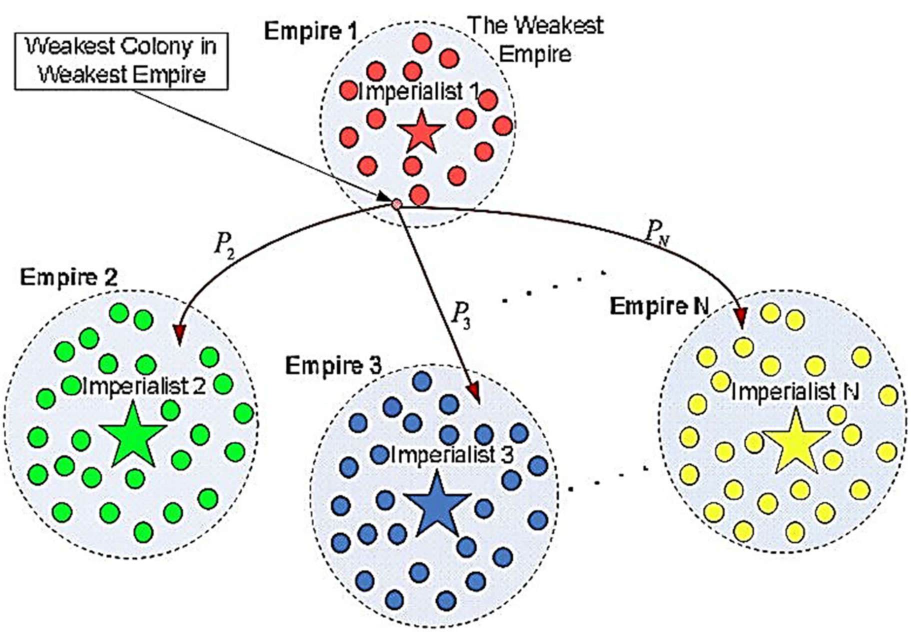
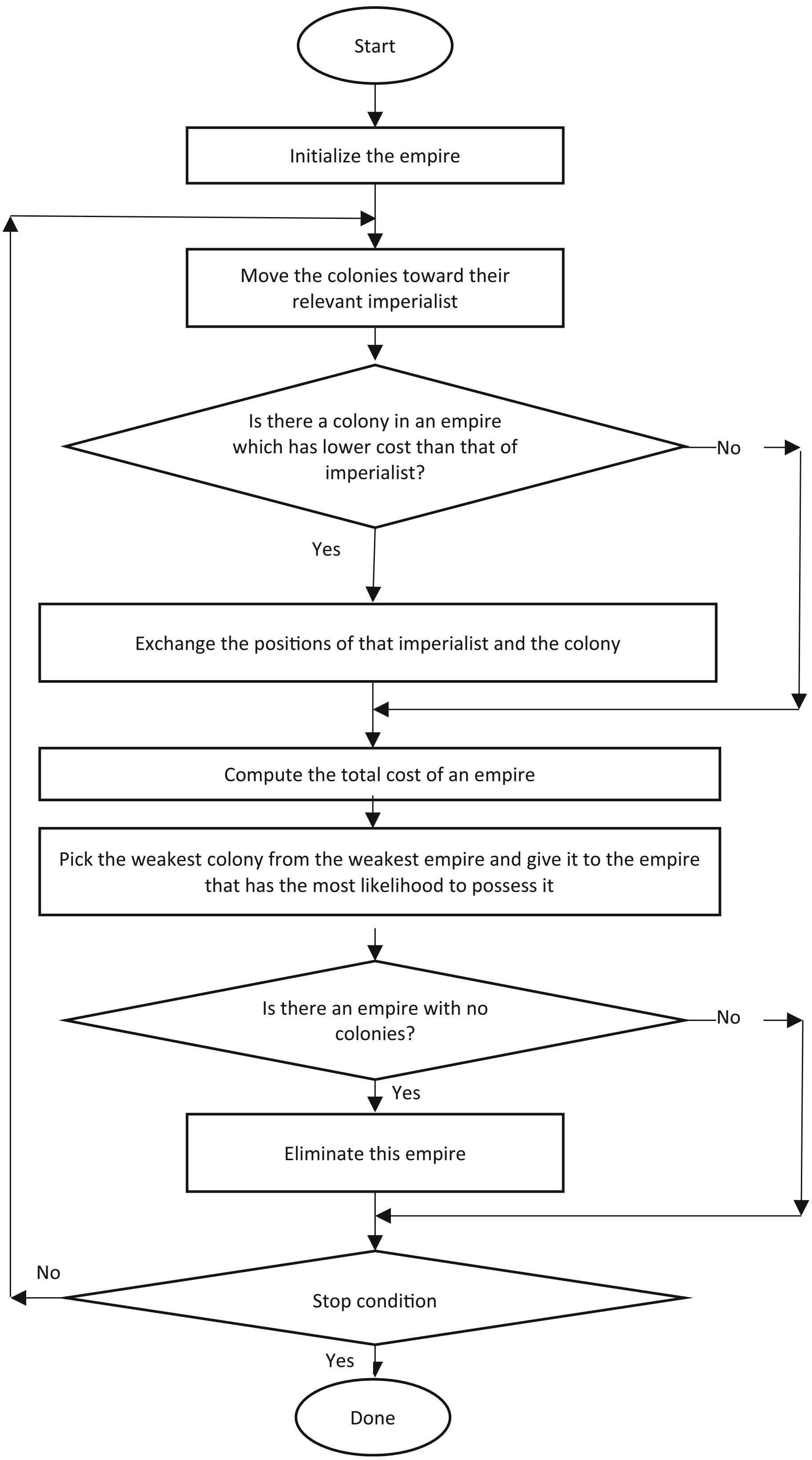


Fig. 7 The schematic procedure of imperialist competitive algorithm to take control of the weaker colony [205]

Fig. 8 Overview of the imperialist competitive algorithm [50]



5 Articles eligibility

For the purpose of eligibility, in this step of review, we independently reviewed each of the full text. However, the selected articles were shortlisted in the last step of the review. The shortlisted articles were selected according to the main objectives of this review paper on the subject of applicability of soft computing and ANN-based techniques in the field of geotechnical engineering. In this regard manuscript that applied ANN (e.g., any source of neural network modeling approach) in the subject of geotechnical engineering were chosen. Noteworthy, editorial notes, book chapters, master and doctoral dissertations, unpublished working papers, a non-English language written papers and textbooks were not involved. In addition, several previous studies have employed other techniques such as geostatistical, limit equilibrium, FE etc.; therefore, in this step also we did not include those studies. At the end of article eligibility decision, we selected 196 articles which used directly the ANN models in the geotechnical engineering. These articles could meet the considered selection criteria.

Table 13 Distribution of papers in the subject of ANN application in geotechnical engineering based on the application areas

Number	Application areas	*N*	%
1	Engineering	101	66.45
2	Geology	52	34.21
3	Computer Science	44	28.95
4	Water Resources	12	7.90
5	Environmental Sciences Ecology	8	5.26
6	Mechanics	8	5.26
7	Materials Science	7	4.61
8	Geochemistry Geophysics	6	3.95
9	Mathematics	6	3.95
10	Construction Building Technology	5	3.29
11	Meteorology Atmospheric Sciences	5	3.29
12	Mining Mineral Processing	4	2.63
13	Instruments Instrumentation	3	1.97
14	Oceanography	3	1.97
15	Science Technology Other Topics	3	1.97
16	Transportation	3	1.97
17	Operations Research Management Science	2	1.316

6 Summarizing and data extraction

In this step of review, some required data was collected and finally 196 articles were summarized and reviewed. In flowing, all selected papers were categorized into different application areas including; engineering, geology, computer science, water resources, environmental sciences, ecology, mechanics, materials science, geochemistry geophysics, mathematics, construction building technology, meteorology atmospheric sciences, mining mineral processing, instruments instrumentation, oceanography, science technology other topics, transportation and operations research management science (see Table 13). In addition, articles were reviewed and summarized according to various criteria such as journals and conferences names, the year of publication, authors, the method and technique used, research objectives, solution and modeling, and results and findings.

7 Conclusion

This review paper discussed the applications and theory with several ANN recent developments in the subject of geotechnical engineering. The ANN is introduced as a reliable tool for complex problems. The authors believe the ANN-based model, as a user-friendly and time-saving, is a good alternative to the FEM and conventional mathematical modeling. This is because, normally, problems in the field of geotechnical engineering evolve with many variables which make it hard to be modeled using conventional mathematical methods. Since the ANN-based methods are able to (1) rank the variables and alternatives, (2) evaluate stronger and weaker criteria, and (3) performing the comparative analysis, recently, ANN research interest increased largely in the geotechnical problems. In contrast, it is important to note that the neural networks have begun to replace by deep structured learning. Throughout this review paper, the use of ANN in the subject of geotechnical engineering were categorized into twenty-five research areas. Apart from the research areas, articles were classified according to the authors, source titles (either journal or conferences names), the year of publication, research areas, the used technique, solution and modeling, and outcomes.

Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interest in presenting this manuscript.

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Affiliations

Hossein Moayedi[1,2] · Mansour Mosallanezhad[3] · Ahmad Safuan A. Rashid[4,5] · Wan Amizah Wan Jusoh[6] · Mohammed Abdullahi Muazu[7]

[1] Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam

[2] Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam

[3] Department of Civil and Environmental Engineering, Shiraz University, Shiraz, Iran

[4] Department of Geotechnics and Transportation, School of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

[5] Centre of Tropical Geoengineering (Geotropik), School of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

[6] Faculty of Civil Engineering and Environment, Universiti Tun Hussein Onn Malaysia, Parit Raja, 86400 Batu Pahat, Johor Darul Takzim, Malaysia

[7] Civil Engineering Department, University of Hafr Al-Batin, Al-Jamiah, Hafr Al-Batin, Eastern Province, Kingdom of Saudi Arabia