Journal of Civil Engineering, Science and Technology

Volume 14, Issue 1, April 2023, 14 – 25

ASSESSING SEISMIC SOIL LIQUEFACTION POTENTIAL USING MACHINE LEARNING APPROACH

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Date received: 06/09/2022 Date accepted: 07/11/2022

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DOI: 10.33736/jcest.4982.2023

Abstract — The liquefaction vulnerability of soil is generally related to a few soil parameters which are ordinarily measured by laboratory tests on distributed and undistributed tests under distinctive test conditions. This study uses methods based on a standard penetration test to assess liquefaction criteria to appraise the liquefaction vulnerability for soil deposits of Chalus City placed in a high seismic area. To overcome the deficiencies of these experimental strategies an ANN-based model has been created utilizing the Artificial Intelligence technique to anticipate liquefaction. The proposed model is a function of the plasticity index, liquid limit, water content, and some other geotechnical parameters. Reliability index (β) and probability of liquefaction (PL) have also been determined for both the proposed methods for a superior understanding of their accuracies and strength. First-order second moment (FOSM) reliability analysis has been embraced in the present paper. The observation drawn from the study illustrates a reliable and conventional expectation rate of the regression as compared to the experimental strategy. A strong regression shown for assessing the liquefaction vulnerability, which is based on field test information for preparatory prediction, would be of extraordinary help within the field of geotechnical designing.

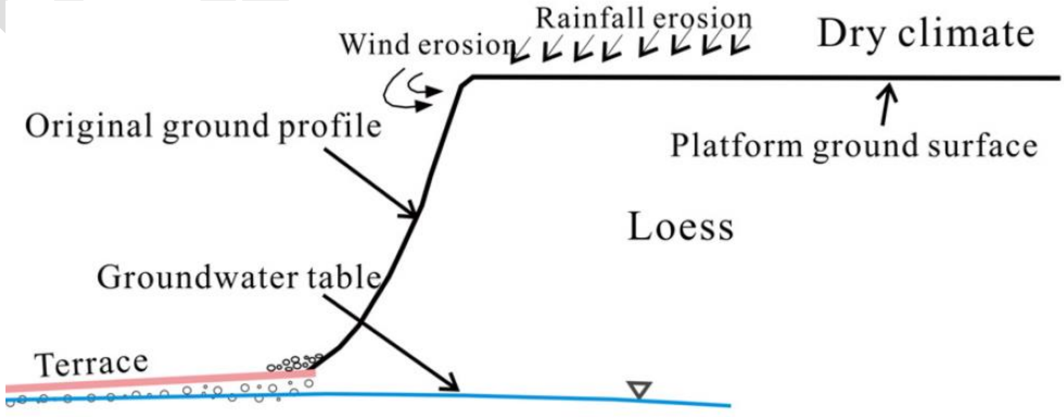
***Keywords*:** Artificial Intelligence (AI), machine learning, soil liquefaction, artificial neural network, seismic

1.0 INTRODUCTION

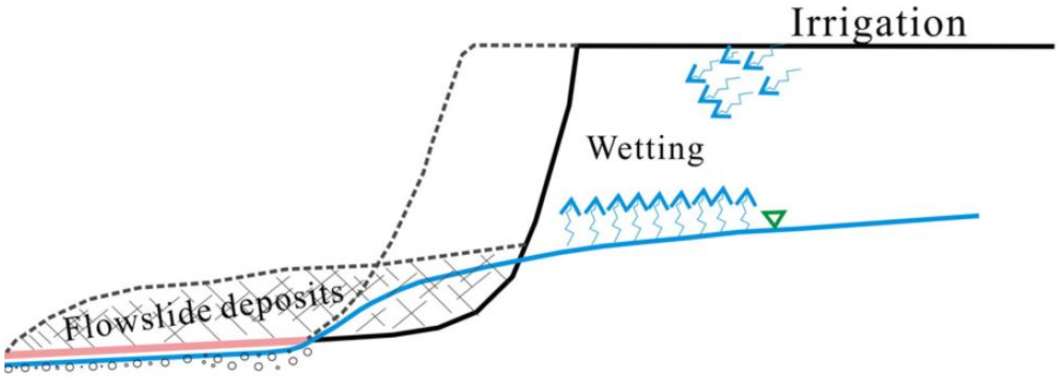
Earthquakes instigated seismic danger has forever been characterized as a questionable and masked foe of climate and humankind. The harm brought about by the disappointment of design areas of strength during earthquakes are as yet a significant issue that needs a long-lasting and legitimate arrangement. Soil liquefaction is one of the most shocking peculiarities that emerges because of quakes and has forever been a central issue for engineers because of the harms and demolition brought about by it, for instance, disappointments of earth designs and foundations. Liquefaction occurs when soil changes to a consolidated state as the pore water strain in the soil increases and strong tension decreases by and large. Therefore, risk assessment for any natural disaster is a crucial practice that governs the extent of damage and harm caused to the property, people and environment affected by it. Numerous agents have investigated and concentrated on liquefaction and proposed a few experimental and ordinary techniques for its assessment. [1] prescribed a framework to survey the liquefaction capacity of sandy soils. In different endeavors, the chipped-away-at rules are used for assessing the liquefaction expected considering the SPT and CPTu tests [2]. For a long time, the term liquefaction peculiarity was utilized for sandy soil silt yet a couple of perceptions during a few tremors displayed the eccentricity of liquefaction in soil with fine fulfilled having medium to low flexibility. [3] was the essential researcher that included the liquefaction of silty sand to some degree sandy build-up soils during the Haicheng, 1975 and Tangshan, 1976 earthquakes and suggested models which communicated that clayey soils should be powerless to liquefaction when all of the three conditions are met: percent of particles under 0.005 mm<15%, LL <35% and WC/LL>0.9 [4, 5]. This standard came to be known as the Chinese measures in view of its beginning stage. Be that as it may, a couple of cases were seen where ground disillusionment made great damage to structures in silty and clayey soils containing more than 15% soil-size particles in seismic earthquakes consequently studying the capability and accuracy of the Chinese Criteria. [6] studied the exact methodology and recommended another appraisal record that changed the traditional Chinese Criteria per US guidelines. Throughout the course of recent years' numerous specialists scrutinized the liquefaction of fine-grained soil utilizing a few geotechnical techniques [7–13]. The result from these analysts shows that interdependency in the center among adaptability and cyclic strength of soil prompts the use of LL and PI as fundamental norms' for the appraisal of liquefaction defencelessness of soil layers. Now, the vast majority of the relevant strategies utilized to decide the liquefaction conduct of soil silt are hypothetical and experimental techniques that are calling for a ton of investment and contain numerous potential factors that might cause vulnerabilities and blunder in the outcomes. The vulnerability and absence of accuracy that happens during testing and getting soil properties to accumulate with weaknesses caused during the calculation of liquefaction potential using the recently referenced careful techniques can incite a false end. A slight space for error and mistakes are allowed in each piece of planning yet concerning safe preparation against liquefaction especially in high seismic zones can be very sabotaging for humanity. As such, dealing with techniques for surveying soil liquefaction is well known among practicing engineers. These strategies are extraordinarily important at the fundamental arranging stage to assess any bet of liquefaction and given that the bet of liquefaction is high an unmistakable assessment ought to be finished to get the liquefaction potential. The Machine learning-based approach is currently generally acknowledged and applied by numerous analysts to conquer the deficiencies of observational methodologies. This approach utilizes specific contributions to foresee an extensive variety of information with an insignificant human connection. ANN is one of the most generally perceived AI models in view of computerized reasoning. Strategy for artificial neural networks in the seismic tremor design to evaluate the liquefaction of the soil is generally acknowledged by analysts [14–16]. In this paper, a semi-exploratory methodology proposed by [17] is utilized as an experimental method for managing assessment liquefaction potential as well as an ANN model has been made to measure the liquefaction defencelessness of soil silt utilizing fitting information boundaries. An assessment has additionally been anticipated in light of the first request and second dependability technique between the ANN and exact strategy [18]. Prediction of results and models in view of dependability examination have been effectively involved by numerous scientists for some affable designing ventures as well concerning liquefaction appraisal [13, 19]. The exactness of an ANN model can be profoundly improved by selecting appropriate inputs and giving expansive datasets for preparing and testing of the model. A powerful ANN model gives more exact and practical results as compared to the conventional strategies. In the present study, an updated semi-empirical approach developed by Idriss and Boulanger [1] is utilized as a conventional approach to evaluate liquefaction potential, as well as an ANN model has been developed to predict the liquefaction susceptibility of soil deposits considering fine content, liquid limit and normal moisture content as input parameters. A comparison has been established between the ANN and conventional Idriss and Boulanger method.

2.0 METHODOLOGY

Liquefaction weakness has been scrutinized by numerous investigators in light of various techniques. For the current study, the information is acquired from an investigation site from two different locales situated in Chalus City, Iran as displayed in Fig. 1. Chalus City is located at a high seismic area and has previous experience with focused energy earthquakes. The chief mark of the review is to check the liquefaction ability of soil buildup for the suggested regions utilizing the experimental technique [16] and extended Levenberg-Marquardt calculation-based ANN model [14]. Further, a dependability technique has been laid out to help the discoveries of the investigation and to reason that the extended ANN model is a better liquefaction prediction model as well as a solid strategy. A correlation has likewise been made between the two procedures and it has been shown that the use of artificial intelligence is an incredible technique as it discards the possible results of human missteps and weaknesses.



(a)



(b)

(c)

(d)

(e)

(f)

(g)

(h)

Figure 1 Area of the study section in the Chalus province and Iran: (a) and (b) A slope evolution model under liquefaction condition; (c), (d), (e), (f), (g) and (h) landslide caused by soil liquefaction

2.1 Experimenal Approach

Idriss and Boulanger [1] extended a refreshed semi-experimental strategy to appraisal liquefaction conduct of soil sediments in light of two exceptionally unmistakable techniques, the first being the seismic reaction of the soil the CSR and the other being the seismic obstruction of the soil. The proportion of CRR to CSR gives the factor of safety (FOS) which thus decides the liquefaction capability of the soil. Soil layers with FOS<1, are possibly liquefiable through soil layers with FOS≤1 are possibly non-liquefiable. Stacking upheld by a seismic development for example cyclic stress ratio (CSR) defined in Equation (1):

$$(CSR)_{7.5} = 0.65 \left(\frac{\sigma_{vo} a_{max}}{\sigma'_{vo}}\right) \frac{r_d}{MSF} \frac{1}{K_\sigma} \tag{1}$$

Cyclic resistance ratio (CRR) defined in Equation (2):

$$CRR = exp\left[\frac{(N_1)_{60cs}}{14.1} + \left\{\frac{(N_1)_{60cs}}{126}\right\}^2 - \left\{\frac{(N_1)_{60cs}}{23.6}\right\}^3 + \left\{\frac{(N_1)_{60cs}}{25.4}\right\}^4 - 2.8\right] \tag{2}$$

The factor of safety (FOS) of a soil layer athwart liquefaction is defined in Equation (3):

$$FOS = \frac{CRR}{CSR} \tag{3}$$

2.2 Machine Learning Approach: Artificial Neural Network (ANN)

Machine Learning is a subset of artificial intelligence (AI), which defines the ability of systems to independently find solutions to problems by recognizing patterns in databases with minimal human involvement. All in all: Machine Learning empowers frameworks to perceive designs based on given or existing calculations and informational indexes to foster satisfactory and solid arrangement. This prompts insignificant vulnerability caused by utilizing experimental deterministic strategies. Artificial neural network is a high level computing approach based on artificial intelligence. A typical ANN model generally comprises three layers, an information layer, a secret layer, and a result/target layer. The ANN model finds the arrangement by fostering a relationship among the information variable and the objective qualities to track down a discrete example in the datasets. A Multi-layer perception (MLP) is the most normally utilized feed-forward network. In this preparation cycle, the organization mistakes are back proliferated into every neuron in the hidden layer and afterward moved into the neuron in the info layer. More indicated the hypothesis and utilization of the Levenberg-Marquardt calculation which has been broadly acknowledged and involved by different analysts for anticipating the liquefaction capability of soil layers [14]. In this preparation system, the goal is to limit the mistake sign of the multitude of result neurons, consequently, it is a machine learning strategy and the most generally involved preparation technique for the multilayer neural networks. The created ANN model depends on information got from the proposed site. It utilizes essential soil properties that are answerable for soils liquefaction opposition, for example, plasticity index, SPT content (N60), fine content (FC), and water content as far as liquid limit (WC/LL), as well as boundaries answerable for the seismic interest of soil layer to go through liquefaction, for example, the proportion of pinnacle ground acceleration increase at the ground surface (a_{max}) and acceleration increase because of gravity, the extent of the earthquake as info boundaries to anticipate liquefaction powerlessness of some random soil layer.

A typical ANN model generally involves three layers, an input layer, hidden layers, and an output/target layer. Figure 2 illustrates descriptive details of a classic ANN model. To detect a compelling pattern/trend in the datasets, the ANN model establishes a link between the input variables and the target values. To reduce the error signal of all the output neurons, network blunders are backpropagated into each neuron in the hidden layer and then transmitted into the neuron in the input layer when preparing the model. As a result, it is thought to be the most supervised learning method. Levenberg–Marquardt application Backpropagation is a method for determining the liquefaction potential of soil deposits that have been extensively recognized and utilized by numerous researchers. Multi-layer perception (MLP), the most commonly used feed-forward network has been employed in the present study. Numerous researchers have employed the ANN model for solving several engineering problems over the past few decades.

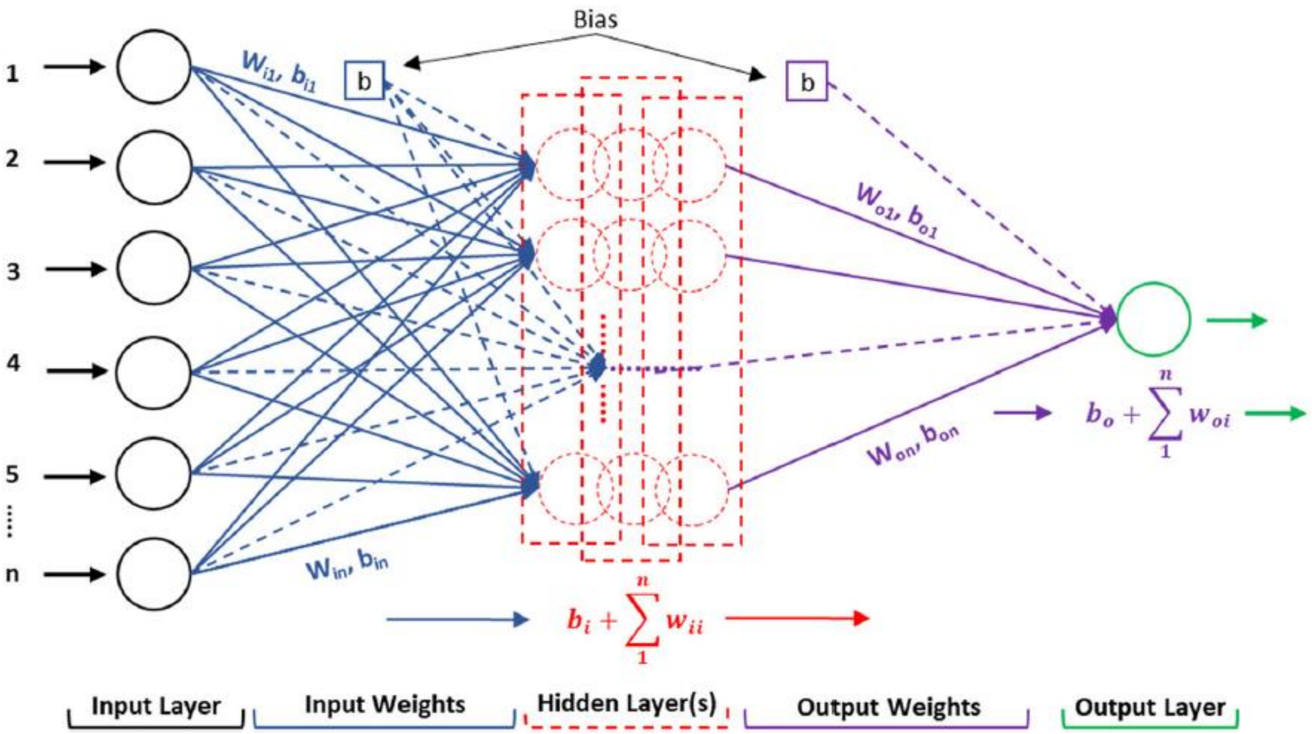


Figure 2 A typical ANN Model

2.3 Reliability Analysis

The factor of safety surveyed from the recently referenced research can't be clearly remembered to be as a strong outcome for risk assessment as an extensive measure of vulnerabilities might be involved, for example, mistakes in depicting the soil properties and blunders related with the embraced logical strategies. To legitimize the vulnerabilities in the previously mentioned strategies and models, and to get the most dependable technique out of the two an unwavering quality study has been performed. In this manner, a First-Order Second-Moment approach has been used to choose the trustworthiness of the suggested strategies.

The FOSM system applies a Taylor series elaboration for the capacity to be surveyed and is overall used to questionable the ambiguities open in the data factors. According to the FOSM methodology, if μZ and σZ are the mean worth and the standard deviations of the show ability Z independently, the constancy file (β) is characterized in Equation (4):

$$\beta = \frac{\mu_Z}{\sigma_Z} = \frac{\mu_R - \mu_S}{\sqrt{{\sigma_R}^2 + {\sigma_S}^2}} \tag{4}$$

The likelihood of liquefaction should be subject to the mean and fluctuation of the gotten variable of safeguards, in this way dependability index (β) as far as a component of factor of safety defined in Equation (5):

$$\beta = \frac{\mu_F - 1}{\sigma_F} \tag{5}$$

Where μF is the mean potential gains of a factor of safety and σF is the standard deviations of a variable of security. The factor of safety gained for different soil stores can be connected and figured out with respect to the probability of better and basic cognizance. The trustworthiness index (β) has a prompt association with the probability of failure. Expecting that all of the sporadic elements are normally appropriated, the probability of failure is characterized in Equation (6):

$$P_F = 1 - \phi(\beta) \tag{6}$$

Where φ (β) is the standard typical combined probability.

3.0 RESULTS AND DISCUSSION

Observation made from the literature suggested that the presence of fine content has a virtuous influence on liquefaction potential. Even some of the researcher suggested that liquid limit and moisture content also affect the liquefaction potential of the soil deposits. So the ANN model developed uses liquid limit (LL), normal moisture content (%) and fine content (%) as input parameter and predicts liquefaction susceptibility. The evaluation for liquefaction potential has been carried out using the conventional Idriss and Boulanger method as well as ANN model, and it has been shown in Table 1, 2 and 3 for all the four sites. Factor of safety has been evaluated using Idriss and Boulanger [1] empirical method, if FOS≥1 the soil is said to be non-liquefiable and is denoted as '1', whereas for FOS ≤ 1, the soil is said to undergo liquefaction and is denoted as '0'. Similarly, the liquefaction susceptibility as per ANN model has been represented, 0 denoting liquefaction and 1 denoting non-liquefaction.

Table 1 Liquefaction susceptibility of site A (Chalus province) as per Idriss and Boulanger and ANN method

LL	**NMC (%)**	**FC (%)**	**FOS = CRR/CSR**	**Liquefaction susceptibility as per Idriss and Boulanger**	**Liquefaction susceptibility as ANN**
0	30.43478	31.9	0.553533	0	0
0	30.43478	31.9	0.971911	0	0
0	34.10138	40.2	0.448921	0	0
0	34.10138	40.2	0.493345	0	1
0	34.10138	40.2	0.342637	0	1
42.5	25.11078	89.2	0.513633	0	0
42.5	25.11078	89.2	1.067642	1	1
41.75	21.28936	90.3	0.768466	0	1
41.75	21.28936	90.3	1.118277	1	1
42	20.94259	84.6	1.195062	1	1
0	18.73467	84.6	1.518655	1	1
0	18.73467	43	1.97942	1	0

Table 2 Liquefaction susceptibility of site B (Chalus province) as per Idriss and Boulanger and ANN method

LL	**NMC (%)**	**FC (%)**	**FOS = CRR/CSR**	**Liquefaction susceptibility as per Idriss and Boulanger**	**Liquefaction susceptibility as ANN**
0	42.10069	40.2	0.242925	0	1
0	42.10069	40.2	0.245777	0	1
0	42.10069	40.2	1.032964	1	1
41.25	26.19647	86.9	0.732484	0	1
41.25	26.19647	86.9	4.654309	1	1
42.2	23.5434	86.9	1.295994	1	1
42.2	23.5434	88.04	0.91503	0	1
42.2	23.5434	88	0.703866	0	0
42.2	23.5434	88	0.90524	0	0
0	15.55248	22	1.211796	1	1
0	15.55248	22.15234	2.541637	1	1
0	19.03	9.073482	1.67194	1	0

Table 3 Liquefaction susceptibility of site C (Chalus province) as per Idriss and Boulanger and ANN method

LL	NMC (%)	FC (%)	FOS = CRR/CSR	Liquefaction susceptibility as per Idriss and Boulanger	Liquefaction susceptibility as ANN
0	36.64596	61.91	0.528431	0	1
0	36.64596	61.91	0.628616	0	1
0	36.64596	91.8	0.447802	0	1
42.5	29.20097	91.77	0.354429	0	1
42.5	29.20097	62.9	1.014233	1	0
35.5	22.61053	62.9	0.520122	0	0
35.5	22.61053	85.4	0.355602	0	0
38	26.43948	85.39	0.366889	0	1
38	26.43948	85.4	0.649645	0	1
38	26.43948	39.5	0.982301	0	0
0	23.3463	39.48	2.113911	1	0
0	23.3463	44.8	2.181767	1	0

The results obtained for the occurrence and non-occurrence of liquefaction by ANN method indicate dissimilar predictions as compared to Idriss and Boulanger method. The overall liquefaction susceptibility of all the sites when evaluated using empirical method was 65%, whereas when the same sites were evaluated using ANN model, the liquefaction susceptibility is reduced to 40%.

Concentrates on completed by different specialists recommend that the presence of fine content prudently affects the liquefaction capability of a soil deposit. Numerous specialists took on plasticity along with the liquidity of a soil deposit as overseeing measures' for liquefaction assessment yet while considering these boundaries the power and extent of the earthquake were disregarded about. Consequently to defeat the disadvantages of ordinary strategies an exceptionally productive ANN model has been broadened which considers liquidity, plasticity, and fineness of the soil as well as the boundaries related to the strength of earthquakes. The evaluation of the liquefaction capability of the suggested site has been performed using the experimental conditions (1), (2), and (3) and their results have been presented in Fig. 3. Soil layers with FOS<1, are named as melted and are plotted under the safety line through soil layers with FOS≤1 are safeguarded athwart liquefaction and are plotted over the safety line. In light of the figure, it very well may be reasoned that soil layers underneath the safety line are thickly populated showing that the proposed site while assessed utilizing experimental technique has a danger to liquefaction and thus relating safety and functionality measures ought to be sanctioned on the site.

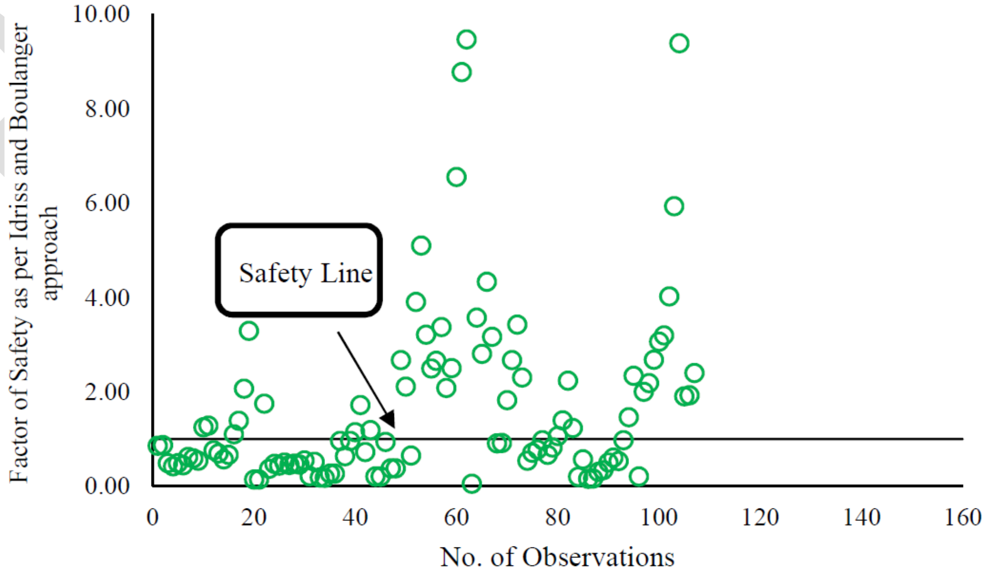


Figure 3 FOS as per Idriss and Boulanger experimental method [1]

Furthermore, a similar site was assessed utilizing the AI-based ANN model. The dataset has been isolated for preparing and testing for extending a compelling and hearty model. The sample was organized as indicated by the factor of safety surveyed from the exploratory technique [7]. Fig. 4 presents the aftereffects of the extended ANN model against the consequences of the experimental technique. The statical execution boundaries which characterize the exhibition of the created model like, root mean square error (RMSE), coefficient of assurance (R2), connection coefficient (r), and execution file (ρ) were utilized to oversee the precision of the created model is introduced in Table 4.

Figure 5 depicts the relation between FOS evaluated using Idriss and Boulanger [1] method and liquefaction prediction by ANN model. The liquefaction prediction of the developed ANN model states that the soil deposits are non-liquefiable irrespective of the factor of safety of soil layers. Such contrast results are caused due to the consideration of plasticity and fine content properties of soil while evaluating liquefaction potential in computer-based approach. Equations (1), (2), and (3) mentioned above that are used evaluated liquefaction susceptibility use SPT *N* values to predict liquefaction, and this limits its predictability as observed in the literature.

Table 4 Statical Performance Parameter of the ANN Model

	No. of Dataset	**RMSE (%)**	**R^2**	**r**	**ρ**
Training	100	0.80	0.98	0.99	0.40
Testing	50	1.37	0.97	0.98	0.69

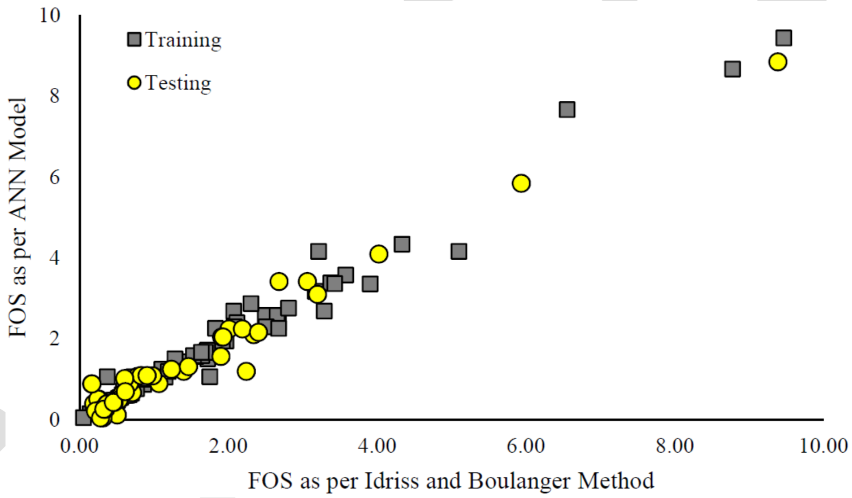


Figure 4 FOS as per empirical method v/s predicted FOS as per ANN method

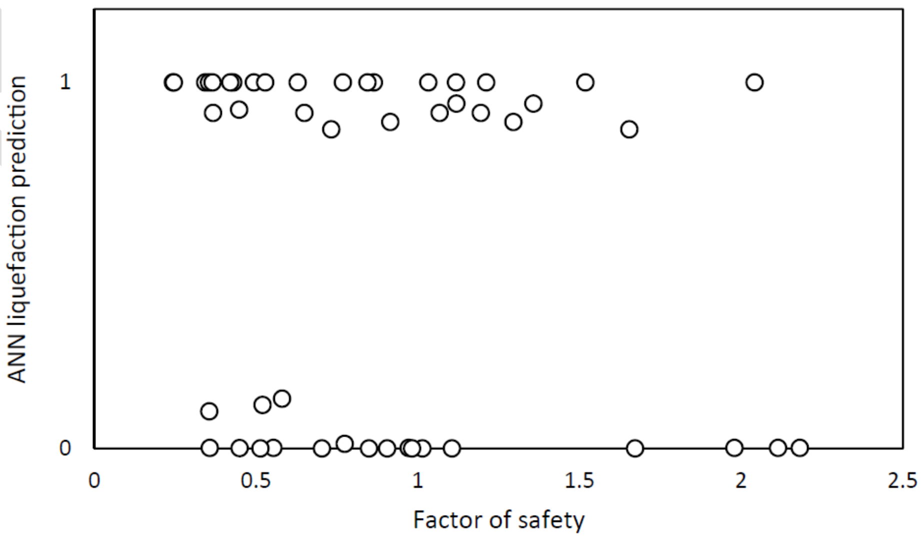


Figure 5 FOS versus ANN liquefaction prediction for all the sites

The above figure obviously shows that the extended ANN technique has a decent anticipate rate. It utilizes fundamental soil boundaries to foresee its liquefaction conduct effortlessly and straightforwardly alongside exactness. The distinction is seen in the outcomes while anticipating liquefaction conduct of soils, while assessed utilizing observational methodology and AI-based approach is primarily because of the utilization of various geotechnical boundaries in both the strategies. To legitimize the fluctuation and appropriateness of the created ANN model, the unwavering quality examination has been performed to show that the proposed model is an exact, effective, vigorous as well as dependable technique, in this way advancing the utilization of AI-based concentrate on the field of seismic assessments of sub and superstructures.

Unwavering quality index (β) has been assessed utilizing the previously mentioned condition (5) and compared to it the probability of liquefaction (PL) has been additionally calculated using Equation (6). Fig. 6 and Fig. 7 show the consequences of reliability indices and probability of failure values against the factor of safety and decided to utilize Idriss and Boulanger's exploratory strategy individually [1]. As the worth of the safety factor builds the dependability esteems additionally increments towards the positive side showing a lower probability of failure. Comparative patterns have been seen in Fig. 8 and Fig. 9 which present the dependability indices (β) and (PL) for created ANN model. The thickness of soil layers with negative β values is less for created ANN model when contrasted with the observational technique demonstrating that fewer soil layers are powerless to liquefaction while assessed utilizing an AI-based approach.

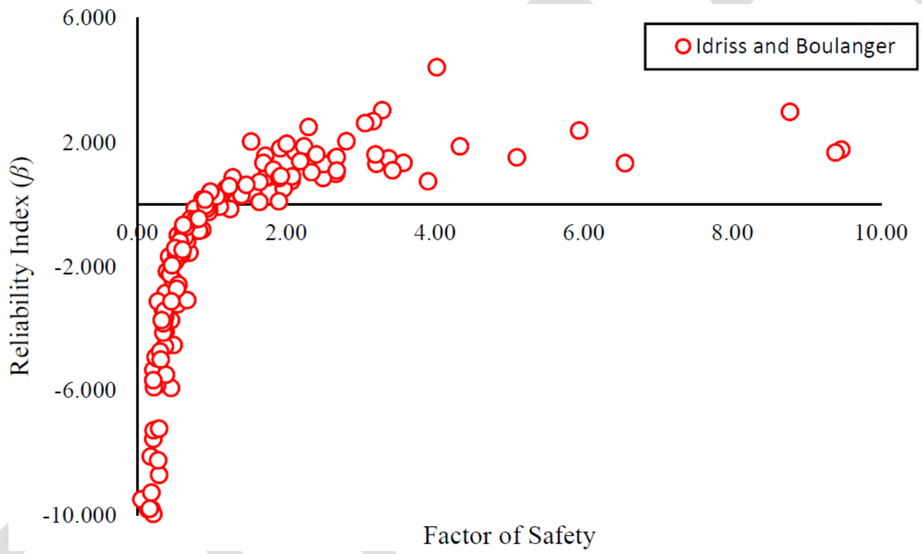


Figure 6 Reliability Index (β) v/s factor of safety

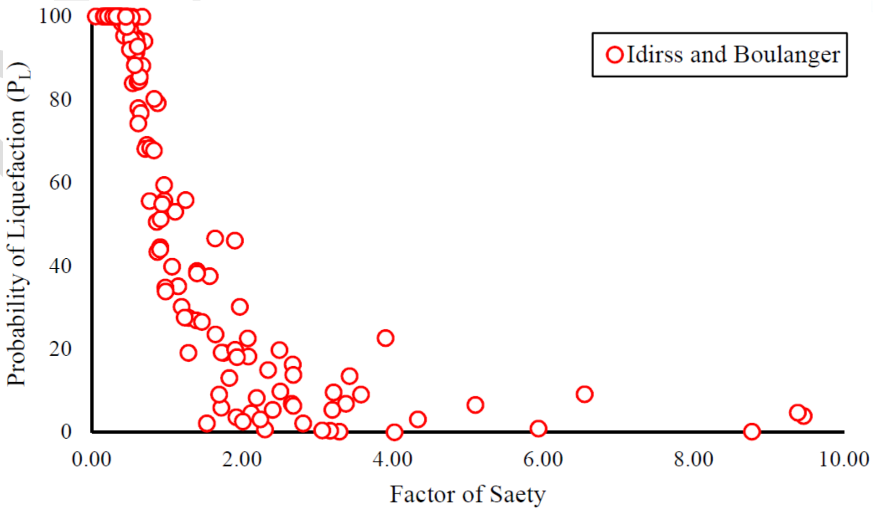


Figure 7 Probability of liquefaction failure against factor of safety

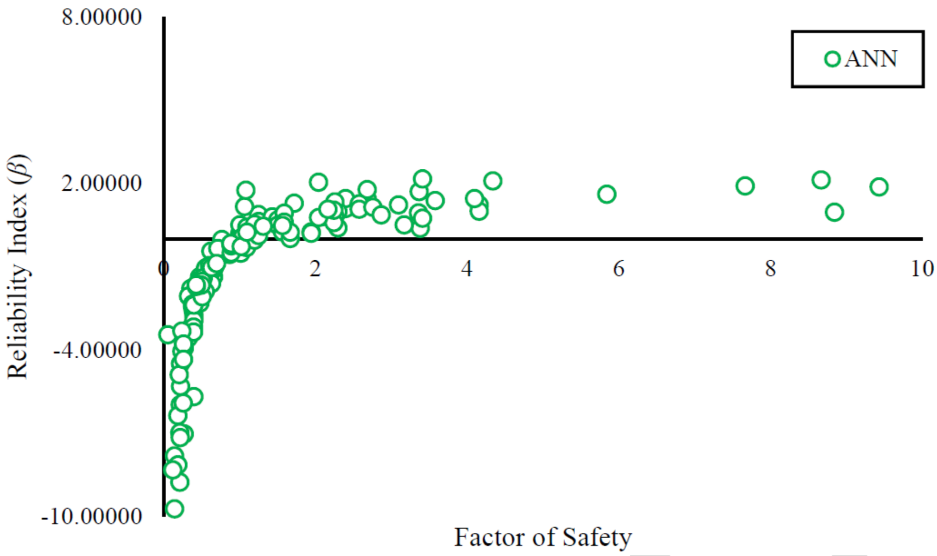


Figure 8 Reliability Index (β) v/s factor of safety as per Idriss and Boulanger Method [1]

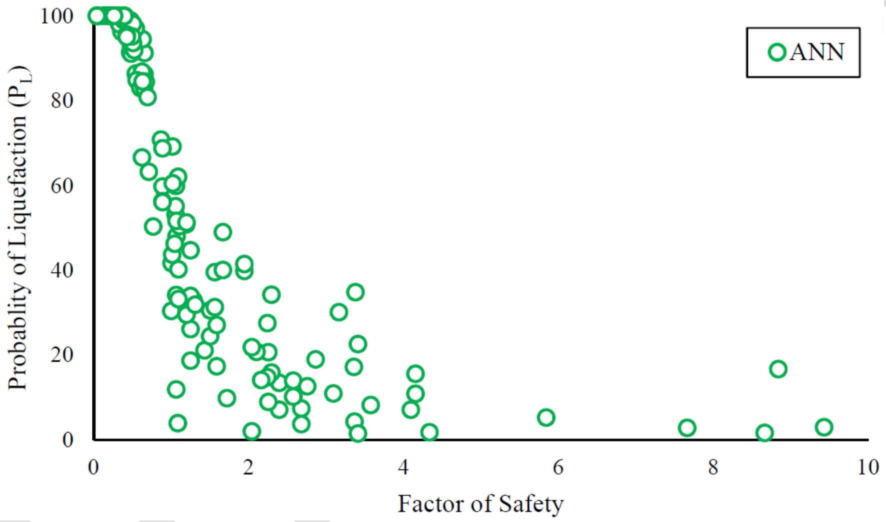


Figure 9 PL against factor of safety

4.0 CONCLUSION

The importance of computer-aided liquefaction prediction in hazard mitigation has been well established based on the comparison between Idriss and Boulanger methods and developed ANN model. The artificial neural network has been developed using MATLAB for the assessment of liquefaction potential based on field and laboratory datasets. The following conclusions can be drawn:

1- The developed ANN model is a robust method in comparison with the empirical method which consists of a complex relationship between the soil and seismic parameters to evaluate liquefaction potential and thus raises the chances of uncertainty and errors.

2- Field and laboratory-based soil parameters may directly be used as input parameters for the developed ANN models, which are much simpler and more responsive than the conventional methods to predict liquefaction potential.

3- The consideration of fine content as an input parameter in the ANN model has significantly reduced the liquefaction potential of all the sites.

4- The results obtained from the ANN model state that the sites, which pose the threat to undergo liquefaction when evaluated using Idriss and Boulanger empirical method, will fall in the non-liquefiable zone, thus eliminating the long-term risk to life, property and environment.

5- Construction of any structure in a liquefiable zone requires a great amount of capital and resources, so the developed ANN model reduces the liquefaction probability, thus contributing to a huge saving of resources in the construction.

Therefore, the use of artificial intelligence for hazard mitigation can save us from incurring massive damages caused by hazards like liquefaction, and due to its cost efficiency and quick predictions, it should be categorized as a sustainable method for evaluating and predicting risk against any hazard.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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