ASSESSING LIQUEFACTION POTENTIAL USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

Liquefaction, a critical geotechnical hazard during seismic events, necessitates accurate assessment methods to mitigate associated risks effectively. Traditional approaches often exhibit limitations in capturing the intricate relationships between earthquake characteristics, soil properties, and liquefaction susceptibility. In this study, we present a novel methodology employing the adaptive neuro-fuzzy inference system (ANFIS) to comprehensively assess liquefaction potential, integrating earthquake parameters (magnitude and maximum acceleration) and soil properties (e.g., fines content, standard penetration test blow count). The ANFIS framework combines the adaptive learning capabilities of neural networks with the interpretability of fuzzy logic, enabling the modelling of complex and non-linear relationships. By training the ANFIS model on a diverse dataset comprising seismic and geotechnical data, we developed a robust tool for predicting liquefaction susceptibility across varying geological and seismic conditions. Our analysis demonstrates the effectiveness of the ANFIS approach in accurately assessing liquefaction potential, surpassing traditional methods by considering multiple influencing factors simultaneously. Through iterative optimization, the ANFIS model yields precise predictions while accommodating uncertainties inherent in input data. Key findings highlight the significant influence of earthquake characteristics and soil properties on liquefaction susceptibility. This research contributes to advancing the understanding and prediction of liquefaction hazards, offering a valuable tool for engineers, planners, and policymakers involved in disaster risk management. The proposed methodology presents a promising avenue for further refinement and application in diverse geotechnical and seismological contexts, ultimately enhancing resilience against seismic events.

Keywords: liquefaction, adaptive neuro-fuzzy inference system (ANFIS), standard penetration test.

1 INTRODUCTION

Liquefaction poses a significant geotechnical challenge during seismic events, often leading to substantial infrastructure damage and posing severe risks to human safety. Traditional methods for assessing liquefaction potential typically rely on empirical correlations and simplified models that may not fully capture the complex interactions between seismic activity and soil properties. While these conventional approaches, such as those pioneered by Seed and Idriss in the late 1960s and early 1970s, have provided foundational insights, they are limited in their ability to integrate and process the multifaceted data influencing liquefaction susceptibility [1], [2].

In recent years, the advent of advanced computational techniques, particularly machine learning (ML), has opened new avenues for more precise and comprehensive analysis of geotechnical phenomena. Various ML algorithms, including logistic regression, support vector machines, neural networks, decision trees, and ensemble methods such as random forests and XGBoost, have been applied to liquefaction assessment, each offering unique advantages [3]–[5]. These methods leverage computational power to analyse large and diverse datasets, incorporating multiple parameters such as soil type, seismic intensity, groundwater depth, and historical case histories to predict liquefaction susceptibility with improved accuracy.

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Among the promising ML techniques, the adaptive neuro-fuzzy inference system (ANFIS) stands out, combining the strengths of neural networks and fuzzy logic. ANFIS provides robust adaptive learning capabilities through its neural network component, while its fuzzy logic framework incorporates expert knowledge and handles uncertainty. This combination is particularly well-suited for modelling the nonlinear and complex relationships inherent in liquefaction potential assessment.

This study introduces a novel methodology utilizing ANFIS to evaluate liquefaction potential by integrating key earthquake parameters, such as magnitude and peak ground acceleration, with critical soil properties, including fines content and standard penetration test (SPT) blow count. By training the ANFIS model on a diverse dataset encompassing a wide range of seismic and geotechnical conditions, we aim to develop a predictive tool that not only surpasses traditional assessment methods but also enhances the reliability and accuracy of liquefaction potential predictions.

Our research demonstrates the efficacy of the ANFIS-based approach, highlighting its ability to consider multiple influencing factors simultaneously and accommodate the uncertainties inherent in input data.

2 ANFIS

In traditional logic, a variable is either a member of a set or not, signified by values of one or zero. However, fuzzy sets, first introduced by Zadeh [6], allow for degrees of membership that can vary between zero and one. This concept implies that an object's membership in a fuzzy set is approximate [7], with the membership function indicating the extent to which an object belongs to a subset [8]. Fuzzy logic is a powerful tool for handling ambiguity and uncertainty. It employs if–then rules within fuzzy sets to infer outputs from input data. One such system is the Sugeno model [9], where outputs are defined either as constant values or linear combinations of the fuzzy inputs.

A significant challenge with fuzzy inference systems is that selecting optimal membership functions to minimize error relies heavily on user expertise and judgment. To address this, Jang [10] combined neural network optimization algorithms with fuzzy inference systems, allowing membership functions to be fine-tuned to minimize errors. This hybrid method, known as ANFIS, consists of five layers as depicted in Fig. 1.

Consider a dataset with two inputs, x_1 and x_2, and two rules:

Rule 1:
If x_1 is A_1 and x_2 is B_1, then $y_1 = p_1x_1 + q_1x_2 + r_1$

Rule 2:
If x_1 is A_2 and x_2 is B_2, then $y_2 = p_2x_1 + q_2x_2 + r_2$

where A_1, B_1, A_2, and B_2 are fuzzy sets, while y_1 and y_2 are outputs. The constants are p_1, q_1, r_1, p_2, q_2, and r_2. In the initial layer, the inputs are mapped to membership functions $\mu_{A1}(x_1)$, $\mu_{A2}(x_1)$, $\mu_{B1}(x_2)$, and $\mu_{B2}(x_2)$. In the subsequent layer, weight factors w_1 and w_2 are computed as:

$$w_1 = \mu_{A1}(x_1) \times \mu_{B1}(x_2) \quad (1)$$

$$w_2 = \mu_{A2}(x_1) \times \mu_{B2}(x_2) \quad (2)$$

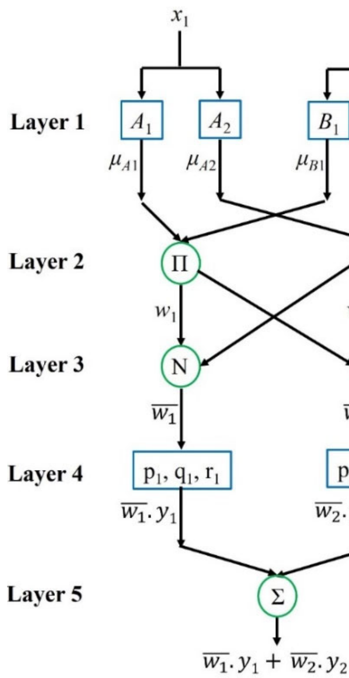

Figure 1: ANFIS Architecture.

These weights are normalized in the third layer using:

$$\overline{w_1} = \frac{w_1}{w_1 + w_2} \tag{3}$$

$$\overline{w_2} = \frac{2}{w_1 + w_2} \tag{4}$$

The normalized weight factors, $\overline{w_1}$ and $\overline{w_2}$, are then multiplied by the corresponding outputs in the fourth layer, resulting in $\overline{w_1}.y_1$ and $\overline{w_2}.y_2$. Finally, the output y is predicted by combining these terms linearly:

$$y = \overline{w_1}.y_1 + \overline{w_2}.y_2 \tag{5}$$

In this study, a hybrid approach combining backpropagation gradient descent and least squares methods are used for optimization. The application of ANFIS in predicting geotechnical and geological phenomena has grown significantly in recent years [11]–[13].

3 DATA AND ANALYSIS

Seed and Idriss [1], [2] presented a stress-based framework for estimating the liquefaction potential, which is still in use. The factor of safety against liquefaction can be obtained by cyclic resistance ratio (CRR) divided by cyclic stress ratio (CSR). The CSR can be determined by:

$$\text{CSR} = 0.65 \frac{\sigma_v}{\sigma'_v} \frac{a_{\max}}{g} r_d \tag{6}$$

where σ_v and σ'_v are total and effective stresses, respectively; a_{max} is the maximum horizontal acceleration, and r_d is a reduction factor. The following equation was also introduced to calculate r_d factor [14]:

$$r_d = \exp[\alpha(z) + \beta(z)M] \tag{7}$$

where $\alpha(z)$ and $\beta(z)$ are functions of depth (z), and M is the earthquake magnitude. The CRR can be determined by:

$$\mathrm{CRR} = \mathrm{CRR}^{*}.\,\mathrm{MSF}.\,K_\sigma \tag{8}$$

where CRR* is a benchmark value adjusted for $M = 7.5$ and $\sigma'_v = 1$ atm; MSF is the magnitude scaling factor, and K_σ is a factor representing the presence of static shear stress. CRR* is a function of corrected SPT blow count ($(N_1)_{60}$), and soil's fines content, while K_σ is a function of σ'_v, $(N_1)_{60}$, and fines content [14]. The MSF can also be determined using the following equation:

$$\mathrm{MSF} = 6.9\exp\left[-\frac{M}{4}\right] - 0.058 \tag{9}$$

Idriss and Boulanger [15], [16] gathered data from earthquakes leading to soil liquefaction in various countries including USA, China and Japan. We used this dataset that included information of 118 liquefied sites and 94 non-liquified sites. The ANFIS model, consisted of six input parameters: M, a_{max}/g, z, σ'_v, fines content, and $(N_1)_{60}$. Factor of safety was selected as the output parameter. Statistical properties of the input variables are shown in Table 1. A histogram of factor of safety is also shown in Fig. 2. The dataset was divided randomly into training and testing sets in such a way that the training dataset consisted of 75% of the total data.

Table 1: Statistical properties of the input variables.

Variable	**Statistical property**		
	Mean	**Max.**	**Min.**
M	7.1	8.3	5.9
1234	1234	1234	1234
a_{max}/g	0.28	0.84	0.05
z (m)	5.2	14.3	1.8
σ'_v (kPa)	63.6	156.0	20.0
Fines content (%)	15.7	92.0	0
$(N_1)_{60}$	14.0	36.9	1.7

4 RESULTS AND DISCUSSION

The ANFIS was executed using a range of influence equal to 0.7 leading to four membership functions for each input parameter. The resulting membership functions are shown in Fig. 3. In order to verify the goodness of fit of the proposed model, the ANFIS model was evaluated using the testing data. The results show that the application of ANFIS on prediction of testing dataset led to $R^2 = 0.89$. Fig. 4 shows the scatter plot of testing and training data and ANFIS prediction along with the bisector line. It is clearly seen that the data lie in close proximity to the bisector line which emphasizes the goodness of the ANFIS prediction.

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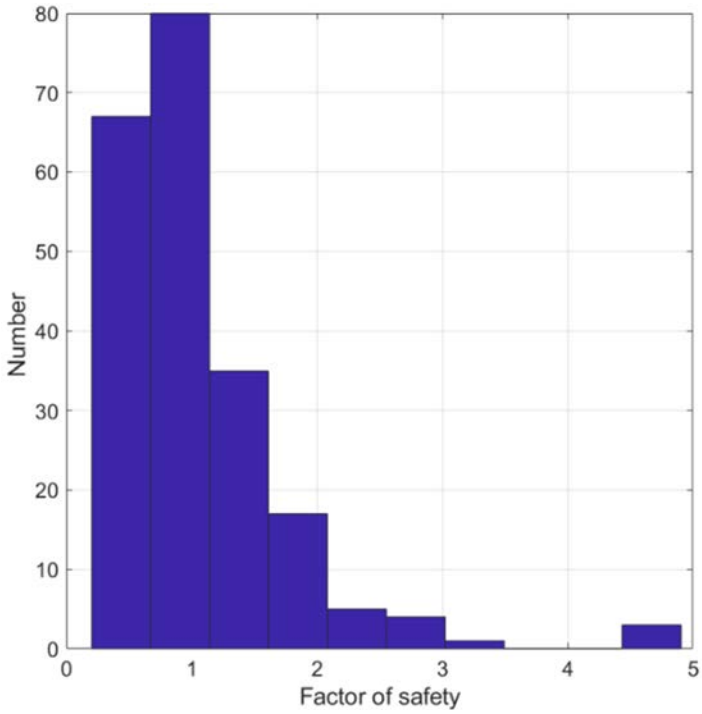

Figure 2: Histogram of factor of safety values.

One of the methods to evaluate the goodness of the fit of the ANFIS model is to perform hypothesis test on the normalized residuals. The normalized residuals (NR) is defined as:

$$\mathrm{NR} = \frac{\mathrm{Comp(FS)} - \mathrm{Pred(FS)}}{\mathrm{std(FS)}} \tag{10}$$

where Comp(FS) and Pred(FS) are computed and ANFIS-predicted factor of safety values, respectively, and std(FS) is the standard deviation of the predicted values.

For a perfect model, normalized residuals should follow a normal distribution with a mean of zero and a unit variance. Fig. 5 shows the histogram and corresponding normal distribution for the testing data. A *z*-test with a significance level of 0.05 was conducted. In this test, the null hypothesis was that the normalized residuals follow a normal distribution with a mean of zero and a unit variance.

The test resulted in a *p*-value of 0.81. A *p*-value higher than the significance level indicates that there is not enough evidence to reject the null hypothesis. Thus, the *z*-test confirms that the normalized residuals follow the standard normal distribution.

5 CONCLUSIONS

The liquefaction potential depends on several factors such as the earthquake magnitude, maximum horizontal acceleration, effective stress, fines content and the standard penetration blow count. In the present study, the authors implemented the ANFIS for predicting the factor of safety against liquefaction. The structure of the proposed ANFIS consisted of six input parameters so that four membership functions were assigned to each input parameter.

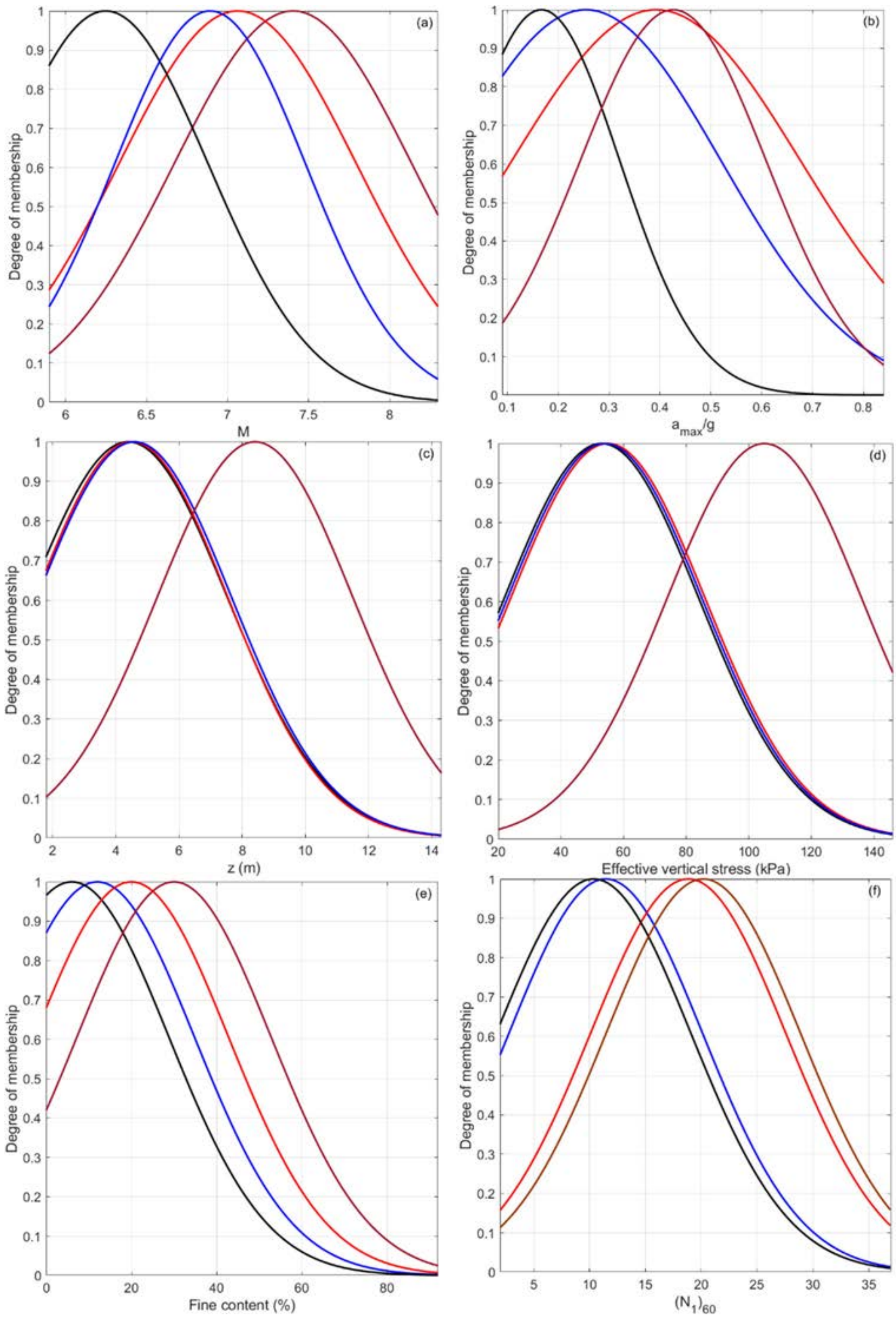

Figure 3: Membership functions of (a) M; (b) a_{max}/g; (c) z; (d) σ'_v; (e) fines content and (f) $(N_1)_{60}$.

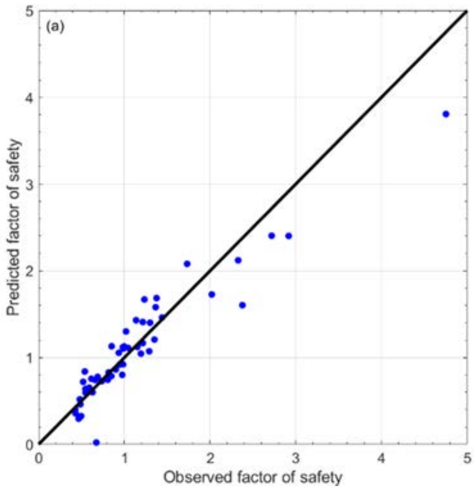

Figure 4: Observed versus predicted factor of safety by ANFIS. (a) Testing data; and (b) Training data.

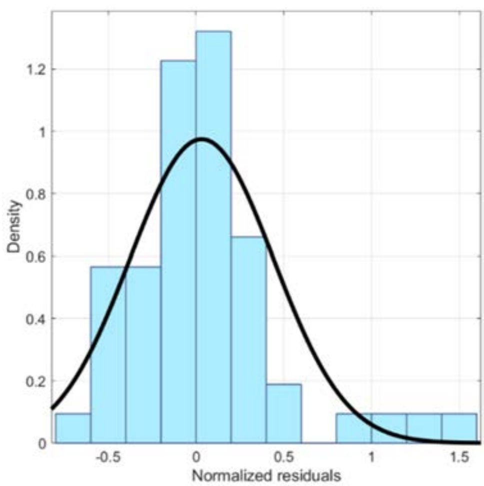

Figure 5: Histogram of normalized residuals.

It was observed that ANFIS is capable to make precise prediction. The R^2 value of the predicting model prediction was 0.89 for the testing dataset. Moreover, a hypothesis test (*z*-test) was applied on normalized residuals to check the goodness of fit of the proposed ANFIS model. The test results showed that the normalized residuals obey a normal distribution function with zero mean and unit variance.

These statistical data seem acceptable for the complex and nonlinear nature of the liquefaction phenomenon and show the high capability of the ANFIS.

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