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Prediction of Safe Bearing Capacity with Adaptive Neuro-Fuzzy Inference System of Fine-Grained Soils

Vaddi Phani Kumar[1*], **Ch. Sudharani**[2]

1. Research Scholar, Sri Venkateswara University College of Engineering, Tirupati, Andhra Pradesh, India
2. Professor, Sri Venkateswara University College of Engineering, Tirupati, Andhra Pradesh, India

Corresponding author: *phani611@gmail.com*

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ABSTRACT

A lot of fieldwork is required to assess the safe bearing capacity (SBC) of fine-grained soil using IS Code, along with performing shear parameters to determine angle of internal friction and cohesion. Standard penetration tests are conducted in order to obtain N-value of soil, and evaluating atterberg limits and dry soil density. Here, it is proposed that Adaptive Neuro-Fuzzy Inference System (ANFIS) is adopted to predict fine-grained soil's safe bearing capacity. For this, input parameters considered for ANFIS system are depth of foundation, dry density, liquid limit, plasticity index, Percentage fine fraction, width/Length ratio, and N-Value. A wide range of safe bearing capacity data from various site locations was investigated and trained on. Four different models were developed with variations in membership function for each input, all the models are used with a gaussbell type of membership function. Among the four, the third model is predicting the nearest value with an R^2 of 0.9738. Based on the conclusion the ANFIS model is the most reliable technique for assessing the SBC of soils. Investigation of soil properties and estimation of safe bearing capacity will be having more difficulty with respect to skilled person to investigate and time required is also more as dimension of the footing changes SBC also varies. So, to overcome this type of problems my model will give you a best suitable and reliable SBC.

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1. Introduction

Essentially, soil's bearing capacity is its ability to bear the weight of its surroundings. Soil carrying capacity refers to the largest possible average contact pressure between a foundation and the soil, which should not lead to soil shear failure. Soil or rock's load-carrying capacity is the greatest weight per unit area that the material can hold without collapsing or displacing. Geotechnical engineers have been working on determining the bearing capacity of soils for the last several years [1,2].

Research efforts have been concentrated on studying the properties and behaviors of soil [3,4], equations & relations [5]. The safe bearing capacity of fine-grained soil is conventionally estimated by means of Terzaghi method (1943) and soil carrying capacity for foundation shear failure was frequently predicted by many people. Several researchers have carried out a variety of analytical studies, including finite element and numerical limit, as well as laboratory studies, including axial, eccentric, experimental model tests, and inclined loading. These studies have been used to draw various conclusions about the phenomenon being investigated [6–8]. [9] have used an explicit finite-difference approach for estimating the ultimate bearing capacity of ridged circular footings. This will help designers make the right theoretical decisions. Using explicit finite-difference coding, It was expected that ridged circular footings, when subjected to axial static stress, would also have an ultimate bearing capacity [9]. Analysis of several safe bearing capacities, load, shape, depth, and surface tilt equations was conducted by [10] to determine which was most reliable.

It is common to use intelligent systems in order to obtain patterns for the existing data or else to simulate complicated relationships with nonlinearity among inputs and output. For projects involving soil engineering, soft computing systems are an excellent tool for reducing uncertainty [11]. The fuzzy logic model, artificial Neural Network, and adaptive neuro-fuzzy inference system are examples of soft computing techniques that have been utilised to predict different geotechnical engineering challenges. There are a variety of geotechnical engineering issues that can be addressed, including the ultimate bearing capacity of piles [12], Geosynthetic soil interface at cohesive stresses was predicted in the laboratory and the peaks were analyzed, [13] settlement of ground is predicted [14], the bearing pressure of shallow foundations [15]. (UCS), and ANN & ANFIS models have been used in the recent past to predict these issues. The ANN model has limitations like poor generalising performance, overfitting difficulties, arriving at a local minimum, sluggish convergence speed, and the inability to characterise any link among the model's input and output due to its "black box" nature. These issues all contribute to the model's inability to generalise well [16–19]. In addition, there is no dependable method for counting the number of hidden layers or the neurons that are included within each layer. Due to the fact that the fuzzy logic model has trouble figuring out the fuzzy rules, the fuzzy system cannot be trained. The design of ANNs trains the learning parameters of the ANFIS fuzzy inference system (FIS) [20–22]. On the other hand, a new and effective artificial intelligence tool based on statistical learning theory is the support vector machine (SVM) [23]. Structured risk minimization (SRM) is a superior generalization strategy to the empirical risk minimization (ERM) concept, since it focuses on the generalization error instead of only decreasing the error on the training data. To reduce training data error, classic neural networks use ERM. Basic goal of the SVR is to decrease empirical risk (i.e., mistakes associated with training set) while also increases generalization capacity of the model concurrently. In contrast to the ANN and ANFIS models, it has the potential to prevent overtraining, as well as the capacity to reach a global minimum and higher levels of generalization [24]. The SVR model may also be improved to take use of new data as it becomes available. In geotechnical engineering, some examples of the use of support vector machines (SVM) include modelling capacity of pile [25], predicting over consolidation ratio (OCR) [18], settling of shallow foundation [24], and modelling carbonate sands' mechanical properties [24,26]. An empirical model for predicting soil's safe bearing capacity has therefore been developed in this study.

Where multiple variables influence a certain quantity or property, the Adaptive Neuro-Fuzzy Inference System can be used. A number of factors can influence the accuracy of parameter values in empirical/theoretical equations when they have been assessed through laboratory and field studies. Because of the possibility of experimental working errors while predicting the bearing capacity using semi-empirical relations, such as from the equations given by Terzaghi and Peck, a designer may choose a conservative design, for example, such parameters value is dependent on laboratory and field experiments, hence in this work, an effort is made to support these relationships. The other purpose of the study is to devise an approach that may be used by ANFIS to estimate the permissible load bearing capability. The shear failure criterion is the only one used in this investigation to determine the safe bearing capacity.

The standard penetration test, Dry density, Atterberg limits, and sieve analysis are the tests that take the least amount of time and are the most straightforward when it comes to analyzing soils from any point even with respect to depth. Researchers have made a great number of attempts to anticipate the safe carrying capacity of soils, taking into consideration the difficulties that have been outlined above. In this paper safe bearing capacity from different sites is calculated using eq-1. A new ANFIS model is proposed for predicting safe bearing capacity from Depth of foundation, Dry density, liquid limit, plasticity index, Percentage fine fraction, N-Value and width/Length ratio kN/m^3.

$$q_{nu} = cN_c s_c d_c \tag{1}$$

Where, $q_{nu} = net\ ultimate\ bearing\ capacity$
C = cohesion
$N_c = bearing\ capacity\ factor$
$s_c = shape\ factor$
$d_c = depth\ factor$

2. ANFIS working behavior

Artificial intelligence is increasingly being adopted in engineering applications. The accuracy of predicting various qualities and values has been improved through the use of Neuro-Fuzzy applications. Matlab's fuzzy logic toolbox is useful for programme analysis, design, and simulation. ANFIS is a typical approach in fuzzy systems. ANFIS uses neuro-adaptive learning to teach the Sugeno systems [27–29]. To train the network, membership function parameters are adjusted. The ANFIS builds a fuzzy interference system based on the input and output datasets that are supplied, and then modifies the system using the backpropagation technique. Membership functions were used as a means of facilitating the learning process. Target and intended outputs were divided by their squared differences in order to calculate the error. By constructing IF-THEN logic, or rules, the purpose of fuzzy logic is to discover the potential inputs that might lead to the proposed outcome. In order and parallel, constructed rules are computed, which may be subject to modification. Each variable will have a set amount of membership functions that will be used to define all terms. Boundaries are well defined in fuzzy logic. Using the membership function, input data is transformed into a membership value between [0, 1]. The function should be defined from a perspective of efficiency, speed, simplicity and convenience.

The membership functions in Matlab's fuzzy logic toolbox are built right in (Matlab Inc). The membership functions 'Trimf' and 'trapmf' are formed using straight lines. The Gaussian Distributive Curve (GDC) is used to form two membership functions, a Two-sided Composite of two independent GC and a basic Gaussian-Curve (GC), and three parameters describe the membership function as generalized bell (gbellmf). The sigmoidal membership function was defined in either direction. There are two types of closed-membership functions of the sigmoidal function: "p sigmf" and "the modification between two sigmoidal functions, which are sigmoidal factors." Membership function 'zmf' has a polynomial curve that opens to the left and an asymmetric polynomial curve. In one form of membership function, both ends are zero, but in the other type, both ends are free to move either way.

Initial Fuzzy Inference System (FIS) creation begins with the loading of data and the selection of either a Hybrid/Back-Propagation optimization strategy. These optimization methods will be used to train the set of data to exclude the training data. Ending the training process occurs when tolerance error targets are satisfied or the epoch number reaches maximum.

The trained FIS is validated by using data sets that are diverse from the training data, such as the error plots and modified MFs stated above.

3. ANFIS Architecture

It is possible to define the Adaptive Neuro-Fuzzy Inference System as an adaptive system using the Sugeno fuzzy model. This makes learning and adjusting the system much simpler. Fig.1 illustrates the Sugeno model's intelligence theory. As a result, ANFIS modelling is more effective and less reliant on master data. Two fuzzy IF-THEN rules, derived from the first order Sugeno Fuzzy model, were responsible for the development of the ANFIS architecture.

Rule I$\Rightarrow$ If (s is A_1) and (v is B_1) then ($t_1 = X_1 s + Y_1 v + G_1$)
Rule II$\Rightarrow$ If (s is A_2) and (v is B_2) then ($t_2 = X_2 s + Y_2 v + G_2$)

where, s, v - inputs,
A_i, B_i - fuzzy datasets,
t_i - outputs, and
X_i, Y_i and G_i - design parameters.

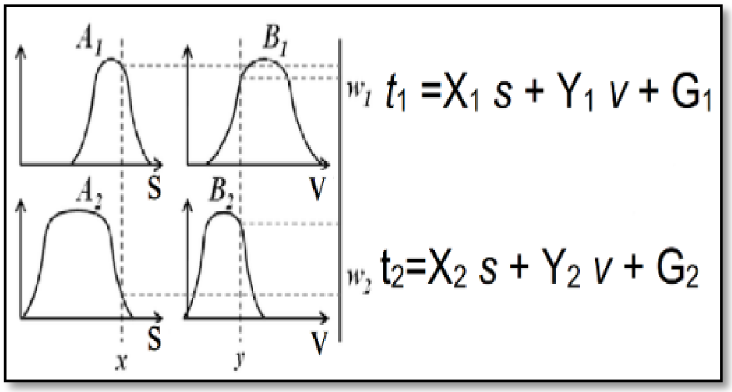

Fig. 1. Sugeno's 1st -order of fuzzy model that has two inputs and two rules.

Fig.2 illustrates how the preceding guidelines are implemented; a square denotes an adjustable node and a circle, a fixed node. The five layers of the ANFIS architecture are illustrated below.

For the current, all inputs in layer 1 are fuzzy membership functions that can be modified by the user.

Fixed and labeled with a π indicate that these nodes are multipliers in the second layer.
Third-layer nodes are labeled N to imply that they play a normalized function in reference to the preceding layer's pushing capabilities.

The nodes can be changed at the fourth layer. In this layer, each node's output is a combination of the third layer's output and the first-order polynomial (for a first order Sugeno model).

In the fifth layer, there is a single fixed node that handles the processing of all incoming signals, which is referred to as Σ.

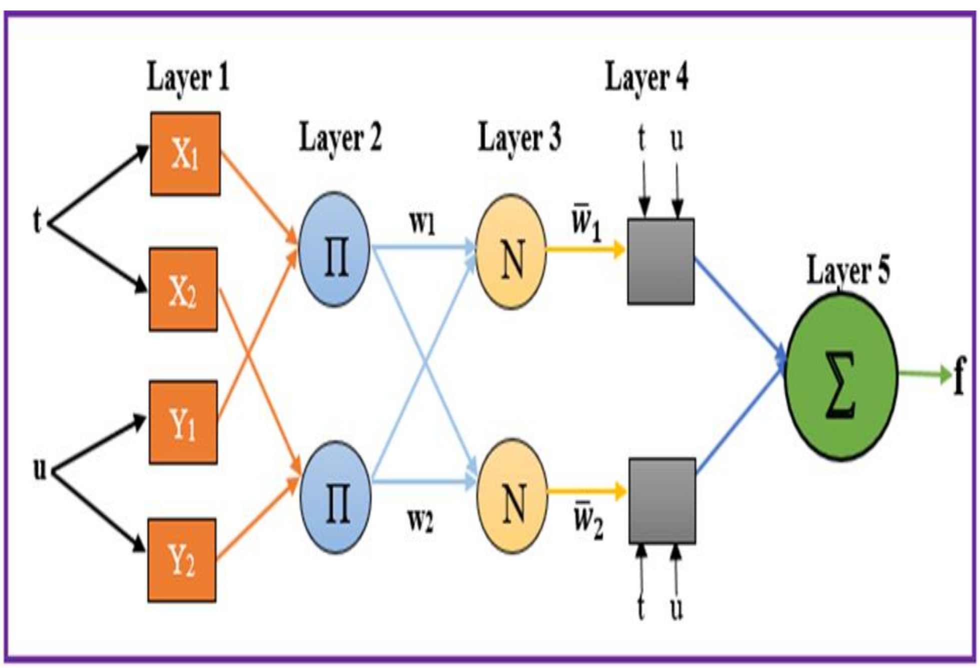

Fig. 2. ANFIS architecture.

There are two inputs and three 'gbell' membership functions in first-order Sugeno fuzzy model (SFM), that generate nine rules. Using an IF-THEN rule, the two possible input values are depicted as fuzzy areas in Fig.3. Premise and Consequence characterize the outcome in the fuzzy zone, respectively.

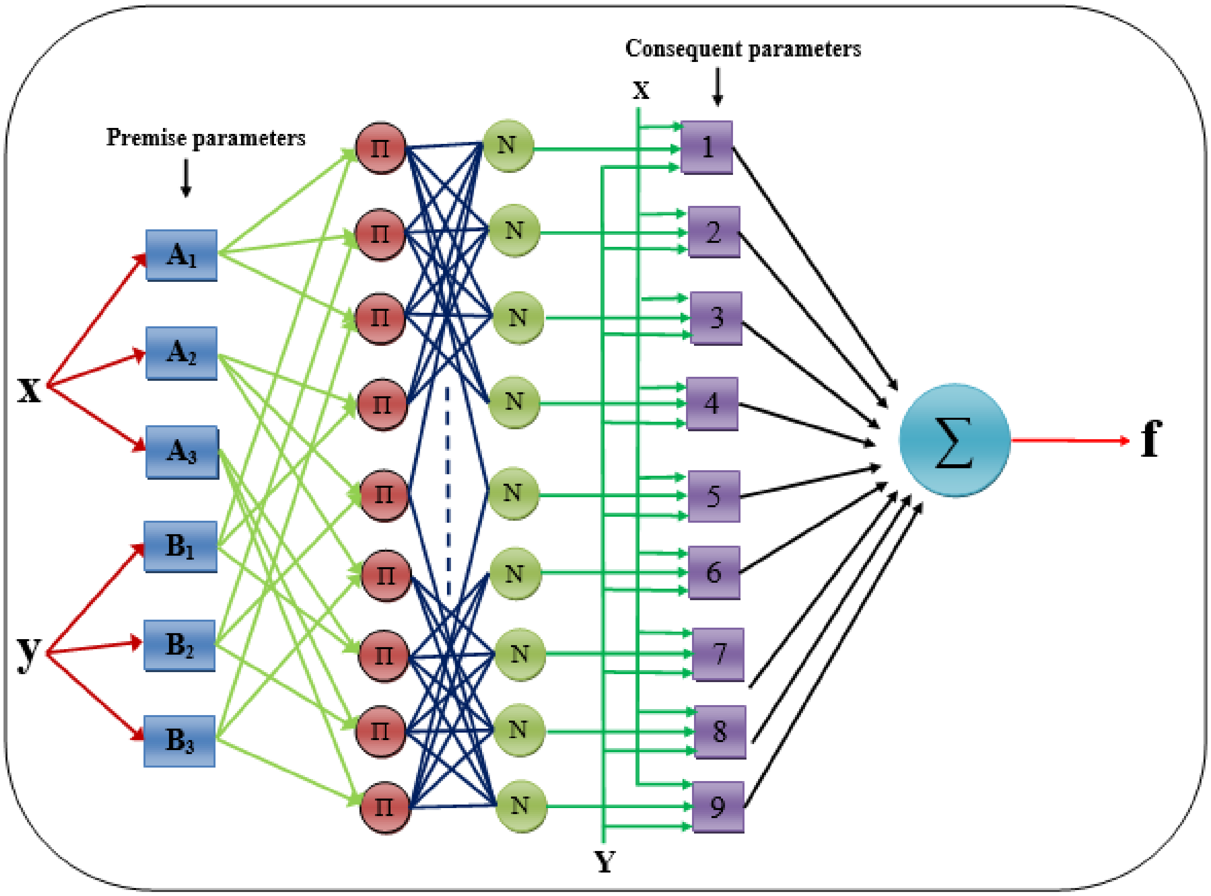

Fig. 3. Two-inputs first-order SFM.

4. Application of ANFIS model for prediction of SBC

ANFIS is utilised in this work to predict the safe bearing capacity based on the soil's basic parameters. Data sets total 2700 are utilized for training, testing, and verification [11,20,30–32]. 2160 of them are used for training, 402 are taken for checking, and 138 are used for testing, with training accounting for the vast majority (80%). Numeric values are used for all input parameters. The first parameter used is depth in m while the second parameter takes dry density in kN/m^3, the third parameter considered is Liquid limit in %. The fourth parameter is plasticity index in %. The fifth parameter is Fine fraction in %. The sixth parameter is N-value. The last parameter is B/L ratio.

Members of all four models are taken into account from the most realistic alternative, as shown in Figures 4 to 7. SBC is considered as an output parameter, which is a single variable with a numeric value. Input data are transformed into membership values using a membership function, which depicts a curve. All parameters are utilized in this way because the gbellmf (Generalized bell Membership Function) achieves smoothness and is possible to construct membership functions with symmetric properties. The fuzzy model is trained using the backpropagation optimization approach. Root Mean Square Error (RMSE) [33] and Correlation of Determination (R^2) are used to estimate the performance of all three models. They are characterized in terms of mathematics as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(K_i - \overline{K_\iota})^2}{n}}$$

Where, measured shear modulus is referred to as "K_i.",
shear modulus predicted is $\overline{K_\iota}$
no. of shear modulus values that have been observed is n

$$R^2 = \frac{\sum_{i=1}^{n}(K_i - \overline{Q_\iota})^2}{\sum_{i=1}^{n}(K_i - \overline{K_\iota})^2}$$

Where, shear modulus, observed is K_i

Mean shear modulus, observed is $\overline{K_\iota}$
shear modulus, predicted is $\overline{Q_\iota}$

Fig. 4. MODEL – I.

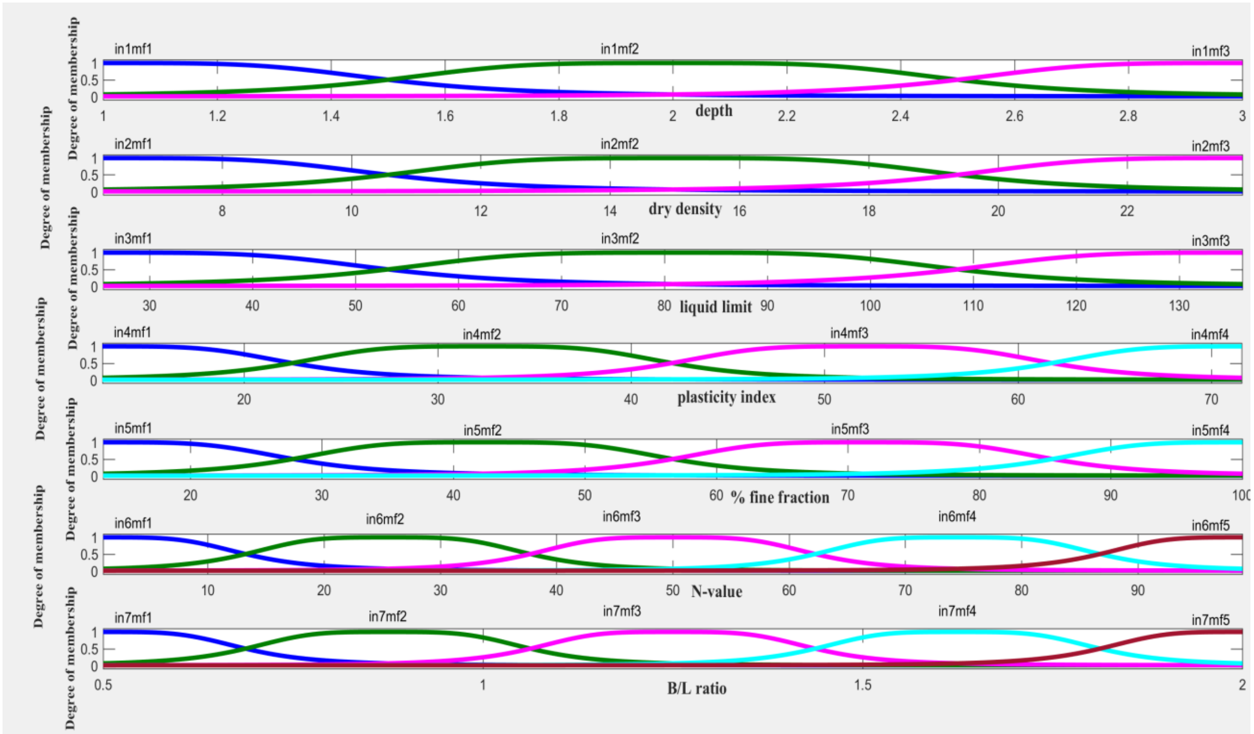

Fig. 5. MODEL – II.

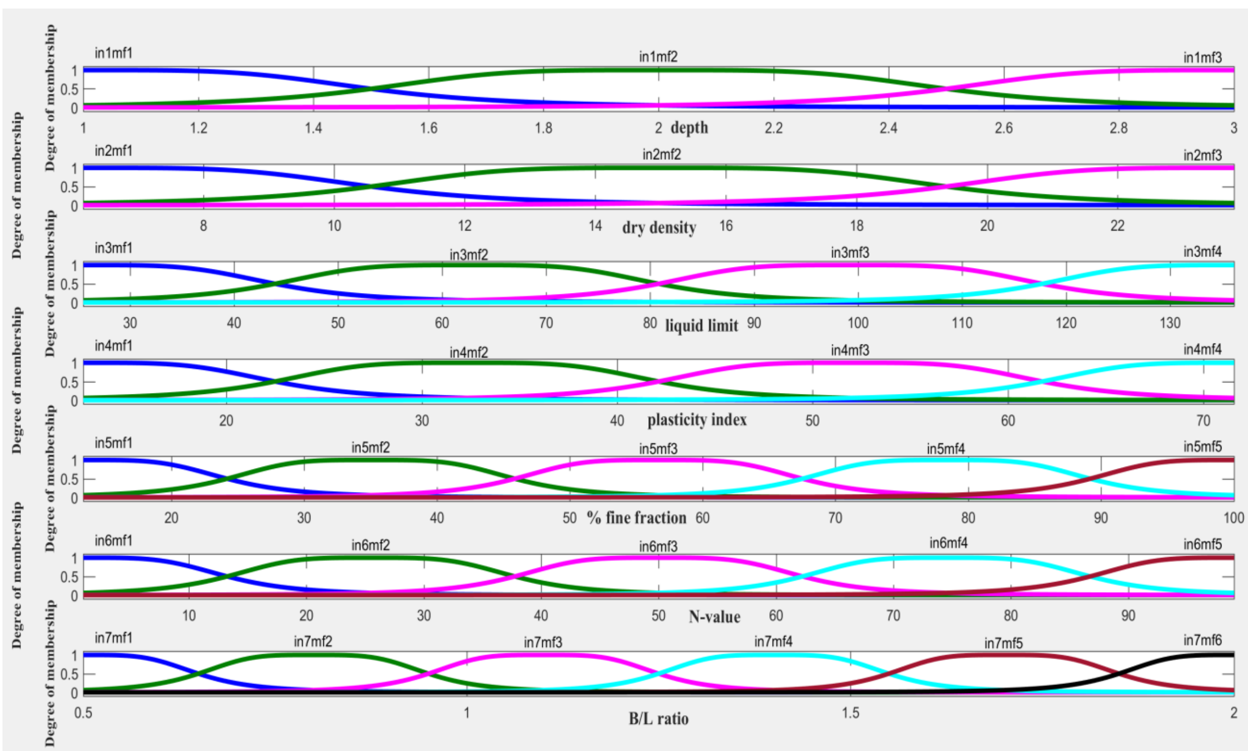

Fig. 6. MODEL – III.

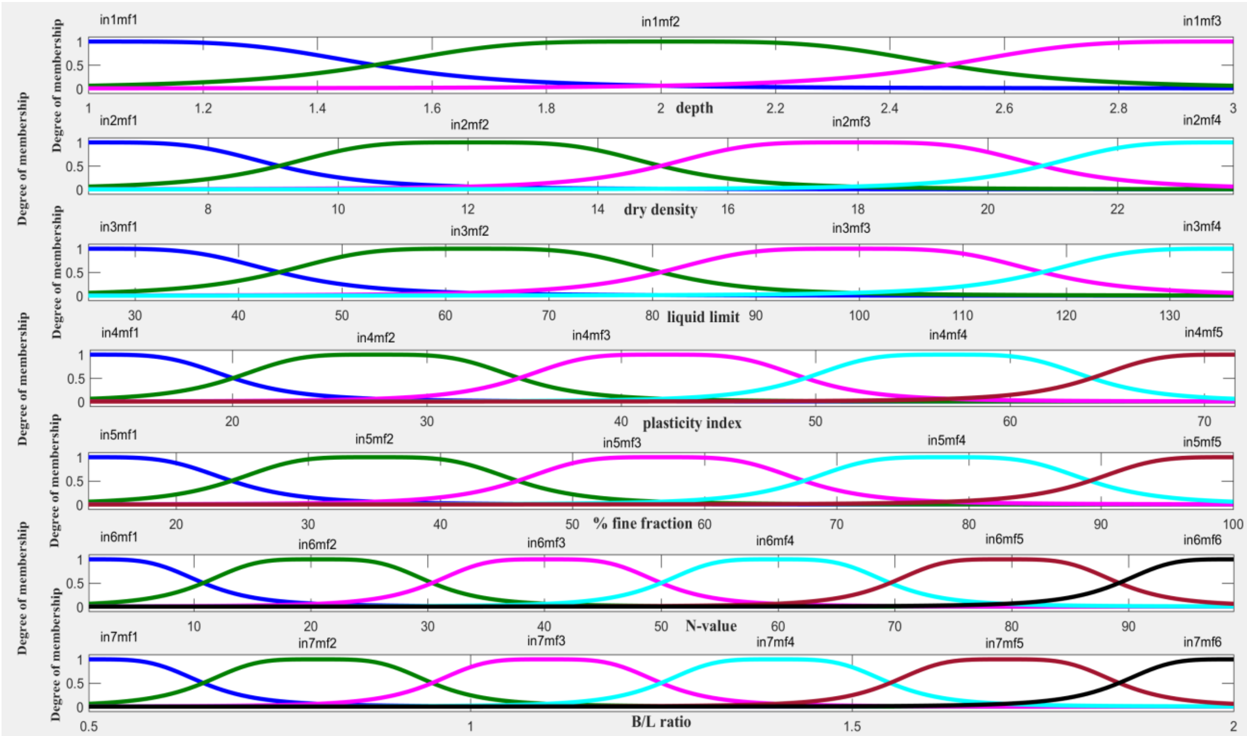

Fig. 7. MODEL – IV.

5. Results and discussions

As discussed before, 138 datasets were used to test and verify the ANFIS model. The goal of this study is to create predictions about the SBC for each dataset, compare those predictions to the actual test results for each of the four models that were taken into consideration, and then draw conclusions based on those comparisons. Table 1 displays the number of epochs and rules that were applied throughout the training process for each model. A fuzzy inference system uses seven inputs and just one output in order to make accurate predictions about SBC. The R^2 and RMSE values are shown in Table 2, and Figure 8 depicts a plot of Target vs Output. The outcomes of the Target Means estimated and the Output Means Prediction are shown below.

Model-III offers a more exact forecast than the other three models, and when compared to the other models, it delivers the most accurate prediction.

Table 1
Properties of Models.

Sl.No.	MODEL	Membership Functions	Epochs	MF type	No. of rules
1	I	[3 3 3 3 4 4 4]	1500	gbellmf	5184
2	II	[3 3 3 4 4 5 5]	1500	gbellmf	10800
3	III	[3 3 4 4 5 5 6]	1500	gbellmf	21600
4	IV	[3 4 4 5 5 6 6]	1500	gbellmf	43200

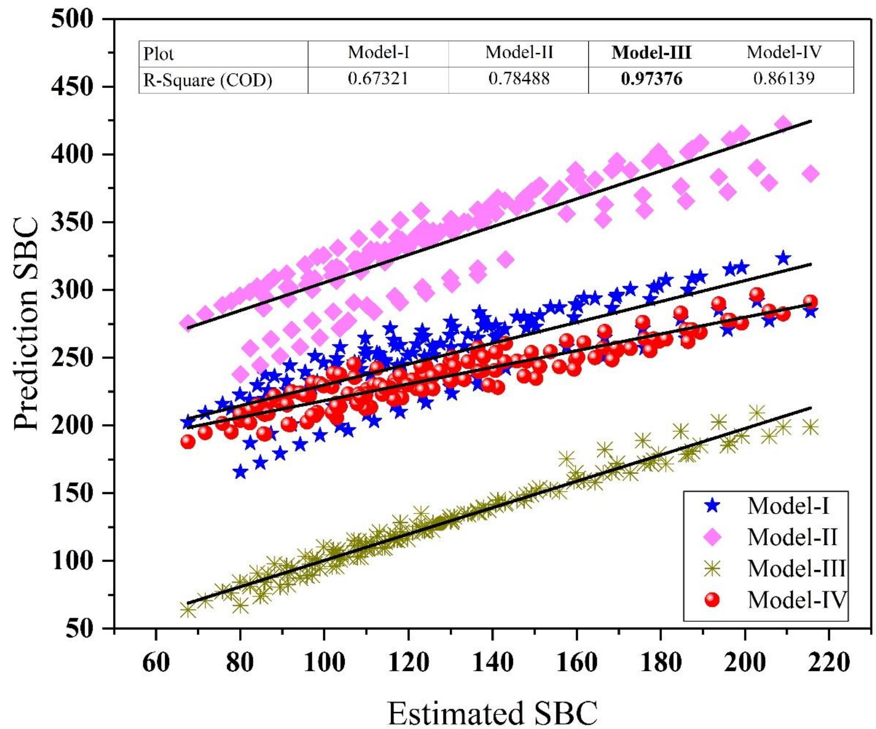

Fig. 8. Estimated SBC vs Prediction SBC.

Table 2
Results of ANFIS.

Sl. No.	MODEL	RMSE	R^2
1.	I	6.841	0.6732
2.	II	7.681	0.7849
3.	III	11.808	0.9738
4.	IV	12.426	0.8614

6. Conclusions

Four different models were used throughout the construction of the ANFIS model's Models I, II, III, and IV. In every single one of these models, the gaussbell type of membership function is utilized for the input parameter. The number of membership functions that were chosen for each input parameter was allowed to vary. In order to calculate SBC, the following data are used as inputs: depth of foundation, dry density, liquid limit, plasticity index, percentage of fine fraction, N-Value, and width to length ratio. A total of 2700 datasets were considered for selection and were then segmented into 80, 15, and 5 parts for this purpose (Training: Checking: Testing). The MODEL-III model is the most accurate of the four models that were taken into consideration; its RMSE is 11.808 and its R^2 value is 0.9738. It has been concluded that the suggested ANFIS is sufficiently competent for precisely predicting the expected output making use of ANFIS.

However, model-III is providing the most accurate results, despite the created model having certain limitations, particularly regarding the shape effect, the water table, and inclined loads. Only footings with a square or rectangular shape are recommended for use with this model since it was designed to accommodate those two shapes. The influence of the water table has not yet been taken into consideration while developing the model. Because the fact that the inclination component is eliminated from the model, it is only appropriate for use with vertical loads.

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Conflicts of interest

The authors declare no conflict of interest.

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