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ORIGINAL ARTICLE

Prediction of bearing capacity of thin-walled foundation: a simulation approach

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Abstract In the recent past years, utilization of intelligent models for solving geotechnical problems has received considerable attention. This paper highlights the feasibility of adaptive neuro-fuzzy inference system (ANFIS) for predicting the bearing capacity of thin-walled foundations. For this reason, a data set comprising nearly 150 recorded cases of footing load tests was compiled from literature. Footing width, wall length-to-footing width ratio, internal friction angle, and unit weight of soil were set as inputs of the predictive model of bearing capacity. In addition, a pre-developed artificial neural network (ANN) model was utilized to estimate the bearing capacity of thin-walled foundations. The results recommend the workability of ANFIS in predicting the bearing capacity of thin-walled foundation. The coefficient of determination (R^2) results of 0.933 and 0.875, and root mean square error (RMSE) results of 0.075 and 0.048 for training and testing data sets show higher accuracy and efficiency level of ANFIS in estimating bearing capacity of thin-walled spread foundations compared to the ANN model ($R^2=0.710$, RMSE = 0.512 for train, $R^2=0.420$, RMSE = 0.529 for test). Overall, findings of the study suggest utilization of ANFIS, as a feasible and quick tool, for predicting the bearing capacity of thin-walled spread foundations, though further study is still recommended to enhance the reliability of the proposed model.

Keywords Thin-walled foundation · Bearing capacity · ANN · ANFIS

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1 Introduction

Proper estimation of bearing capacity is a key factor in designing geotechnical structures. There is famous equation for estimating the bearing capacity of structures; however, when it comes to thin-walled foundations, to the best of authors' knowledge, few studies proposed analytical bearing capacity equations for thin-walled foundations. This is generally attributed to the fact that utilization of thin-walled foundation is not common. Thin-walled foundations are used in soils with low strength at the surface-like costal projects. Therefore, in the recent past years, attempts have been made to predict the bearing capacity of this kind of foundations using relatively new techniques like artificial intelligence [1]. Several authors also showed that when possible thin-walled foundations perform better compared to the conventional footings in terms of bearing capacity. In this regards, Rezaei et al. [1] conducted an experimental study to investigate the effect of walls on the bearing capacity of foundations. Their results suggest when wall length-to-footing width ratio (L_w/W) increases from 0.5 to 1.12, the bearing capacity of the foundation is enhanced 0.5 times. Their footing load tests were conducted in both loose and dense poorly graded sands.

Alaghbari and Mohamedzein [2] and Eid et al. [3] mentioned that incorporation thin walls for the spread foundation provide an enclosure in which the soil is confined which consequently leads to an enhancement in the bearing capacity of foundations. According to Alaghbari and Mohamedzein [2] study, when walled foundation is used instead of the conventional foundations, enhancement of bearing capacity in the range of 1.5–3.9 is expected. In another study, Al-Aghbari and Dutta [4] reported that providing thin walls leads to an increase in the bearing capacity from 11 to 70%.

Mana et al. [5] stated that the failure mechanism of a footing with two structural skirts is similar to a conventional footing which has an embedded depth equal to skirt lengths. Their conclusion recommends the importance of thin walls in increasing the bearing capacity. Similar conclusions were drawn by Nazir et al. [6, 7]. Eid [8] also stated that providing thin walls can lead to improvement in the bearing capacity by a factor in the range of 1.4–3. Wakil [9] and Wakil [10] also observed remarkable enhancement in the bearing capacity of foundations when structural skirts are used. In a more recent study, Momeni et al. [11] concluded that providing thin walls for spreads foundations can improve their bearing capacities by a factor of 2. Saleh [12] stated that skirted foundations perform better compared to the conventional spread footings. Fattah et al. [13] also stated that the use of skirted foundations is common more especially when the likelihood of scour from water is high.

In general, there are various methods for estimating the bearing capacity of foundations. These methods include empirical methods, analytical methods, numerical methods, and intelligent methods. The scope of this paper is on the latter methods. Many studies highlighted the feasibility of artificial technique in predicting the bearing capacity of foundations. For example, Shahin [14] reported that artificial neural network (ANN) is a practical and quick tool for estimating the bearing capacity of spread foundations. Momeni et al. [15, 16] highlighted the applicability of ANN in predicting the bearing capacity of deep foundations. Another artificial intelligence technique which is recommended in the literature for solving geotechnical problems is adaptive neuro-fuzzy inference system or ANFIS [17, 18].

To the best of authors' knowledge, so far, the feasibility of ANFIS in predicting the bearing capacity of thin-walled foundations is not investigated in the literature. Therefore, in this paper, an effort has been made to introduce an ANFIS-based predictive model of bearing capacity for thin-walled foundations.

2 Intelligence techniques

2.1 Artificial neural network

Artificial neural network (ANN) is a computational model which incorporates a Human-like thinking process. This method contains three main components, algorithm of learning, network formation, and shifting function [19]. ANNs are divided into two main categories: feed-forward (FF) neural networks and recurrent neural networks. The behaviour of FF does not depend on time; therefore, it can be applied if no time-dependent parameters are used [20]. One of the most famous FF-ANNs is the multi-layer perceptron (MLP) neural network which contain many nodes or neurons [21, 22]. Neurons in three layers (input layer, hidden layer, and output layer) are connected to each other by connections. MLP-ANN has the highest efficiency in estimating diverse functions in high-dimensional spaces [23]. In spite of that, ANN requires to be trained prior interpreting the results. An algorithm called back-propagation (BP) is considered as commonly-used algorithm between many types of algorithms to use for training MLP-FF [24]. The imported values in the input layer begin to spread to hidden neurons through connection weights in a BP-ANN [25]. The values of inserted data of every neuron in the last layer, $I_{i,}$ are increased by a convertible coefficient or weight, W_{ij}. Bias value, B_{ij}, is a threshold value to which results are added (Eq. 1). In addition, non-linear transfer function f (J_j) like a sigmoidal function (Eq. 2) is applied on the values to make new result from neuron. In general, the input of every neuron is the output resulted from neuron of the previous layer. These series of steps are done repeatedly until the final output is created. The predicted output and the target output are compared for error assessment. To minimize the error (such as root mean square error, RMSE), the BP is trained frequently for adjusting the weights between the neurons. More details on the BP algorithm can be found elsewhere [26]. In addition, readers can refer to more recent studies on the application of ANN in geotechnical engineering which is highlighted in many studies (e.g., [27–31]):

$$J_j = \sum (w_{ij} I_i) + B_j, \tag{1}$$

$$y_i = f(J_j). \tag{2}$$

2.2 Adaptive neuro-fuzzy inference system

Adaptive neuro-fuzzy inference system (ANFIS) was created in accordance with Takagi and Sugeno [32] fuzzy inference system (FIS) by Jang [33]. This system is known as a general predictive model that has the ability of approximating real continues functions. Actually, ANFIS assimilates the fundamentals of ANN and FIS and thus offers all the advantages of them in a single special framework. The importance and workability of ANN are highlighted in the literature (e.g., [34, 35]); however, the proposed system by Jang [33] can analyse the relationships existing between target data and the input utilizing hybrid learning (Fig. 1), which is done by deriving the optimum distribution of membership functions (MFs). ANFIS body is comprised of premise and consequent parts. ANFIS configuration can be equalled with five layers, as shown in Fig. 1b. ANFIS is used comprehensively in the field of engineering because of its strong capability to approximate non-linear connections between system inputs and system output. It should be noted that to define an ANFIS model procedure, an FIS system is Considered. The system is composed of two inputs (*x, y*), an output (*f*) and a rule base system with two set rules, "if-then" as it can be seen as follows [36]:

1st rule:

Assume
x is A1
y is B1
Then: $f_1 = p_1x + q_1y + r_1$.

2nd rule:

Assume
x is A2
y is B2
Then: $f_2 = p_2x + q_2y + r_2$.

In the rules above, p_i, q_i, and r_i are fixed consequent parameters. An ANFIS predictive model consisting of five different layers and two rules is described as follows:

1st Layer Each node (i) in this layer produces a membership grade of a linguistic label. For example, for the i^{th} node, the node function is defined as below:

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x-v_i}{\sigma_1}\right)^2\right]^{b_i}}, \tag{3}$$

where x is input to node i and Q_i^1 is MF. Ai is used as a reference to node i and σ_1, v_i, b_i are functions altering the shape of MF. Parameters that can be found in 1st layer are in connection with the previous part (see Fig. 1a).

2nd Layer Every node/neuron in this layer calculates the firing strength of each rule by amplification:

$$Q_i^2 = w_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \quad i = 1,\ 2. \tag{4}$$

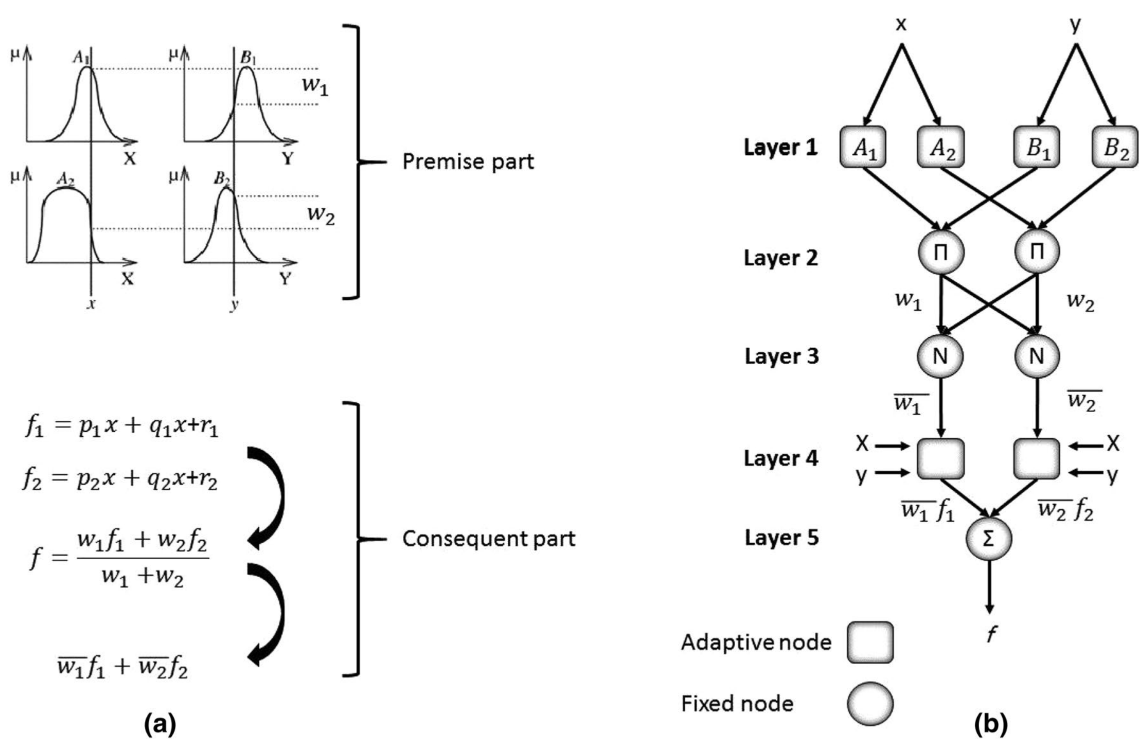

Fig. 1 ANFIS system structure

3rd Layer This layer contains calculation of the firing strength ratio of the i^{th} rule to the total amount of firing strengths of all rule:

$$Q_i^3 = W_i = \frac{w_i}{\sum_{j=1}^{2} w_j} \qquad i = 1, 2. \tag{5}$$

4th Layer Each node/neuron (i) is a node function although W_i is output of 3rd layer. Elements of this layer are in relation with consequent part:

$$Q_i^4 = W_i f_i = W_i\left(p_i x + q_i y + r_i\right). \tag{6}$$

5th Layer In this layer, sum of all incoming signals are calculated and generate an overall value of system output:

$$Q_i^5 = \text{Overall output} = \sum w_i f_i = \frac{\sum w_i f_i}{\sum w_i}. \tag{7}$$

Table 1 Summarized data set

Value	Model parameters				
	Inputs				Output
	W (mm)	γ (kN/m^3)	Φ	L_w/W	Qu
Min	36.55	10.34	29.23	0	17.1
Max	144	18.2	44.75	2	8005
Average	71.16	15.5	38	0.9	607

Table 2 PIs results for ANN and ANFIS models

Model	Network performance			
	Train		Test	
	R^2	RMSE	R^2	RMSE
ANN	0.710	0.512	0.420	0.529
ANFIS	0.933	0.075	0.875	0.048

3 Database

Selection of input data is prerequisite to model development. However, the input parameters should be selected in a proper way as they form the essential part of a predictive model. In general, input parameters can be selected if there is a relationship between a model input and the output of the model. Probably, the best way to select input parameters for a specific problem is to look at the previous well-respected-related studies. It is highlighted in the literature that footing geometrical properties and soil properties such as unit weight, γ, and internal friction angle, Φ, are influential parameters on the bearing capacity of foundations [1, 16, 17, 37–40]. Apart from that, Meyerhof famous bearing capacity equation for sandy soils suggests that width of foundation, W, γ, and Φ, is essential parameters for bearing capacity problems. Moreover, as discussed in the first section, the wall length also plays an important role in bearing capacity problems. Needless to say that the reliability of a predictive model or model output totally depends on the model inputs which in this study include soil properties. Several studies highlight the importance of the estimation of geotechnical properties of soil and the consequences if these properties are not estimated properly (e.g., [41–45]). To provide a data set for the model development, an extensive literature review was conducted and a data set was compiled from the literature [1–3, 10, 11, 46, 47]. The data set comprises 150 recorded cases of thin-walled footing load tests. Details on the experimental procedure are beyond of the scope of this paper which highlights the application of artificial intelligence in thin-walled foundation. However, since eight of the recorded footing load tests were performed by some of the authors, for clarification purpose, brief information is presented here. More details can be found in studies conducted by Momeni et al. [11] and Rezaei et al. [1]. In performing the aforementioned tests, the load was applied slowly to the model footings with 80 mm width through a pneumatic loading shaft in a continuous operation. A 20-kN load cell with an accuracy of $+0.01\%$ was utilized to measure the load. The load cell was rested between the footing and the load frame. The footing settlement was monitored using two linear variable displacement transducers. The load was increased if the rate of settlement change was less than 0.003 mm/min over three consecutive minutes. Finally, the footings were loaded in relatively loose and dense sands until the soil settlement reached almost 25 mm. However, since the number of load tests was high, only a summary of the data is presented in Table 1. As tabulated in Table 2, the input data for the predictive model of bearing capacity, Qu, include width of foundation, W, L_w/W, γ, and Φ.

4 Prediction of bearing capacity of thin-walled foundations using ANFIS

In this section, ANFIS modelling process in predicting bearing capacity of thin-walled spread foundations is described. To determine the number of fuzzy rules, several ANFIS models with a process of trial-and-error were employed, where the results of RMSE were only considered to assess the quantity of fuzzy rules. Based on the literature, Gaussian membership function (MF) in fuzzy systems can solve engineering problems better compared to other MF types; hence, this type of MF was chosen in the modelling [48]. Each input data with 4 fuzzy rules shows the best results for bearing capacity prediction, and therefore, a number of $(4 \times 4 \times 4 \times 4)$ fuzzy rules are appropriate for approximating the mentioned problem using ANFIS system.

The linguistic variables of very low (VL), low (L), high (H), and very high (VH) were assigned in modelling process. Figures 2, 3, 4, 5 indicate the Gaussian MF of model inputs (which were set after model construction) for the selected

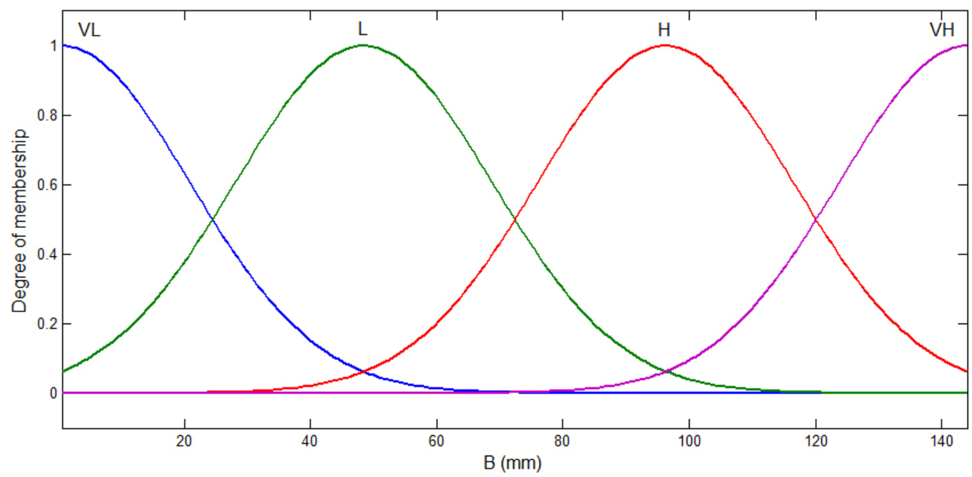

Fig. 2 MF of the footing width

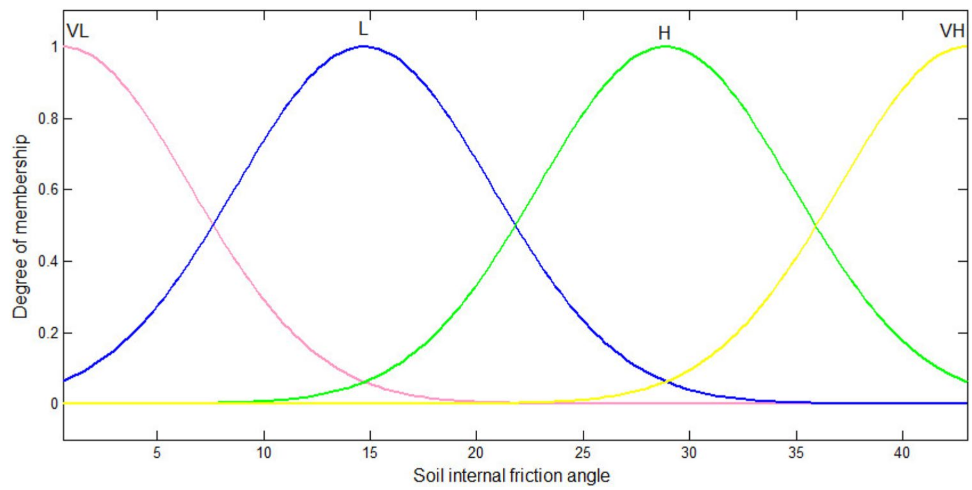

Fig. 3 MF of the soil internal friction angel

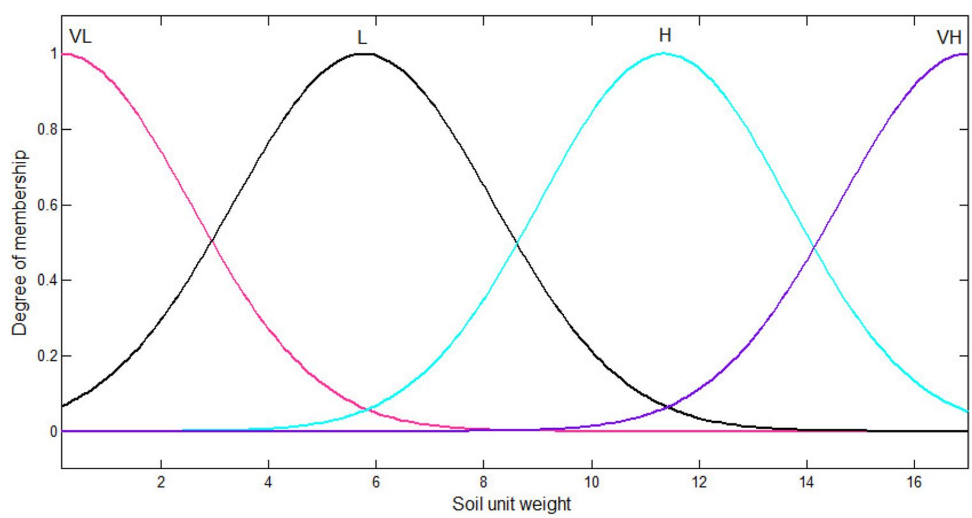

Fig. 4 MF of the soil unit weight

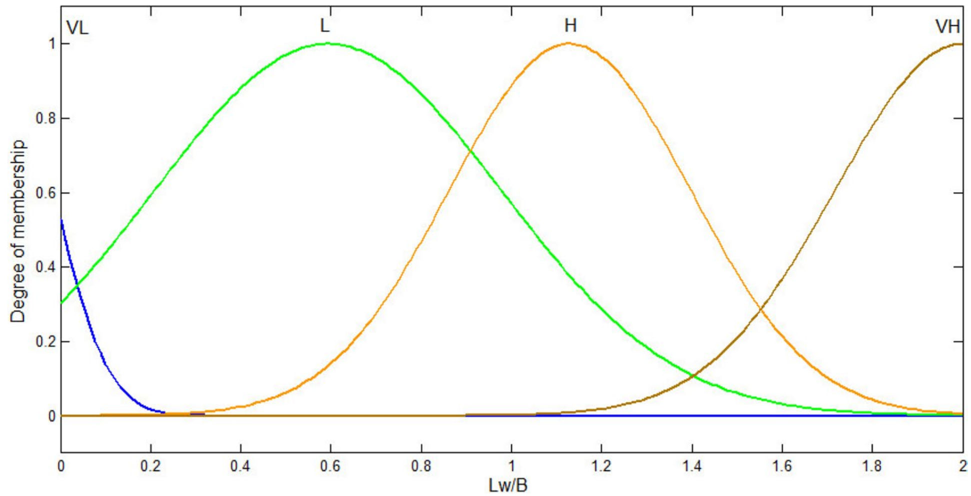

Fig. 5 MF of *Lw*/*B*

ANFIS model. In addition, Gaussian MFs of linear and constant were applied in the modelling and the best performance was obtained for linear type. In the best ANFIS predictive model after epoch number 52, there are no changes in network performance. The structure of the selected ANFIS system is displayed in Fig. 6. R^2 values of 0.933 (train) and 0.875 (test) were achieved for the best ANFIS system). It should be mentioned that 80% of the data was used for training purpose and the rest was used for testing purpose. Note that, the ANFIS model was modelled in MatLab environment version 7.14.0.739 [49].

5 Results and discussion

The present section describes evaluation of the proposed models in estimating bearing capacity of thin-walled foundation. ANFIS models were constructed according to their effective factors. To evaluate the developed models, based on the previous investigations, performance indices (PIs) should be considered and computed. As highlighted in many studies, e.g., Bejarbaneh et al. [50], R^2 and RMSE are considered as well-known PIs. Their formulas can be found in the other studies, e.g., Bejarbaneh et al. [50] and Sharma and Singh [35]. It is important to note that an ANN or ANFIS model with R^2 of one and RMSE of zero is defined as an excellent model. Calculated PIs of the proposed methods are shown in Table 2. The PI values ($R^2=0.933$, RMSE = 0.075, train, $R^2=0.875$, RMSE = 0.048, test) show high accuracy and

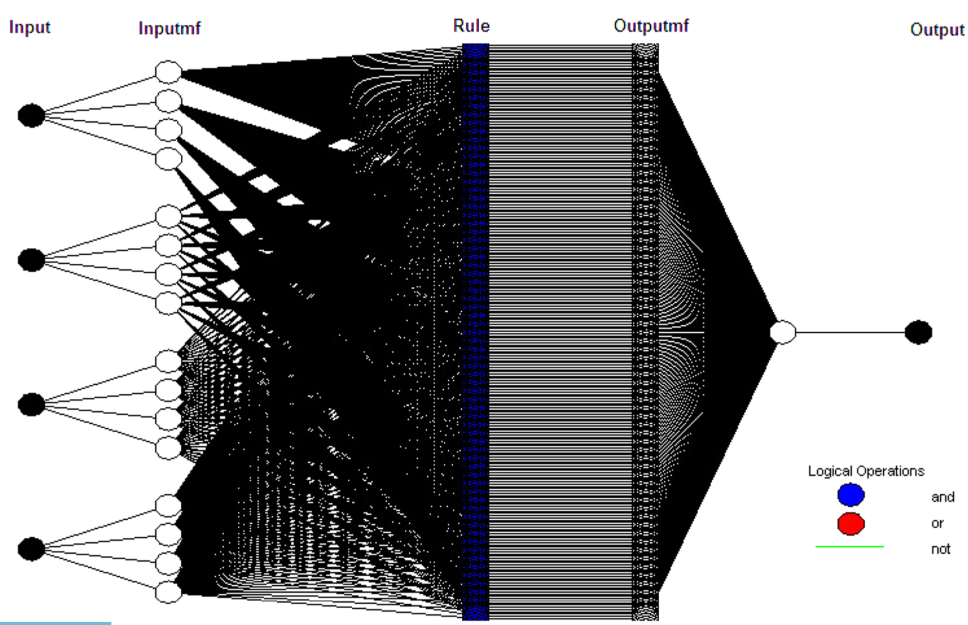

Fig. 6 Suggested ANFIS structure

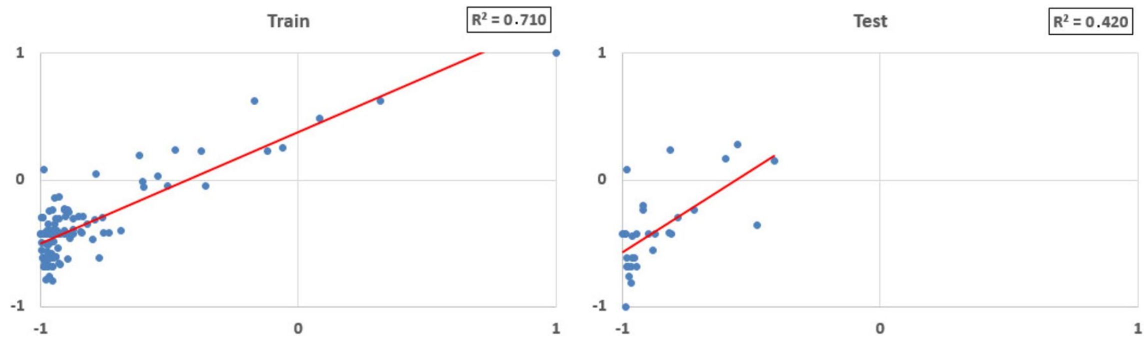

Fig. 7 Results of ANN model for training and testing data sets

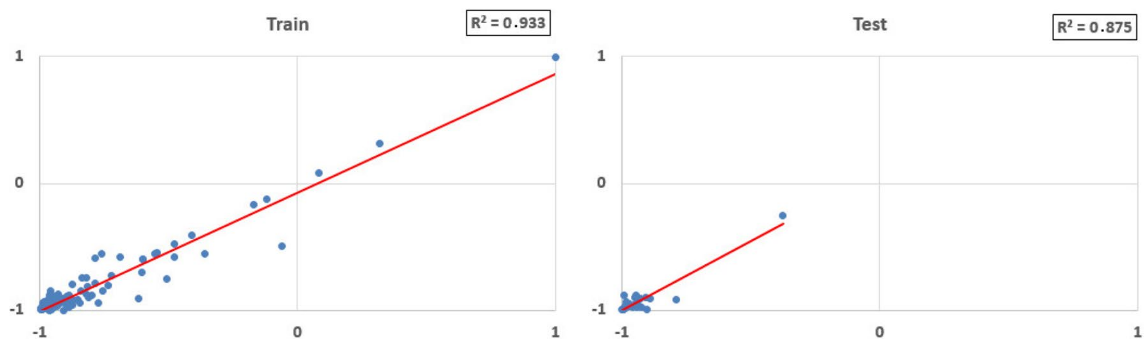

Fig. 8 Results of ANFIS model for training and testing data sets

efficiency level of ANFIS in estimating *Qu* of thin-walled spread foundations compared to ANN model ($R^2 = 0.710$, RMSE = 0.512, train, $R^2 = 0.420$, RMSE = 0.529, test). Rezaei et al. [1] implemented the data set used in this study for developing the conventional and improved ANNs models for predicting *Qu* of thin-walled spread foundations. ANFIS results obtained in this study are better than the conventional ANN model and the ANN model improved with genetic algorithm in both training and testing phases. In addition, in the training process, the proposed ANFIS model in this study outperforms the ANN model improved with particle swarm optimization (PSO) algorithm which is suggested by Rezaei et al. [1]. However, PI results of testing data sets of PSO-ANN model are better compared to ANFIS model. The predicted *Qu* values by ANN and ANFIS models against those of measured *Qu* values are displayed in Figs. 7 and 8, respectively. Overall, it was found that by incorporating ANFIS, performance prediction (i.e., R^2) of ANN model can be increased from 0.710 to 0.933 (for training data sets) and from 0.420 to 0.875 (for testing data sets). In addition, the proposed ANFIS model works better compared to an ANN-based model which was improved with imperialist competitive algorithm and introduced by Nazir et al. [7]. Overall, it can be concluded that ANFIS predictive model is an accurate technique and it can be implemented for assessment on the bearing capacity of thin-walled spread foundations. Nevertheless, further studies are recommended to enhance the reliability of the proposed models.

6 Conclusions

This paper investigated the feasibility of the ANFIS model for predicting the bearing capacity of thin-walled foundation mainly, because to the best knowledge of authors, no reported case was found in the literature in this regard. Footing width, wall length-to-footing width ratio, soil unit weight and internal friction angle of the soil form the inputs of the proposed model. 150 reported cases of footing load tests in the literature were used for model development purpose. The coefficients of determination (R^2) equal 0.933 and 0.875 for training and testing data sets, respectively, recommended that the proposed predictive model can be implemented for predicting the bearing capacity of thin-walled foundation. In addition, comparison between ANFIS results and similar suggested models in the literature which are developed using the conventional ANN and GA-based ANN revealed that ANFIS-based predictive model works much better.

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