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Prediction of Bearing Capacity for Thin-wall Spread Foundations Using ICA-ANN Predictive Model

Ramli Nazir, Ehsan Momeni, Kadir Marsono
Universiti Teknologi Malaysia
Skudai, Malaysia
ramlinazir@utm.my; mehsan23@live.utm.my; akadir@utm.my

Abstract- Thin-wall spread foundations are used in places where the soil has relatively low strength. In this paper, a literature review was conducted to investigate the beneficial effect of providing thin-walls to spread foundations on bearing capacity. Overall, the literature suggest that , in terms of bearing capacity, thin-wall foundation works better compared to surface (simple) foundations. Nevertheless, due to the fact that famous bearing capacity equations are proposed for conventional footings rather than thin-wall footings, developing a predictive model in this regard is advantageous. Therefore, in this study, apart from the relatively extensive literature review, an effort was made to develop a predictive model of bearing capacity for the aforementioned footings using an artificial neural network (ANN) technique enhanced with imperialist competitive algorithm (ICA). For this reason, a relatively large dataset comprising 149 recorded cases of thin-wall footing load tests were compiled from literature. The dataset consisted of footing width, wall to width ratio of footings, internal friction angle and unit weight of soil as well as bearing capacity of footings. Apart from the latter, other parameters were used as input parameters of the predictive model. The correlation coefficient and mean square error equal to 0.95 and 0.01 for testing data respectively indicate the relative reliability of the ICA-based ANN predictive model of bearing capacity for thin-wall spread foundations.

***Keywords*:** Bearing capacity, ICA-ANN, predictive model, thin-wall spread foundation.

1. Introduction

Thin-wall spread foundations are often used in near shore projects where the ground water level is relatively high. They can be also utilized in places where the soil strength is low. The fact that famous bearing capacity equations are proposed for conventional foundations encouraged several researchers to investigate the load-carrying capacity of thin-wall foundations. Among others, Al-aghbari and Mohmedzein (2003) recommended that by providing thin-walls, the bearing capacity of foundations can be increased by a factor in the range of 1.5 to 3.9. However, they mentioned that the amount of this factor depends on footing (including skirts) geometrical and structural properties, soil characteristics as well as the interface condition of the soil-footing system. They suggested adding a skirt factor, $F\gamma$, to Terzaghi bearing capacity equations (see equation 1). They mentioned that skirt factor is a function of foundation base friction factor, skirt depth factor, skirt side roughness factor, skirt stiffness factor, and soil compressibility factor. Nevertheless, they reported that the skirt factor ranges from 1.3 to 1.5.

$$Q_u = \gamma(D_{fs} + D_s)N_q + \frac{1}{2} B'\gamma N_\gamma F_\gamma \tag{1}$$

In equation 1, Q_u and γ are the ultimate bearing capacity and unit weight of the soil respectively; N_q and N_γ are bearing capacity factors. D_{fs} represents the depth of the foundation base below ground level, D_s denotes the depth to the lower edge of the skirt at footing tip, B' shows the total width of foundation including skirts ($B+2B_s$) and the skirt thickness is symbolized by B_s. However, in another study, after numerous laboratory footing load tests, Al-aghbari and Dutta (2008) reported 10% to 70% increase in the sand bearing capacity due to incorporation of structural skirts.

According to their study, due to the presence of thin-walls, there will be an increase in the total length of failure surface and as a consequence more shear strength mobilization is expected. Eid *et al*. (2009) performed laboratory footing load tests in sand and concluded that the existence of walls, which surrounds a surface foundation, significantly reduces its settlement and increases its bearing capacity. In another study, Eid (2012) compared the axially loaded behavior of surface, skirt, and pier foundations rested on poorly graded sand with mean grain size of 0.21 *mm*, maximum and minimum dry unit weights of 17.5 and 15.6 kN/m^3 respectively. The results of his study show that the bearing capacity of thin-wall foundations is almost 93% of that of pier foundations. Nevertheless, his numerical findings indicate that the bearing capacity of skirt foundations is higher than that of surface footing by a factor of 1.4 for D_w/B of 0.5 and a factor of 3 for D_w/B of 2. This is in good agreement with the Al-Aghbari and Mohmedzein`s study. Wakil (2013) reported 1.3 times increase in bearing capacity of thin wall foundations in dense sands when the wall to width ratio is increased from 0.5 to 1.

2. Further Investigations

Nazir et al. (2013) highlighted the suitability of precast thin-wall spread foundations for Industrialized Building Systems (IBS). After conducting a parametric study, they proposed a specific thin-wall foundation known as IBS footing. Their numerical investigation shows the workability of the aforementioned footing from the geotechnical point of view. Figure 1 shows their proposed footing. However, in another study, Momeni et al. (2015[a]) experimentally investigated the load carrying capacities of the small-scale IBS footing (18.75 smaller compare to given dimensions in Figure 1) as well as a surface footing (see Figure 2) with same width (80 mm) in sand with internal friction angle and unit weight of 36° and 15.54 kN/m^3 respectively. According to their results (see Figure 3), for 10% B limited settlement, the IBS footing exhibits higher bearing capacity *i.e.* almost 2 times compared to surface footing.

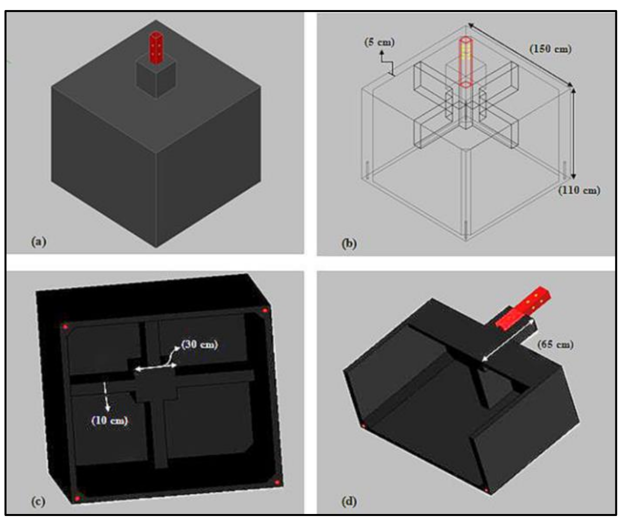

Fig. 1. Proposed IBS footing: a) isometric view, b) Bracing system, c) bottom view, d) cross sectional view (from Nazir et al., 2013)

The same conclusion was reported by El Sawwaf and Nazer (2005) for circular-model footings resting on sand and surrounded by confining cylinders. According to their justification, the existence of such thin cylinders results in transferring the foundation loads to the laterally confined sand and then to deeper sand layers that are more confined than shallow layers due to an increase in overburden pressures. Therefore, the increase in bearing capacity is expected.

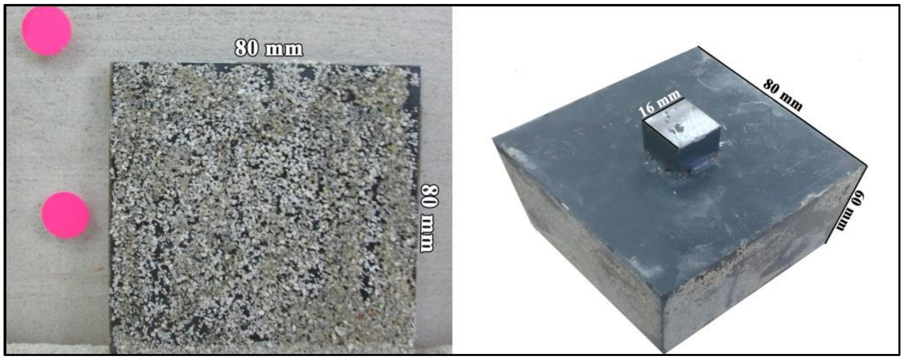

Fig. 2. Surface (left side) and IBS (right) small scale footings (from Momeni *et al*., 2015[a])

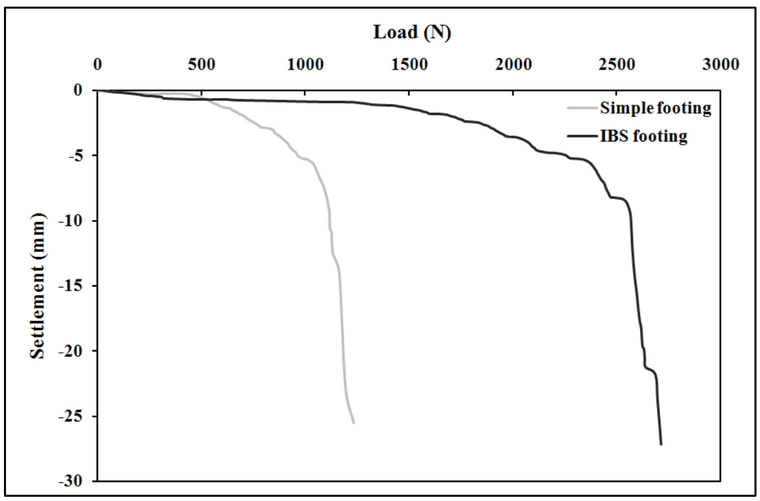

Fig. 3. Load-displacement curves of simple and IBS footings in dense sand (from Momeni *et al*., 2015[a])

Nevertheless, as mention earlier, due to the shortcoming of having well established analytical or semi empirical formula for estimating the bearing capacity of thin-wall spread foundations, developing predictive models of bearing capacity for the aforementioned footings is of interest. In this regard, several studies suggest the feasibility of conventional and improved artificial neural networks (ANN) in predicting the bearing capacity of foundations (Shahin, 2014; Kalinli, 2011; Momeni *et al*., 2014). In general, in these methods, an intelligent system (predictive model) is built with the aid of a database that comprises available recorded cases of footing load tests. This system can be easily recalibrated later for predicting the future data. Apart from reviewing the recent studies on thin-wall spread foundations, the current study also propose an improved ANN-based predictive model of bearing capacity for the aforementioned footings.

3. Artificial Neural Network

Artificial neural networks (ANN) are function approximation tools that are used when finding close form solutions for problems are difficult. As stated by Garret (1994), when the contact nature between some input parameters (independent variables) and output parameter (dependent variable) is unknown, the use of ANNs is advantageous. Among different types of ANNs, feedforward multilayered perceptron (FW MLP) is one of the most popular ANN architectures (Dreyfus, 2005).

In FW MLP, the network comprises a number of layers (input, hidden, output) that consisted of one or several nodes connected to each other through connection weights. Nevertheless, ANNs need to be trained before utilization. One of the most widely used training algorithms in ANN, is back-propagation algorithm (Dreyfus, 2005). In BP ANN, the influential parameters on model output are presented in input layer. The network subsequently starts to feedforward to the next layer *i.e.* hidden layer. Every hidden node in the hidden layer receives the signals from input layers. In fact, each input parameter is multiplied by an adjustable connection weight and subsequently the summation of all input signals in addition to a threshold value known as bias forms the net input of each hidden nodes. On the other hand, the output of each hidden node is determined after applying a transfer function on the net input of the hidden nodes. The same procedure is repeated until the predicted-model output is generated. The predicted output is then compared with the actual output and the error is determined. If the error is more than desirable error, the network back propagates and updates its adjustable connection weights in a manner that leads to better prediction performance. In fact, the essence of using BP algorithm is to optimize the connection weights. It should be mentioned that usually, the squared difference between predicted and actual outputs (MSE) are used for assessing the performance of different ANN models. The aforementioned procedure, which to some extent described the story behind conventional ANNs, is shown schematically in Figure 4.

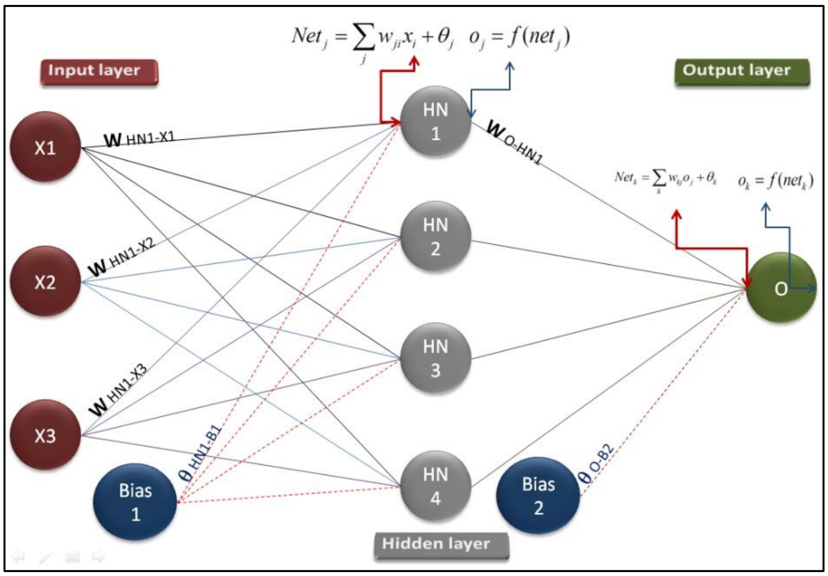

Fig. 4. Typical ANN architecture

3. 1. ANN Improvement by Imperialist Competitive Algorithm

Imperialist competitive algorithm (ICA) is a relatively new optimization algorithm inspired by social-political process of imperialist competition. It was first developed by Atashpaz-Gargari and Lucas (2007). As stated in their study, like other evolutionary algorithms, ICA starts with an initial population. Population individuals (countries) are divided into two categories: colonies and imperialists that in overall shape some empires. Imperialistic competition among these empires forms the basis of ICA.

Owing to ANN major draw backs in getting trapped in local minima as well as their slow rate of learning (*e.g.* Jadav and Panchal, 2012) the use of optimization algorithms in improving the ANN performance has recently drawn attention (*e.g.* Momeni *et al*., 2014; Mohamad *et al*., 2014). Several studies have shown the feasibility of ICA in improving the conventional ANN performance (*e.g.* Duan and Huang, 2014).

In fact in ICA-based ANN, to overcome conventional ANN deficiencies, the adjustable connection weights, instead of conventional back propagation algorithms, are optimized with ICA. For brevity purpose, the mathematical formulation of ICA is not discussed here and it is reported elsewhere (Atashpaz-Gargari and Lucas, 2007). Nevertheless, the flowchart of ICA is shown in Figure 5. It should be mentioned that in these methods, usually a number of iterations (decades in ICA terminology) is used as termination criteria which is a condition that upon being met, ends the iterative procedure.

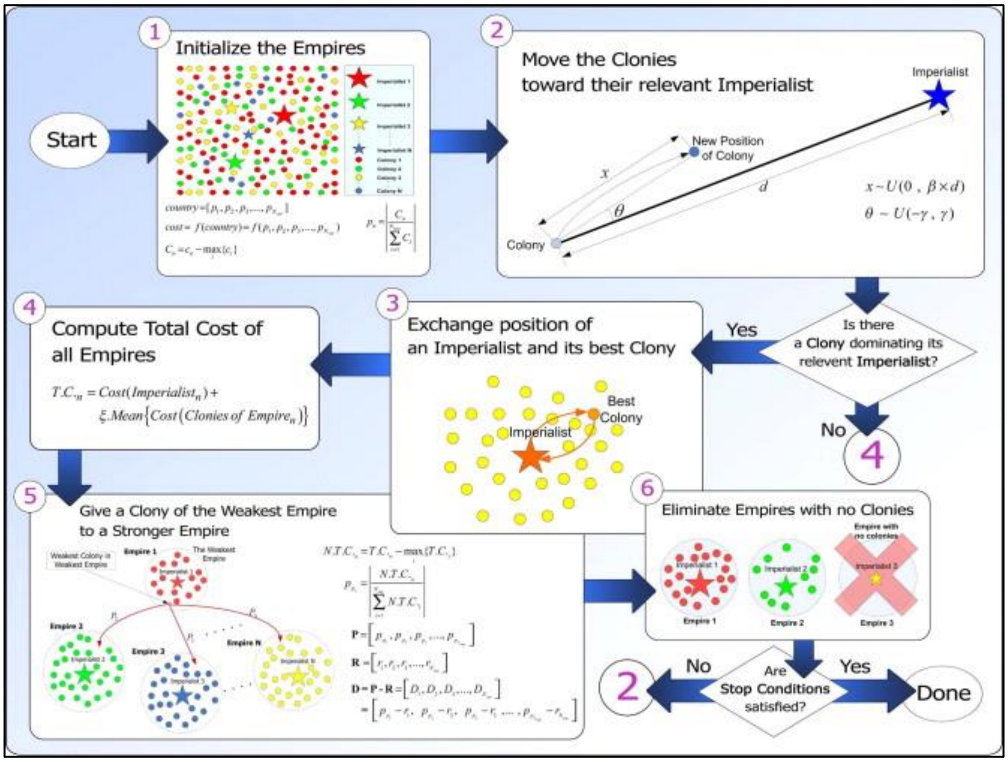

Fig. 5. ICA flowchart (Atashpaz-Gargari and Lucas, 2007)

4. Dataset

To develop a required dataset for establishing predictive model of bearing capacity, through an extensive literature review, a dataset comprising 149 recorded cases of thin-wall footing load tests was compiled from literature (Eid *et al.*, 2009; Tripathy, 2013; Al-aghbari and Dutta, 2008; Wakil, 2013; Villalobos, 2013; Momeni, 2015[c]). It should be mentioned that compiling recorded cases for developing ANN-based models is common in foundation engineering (Kalinli *et al*., 2011; Shahin, 2002). The use of large dataset is of interest mainly because there is no credit for limited dataset in foundations engineering as soil behavior varies from a place to another place. However, there should be a meaningful relationship among predictive model inputs and outputs.

Needless to say that the bearing capacity of thin-wall spread foundations in cohesionless soils is a function of footing width, B, soil internal friction angle, ϕ, soil unit weight, γ, and the footing skirt ratio D_w/B. Therefore, these parameters were used as the input parameters of the predictive models described in the next section. The bearing capacity of the thin-wall spread foundations in cohesionless soils, Qu, was set as the model output. Table 1 summarizes the minimum, maximum, as well as the average values of the dataset used in this study.

Table. 1. Summarized dataset

Model paramters	Dimension	Minimum	Maximum	Average
B	mm	36.55	144	71
D_w/B	-	0	2	0.9
ϕ	-	29.23	44.75	38

γ	kN/m^3	10.34	18.20	15.5
Qu	kPa	17.10	8005	600

5. Model Development Procedure

To construct a relatively reliable ICA-based ANN model, there is a need for determining the optimum ICA parameters. Therefore, a parametric study was conducted to identify the optimum number of decades, countries, and imperialists in the ICA. In conducting the preliminary parametric study, an ICA-based ANN model consisting of 7 hidden nodes in one hidden layer was used. Eighty percent of the dataset was set for training the network and the other 20% was used for testing the performance of the network.

The first series of the parametric study involved determining the optimum number of decades (iterations). Nevertheless, to investigate the importance of decades, a model with 500 countries, 50 imperialist and default decade number of 500 was run. MSE was used for assessing the model performance. Figure 6 shows the importance of the number of decades to the network performance. As shown in this figure, the change in the network performance (MSE) after 200 is not significant and remarkable. Hence, the optimum number of decades was set to be 200.

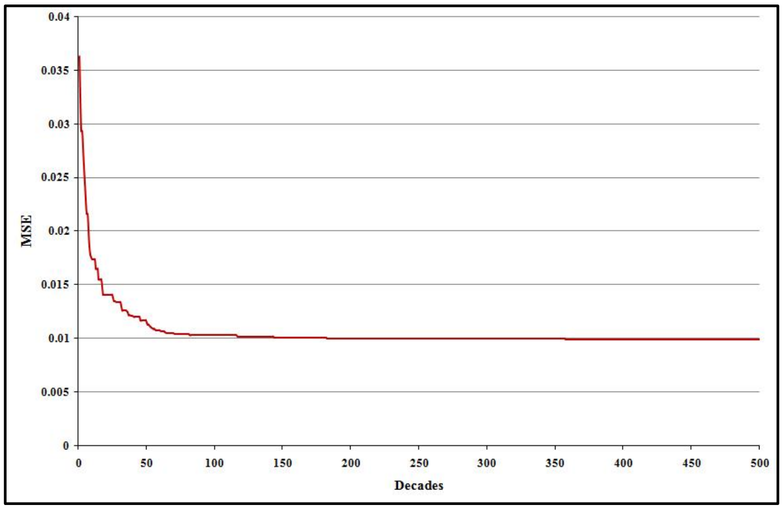

Fig. 6. Decades number effect on the performance of ICA-based ANN model

Subsequent to determining the optimum number of decades, to investigate the effect of the number of countries on the model performance, several ICA-based ANN models with various numbers of countries were run. It is worth mentioning that, at this stage, the numbers of imperialist were set to be 10 percent of the number of countries. Other ICA parameters including θ and ζ (see Figure. 5) were set to be $\pi/4$ and 2, respectively, as suggested in the literature (Atashpaz-Gargari and Lucas, 2007). Table 2 presents the effect of the number of countries (ranging from 150 to 600) on the network performance. As shown in this table, the performance of model No. 2 to 4 is close to each other. Nevertheless, considering correlation coefficient of testing data (R = 0.96), the third model with 250 countries was selected.

Table. 2: Countries number effect on the network performance

Model No	**No of country**	**MSE train**	**MSE test**	**R train**	**R test**
1	150	0.008	0.043	0.84	0.91
2	200	0.016	0.014	0.88	0.92
3	250	0.012	0.039	0.82	0.96

4	300	0.015	0.036	0.82	0.94
5	400	0.026	0.023	0.76	0.90
6	500	0.014	0.042	0.84	0.87
7	600	0.009	0.052	0.81	0.88

Knowing the optimum number of countries, to achieve the optimum number of imperialists, another parametric study was conducted in which the numbers of the imperialists were varied, *i.e.* from 13 to 38, and the other parameters were kept constant. As shown in Table 3, the best network performance was observed when the ratio of imperialists to countries was 1/10, *i.e.* 20 imperialists.

After determining the optimum number of ICA parameters, the network architecture of the ICA-based ANN predictive model (optimum number of nodes) needs to be determined. Using a trial-and-error method, the optimum number of hidden nodes was determined. In the trial-and-error method, the numbers of nodes ranged from 4 to 7. Table 4 shows the performance of the different ICA-based ANN predictive models of bearing capacity for thin-wall spread foundations. To determine the best network architecture, apart from correlation coefficients, the MSE values were also considered. Table 4 indicates that when the number of hidden nodes is set to be 5, the best network performance is expected. According to this table, for the ICA-based ANN predictive model of bearing capacity with 5 hidden nodes, the R and MSE values for the testing dataset are 0.95 and 0.010 respectively.

To investigate the prediction power of the improved ANN models, the prediction performance of the hybrid model was compared with that of a conventional ANN. For this reason, using an ANN model built with 7 hidden nodes in one hidden layer, the bearing capacities of the thin-wall spread foundations were predicted. It is worth mentioning that the learning rate for conventional ANN was set to be 0.1. The model was trained with Levenberg–Marquardt learning algorithm due to its efficiency for training networks which have up to a few hundred weights (Hagan and Menhaj, 1994). However, similar to improved ANN models, in conventional ANN model, 80 percent of the dataset was used for training purpose and the remaining was used for testing the model performance.

Table. 3: Country to Imperialist ratio effect on the network performance

Model No	Count/Imp %	Imp No	MSE train	MSE test	R train	R test
1	5	13	0.017	0.017	0.88	0.87
2	7.5	19	0.013	0.023	0.70	0.91
3	10	25	0.012	0.039	0.82	0.96
4	12.5	31	0.019	0.015	0.85	0.87
5	15	38	0.016	0.043	0.81	0.91

Table. 4: Number of hidden nodes effect on the network performance

Model	Number of nodes	Training		Testing	
		MSE	R	R	MSE
1	4	0.017	0.85	0.83	0.048
2	5	0.016	0.88	0.95	0.010
3	6	0.016	0.87	0.86	0.018
4	7	0.012	0.82	0.96	0.039

6. Results and Discussion

Figure 7 displays the reliability of the developed ICA-based ANN predictive model of bearing capacity for both training and testing datasets respectively. The correlation coefficients equal to 0.88 and 0.95 for training and testing datasets respectively suggest that the proposed model is relatively reliable.

On the other hand, the normalized measured bearing capacities of thin-wall spread foundation versus the predicted bearing capacities using the conventional ANN model for training and testing datasets are also plotted in Figure 7. The correlation coefficients of 0.84 and 0.64 of these dataset show the relatively poor prediction performance of the conventional ANN model. However, as the following figure suggests, the ICA-based ANN model performs better in comparison with conventional ANN. Therefore, this study proposes the use of ICA-based ANN model in predicting the bearing capacity of thin-wall spread foundation. In general, as stated by Shahin (2002), the ANN-based predictive models have the advantage that once the model is trained, it can be used as a relatively accurate, feasible and quick tool for estimating the bearing capacity of foundations without a need to perform any manual work such as using tables or charts. In fact, owing to the stochastic and flexible nature of the ANNs, as discussed by Garret (1994), ANNs can be recalibrated easily as the new data becomes available.

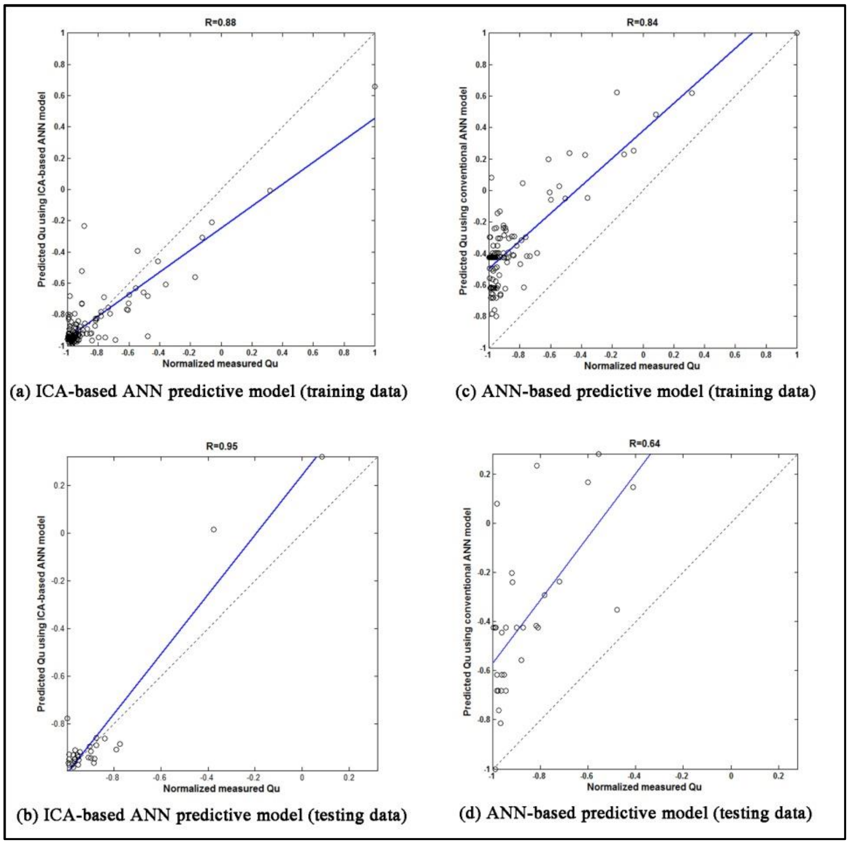

Fig. 7. Prediction performances of ANN-based models

7. Conclusion

A review of recent studies showed the thin-wall spread foundations exhibit considerably higher bearing capacity compared to surface footings. Additionally, using a relatively large dataset, an ICA-based ANN predictive model of bearing capacity for thin-wall spread foundation was proposed. The R = 0.95 for testing data suggests the relative reliability and feasibility of the predictive model.

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