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ARTIFICIAL NEURAL NETWORK BASED PULLOUT CAPACITY PREDICTION FORMULA FOR PLATE ANCHORS IN SAND

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ABSTRACT

The problem of estimating the pullout capacity of plate anchors on sand is very complex and not yet entirely understood. Most of the existing theories for the prediction of pullout capacity of anchor foundation are based on the assumptions of the failure surface. The failure surfaces have been simplified by the investigators to simplify the computation of pull out capacity. Hence, the theoretical result shows great deviation and experimental result. In this study, artificial neural network is used for the prediction of pullout capacity of plate anchors on the sand and have been found to outperform the most commonly-used traditional methods. This paper presents a new hand-calculation design formula for the prediction of pullout capacity of plate anchors on sand based on a more accurate pullout capacity prediction model using artificial neural network. A large database of 583 individual cases of laboratory and field measurements is used to develop and verify the ANN model. Random data division technique is used to divide the data into three subsets: training, testing, and validation sets containing a different percentage of data. Feed Forward Backpropagation algorithm is used to train the network. The ANN geometry (no. of hidden neurons, no. of hidden layers, and training functions) were also varied to optimize the network weight i.e. minimum error and maximum correlation coefficient value. Finally based on the optimum weight combination a design formula is proposed from which pullout capacity can be calculated easily without the need for computers.

Keywords: *Plate anchor, ANN, Back propagation*, *Pull out capacity, Correlation*

1. INTRODUCTION

Anchors are lightweight foundation systems designed and constructed to resist vertical or horizontal uplift resistance or overturning moment acting on structures such as transmission towers, sheet piles, retaining walls, deepwater offshore developments, airport hangars, wind loads on tall structures, buoyancy forces on buried pipelines under water, earthquake, ice forces (Hanna et al. 2014). The pullout capacity of soil anchors is mainly influenced by anchor geometry and local soil conditions. Several researchers have investigated the effect of anchor geometry on the pullout capacity of plate anchor (Hanna et al. 2011). Kumar and Kouzer (2008) have studied the effect of embedment ratio and frictional angle on the pullout capacity of plate anchor in the sand and found that the pullout capacity increases with the increase in the embedment ratio and the frictional angle.

Plate anchor could be installed vertically, horizontally as well as with different inclination to meet the field requirements. Horizontal anchors are generally used to resist vertical uplift forces, while vertical anchors are often used to resist passive resistance in retaining walls, sheet piles, and bulkheads. Hanna et al. (1988) has conducted both experimental and analytical investigation on the pullout capacity of shallow strip inclined plate anchor in the sand and recommended a design procedure for the practicing engineers. However, these methods are inconsistent with each other and with the experimental results.

In the last few years, ANNs have been employed for the solution of a wide range of problems in Geotechnical Engineering. Shahin et al. (2001) have summarized the application of ANN to problems in geotechnical engineering such as bearing capacity of piles, settlement predictions, liquefaction and slope stability. Padmini et al. (2008a) have developed models using ANN, Fuzzy and Neurofuzzy techniques that have been used successfully for the prediction of the ultimate bearing capacity of shallow foundations on cohesionless soils. Wojciechowski (2011) has investigated the application of Artificial Neural Network in soil parameter identification for deep excavation. Padmini et al. (2008b) have applied ANN to predict the pullout capacity of the circular anchor.

This work will present the development of ANN model for the prediction of pullout capacity of plate anchor in sand. The conventional Back Propagation Algorithm is used for training the network. The performance of the ANN model is compared with some of the most commonly used traditional methods. Finally, based on the ANN model an equation is proposed to predict the pullout capacity of plate anchor.

2. METHODOLOGY

The steps used to develop the ANN model to predict the pullout capacity of anchor foundation include the preparation of the database, selection of model inputs, data division and preprocessing, determination of the ANN architecture, model optimization, stopping criteria and model validation.

2.1 Database Preparation

A database consisting of 583 individual cases is used to develop and validate the model. The database includes both chamber, centrifuge model test and field test data. The data cover a wide range of variation in anchor geometry and soil properties. The datasets are collected from the published journals and conference papers. The personal computer based software MATLAB 2015 is used in this work to simulate the ANN operation.

2.2 Selection of Model Inputs

Thorough investigation of the factors affecting the pullout capacity of anchor foundation is very important to propose a successful prediction model. The anchor geometry (L/B), unit weight of soil (γ), friction angle of soil (φ) and anchor width (B) are the most important factors affecting the bearing capacity of shallow foundation in cohesionless soils (Burland and Burbridge 1985). Murray and Geddes (1989) carried out laboratory model tests on both horizontal, vertical and inclined anchors and showed that the embedment ratio (H/B) and the anchor rotation (θ) has also a significant effect on the pullout capacity of anchor foundation. Thus the anchor geometry (L/B), anchor embedment ratio (H/B), unit weight of soil (γ), friction angle of soil (φ), anchor rotation (θ) and anchor width (B) is used in the ANN model as the input variables while the dimensionless pullout capacity factor (N_q) is the single output variable. The data range used to investigate the pullout behavior of plate anchor in sand is presented in Table 1.

Table 1: Data ranges of the input variables used to train the model.

	H/B	L/B	B (mm)	θ (°)	γ (kN/m^3)	φ (°)
minimum	0.47	1	18	0	12.99	30
maximum	12	10.5	2350	90	18.32	48

2.3 Data Division

Data division is one of the most important features that affect the model performance of ANN model. However, there is no precise rule for the data division. Though different investigators have used different methods of data division the most common practice is to divide the data into two subsets: a training set and validation set. The training data set is used to construct the prediction model and the validation data set is used to justify the performance of the model (Twomey and Smith 1997). However, dividing the data into two subsets may lead to overfitting the model (Shahin et al. 2002). In order to avoid overfitting, Stone (1974) suggested using cross-validation as stopping criteria, when sufficient datasets are available. In this investigation, cross-validation was used as stopping criteria. Thus the total dataset was divided into three subsets: training, testing, and validation. There is no clear relationship between the proportions of data used for training, testing, and validation and the model performance (Shahin et al. 2004). Therefore, to obtain the optimum ratio of training, testing, and validation dataset, several random combinations of the three data sets are tried and finally, the proportions of the data points are selected based on the best model performance.

2.4 Data Pre-processing

It is important to preprocess the input and output variables to ensure that all variables receive equal attention during the training process. It aims at transforming the data into a better form for the network to use and reduce the chances that the ANN gets stuck in a local minimum (Demuth 2008). It is essential, as they have to be equal with the limits of the transfer functions used in the output layer. As the pureline and tansigmoid transfer functions are used in the input-hidden and hidden-output layer, respectively. In this investigation input and output variables are scaled between -1.0 and +1.0 using the following equation.

$$x_n = 2\frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \tag{1}$$

Where, x_{min} and x_{max} are the minimum and maximum value of each input variable, respectively.

2.5 ANN Model Architecture

Construction of network architecture is one of the most essential and tedious jobs in ANN model development. It is usually achieved by fixing the number of hidden layers and number of nodes in each layer. The number of nodes used in the input and output layers is restricted by the number of input and output parameters, respectively. Hence the input layer consist of 6 nodes, includes H/B, L/B, B,γ, θ and φ, while the output layer consists of one node representing N_q. Trial and error techniques are used to obtain the optimum number of hidden layers.

Shahin (2002) mentioned that the number of hidden layer nodes should be determined in such a way that the relationship obtained by the ANN can be interpreted in the physical sense. Therefore, the model should have sufficient free parameters (weights) to be able to approximate the functions with the desired minimum error and not having too many so as to avoid overtraining. In order to obtain the optimum network geometry, the model is trained several times by changing the number of hidden layer nodes. Finally, the number of hidden layers and the number of hidden layer nodes are selected based on the best model performance.

2.6 Model optimization

To obtain a model with the best performance and maximum generalization ability, the connection weights between the input–hidden–output neurons are adjusted. The most popular method for finding the optimum weight combination is feedforward back-propagation neural network. Back-propagation neural network can be trained with a wide range of training algorithms available in the literature. In this study, the model is trained using a number of training algorithms and finally, the training algorithm is selected based on the model performance.

2.7 Stopping Criteria

In this study, cross-validation is used as the stopping criteria for training. Smith & Davey, (1993) mentioned that, cross-validation is the most valuable tool to avoid overfitting when sufficient data are available to create training, testing and validation sets. The training set is used to adjust the connection weights and the testing set is used to measure the ability of the model to generalize.

2.8 Model Validation

The performance of the model is validated to ensure that the model has the ability to generalize within the ranges defined by the training data. The coefficient of correlation (r), root mean squared error (RMSE) and mean absolute error (MAE) are used to validate the model performance. The coefficient of correlation is used to determine the relative correlation and the goodness-of-fit between the expected and experimental data. It is a measure of linear relationship between the predictions and the actual values. The most commonly used measure of error is the root-mean-squared error (RMSE) which has the advantage that large errors receive greater attention than smaller ones (Hecht-Nielsen 1990) and the Mean Absolute Error (MA*E*) is a measure of closeness of predictions to actual values.

2.9 Traditional Methods for Pullout Capacity Prediction

It is essential to verify experimental results with theoretical solutions wherever possible as the results obtained from laboratory testing alone are typically problem specific. Besides, it is difficult to perform laboratory tests on each and every field problem combination, so it is necessary to be able to predict soil uplift resistance theoretically for the purposes of design. Many traditional methods are available in the literature to predict the pullout capacity of horizontal and vertical anchors but the traditional methods available to predict the pullout capacity of the inclined anchor is very limited. Among all these traditional methods some most commonly used methods are recalled here to assess the relative performance of ANN.

3. RESULTS AND DISCUSSION

3.1 Effect of Data Division

The performance of the model using different data proportions for training, testing, and validation of the model are presented in Table 2. The first, second and third Figure in the second column of Table 2 is the data proportions assigned to the validation, testing and training sets respectively. This Table shows that the effect of the ratio of training, testing and validation subsets on the model performances is not very significant but the best possible performance is obtained when 70% of the available data is used for the training, 15% for the testing and 15% for the validation of the model. So this ratio is used for the final development of the model. As ANN cannot extrapolate beyond the ranges of data used for training of the model, so the datasets used for testing and validation of the model is kept within the limit of the training datasets. Besides, the Artificial Neural Networks cannot extrapolate beyond the ranges of their training data, so to achieve the best possible model the datasets used for testing and validation sets is kept within the ranges of training datasets.

Table 2: Performance of the ANN model for different data proportions

Category No.	Data proportion and data set	RMSE	MAE	r
1	**80 10 10**			
	Training	8.148	5.350	0.920
	Testing	7.244	4.656	0.908
	Validation	7.470	5.297	0.960
	Overall	7.997	5.276	0.925
2	**70 20 10**			
	Training	7.293	4.216	0.931
	Testing	7.873	4.018	0.933
	Validation	6.498	3.993	0.965
	Overall	7.339	4.154	0.934
3	**60 30 10**			
	Training	7.550	4.583	0.922
	Testing	7.482	4.533	0.940
	Validation	6.221	3.826	0.970
	Overall	7.408	4.493	0.933
4	**70 10 20**			
	Training	7.256	4.179	0.932
	Testing	7.048	3.350	0.911
	Validation	7.586	4.369	0.953
	Overall	7.303	4.135	0.935
5	**60 20 20**			
	Training	7.519	4.598	0.923
	Testing	7.948	4.777	0.932
	Validation	6.398	4.172	0.958
	Overall	7.398	4.548	0.933
6	**50 30 20**			
	Training	7.657	4.285	0.910
	Testing	6.908	3.866	0.953
	Validation	7.129	4.353	0.952
	Overall	7.334	4.173	0.935
7	**50 25 25**			
	Training	7.657	4.285	0.910
	Testing	7.036	3.930	0.953
	Validation	6.958	4.192	0.952
	Overall	7.334	4.173	0.935
8	**70 15 15**			
	Training	7.242	4.169	0.932
	Testing	7.902	4.624	0.951
	Validation	6.951	3.494	0.934
	Overall	7.302	4.136	0.935
9	**60 10 30**			
	Training	7.492	4.558	0.923
	Testing	7.594	4.268	0.901
	Validation	7.084	4.437	0.954
	Overall	7.382	4.493	0.934
10	**50 20 30**			
	Training	7.657	4.285	0.910
	Testing	7.153	3.977	0.946
	Validation	6.892	4.117	0.957
	Overall	7.334	4.173	0.935
11	**40 30 30**			
	Training	7.983	4.946	0.902
	Testing	7.788	4.935	0.938
	Validation	7.752	4.894	0.936
	Overall	7.856	4.927	0.925

3.2 Effect of ANN Model Geometry

This section includes determining the most suitable training function and an optimum number of hidden layers and neurons for the available dataset.

3.2.1 Effect of Training Function

Literature reveals that different types of training functions are available in backpropagation algorithm. To select the appropriate training function for the problem, the performance of the model is checked by training the network with different types of training functions. The training functions used in this study to check the performance of the model is presented in Table 3. The performance of the model using different training functions are presented in Table 4. From this table, it is clear that the Levenberg-Marquardt (LM) training function can produce a better correlation between the observed and predicted pullout capacity factors than any other training functions, as the obtained value of correlation coefficient is very close to 1. The error criteria (RMSE and MAE) for this training function is also the lowest one. So, LM is the most appropriate training function for the available database.

Table 3: Training functions used in backpropagation algorithm

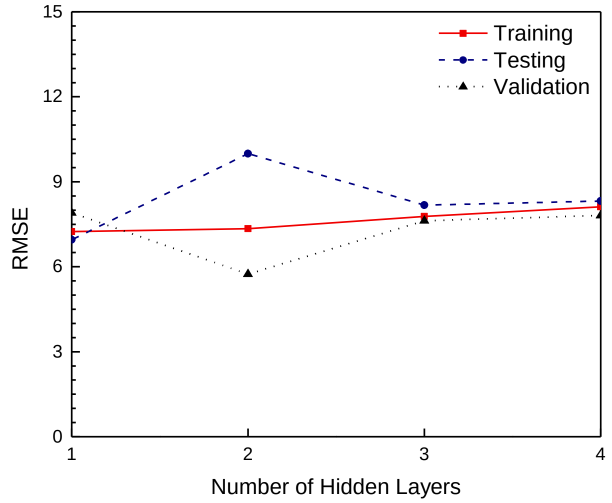
Acronym	Algorithm	
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	Quasi-Newton
SCG	trainscg	Scaled Conjugate Gradient
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGP	traincgp	Polak-Ribiére Conjugate Gradient
OSS	trainoss	One Step Secant
RP	trainrp	Resilient Backpropagation

Table 4: Performance of ANN models with different Training Function

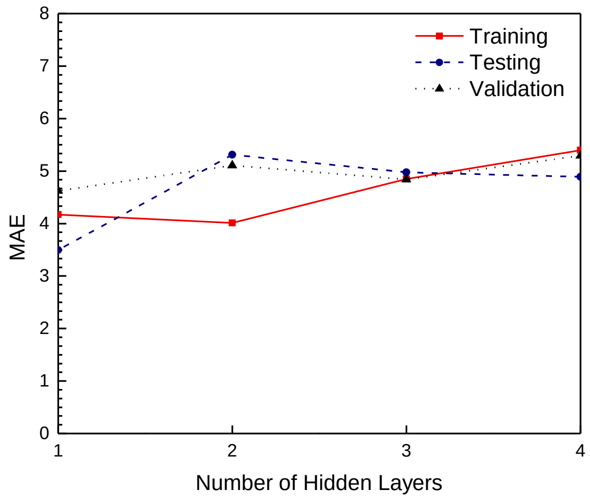
Training Function	RMSE				MAE				Correlation Coefficient (R)			
	Training	Testing	Validation	Overall	Training	Testing	Validation	Overall	Training	Testing	Validation	Overall
LM	7.29	7.19	7.31	7.28	4.21	4.31	4.16	4.22	0.94	0.92	0.92	0.94
BFG	11.79	8.49	10.08	11.11	6.75	5.14	6.01	6.40	0.85	0.86	0.84	0.84
SCG	9.36	9.07	7.77	9.09	5.33	5.51	4.32	5.21	0.88	0.93	0.91	0.90
CGF	11.14	9.61	8.98	10.62	6.33	5.65	4.87	6.01	0.84	0.92	0.89	0.86
CGB	8.05	7.69	7.57	7.92	4.95	4.73	4.39	4.83	0.91	0.96	0.92	0.92
CGP	8.17	7.81	7.64	8.04	4.95	4.76	4.31	4.83	0.91	0.95	0.92	0.92
OSS	9.11	8.47	7.48	8.79	5.69	5.62	4.68	5.53	0.89	0.94	0.92	0.91
RP	8.84	8.77	7.36	8.62	5.13	5.20	4.15	5.00	0.90	0.94	0.93	0.91

3.2.2 Effect of the No. of Hidden Layer

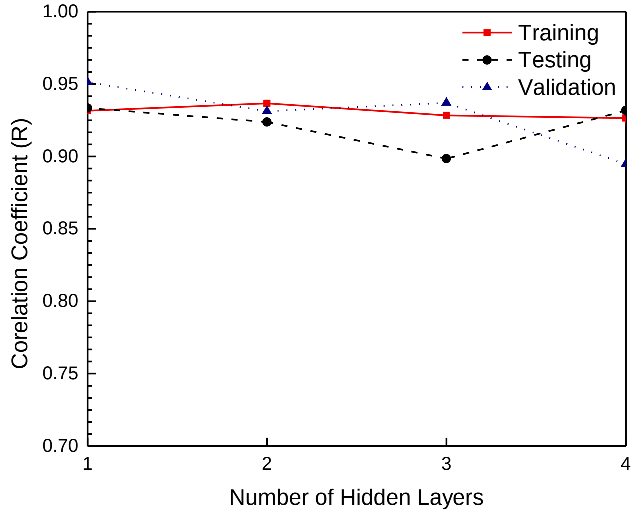
The selection of the number of hidden layers (s) is the most challenging part of the total network development process (Noorzaei et al. 2008). Unfortunately, there are no fixed guidelines available for this purpose and hence this is done by the trial-and-error method (Kartalopoulos 2002). The variation of RMSE, MAE and correlation coefficient (r) with the number of hidden layers are shown in Figure 1(a), (b) and (c) respectively. These Figures indicate that the network having one hidden layer produces minimum errors and shows the best correlation between the measured and predicted pullout capacity factor for both training, testing, and validation subsets. Besides, Hornik et al. (1989) have shown that a network with one hidden layer can approximate any continuous function. Therefore, the network with one hidden layer is the optimal network for the available dataset.



(a)



(b)



(c)

Figure 1: Performance of ANN models with different hidden layers for testing data set (two hidden nodded network)

3.2.3 Effect of No. of Hiddn Neurons

The number of hidden layer nodes should be determined so that the model has sufficient parameters to be able to approximate the functions with the desired minimum error. To achieve this, the model network is trained several times with different numbers of hidden neurons using the Levenberg–Marquardt training algorithm, which is a modification of the Newton method (Martin and Green 1995). The performance of the model using a different number of hidden neurons is presented in Figure 2. It can be observed that the number of hidden layer nodes has a very little impact on the model performance. The RMSE and MAE of the model changes in almost zig-zag ways with the number of hidden neurons. Figure 2 indicates that the network having eight hidden layer nodes has the lowest prediction error in most of the cases but the network having two hidden layer nodes is considered optimal, as the prediction error of the network having two hidden layer nodes is very close to that of the network having eight hidden layer nodes and it can easily be physically interpreted.

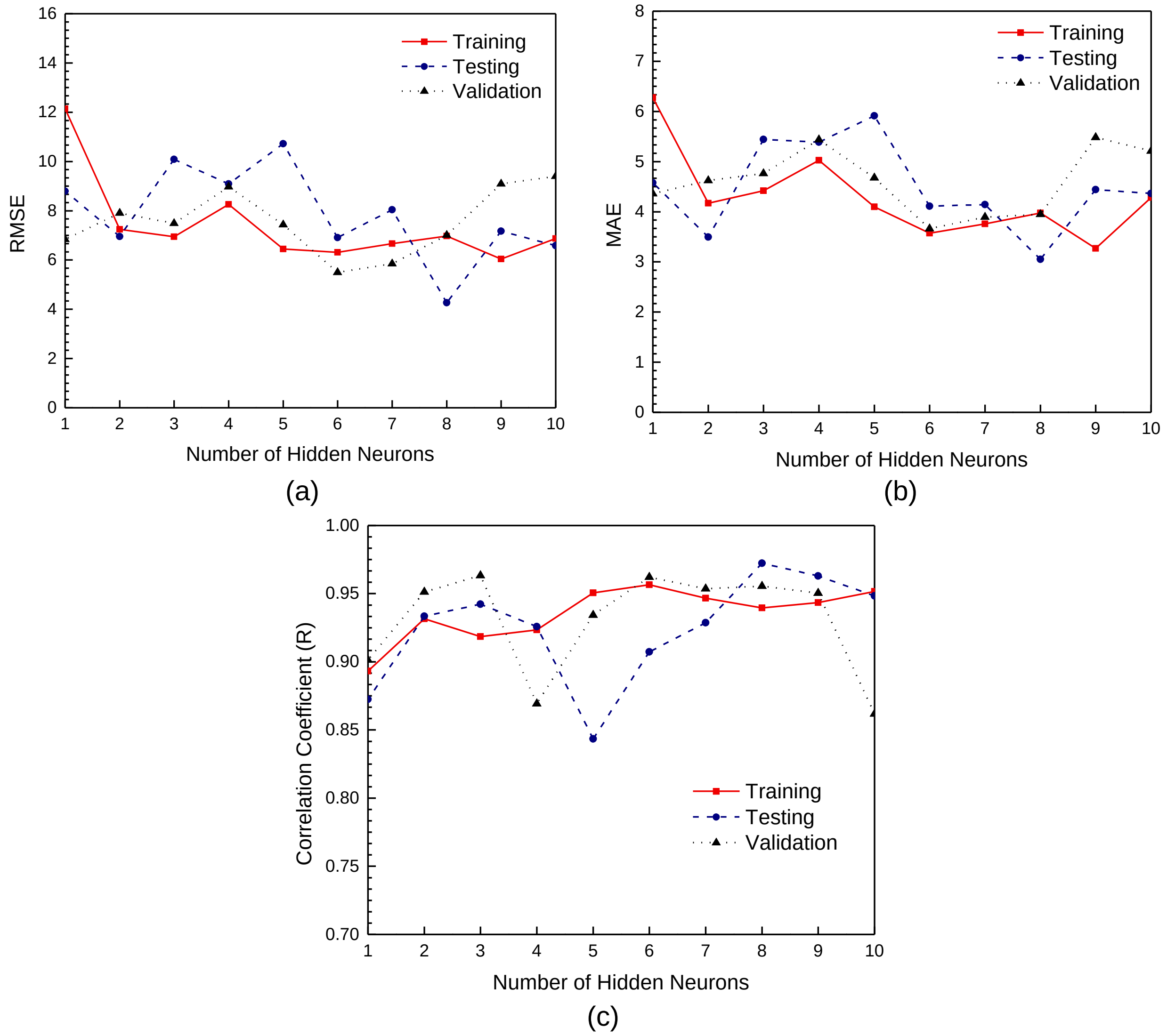


Figure 2: Performance of ANN model with different number of hidden layer neurons for the testing dataset

3.3 Performance of proposed ANN Model

Finally, the 6-2-1 network (6 input layer nodes, 2 hidden layer nodes, and 1 output layer node) with the LM training algorithm is selected as the optimal network. The predictive performance of the optimal ANN model is presented in Table 4. This table indicates that the ANN model performs reasonably well with a coefficient of regression of 0.934, RMSE of 3.494 and MAE of 6.951 for the validation dataset. Besides, the performance of the model is also consistent with the training, testing and validation dataset which indicates the good generalization ability of the proposed model.

Table 4: Performance of the ANN model.

Dataset	MAE	RMSE	r
Training	7.242	4.169	0.932
Testing	7.902	4.624	0.951
Validation	6.951	3.494	0.934
Overall	7.302	4.136	0.935

3.4 Comparison of the ANN model with the Traditional Methods

To increase the reliability of the model, the performance of the model is also compared with some of the most commonly used traditional methods which are presented in Figure 3. To provide an evaluation of the model's predictive abilities, quantitative assessments of the degree to which the model simulations match the actual output are very necessary. The linear correlation between the actual and predicted pullout capacity factors of horizontal, vertical and inclined anchors are shown in Figure 3(a), (b) and (c) respectively. It is seen that the prediction of the ANN model is more close to the measured pullout capacity factor compared to the commonly used traditional methods.

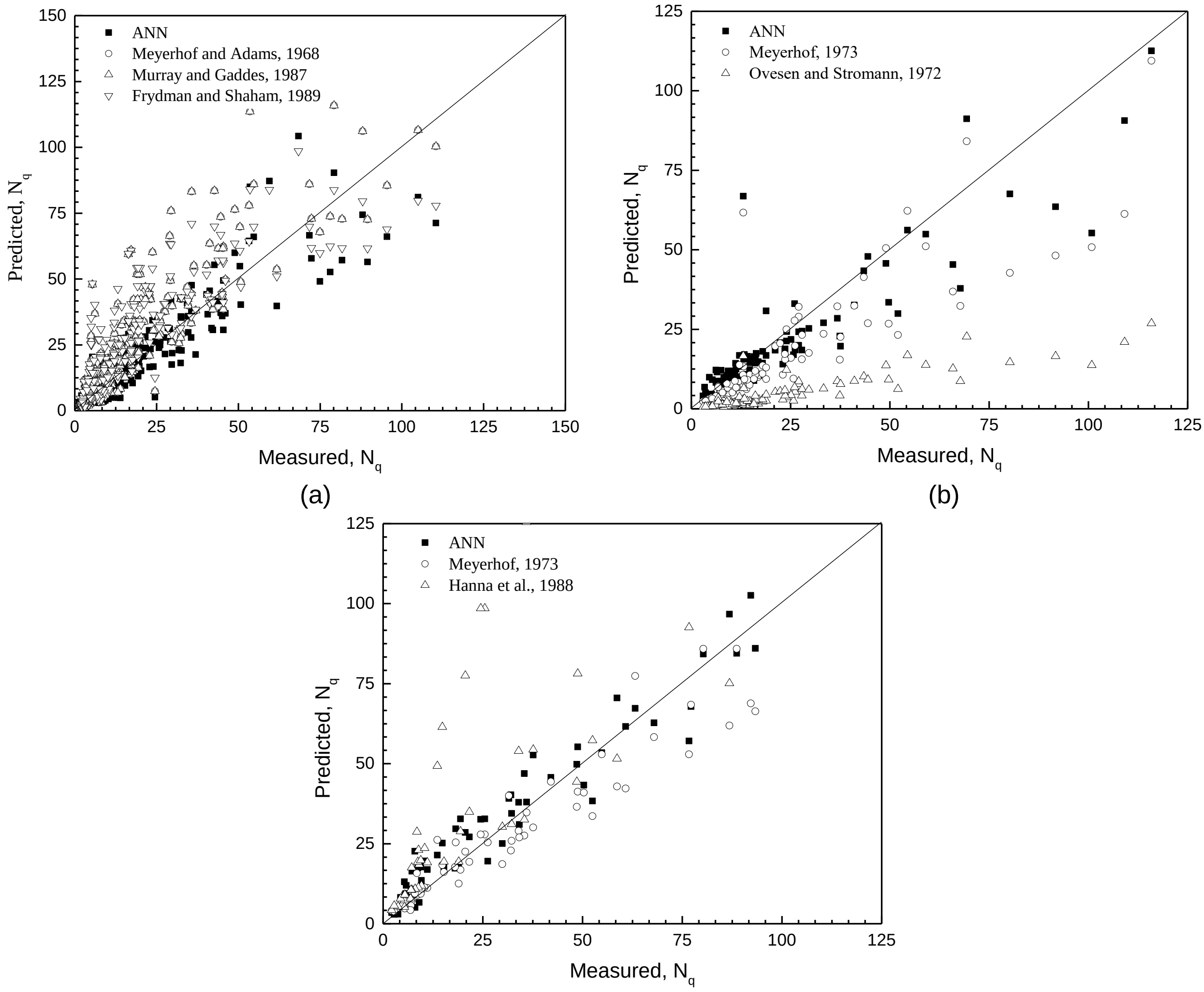


Figure 3: Comparison between the predicted and measured pullout capacity factor of (a) horizontal anchor (b) vertical anchor and (c) inclined anchor.

3.5 ANN Based Formulation:

The pullout capacity factor of anchor foundation can be calculated based on the validated artificial neural network model using the following procedure-

The structure of the optimal Artificial Neural Network architecture is presented in Figure 4. Using this network an equation is developed to predict the pullout capacity factor directly. The input-hidden and hidden-output layer connection weights and the threshold values obtained from the proposed model are summarized in Table 5.

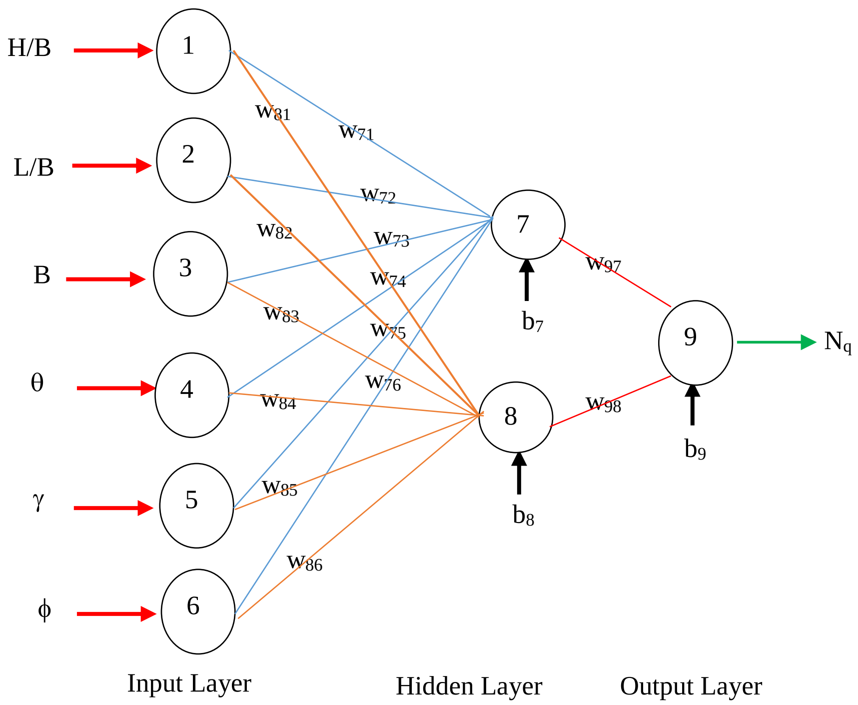


Figure 4: Structure of the proposed Artificial Neural Network

Table 5: Weights and threshold values for the ANN model

Hidden layer nodes	w_{ji} (weight from node i in the input layer to node j in the hidden layer)						Hidden layer threshold (b_j)
	i=1	i=2	i=3	i=4	i=5	i=6	
j=7	-1.340	4.164	0.143	-0.140	-0.214	-1.523	5.184
j=8	0.399	-0.085	-0.012	0.184	0.075	-0.031	-0.966
Output layer nodes	w_{ji} (weight from node i in the hidden layer to node j in the output layer)						Output layer threshold (b_j)
	i=7	i=8	--	--	--	--	
j=9	-0.645	1.000	--	--	--	--	0.559

The small number of connection weights of the neural network enables the ANN model to be translated into a relatively simple formula. As tanh and purelin activation functions are used in the hidden-output and input-hidden layer respectively the pullout capacity factor can be expressed as follows (Equation 2):

$$N_q = b_9 + w_{97}\tanh(x_1) + w_{98}\tanh(x_2) \tag{2}$$

Where,

$$x_1 = b_7 + w_{71}\frac{H}{B} + w_{72}\frac{L}{B} + w_{73}B + w_{74}\theta + w_{75}\gamma + w_{76}\varphi \tag{3}$$

$$x_2 = b_8 + w_{81}\frac{H}{B} + w_{82}\frac{L}{B} + w_{83}B + w_{84}\theta + w_{85}\gamma + w_{86}\varphi \tag{4}$$

It should be noted that, before using Equations 3 and 4, all input variables (i.e. H/*B*, L/B, *B*, θ, γ and φ) are needed to be scaled between -1.0 and +1.0 using equation 1 within the data ranges given in Table 1. As the predicted pullout capacity factor obtained from Equation 2 is scaled between -1.0 and +1.0 and in order to obtain the actual value, this pullout capacity factor has to be rescaled.. Using such a procedure for scaling and substituting the values of weights and threshold levels from Table 5, Equations 2, 3 and 4 can be rewritten as follows:

$$N_q = 99.317 - 40.548\tanh(x_1) + 62.865\tanh(x_2) \quad (5)$$

and,

$$x_1 = 9.45 + 10^{-2}\left[-23.24\left(\frac{H}{B}\right) + 87.66\left(\frac{L}{B}\right) + 0.01(B) - 0.31(\theta) - 8.05(\gamma) - 16.92(\varphi)\right]$$

(**Error! No text of specified style in document.**)

$$x_2 = -1.77 + 10^{-2}\left[6.93\left(\frac{H}{B}\right) - 1.79\left(\frac{L}{B}\right) - 0.001(B) + 0.41(\theta) + 2.81(\gamma) - 0.34(\varphi)\right] \quad (7)$$

It should be noted that these equations are valid only for the ranges of values of *H/B, L/B, B,* θ, γ and φ given in Table 1. This is due to the fact that ANNs should be used only in interpolation and not extrapolation (Minns and Hall 1996).

4. CONCLUSIONS

Though a number of traditional methods are available to predict the pullout capacity of anchor foundation, the results of all these methods are inconsistent with each other as well as with the experimental results. As the ANN model is developed based on the experimental results, it is found to outperform most of the traditional methods. The following conclusions can be drawn from the results of the above study.

i) Random data division technique is used to divide the data into training, testing and validation of the model. The optimum model performance is obtained when 70% data is used for training, 15% data is used for testing and 15% data is used for validation of the model.
ii) The 6-2-1 network (6 input nodes, 2 hidden layer nodes, and 1 output node) with the LM (Levenberg–Marquardt) training algorithm is obtained as the optimum ANN geometry as it shows a better correlation with minimum errors than any other network.
iii) From the comparison between the experimental results and the prediction of the ANN model, it was obtained that the ANNs has the ability to predict the pullout capacity of anchor foundations with sufficient reliability (r=0.935, RMSE=4.136 and MAE=7.302).
iv) Comparison between the predictions of the ANN model and the most commonly used traditional methods has shown that the prediction of the ANN model matched more closely with the experimental results than the prediction of traditional methods for both horizontal, vertical and inclined anchors.
v) Finally, a tractable and relatively simple formula is proposed for the design engineers to predict the pullout capacity of anchor foundation more easily based on the ANN model which is suitable for hand calculation.

The main limitation of the ANN-based proposed formula is that, as the ANN model is based on experimental data and is suitable for use in an interpolative sense, it may not perform well in all design situations. The range of applicability of the ANN-based design formula is constrained by the data used in the model training phase and in order to update the model and make it more accurate in the future, it would be desirable to include additional data so that the model can be re-trained. Despite of having some limitations, the proposed formula can be considered as a powerful, quick and practical tool for prediction of the pullout capacity of anchor foundations on the cohesionless soils as the above study showed that the ANN method can outperform any other traditional methods within the data ranges used to train the model. Besides the predictions of ANNs are based on the experimental results, so there is no need to consider any assumptions. Whereas most of the traditional methods are based on different assumptions.

REFERENCES

Burland, J. B., and Burbridge, M. C. (1985). “ettlement of foundations on sand and gravel.” *In Institution of Civil Engineers, Proceedings*.

Demuth, H. (2008). *Neural Network Toolbox TM 6 User ’ s Guide*. *MATLAB*.

Hanna, A., Foriero, A., and Ayadat, T. (2014). “Pullout Capacity of Inclined Shallow Single Anchor Plate in Sand.” *Indian Geotechnical Journal*, 45(1), 110–120.

Hanna, A. M., Das, B. M., and Foriero, A. (1988). “Behavior of Shallow Inclined Plate Anchors in Sand,.” *Geotech. Spec. Tech, ASCE*, 16, 54–72.

Hanna, A., Rahman, F., and Ayadat, T. (2011). “Passive earth pressure on embedded vertical plate anchors in sand.” *Acta Geotechnica*, 6(1), 21–29.

Hecht-Nielsen, R. (1990). “On the algebraic structure of feedforward network weight spaces.” *Advanced Neural Computers*, 129–135.

Hornik, K., Stinchcombe, M., and White, H. (1989). “Multilayer feedforward networks are universal approximators.” *Neural networks*, 2(5), 359–366.

Kartalopoulos, S. V. (2002). “Elastic bandwidth [optical-fiber communication.” *IEEE Circuits and Devices Magazine*, 18(1), 8–13.

Kumar, J., and Kouzer, K. M. (2008). “Vertical uplift capacity of horizontal anchors using upper bound limit analysis and finite elements.” *Canadian Geotechnical Journal*, 45(5), 698–704.

Martin, S. J., and Green, D. R. (1995). “Protease activation during apoptosis: death by a thousand cuts?” *Cell*, 82(3), 349–352.

Minns, A. W., and Hall, M. J. (1996). “Artificial neural networks as rainfall-runoff models.” *Hydrological sciences journal*, 41(3), 399–417.

Murray, E. J., and Geddes, J. D. (1989). “Resistance of Passive Inclined Anchors.” *Geotechnique*.

Noorzaei, J., Hakim, S. J. S., and Jaafar, M. S. (2008). “An approach to predict ultimate bearing capacity of surface footings using artificial neural network.” *Indian Geotechnical Journal,* 38(4), 515–528.

Padmini, D., Ilamparuthi, K., and Sudheer, K. P. (2008a). “Pullout Capacity Prediction of Circular Plate Anchors in Cohesionless Soils using Artificial Neural Networks.” *12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG)*, Goa, India, India, 1818–1826.

Padmini, D., Ilamparuthi, K., and Sudheer, K. P. (2008b). “Ultimate bearing capacity prediction of shallow foundations on cohesionless soils using neurofuzzy models.” *Computers and Geotechnics*, 35(1), 33–46.

Shahin, M. A., Jaksa, M. B., and Maier, H. R. (2001). “ARTIFICIAL NEURAL NETWORK APPLICATIONS IN GEOTECHNICAL ENGINEERING.” *Australian Geomechanics*, 49–62.

Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2002). “Predicting Settlement of Shallow Foundations using Neural Networks.” *Journal of Geotechnical and Geoenvironmental Engineering*, 128(9), 785–793.

Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2004). “Data Division for Developing Neural Networks Applied to Geotechnical Engineering.” *Journal of Computing in Civil Engineering*, 18(2), 105–114.

Smith, P., and Davey, S. (1993). “Evidence for the competitive exclusion of Aeromonas salmonicida from fish with stress-inducible furunculosis by a fluorescent pseudomonad.” *Journal of Fish Diseases*, 16(5), 521–524.

Stone, M. (1974). “An asymptotic equivalence of choice of model by cross-validation and Akaike’s criterion.” *Journal of the Royal Statistical Society. Series B (Methodological)*, 44–47.

Twomey, J. M., and Smith, A. E. (1997). “Validation and verification.” *Artificial neural networks for civil engineers: Fundamentals and applications*, 44–64.

Wojciechowski, M. (2011). “Feed-forward neural network for python.” *Technical University of Lodz (Poland), Department of Civil Engineering, Architecture and Environmental Engineering*.