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Article

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Piles in sandy soil: A numerical study and experimental validation

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Abstract

Pile foundations are structural elements, highly recommended as a load transferring system from shallow inadequate soil layers into competent soil strata with high performance. There are several theoretical and numerical approaches available concerning the pile bearing capacity in cohessionless soil, however, there is a need for the development of an accurate and more robust predictive model. In this technical note, the details of experimental work to investigate the pile bearing capacity penetrated in dense sub rounded sand as confirmed by scanning electronic microscopy (SEM) tests with a Dr of 85% is discussed. A testing programme comprised of three types of model piles (steel open-end, steel closed-end and concrete pile). The piles slenderness's ratios (lc/d) are varied from 12, 17 and 25 to simulate the behaviour of both flexible and rigid pile designs. In addition, a novel approach of multi-layered artificial neural networks (ANNs) based on the Levenberg-Marquardt approach (LM) was developed. Finally, the accuracy of the developed ANN model was evaluated using independent test data. The results indicated that the optimised model is highly suited for predicting of the pile-load capacity for the described soil with correlation coefficient, R and root mean square error (RMSE) of 0.97095 and 0.074025 respectively.

Keywords: Pile foundation; slenderness ratio; artificail neural network; cohessionless soil.

1. Introduction

Pile foundations are slender structural elements underneath superstructures commonly used as load transferring systems at sites encountering inadequate sub-soil layers. Pile bearing capacity and associated settlement at certain applied loads play a key role on the pile foundation design process [1]. Bearing capacity is normally achieved by dividing the ultimate applied load by a certain factor of safety depending on the building serviceability requirements

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[2]. However, Murthy [3] stressed that if the above criterion is adopted for certain piles in specific soil conditions (e.g., large diameter pile penetrated in clay soil), then the measured settlement from the applied working load may be excessive.

Currently, in the absence of reliable pile-load test data, the on-site full-scale pile load-settlement test is normally conducted to precisely evaluate the pile bearing capacity and associated settlement [1, 2]. Being expensive, time consuming and due to the difficulty of obtaining undisturbed soil samples, alternative predictive approaches such as Standard Penetration Test (SPT), Pressure Metre Test (PMT) and Cone Penetration Test (CPT), are normally adopted to assess the pile bearing capacity [4, 5].

Moreover, Shahin [6] addressed the feasibility of the recurrent neural networks (RNN) by using cone penetration test data to model steel piles subjected to axial load. Six model input parameters were found to be the most important factors affecting the steel pile bearing capacity, these parameters comprised from the diameter of pile, the pile effective length, the weighted average cone point resistance over the pile tip zone of failure, the weighted average friction resistance over the pile effective depth, the weighted average cone point resistance over the penetrated depth and the weighted average friction ratio over the pile embedment depth.

The current technical note has been devoted to fill the gaps in literature and to differentiate from the previous studies in terms of the experimental tests and the ANN approach in three main aspects:

- Conducting experimental works by using three types of model piles (steel open end, steel close end and concrete), having three slenderness's ratios (12, 17 and 25) to develop the ANN database for model inputs and output parameters;
- Relatively simple model input parameters are required to train the network without the need for in-situ tests such as pile-load test (PLT), cone penetration test (CPT) and standard penetration test (SPT);
- Development of MATLAB code using the Levenberg-Marquardt approach (LM) to the implementation of an ANN model as it is the most reliable method in comparison to all computational intelligence approaches [7].

Nomenclature

LM	Levenberg-Marquardt
μ	combination coefficient
I	matrix identity
l_c/d	slenderness' ratio
SEM	scanning electronic microscopy
SP	poorly graded sand
w_j	weight
b_j	biases
RMSE	root mean square error
USCS	unified soil classification system

2. Experimental study

The sand used in this study is dense sand. As confirmed by the scanning electronic microscopy (SEM) observation, Fig. 1a and b at 500µm and 200µm respectively, the sand was composed of sub-rounded particles. Based on the Unified Soil Classification System (USCS), the sand is classified as a poorly graded (SP). Moreover, the sand coefficient of uniformity, Cu and the coefficient of curvature, Cc are 1.786 and 1.142 respectively. It should be mentioned that the dense sand was prepared in four layers placed at about 32cm thick in a calibration chamber with internal dimensions 90cm by 90cm and 125 cm in depth with each layer densified using a vibratory compactor. The test was run following the procedure as recommended by Akdag and Özden [8]. A repeatable process of compaction was utilized where the sand chamber was divided in 36 equal segments. Moreover, to maintain the influence of the grain size distribution on the combined pile-soil interaction, the ratio between the proposed pile diameter to the medium diameter (d50) of the sand specimen should be (45) [9]. To minimize the scale effect and to give precise simulation of the sand-pile interaction, it has been proposed by Remaud [10] that the ratio must be at least (60) times pile diameter. Whereas, Taylor [11] stated that the ratio should be at least (100). In this research study, the ratio between pile diameters to minimum medium diameter (d/d50) is about (133) as shown in Fig. 2, matching the scaling law criteria.

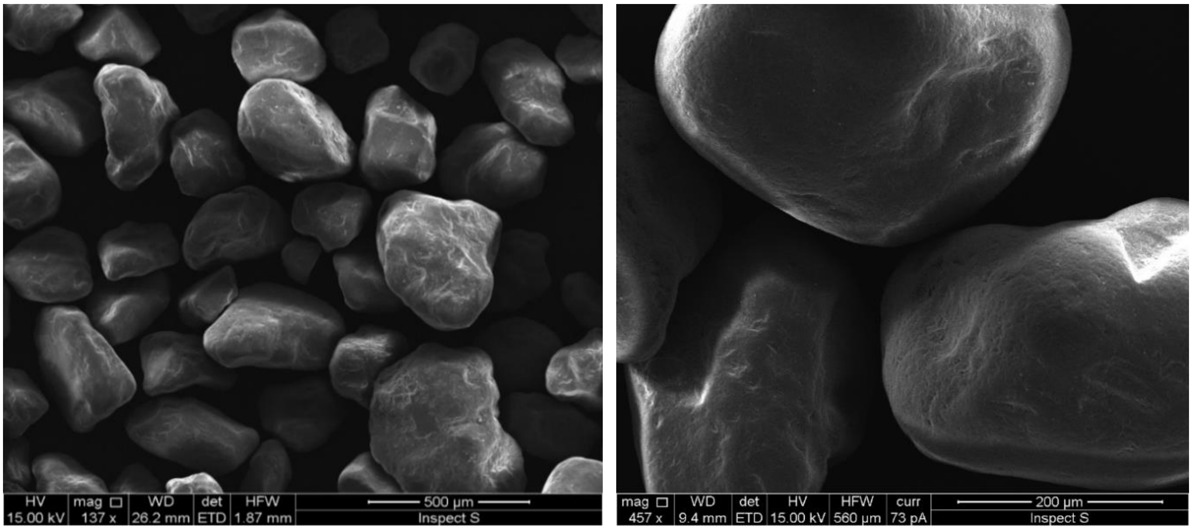

Fig. 1. (a) and (b). Scanning electronic microscopy, (SEM) test of the sand specimen.

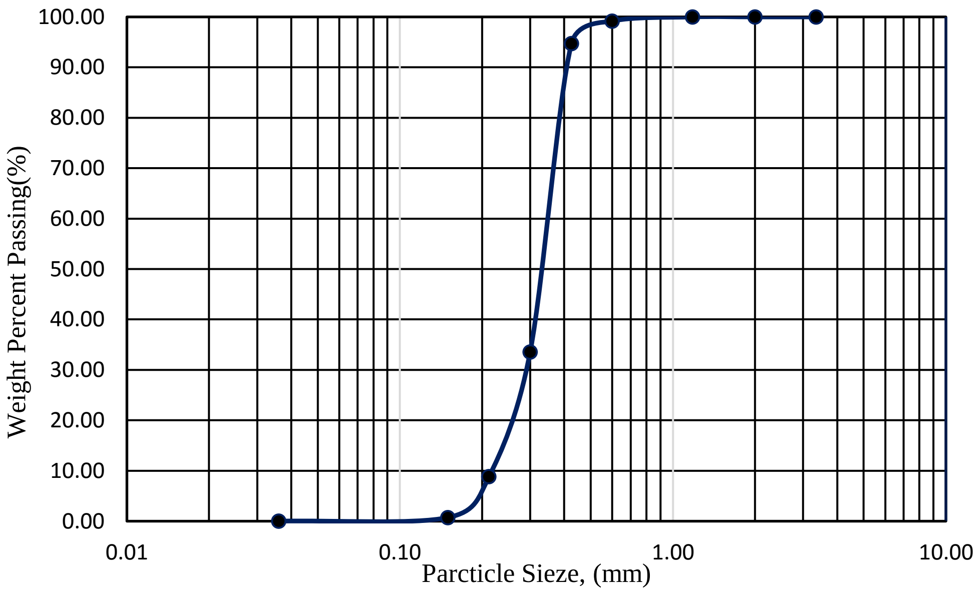

Fig. 2. Particle size gradation curve of the sand sample.

3. Model piles

Three types of circular steel open end, circular steel close end and square concrete piles were used as models. Pile aspects ratios, (Lc/d) were varied from 12, 17 and 25 with 40 mm diameter/square section used in the current study to simulate the behaviour of both rigid and flexible piles. A pile having a slenderness ratio more than 23 behaves as long/flexible pile, while, the model pile having a slenderness ratio less than 23 behaves as short/rigid pile [12]. The pile penetration depths are 480mm, 680mm and 1000mm respectively. It should be noted that an extra length of about 50mm was employed to serve as the load support and to minimize the contact load with the soil surface with the model pile head. Furthermore, the pile wall thickness is 1.5mm giving d/t ratios of 26.67 within the range of (15-45) for the open end model pile as recommended by Jardine and Chow [13].

4. Construction of the (ANN) model

In this paper, multi-layered back-prorogation ANNs were used to develop a numerical solution for the model inputs and output by applying the Levenberg-Marquardt technique (LM). The adopted (LM) approach is a second order non-linear optimization tool. In addition, the (LM) algorithm is employed in this study as it is more reliable and a faster approach than all other Artificial Neural approaches [7].

Furthermore, the typical ANN structure comprises of a series of processing elements, or nodes, that are usually assembled in different layers: an input layer, one or two hidden layers and one output layer. The connection weight wij is used to linear link the processing elements between each specific layer. Each of the model input parameters, xi form each processing element and is multiplied by a connection weight. The weighted value from each of the model input parameters and a threshold value, θi is either subtracted or added [14]. The combined model input is then passed to the next layer through a specific transfer function (i.e. liner, or non-linear) to generate the adjustable output passed as input to the other certain node for the next layer [15].

In the present study, the optimum number hidden layers and the output layer is 1 with 10 hidden nodes. In addition, the activation functions utilized in the hidden layer and the output layer are log-sigmoid and linear function as described in Equations (1 and 2).

The Levenberg-Marquardt (LM) algorithm has to be trained in order to get the best approximate values of the biases b j and the connections weights w i j. It should be noted that a bias is much like connection weights except that they have a value of 1, but they are not necessarily to be included in Equations 1 and 2. The main objective from the training of the ANN is to reduce the mean square error (MSE) between the measured (target) and the estimated (output) values, as described in Eq. 3 [16]. In this study, the optimum (MSE) is selected during the training process at the best validation performance of 0.0040617.

$$y = \sum_{1}^{5} w_j^{(2)} \; z_j \pm b^{(2)} \qquad 1$$

$$Z_j = \frac{1}{1 + exp\ (\sum_1^5 \pm w_{ij}^{(1)}\, x_i \pm b_j^{(1)})} \qquad 2$$

$$MSE = \frac{1}{n}\left(\sum_{1}^{n} (measured(ij) - predicted(ij))^2\right) \qquad 3$$

5. Pre-processing and data classification

The experimental database used comprises 374 recorded load-settlement curves obtained from 9 pile load-tests. To construct the ANN model and to eliminate the over-fitting, the database is randomly divided into three subcategories: training, testing and validation [15]. The training set objective is to create the network and fit the model, the testing set have no effect on training and so provide an independent check of network performance during and after the training process and the validation set is used to estimate the prediction error for the optimum ANN model as reported by Shahin [15]. In total, 70% of the database (262) was used for the training and 15% (56) was taken for the testing and the remaining 15% (56) was utilized for the validation set respectively.

6. Model inputs and output

Five factors were considered the most significant inputs parameters affecting the pile bearing capacity and the ANN model architecture. These factors were, applied load (P), pile slenderness's ratios (lc/d), pile axial rigidity, (EA), pile effective length, (l), sand-pile friction angle, (δ), the model output was the pile settlement. A summary of the model inputs and output are illustrated in Tab. 1.

Table 1: Input and output statistics for the ANN model

Data Set	Statistical Parameters	Input Variables					Output
		Load (kN)	Slenderness ratio Lc/d	Pile length, (m)	Pile axial rigidity, (EA), (MN)	Sand-pile friction angle, δ	Settlement, (mm)
All data	Maximum	6.533	25	1	251.2	30.2	14.243
	Minimum	0.031	12	0.48	47.2	24.6	0.002
	Mean	3.596	12.989	0.719	195.018	26.142	6.558
	Std. dev	1.796	5.376	0.215	91.252	2.504	4.376
	Range	6.502	13	0.52	204	5.6	14.241
Training Set	Maximum	6.533	25	1	251.2	30.2	14.2435
	Minimum	0.031	12	0.48	47.2	24.6	0.0025
	Mean	4.012	18.023	0.721	196.696	26.097	6.555
	Std. dev	1.97	5.3	0.212	90.44	2.4827	4.568
	Range	6.502	13	0.52	204	5.6	14.241
Testing Set	Maximum	6.521	25	1	251.2	30.2	13.76
	Minimum	0.087	12	0.48	47.2	24.6	0.0267
	Mean	4.11	1218.625	0.745	192.914	26.2	6.08
	Std. dev	1.96	5.535	0.2214	93	2.552	3.905
	Range	6.435	13	0.52	204	5.6	13.738
Validat-ion Set	Maximum	6.533	25	1	251.2	30.2	13.888
	Minimum	0.0652	12	0.48	47.2	24.6	0.0026
	Mean	3.8941	17.196	0.688	189.271	26.3	7.5121
	Std. dev	1.9	5.577	0.223	94.648	2.598	4.1365
	Range	6.4677	13	0.52	204	5.6	13.885

7. Results and discussion

A compression between the experimental pile-load tests and the predicted ANN model results is discussed in this section. The ANN model used in this study is based on the Levenberg-Marquardt (LM) training function. As mentioned earlier, the database is divided in three subsets, training, testing and validation. However, for validation the accuracy of the ANN model has been independently checked using the testing database. The ANN model yielded good agreement between the observed and the predicted pile load carrying capacity, and the performance of the model in the training and validation are illustrated in Figs 3, 4and 5 respectively. The ANN output results reveal that there is excellent agreement between the observed and simulated results for all model piles (steel open-ended, precast concrete piles and the steel closed ended with aspect ratios varying between 12, 17 and 25. The results also prove that the adopted ANN approach has the ability to predict the high non-linear relationship of the pile-load settlement.

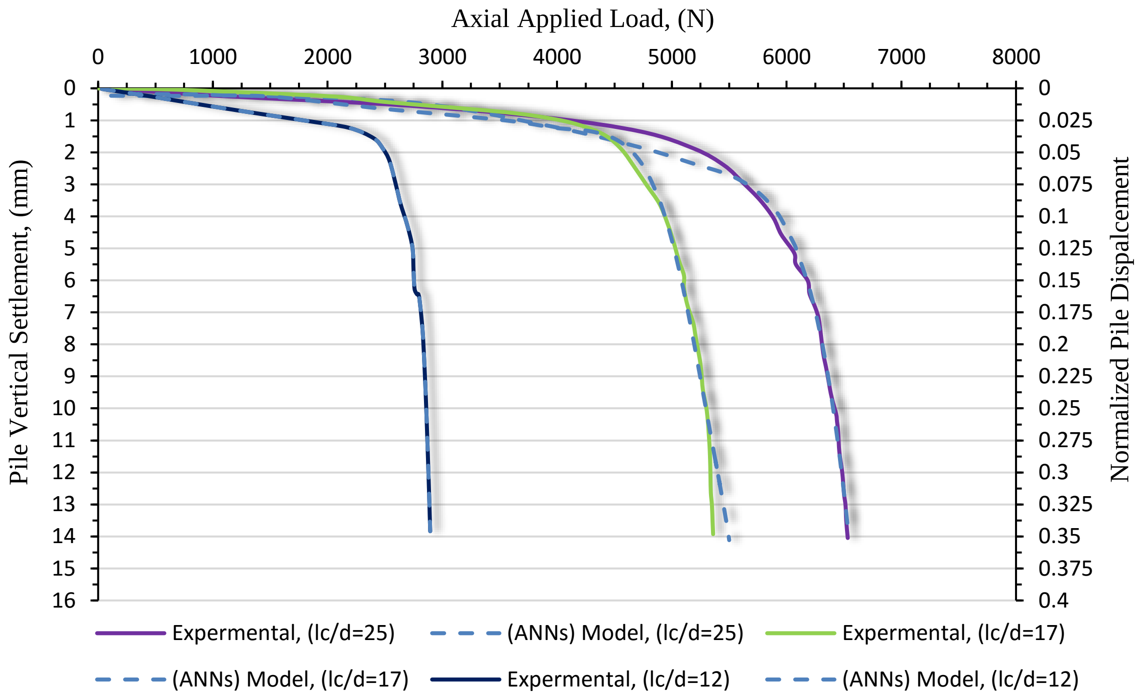

Fig. 3. Comparison between measured and predicted (ANNs) model for the concrete piles.

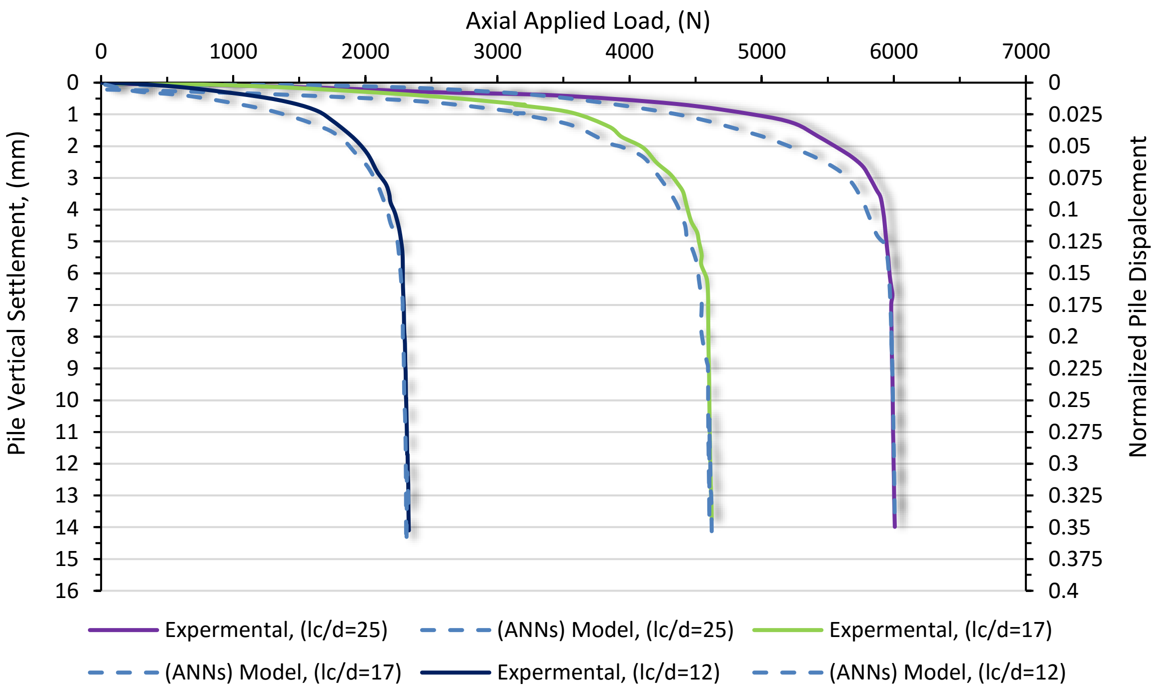

Fig. 4. Comparison between measured and predicted (ANNs) model for the steel close-ended piles.

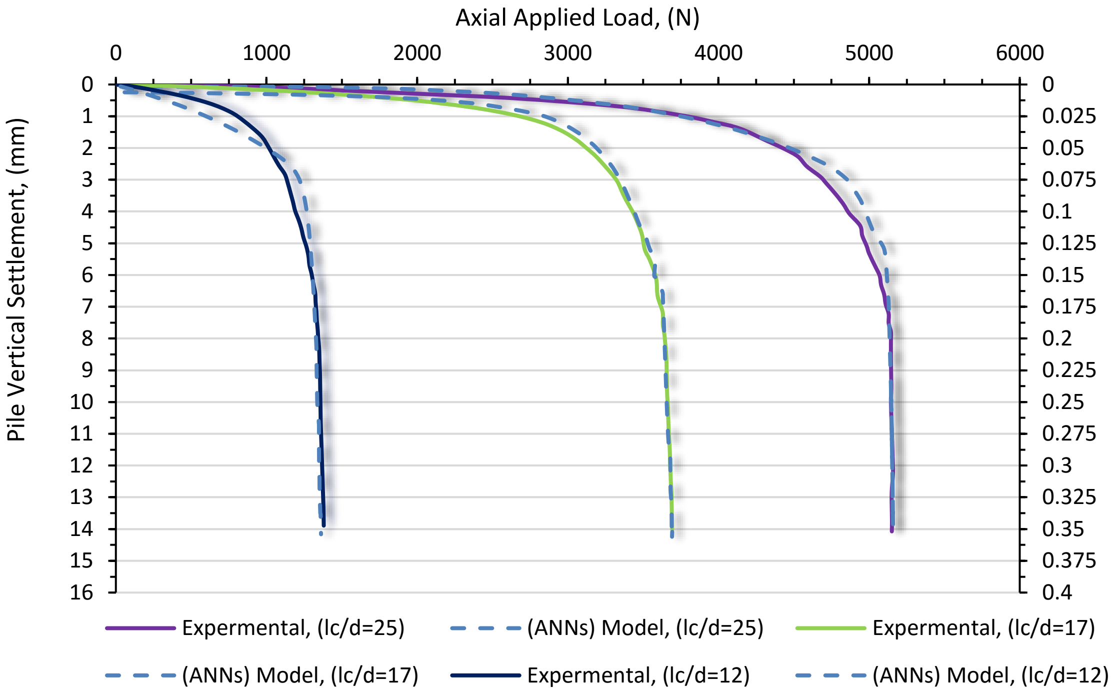

Fig. 5. Comparison between measured predicted ANN models for the steel open-end model piles.

Moreover, the generalisation ability and efficiently of the ANN that best matched of the measured pile-load settlement for the testing set is expressed in terms of the correlation coefficient, R and root mean square error, RMSE as shown in Fig 6 at a 5% level of significance. It can clearly be realized that the developed neural network model is successful in its ability to simulate the high nonlinear relationship between the target and the fitted value with R and RMSE values of 0.97095 and 0.074025 respectively.

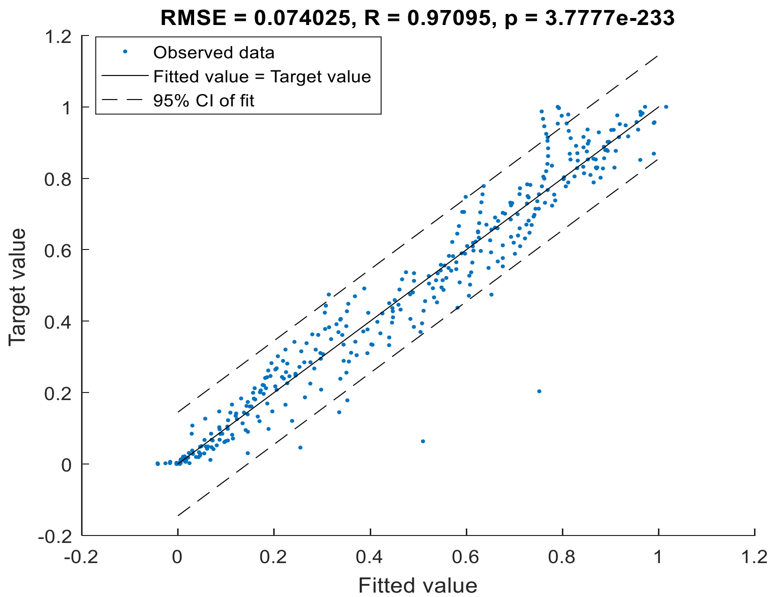

Fig. 6. Regression calibration curve between targets versus fitted values for the optimum ANN model at a 5% level of significance.

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