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Proposing a Model to Predict the Bearing Capacity of Hammered Piles Using Genetic and Lorenberg Algorithms

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Abstract

This research aimed to predict the bearing capacity of hammer piles using genetic and Lorenberg algorithms and Machine Learning (ML) methods. The studied samples as input parameters in this research include the parameters of soil internal friction angle, soil elastic modulus, pile diameter (D), and pile length (L) as input to the considered models, and the target in this research is the bearing capacity of the pile. 15% of the input data were considered training data, 15% validation data, and neural network training was done. At first, using the trial and error method, the number of hidden layers was determined as 6, and the target network was trained using the genetic algorithm. The results of training the target network using the genetic algorithm showed that the regression coefficient obtained from the model prediction for the learning and validation data was 99. 0 has been obtained. The results of neural network training using Lorenberg's algorithm showed that the correlation coefficient between training and validation data is 0.96548 and 0.993889, respectively. By comparing the results of the neural network with the laboratory data, it has been observed that the genetic algorithm can make the desired prediction better.

Keywords: Neural network, Impact pile bearing capacity, Genetic algorithm, Lorenberg algorithm.

1 | Introduction

Piles are one of the most essential components to construct buildings, bridges, and tunnels. Piles are used when the soil has a low bearing capacity, and not using them can destroy the building and cause severe damage to the structure. One of the critical and influencing factors on the bearing capacity of piles is the soil's

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properties and parameters and the pile's geometry. The piles used should be such that they pass through the soil layers with low capacity and enter stable layers. Therefore, studying piles' geometrical properties and specifications has been an important issue affecting their bearing capacity, and it is necessary to conduct studies around them [1], [2].

The purpose of research by Benali et al. [3] was to determine the load capacity of hammer piles in sandy soil using Artificial Neural Networks (ANNs). For this purpose, he used two ANNs: a Perceptron multilayer neural network and a neural network. His inputs for this study were the length and diameter of the pile, the modulus of elasticity, the angle of internal friction of the soil as input, and the bearing capacity of the pile as output. To train the network, he used actual pile tests conducted by consulting engineers (Omran Rahor Research) during the engineering study of dry tank foundations in the Hormozgan region. In addition, several load-bearing capacity tests of piles with smaller dimensions were performed in the laboratory according to the definition of more input. After validating the model with experimental values, he concluded that the model successfully predicted the bearing capacity of piles.

Harandizadeh et al. [4], using PLAXIS finite element software, investigated the factors affecting the estimation of pile-bearing capacity. They found that soil adhesion parameters, friction angle, and interfacial resistance parameters were relatively the most important, while Poisson's ratio and expansion angle had the least effect. In addition, the optimal conditions provided by Taguchi's method are in good agreement with the experiments.

In research, Tahay et al. [5] estimated hammer pile bearing capacity using Machine Learning (ML) models. The bearing capacity of driven piles is an essential parameter in the design of the structure's foundation. In the present study, three ML methods, i.e., Adaptive Neural Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and ANN, were used to estimate the bearing capacity of driven piles. The limited engineering parameters of piles and soils were obtained from 75 test sites in Vietnam. These parameters include pile diameter, pile length, tensile strength of main longitudinal steel rebar, compressive strength of concrete, average SPT index at the tip of the pile, and average SPT index in the pile body. Validation of the methods was confirmed using standard statistical measures, i.e., Root Mean Square Error (RMSE) and correlation coefficient (R). The results show that all the proposed models have a good potential in correctly predicting the bearing capacity of excavated piles on training data ($R>0.93$) and test data ($R>0.88$), but the performance of the SVM model is the best ($R = 0.985$ for training and $R = 0.958$ for testing); Therefore, the SVM model can be used to accurately predict the bearing capacity of driven piles for the appropriate design of civil engineering structure foundations.

Moayedi et al. [6], researched predicting the ultimate bearing capacity through different evolutionary models and neural networks. In the present study, various models of evolutionary artificial intelligence and ML, including optimal ANN, Genetic Algorithm optimized with ANN (GA-ANN), Particle Swarm Optimization with ANN (PSO-ANN), Differential Evolution Algorithm (DEA), fuzzy Adaptive Neural Inference System (ANFIS), Generalized Regression Neural Network (GRNN) and Feed Forward Neural Network (FFNN) were optimized and applied to predict the ultimate bearing capacity (Fult) of shallow foundation in double-layer soil conditions. Due to many input variables such as (upper layer thickness/footing width ratio (h/B), footing width (B), and top and bottom soil properties), it is difficult to find a reliable solution for such a complex engineering problem. Most of the available solutions are based on very limited empirical work.

In a study, Kardani et al. [7] evaluated the group effect's simulation on the bearing capacity of piles dug in granular soil using load transfer functions. Load transfer functions, such as t-z and q-z curves, and numerical methods implemented by computational programs are widely used in the geotechnical design of deep foundations today.

Huu et al. [8], analyzed the bearing capacity of excavated piles from a two-way load test: a case study in Quang Ngai province. This paper presents the vertical bearing capacity of drilled piles from a two-way load test (O-Cell method) in the Tra Khok Dam Bridge Project in Quang Ngai Province. The dam structure is supported by approximately 400 driven piles with a diameter of D1200 mm and a length of 27 m to 50 m. The ground consists of sand, clay, and weathered rock layers with an SPT index (N30) from 8 to 80. The pile tip is embedded in the granite layer with an average compressive strength of 18.6 MPa. Two test piles with a length of 29.1 m (T1N) and 42.75 m (T8N) of the O-Cell test were carried out. Lateral friction of soil layers and pile tip resistance were analyzed.

Borthakur and Das [9] conducted research titled Modeling the capacity of microwaved boat foundation on soft clay soil using an ANN approach. The micro-candle boat foundation shows its ability to solve a special type of foundation problem, i.e., building structures of medium height and weight on deep and soft clay sediments. In this study, the potential of the ANN method was used to evaluate the capacity of the microwave boat foundation under a particular settlement in soft clay soil, considering the complex nonlinear load settlement behavior. Experiments were conducted on a microcantilever boat base constructed with different variables in a soft clay soil bed in a field test pit, and a database of load-settlement diagrams was prepared, which were used to develop other ANN models. The study observed that the Bayesian adjustment algorithm performs best with a 90% to 10% validation model. A sensitivity analysis was performed to determine the relative importance of the input variables, and a neural interpretation diagram was prepared. An empirical equation with the best-fitting ANN model was proposed, and an example was shown.

In the past few decades, the use of steel and prestressed and in-situ concrete piles has been expanded for the stability and design of various structures in various civil engineering projects. Considering the different conditions of field and laboratory studies, especially the physical conditions of different soils, it goes without saying that no empirical relationship can be used to estimate the bearing capacity of piles in all cases. Extensive laboratory, field, and numerical studies have been conducted in the past few years to investigate the bearing capacity of piles, but the mechanisms still need further study.

2 | Methodology

The requirement to use artificial intelligence ANNs is to use multiple inputs and define their outputs, which use internal rules and algorithms that the network has to analyze the data and determine the answer with a certain percentage [10].

2.1 | Database

Fifty data sets are available for training, evaluation, and testing of the network, of which 50 data are used for training information, 15% for evaluation information, and 15% for test information.

2.1.1 | Input parameters

The input parameters in this study include the parameters of soil internal friction angle, soil elastic modulus, pile diameter (D), and pile length (L) as input to the considered models. According to *Table 1*, the input data is considered input.

2.2 | Appropriate Structure of ANN Model

As mentioned in the previous chapter, building a neural network model requires choosing the appropriate structure. The structure of a neural network determines how the components of a neural network are placed next to each other and how they are related to each other.

Since your network structure dramatically impacts the accuracy of your results, you should check the existing structures of neural networks to choose the right type for the job [11]. Finally, the overall structure of the neural network can be optimized to achieve the desired result. Choosing the optimal network predicts the result in a helpful way [12]. In the following, several existing neural network models were compared, and the most suitable option among them was selected to build the pile-bearing capacity prediction model. The neural network used in this research is a multilayer perceptron neural network as follows. Perceptron neural networks, especially multilayer perceptrons, are among the most practical neural networks. These networks can handle the nonlinear mapping between input and output with reasonable accuracy by choosing the appropriate number of layers and neurons, which are often not large [13].

Table 1. The database of the used data.

Candle Diameter	Pile Length (M)	Internal Friction Angle (Degree) of the Soil	Modulus of Elasticity of Soil
0.3	5	30	19
0.3	6	30	19
0.3	7	30	19
0.3	8	30	19
0.3	9	30	19
0.3	10	30	19
0.3	11	30	19
0.3	12	30	19
0.4	8	30	19
0.4	9	30	19
0.4	10	30	19
0.4	11	30	19
0.5	5	30	19
0.5	6	30	19
0.5	7	30	19
0.5	10	30	19
0.5	11	30	19
0.6	7	30	19
0.3	5	30	20
0.3	6	30	20
0.3	7	30	20
0.3	8	30	20
0.3	9	30	20
0.3	10	30	20
0.3	11	30	20
0.3	12	30	20
0.6	8	35	20
0.6	9	35	20
0.5	12	35	20
0.5	13	35	20
0.5	5	35	20
0.5	12	35	20
0.5	13	35	20
0.5	8	35	20
0.6	7	35	20
0.5	5	35	20
0.5	6	35	20
0.5	9	35	25
0.5	11	35	20
0.4	15	35	35
0.4	14	35	20

Table 1. Continued.

Candle Diameter	Pile Length (M)	Internal Friction Angle (Degree) of the Soil	Modulus of Elasticity of Soil
0.4	13	35	20
0.4	12	35	20
0.4	10	35	20
0.4	9	35	20
0.3	13	35	20
0.3	14	35	20
0.3	15	35	20
0.6	10	35	19
0.3	5	35	20

2.3 | Prediction Results Using Genetic Algorithm

MATLAB 2015 software is used to implement, train, and test networks. The Lundberg Marquette (ML) method was used to train the networks and increase the generalization power of the network; the cross-validation method was trained to stop. Since the number of intermediate neurons plays a significant role in the behavior of networks, different networks were evaluated with 1, 2, 3, 4, 5, 6, 7 and 8 intermediate neurons. The correlation coefficient and the mean square error index of the evaluation data for MLP networks with different numbers of neurons are shown in *Table 2*. For this purpose, each network with a fixed number of neurons was trained 20 times, and at the end, the networks with the least errors were saved, as is evident from *Table 2*.

Table 2. Values of errors for a network with different numbers of neurons in a hidden layer for evaluation information.

MSE	R	Number of Neurons
0.0038	0.91	1
0.0079	0.84	2
0.14	0.35	3
0.24	0.90	4
0.0027	0.75	5
0.0037	0.96	6
0.35	0.44	7
0.18	0.91	8

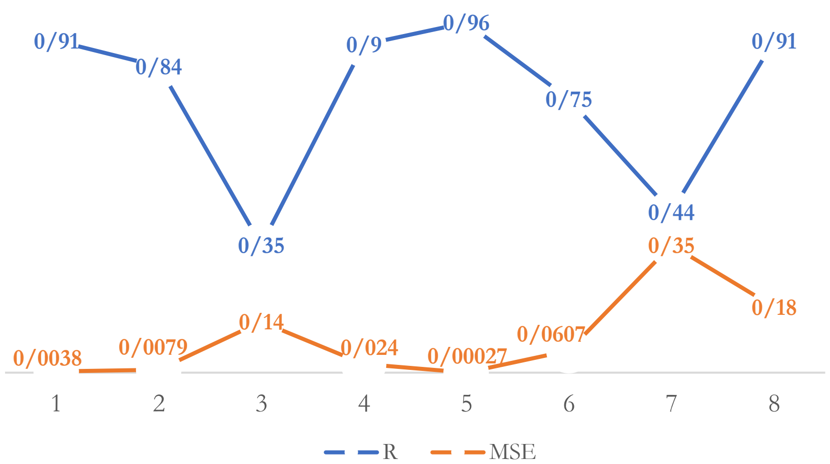

Fig. 1. Calculation error values of each feedforward neuron based on the constructed model.

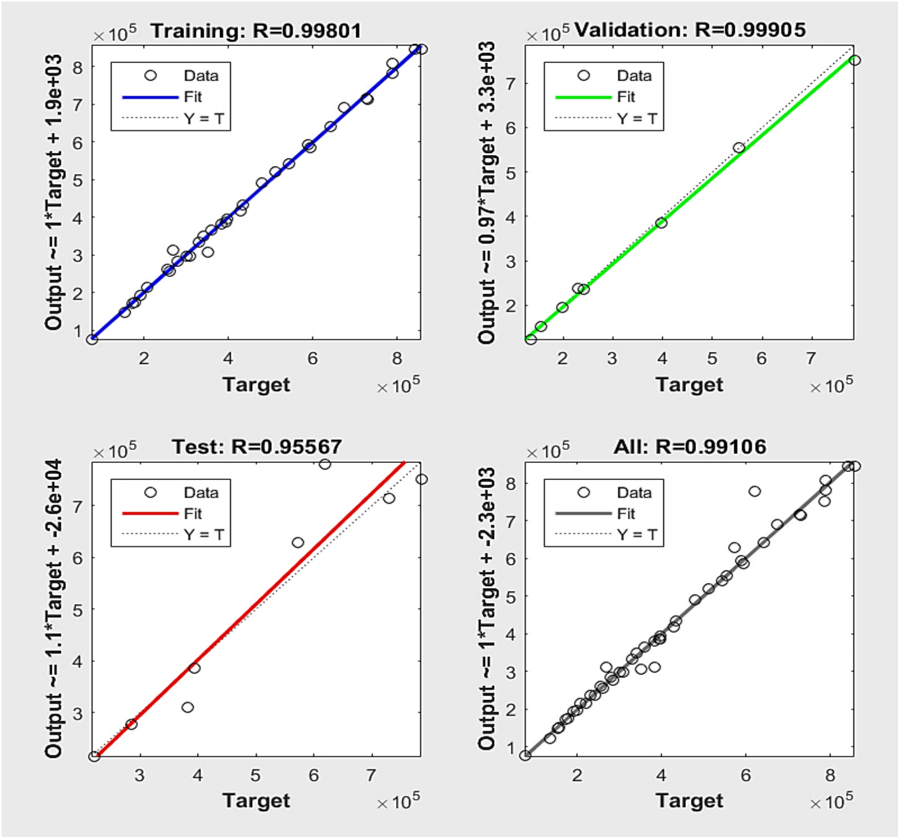

Fig. 2. Regression chart (R) of training data, validation, and test of all data.

According to *Fig. 1*, the regression coefficient for the training group is equal to 0.999, and for the experimental group, it is equal to 0.99801. *Fig. 2* is a performance diagram of the designed neural network, including the training data's regression diagram (R) and the validation and testing of all the data presented.

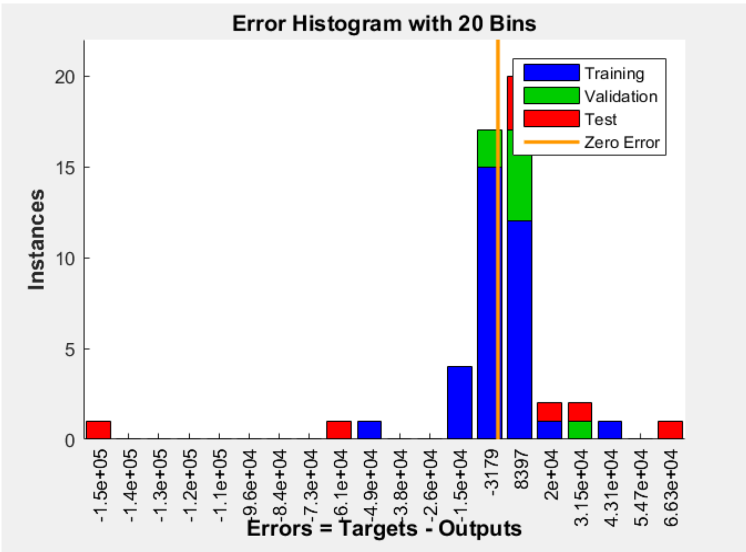

Fig. 3. The performance of the selected ANN.

Fig. 3 shows the performance of the ANN with Lorenberg's algorithm. According to *Figs. 2-4*, the regression value of the selected network has been investigated in different stages of modeling after five epochs, and it shows the drop in the least squares of the error. Also, the Mean Square Errors (MSE) in different learning epochs, considered according to the convergence criterion, show that the learning in epoch five is well done.

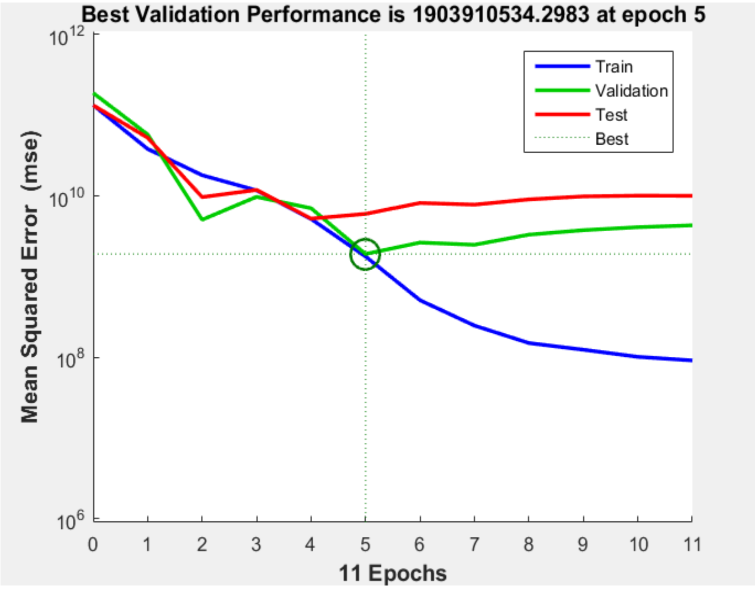

Fig. 4. also compares the neural network results with genetic algorithms and real data.

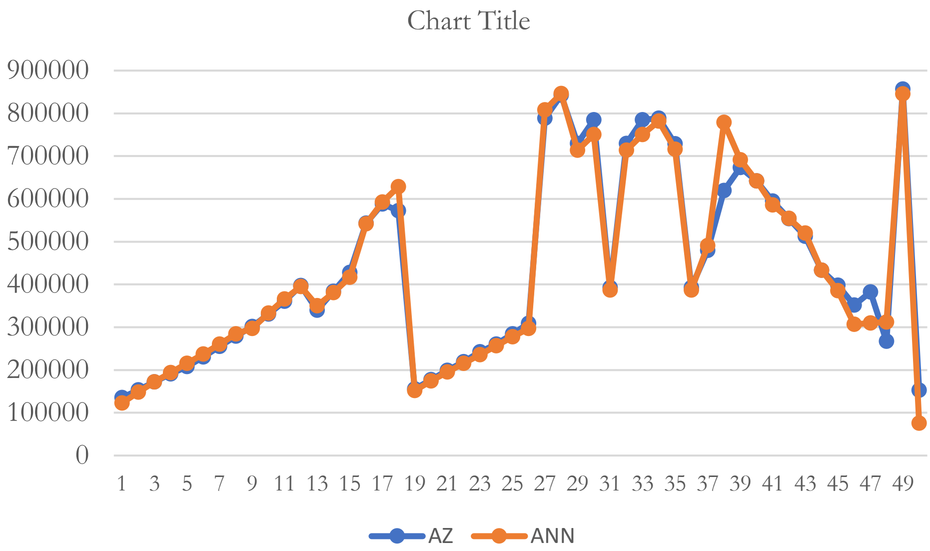

Fig. 5. Comparison of pile bearing capacity results with neural network and laboratory data.

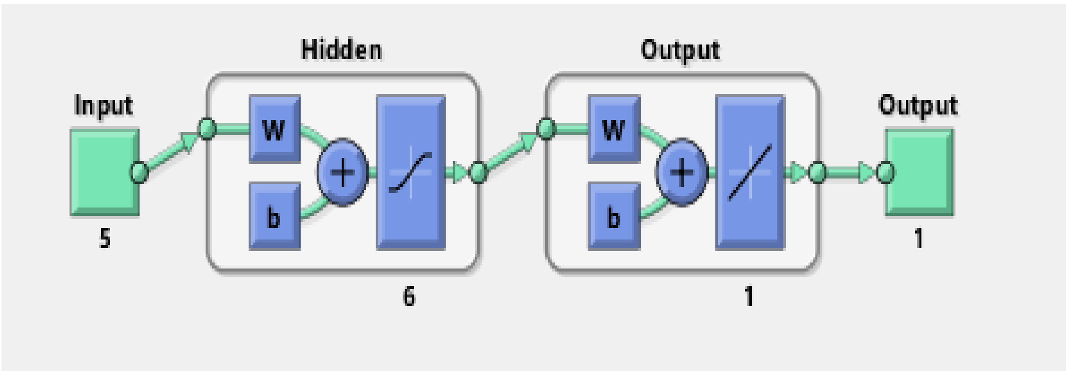

Fig. 6. Structure of neural network for training with genetic algorithm.

3 | Prediction Results Using Lorenberg's Algorithm

Fig. 7 is the performance diagram of the designed neural network, including the data regression (R) diagram of training, validation, and testing of all the data presented. According to *Figs. 7*, the regression coefficient for the training group is 0.96, for the test group, it is 0.97, and for the validation data, it is 0.99, which indicates that the genetic algorithm performs better than the Lorenberg algorithm.

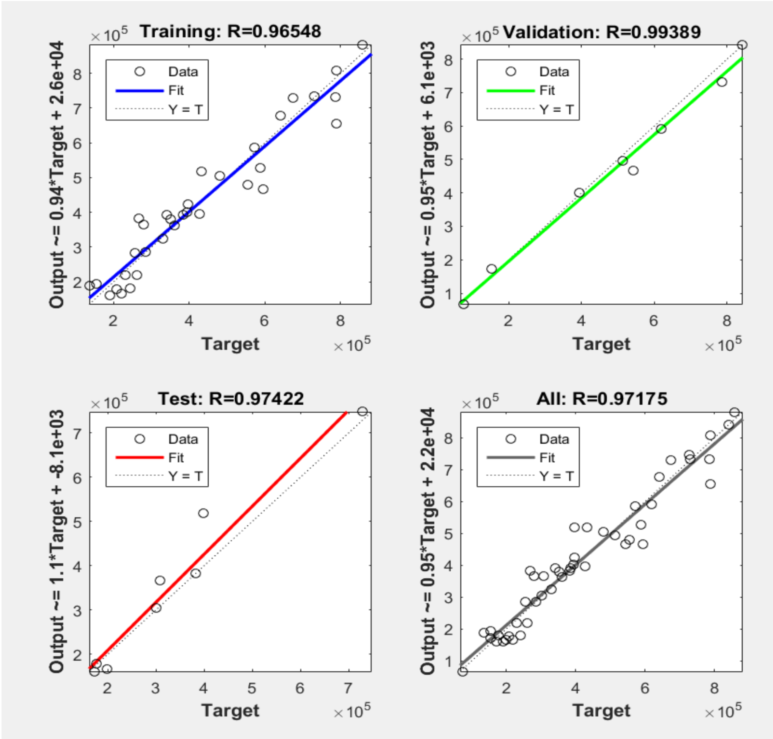

Fig. 7. Regression chart (R) of training data, validation, and test of all data.

Fig. 8. shows the performance of the ANN with Lorenberg's algorithm. According to *Figs. 8*, the regression value of the selected network has been examined in different stages of modeling after 11 epochs, and it shows the drop in the minimum square error. Also, the MSE in different learning epochs, considered according to the convergence criterion, show that the learning is done well in epoch 11.

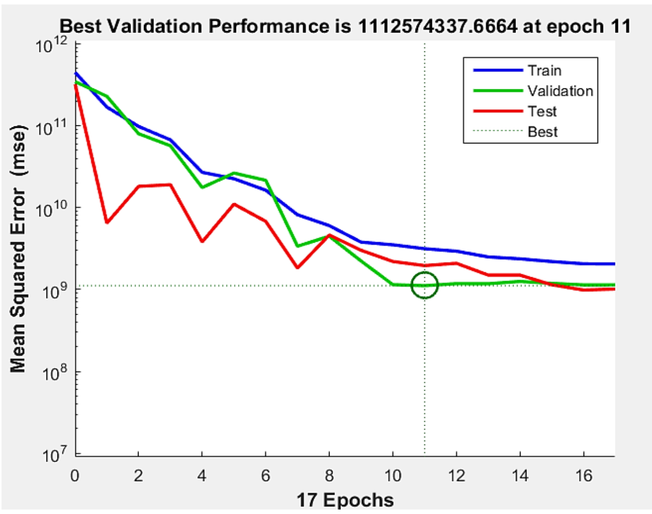

Fig. 8 .Performance of ANN selected with Lorenberg's algorithm.

The structure of the neural network used is shown in *Fig. 9*.

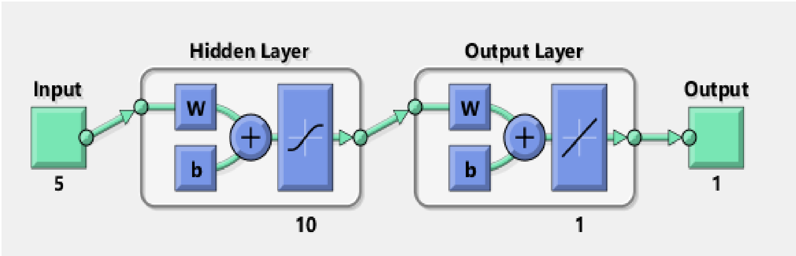

Fig. 9. The structure of the neural network used for training with Lorenberg's algorithm.

According to *Fig. 10*, the desired neural network has 5 inputs, one output, and 10 hidden layers.

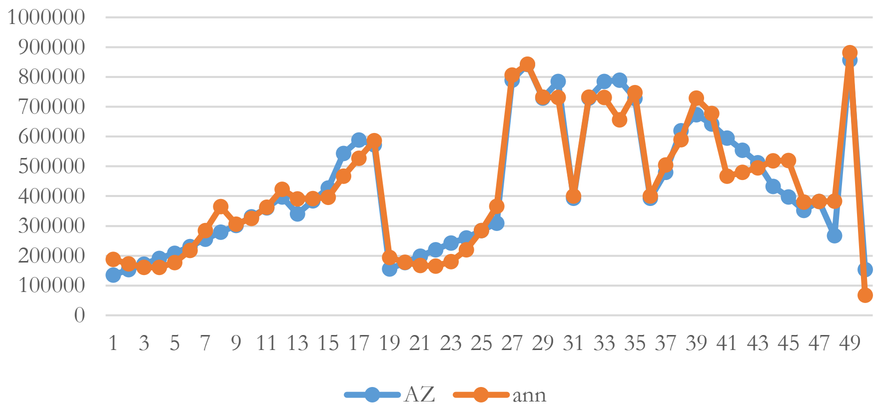

Fig. 10. Comparison of neural network results and real data for Barbie candle capacity.

4 | Conclusions

Based on the performed hash, the following results are obtained:

I. The genetic algorithm has a greater ability to predict and model to predict the bearing capacity of piles.

II. Choosing the right number of hidden layers plays a significant role in increasing the accuracy of the designed network.

III. Also, the amount of error of the optimized network in this article with this number of tested concrete samples is at most 15%; according to the available statistical information from the research results, 30 errors are less than 5%, 20 errors are between 5% and 10%, and 9 errors are They had between 10 and 15%, and a total of 99% of the results predicted by the ANN had an error of less than 15% with laboratory samples; therefore, it can be said that the use of the optimal network introduced in this research is a suitable solution for predicting the bearing capacity of driven piles in non-cohesive soils.

IV. The comparison of the regression coefficient (R) of the neural network obtained from this research with the research of the researchers indicates the superiority of the accuracy and performance of the prediction system of this article compared to other methods acquired in the study of the researchers.

V. To determine the effect of each of the input parameters on the bearing capacity, a sensitivity analysis was performed using the Milne method with adjusted weights and the result of the optimal neural network, and the results indicate a high effect on the length and cross-sectional area of the pile.

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Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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