PREDICTION OF PILE CAPACITY USING ARTIFICIAL NEURAL NETWORK WITH TWO HIDDEN

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Abstract: *The bearing capacity of the pile is an important factor in the design of the pile foundation. Determining the bearing capacity of piles through in situ load testing is costly and time consuming. The purpose of this study is to show the applicability of artificial neural network (ANN) to predict the axial load capacity of piles. The data set used to build and verify the ANN simulation tool includes 100 data of test results of pile load testing in Dong Van industrial zone - Ha Nam. After conducting trial and error, the structure of the selected ANN includes 10 input parameters, two hidden layers with the number of neurons in the two layers of 12 and 10 neurons, respectively. Programmed and run in the Python platform, the authors use the ANN model to predict the axial load capacity of the pile. The results show that ANN has good potential to be used as a pile bearing capacity prediction tool to help design engineers predict pile load capacity for minimizing the time experimental and expensive.*

Keywords: *Artificial Intelligence (AI), Artificial Neural Network (ANN), bearing capacity; pile foundation.*

1. INTRODUCTION

The bearing capacity of the pile is one of the most important parameters in the design process of the pile foundation [1]. To determine the current load capacity of piles, we often use the following method [1], [2]: static analysis, dynamic analysis, dynamic testing, pile load test and in-situ testing [2]. In those methods, the pile load test method is the most reliable method to determine the bearing capacity of piles, but this method is time consuming, expensive and often applicable to large-scale projects. In addition, according to the traditional method, we can also determine based on the results of field tests such as standard penetration test (CPT) and static penetration test (SPT). In study by Jesswei et al [3] the calculation of the bearing capacity of piles according to SPT is not completely reliable and inaccurate because the determination formula is still assumed, although it is easy to implement and low cost. This calculation method is considered impractical, as it is based on too many assumptions and simplifications [4]. In addition, Farsakh and Titi [5] argue that the method of pile empirical analysis or static analysis is high cost and low accuracy due to the choice of many safety factors. Other way, for the static pile compression method, although it has high reliability, it is time consuming, expensive and the equipment is often cumbersome [6]. The dynamic analysis method relies heavily on the characteristics of the pile, the compressive load and the position of the pile to predict the bearing capacity of the pile without considering the influence of the soil [7], [8]. Finally an equally important method is finite element based, it is basically an approximation method and the result

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depends heavily on the modeling process [9], [10]. In specific conditions, the above methods all have advantages, but besides that, there are still disadvantages, so we need to consider when applying them to specific.

In recent years, many scientists have used new approaches to the problems related to the foundation of building [4]. That method is called artificial intelligence (AI) [11]. Based on the development of computer science, AI has gradually proven its outstanding effectiveness in many different fields such as construction, transportation, medical, security [12]. The essence of AI algorithms is a combination of mathematics, algorithms and creativity. AI allows solving complex problems and many unknowns, so it is very suitable for nonlinear problems in geoengineering [4]. Likewise, to determine the load capacity of piles, a large number of studies have used AI as a reliable method [4], [7], [13]. Scientists have used many different AI algorithms to solve the pile load prediction problem, which can be named as artificial neural network (ANN), fuzzy inference system (FIS), and genetic programming (GP), random forest (RF). All of the above studies give good predictive efficiency and are expected to become a highly generalized tool in predicting the bearing capacity of piles. The main objective of this study is to use the hidden 2-layer artificial neural network model to determine the axial load capacity of piles on the basis of a dataset of 100 experimental results that have been published in peer-reviewed journals reputation. Based on that, the results of this study provide construction engineers with a reference to quickly and accurately determine the pile load capacity.

2. DATABASE AND MODELING

2.1. Data used

In this study, data were collected from the results of static compression tests of 4720 reinforced concrete piles published by Pham Tuan Anh et al [14]. The input parameters to determine the load capacity of the pile include: (i) Diameter of pile (D), (ii) Length of first pile (Z1), (iii) Length of second pile (Z2), (iv) Pile tip length (Z3), (v) Natural ground elevation (Zp), (vi) pile top elevation (Zg), (vii) Guide pile stopping elevation (Zt), (viii) Pile tip height (Zm), (ix) average SPT value over pile length (Nsh), (x) average pile tip SPT value (Nt). The output parameter is the bearing capacity of the pile (Pu). The data of the model (*Table 1*). For illustrative purposes, *Fig 1* shows the graph of the correlation between input and output parameters of the parameters in this study.

Table 1: Statistical analysis of databases

	D	Z1	Z2	Z3	Zp	Zg	Zt	Zm	Nsh	Nt	Pu
count	472	472	472	472	472	472	472	472	472	472	472
mean	363.77	3.83	6.58	0.33	2.80	3.50	2.92	13.54	10.74	7.06	0.98
std	48.12	0.48	1.64	0.46	0.62	0.08	0.60	1.80	2.26	0.66	0.35
min	300.00	3.40	1.50	0.00	0.68	3.04	1.03	8.30	5.60	4.38	0.41
25%	0.75	3.40	5.25	0.00	2.05	3.45	2.15	12.05	8.65	6.75	0.61
50%	1.00	3.45	7.31	0.00	2.95	3.48	3.28	14.11	10.80	7.18	1.07
75%	1.00	4.35	8.00	0.94	3.40	3.54	3.42	15.34	13.25	7.60	1.32
max	400.00	5.72	8.00	1.69	3.40	4.12	4.35	16.09	15.41	7.75	1.55

In this study, the data used is divided into two data used: training and testing. The first data (including 70% data) is used to train the ANN network model; The second dataset (30% remaining data) is used to test the model. With the above division, the dataset consists of 472 data with 330 samples for the training dataset and 142 samples used to estimate the predictive performance of the ANN. The data set in this study, including input parameters and output parameters, is normalized in the range [0-1]. This method is mainly used in artificial intelligence problems to minimize the error generated by the simulation.

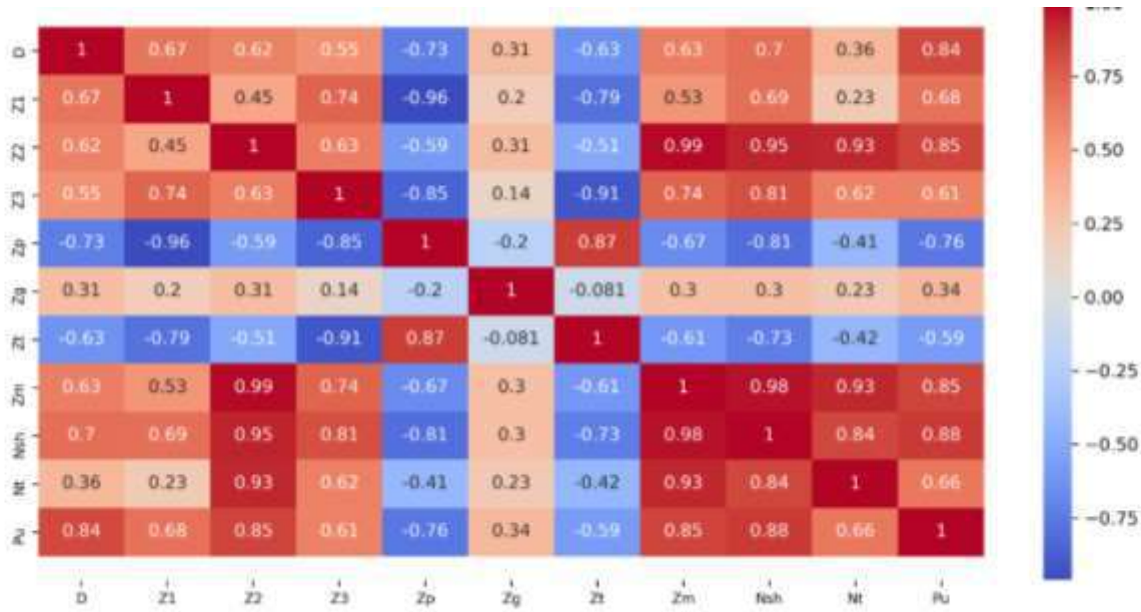

Figure 1: The chart of input and output parameters

2.2. Artificial neural network

Artificial Neural Network (ANN) is a powerful machine learning-based data analysis algorithm that is a model of biological neural networks. They provide a wide range of mathematical calculations used to model biological mechanisms of the human brain, such as knowledge and memory [15], [16]. Compared with conventional computational methods, ANN algorithms are especially useful in solving problems of high complexity. So far, the use of artificial neural networks has been widely applied in many fields [17]–[19]. ANN model, information inputs are provided to an artificial neuron; each input is associated with a weight and an offset. The backpropagation (BP) algorithm is a popular tool used to adjust the weight and bias of each neuron in the network. A set of inputs is fed into some presumptive system to derive an output value, which is then compared with the actual value. If there is no difference, then no testing is needed, otherwise the weights will be changed during the back-propagation in the neural network to reduce the difference. A backpropagation network usually has one or more hidden layers with sigmoid neurons and an output layer of neurons with a linear transfer function. Multilayer networks using back-propagation learning are the most widely used in the field of neurons. However, the underlying BP algorithm is still too slow for applications. The study of faster algorithms has been proposed to speed up the convergence for the ANN training phase. In this study, the BFGS Quasi-Newton (BFG) back-propagation algorithm is used to optimize the ANN training that predicts the 28 days compressive strength of concrete.

The BFGS method is a network training algorithm that updates the weights and bias values according to the Quasi-Newton method. The BFGS algorithm is one of the algorithms used to solve the nonlinear optimization problem without any constraints:

$$\min f(x), \quad x \in R^n \qquad (1)$$

The algorithm proposed by Broyden [20], Fletcher [21], Goldfarb [22] và Shanno [23] is implemented including the following steps:

Step 1: Let $x_1 \in R^n; B_1 \in R^{n\times n}$ be positively defined. Calculate $g_1 = \nabla f(x_1)$. If $g_1 = 0$ then stop, if not set k = 1.

Step 2: Set $d_k = -B_k^{-1} g_k$

Step 3: Do a search along d_k; receive

$\alpha_k > 0$, $x_{k+1} = x_k + \alpha_k d_k$ and $g_{k+1} = \nabla f(x_{k+1})$;

Step 4: Set

$$B_{k+1} = B_k - \frac{B_k s_k s_k^T B_k}{s_k^T B_k s_k} + \frac{y_k y_k^T}{s_k^T y_k} \qquad (2)$$

With $s_k = \alpha_k d_k$, $y_k = g_{k+1} - g_k$

Step 5: k = k+1, go back to step 2

2.3. Performance Evaluation

To evaluate the accuracy of the ANN model between the predicted results and the actual results, the authors used three indexes: Root mean square error (RMSE), the coefficient of determination (R^2) and namely the mean absolute error (MAE). The R^2 value allows to determine the statistical relationship between the predicted values and the experimental results. R^2 having values in the range of [-∞ ÷ 1], the model will be said to be more accurate as R^2 to 1. Conversely, the lower the values of RMSE and MAE, the more accurate the calculation results. The values of R^2, RMSE, MAE are calculated using the following formulas:

$$\text{RMSE} = \sqrt{\frac{1}{k}\sum_{i=1}^{k}\left(y_i - \bar{y}_i\right)^2} \qquad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{k}\left(y_i - \bar{y}_i\right)^2}{\sum_{i=1}^{k}\left(y_i - \bar{y}\right)^2} \qquad (2)$$

$$\text{MAE} = \frac{1}{k}\sum_{i=1}^{k}\left(y_i - \bar{y}_i\right) \qquad (3)$$

Where k: number of samples; y_i và $\bar{y}_i$ are the actual and predicted outputs, respectively; $\bar{y}$: is the mean value of y_i .

3. RESULTS AND DISCUSSION

In this part, the authors use the ANN artificial neural network model with 2 evaluation hidden layers with the number of error correction iterations of 100. Using two root mean square error (RMSE) and namely the mean absolute error (MAE) selected for the optimization problem. The evaluation of 2 error functions during the optimization process for the training and testing datasets is presented in *Figure 2*. The results show that there is no sudden change in the optimization process for the training data set. training and testing data set with 100 iterations. Therefore, the number of iterations for the optimal process with a training set of 100 has good results for successfully predicting the bearing capacity of pile.

The optimal ANN defined in the above section allows to predict the pile load capacity for the training and testing. *Figure* 3 shows the value of the pile bearing capacity as predicted by the ANN model for the training and testing datasets. These values are compared with the experimental data. The results show that the proposed algorithm is capable of predicting quite accurately about the value of the bearing capacity of piles with experimental data. The error of the model for the training and testing data is small compared to the test data. Figure 4 shows the error value frequency of the training and testing data. The error value of the training and testing data is small, with only a few errors in the range [-0.2; 1.0] (kN). These small error values show that the predictive ability of the ANN model is very good.

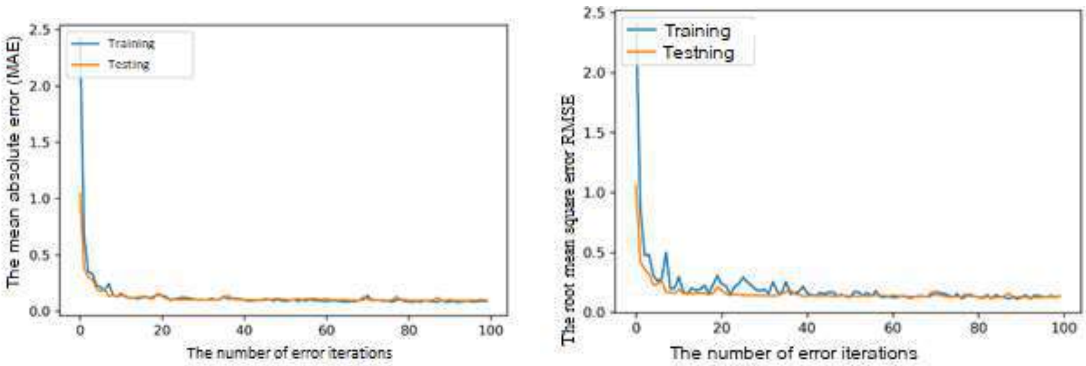

Figure 2: Evaluation of MAE and RMSE functions during optimization

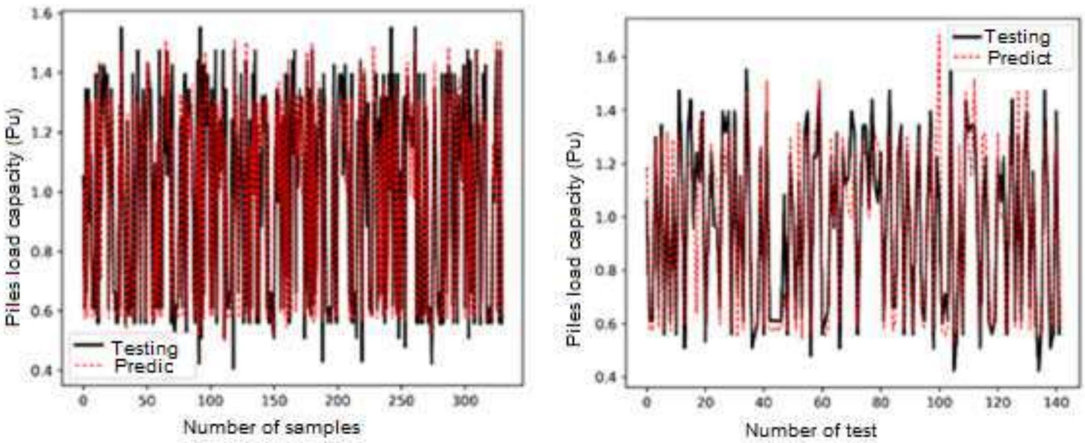

Figure 3: Value of bearing capacity of pile according to experimental data and ANN

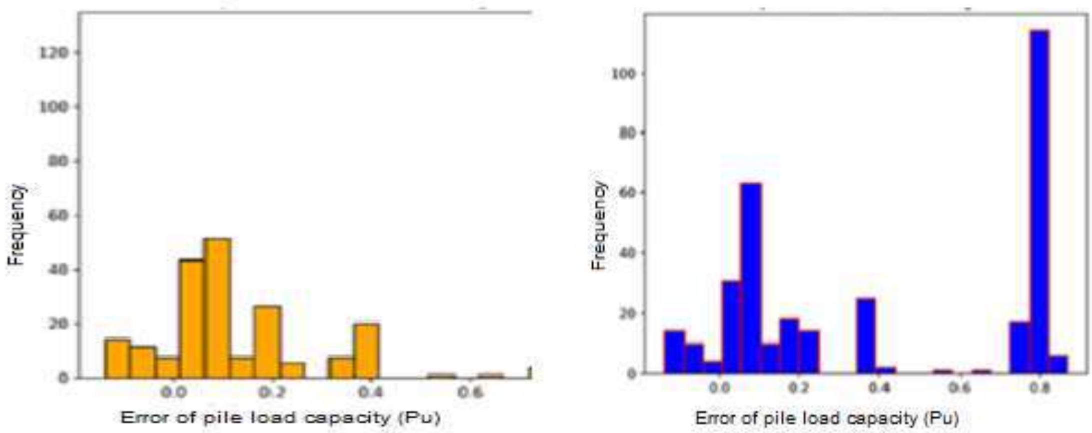

Figure 4: Error on the bearing capacity of piles of the ANN

Figure 5 shows the correlation of the pile load capacity between the simulated and experimental values using the ANN. The results are listed in *Table 2*. The values of the model show that the difference between training and testing is not large, which shows that the application of the hidden 2 layers ANN to predict the load capacity of piles is highly effective and feasible.

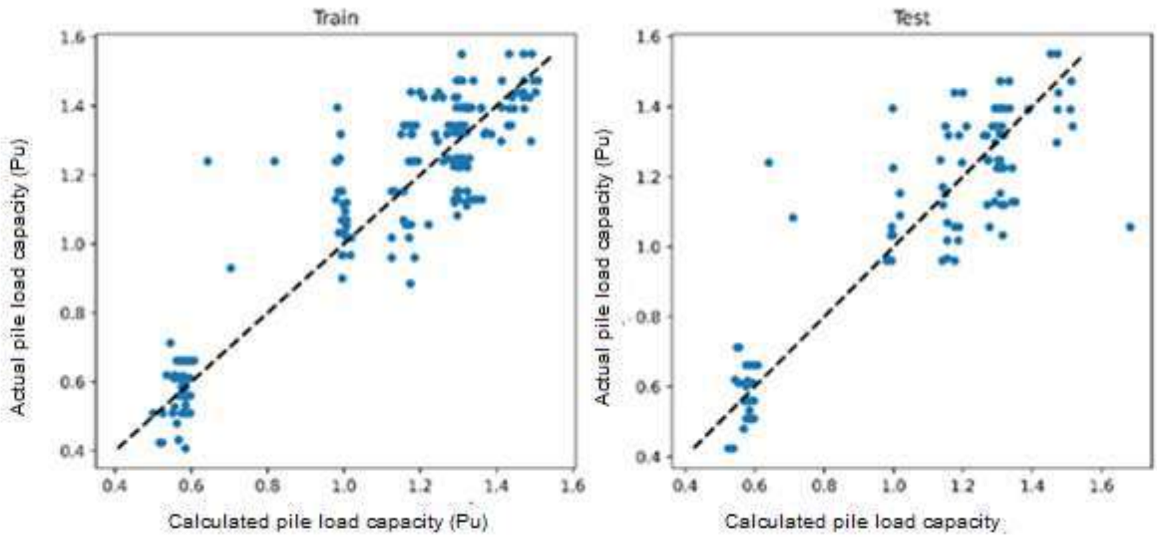

Figure 5: The results between simulation value and experimental value

Table 2: Statistics for the model with training and testing sets

Model rating index	R^2	RMSE	MAE
Training	0,903	0,11	0,081
Tesning	0,873	0,13	0,087

4. CONCLUSIONS

In this study, the ANN artificial neural network model with 2 hidden layers is used to predict the bearing capacity of piles. A data set of 472 field pile static compression test samples was used to build, develop and verify the model.

The results showed that the ANN model with 2 hidden layers with training and verification datasets showed nearly identical values (training: R^2 = 0,903, RMSE = 0,11 kN, MAE = 0,081 kN; testing R^2 = 0,873, RMSE = 0,13kN, MAE = 0,087 kN).

The hidden 2 layers ANN model has advantages over the conventional method, when there is training model data we can quickly and accurately determine the load capacity of the pile.

Correlation analyses between the dataset and training showed the parameters of pile length, pile height. (Z_1, Z_2, Z_m), the average SPT value along the Nsh pile length has the most significant effect on the prediction of pile load capacity.

The results of this study indicate that the ANN hidden 2-layer model allows us to predict the load capacity of piles more accurately than traditional methods.

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