Evaluation of axial pile bearing capacity based on pile driving analyzer (PDA) test using Neural Network

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Abstract. A few decades, many methods have been developed to predict and evaluate the bearing capacity of driven piles. The problem of the predicting and assessing the bearing capacity of the pile is very complicated and not yet established, different soil testing and evaluation produce a widely different solution. However, the most important thing is to determine methods used to predict and evaluate the bearing capacity of the pile to the required degree of accuracy and consistency value. Accurate prediction and evaluation of axial bearing capacity depend on some variables, such as the type of soil, diameter, and length of pile, etc. The aims of the study of Artificial Neural Networks (ANNs) are utilized to obtain more accurate and consistent axial bearing capacity of a driven pile. ANNs can be described as mapping an input to the target output data. The method using the ANN model developed to predict and evaluate the axial bearing capacity of the pile based on the pile driving analyzer (PDA) test data for more than 200 selected data. The results of the predictions obtained by the ANN model and the PDA test were then compared. This research as the neural network models give a right prediction and evaluation of the axial bearing capacity of piles using neural networks.
Keywords: axial bearing capacity, driven pile, neural networks, pile driving analyzer

1. Introduction

Analytical and empirical estimation of the axial bearing capacity of piles based on properties of soil has improved considerably over the years. The results are still not capable subject to many factors such as inherent soil variability. Furthermore, interpretation of site investigation data, and different assumptions used in the prediction methods as well as disturbance during pile penetration. Dynamic formulas were introduced for the driven pile, but the stages are inaccurate due to the simplicity in modeling the driving system. Therefore, most design codes require some Static Load Test (SLT), (ASTM-D5780-10, 2010) to be performed at construction sites to make sure that the actual capacity of the piles.

The SLT is not favored by practicing engineers because it is costly and time-consuming. In some cases such as very soft near surface soil and marine environment, the test is unmanageable due to the massive setup. Some researchers [1], [2] and [3] developed a High Strain Dynamic Pile Test (HSDPT) to study the strain, internal loading and acceleration of a pile under an push loading. The data is used to estimate the bearing capacity and the structural integrity of the pile. Moreover, the hammer performance, pile stresses and soil characteristics such as damping coefficients and quake values are also evaluating by the engineer. The procedure is standardized in ASTM-D4945-08, 2008. The HSDPT system is most widely employed using a combination of Pile Driving Analyzer (PDA) and Case Pile Wave Analysis Program (CAPWAP) software, because of the data more simplicity and quick handling.

The capability of the HSDPT to accurately predict static capacity from dynamic pile testing has been the subject of many studies. Based on the previous research concluded that, if performed and interpreted correctly, the high strain dynamic re-strike testing with CAPWAP analysis can provide reasonable agreement with the results of SLT regarding design capacity [4]. However, it indicated that the accuracy of HSDPT output relies mainly on the input parameters such as hammer efficiency and damping factor [5]. Therefore, many researchers still unwilling to adopt the estimation of pile bearing capacity according to the PDA test. There are some cases due to the uncertainty parameters such as hammer system and estimate of the soil damping factor and wave stress propagation theory. The use of the reduction factor was proposed in design codes [6] (e.g., Australian Standard AS2159) when using CAPWAP simulated static load test.

2. Research Method

2.1. Concept of ANN

ANN are scientific inventions inspired by the function of the human brain and nervous system. The ANN must be trained by inputting data repeatedly together with target output. The ANN learned to know the patterns of the data, hence; creating an internal model of the governing data process. The ANN uses the internal model to make estimations for new input. The variables of the input as known as neurons, and neurons send signals to other neurons. Some inputs to the neuron could have greater importance than the other, and this is modeled by weighting the input to the neuron Figure 1. Thus, the neuron can be thought of as a small computing engine that takes in inputs, processes them, and then transmits an output. Equation.1 gives the output of the neuron.

$$z_j = f\left(\sum_{i=0}^{n} w_{ji} x_i\right) + \theta_j \tag{1}$$

$$y_j = f(z_j)$$

Whereas,

- z : output prediction
- wji : connection weight ke-i
- xi : input data ke-i
- f() : a non linear transfer function
- n : number of iteration
- θ : bias
- y : target output

In this study, a three-layer feedforward backpropagation network was investigated. Some hidden neurons is an essential thing in backpropagation networks. Furthermore, there is no exact method for determining the number of hidden layer neurons. Using too many will make the training time longer, but using fewer hidden layer will make learning algorithm becoming trapped in local minimum [4]. Thus, it is trial and error that we use an absolute minimum number of hidden neurons, which will perform adequately. It suggested that the nodes on the hidden layer should be between average and the sum of the nodes on the input and output layers [5]. There are rough estimations to find the best-hidden layer size.

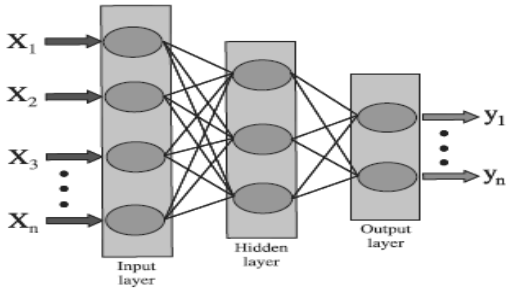

Figure 1. Artificial Neural Networks with inputs and outputs.

A variety of different transfer functions were investigated to achieve the best results in training. The optimal performance was obtained from tan sigmoid-log sigmoid-log sigmoid-linear activation functions in the first, second, third and output layers respectively.

2.2. Data Collection

The dynamic load test data were performed using a PDA test and based on ASTM D 4945, and the analysis of bearing capacity was evaluated by CAPWAP (Case Pile Wave Analysis Program). The PDA test data used in this study were collected from the two areas:
(a) 119 load test records got from Malaysia area
(b) 97 load test records got from Indonesia area

The database consists of a full spectrum of variety in a pile diameter, D. The embedment length is L, compression stress is CS, tension stress is TS, vertical displacement is DFN, ram weight is W, drop height is H, and energy is EMX. The axial bearing capacity of the single pile, Q is the only target output variable. All of the pile load tests are spun piles and made of the concrete piles.

The data of the factors recorded in the test are ordered to emphasize individual effect on the axial bearing capacity of the pile. This spun pile used in this study are the circular shape of which the diameter ranges from 300 to 500 mm and rectangular way of which the side length from 200 to 400 mm. The measures of the piles are varied from 10 to 35 m, and bearing capacity of the single piles is about 50 to 250 ton.

2.3. Calculation and Data Analysis

All databases are prepared for the training and testing procedure of the neural network. The data were divided into training subject constitutes 70% of database whereas the testing 30%. All of the input and target output variables were normalized in the values range between 0 - 1 before training. The rescaling is often accomplished by using a linear interpolation formula [6]. The following Equation.2 gives the method :

$$x_i' = \left(max_{target} - min_{target}\right)\left[\frac{(x_i - min_{value})}{(max_{value} - min_{value})}\right] + min_{target} \tag{2}$$

Whereas,
$\left(max_{target} - min_{target}\right) \neq 0$, when $\left(max_{target} - min_{target}\right) = 0$or a feature, it indicates a constant value for the feature in the data. . When a feature value is found in the data with a constant value, it should be removed because it does not provide any information to the neural network. The network was trained with the backpropagation algorithm. Back-propagation neural networks can provide accurate predictions to any continuous function with sufficient neurons. In ANN model, we are not looking for the best training data, but we looked for the best responds of the training data that used for testing data in a better manner. However, to get the good reliable model, the number of hidden nodes and the value minimum sum-squared error goal was varied based on the coefficient of determination R2 of the testing result [7]. The R2 value described the contribution of input value in predicting the

target output value, which means by how many errors are happened when predicting the axial bearing capacity of a driven pile by using the input information.

In this study, the model neural network uses eight nodes in the input layer, eight nodes in the hidden layer, and a node in the target output, as shown in Figure 2.

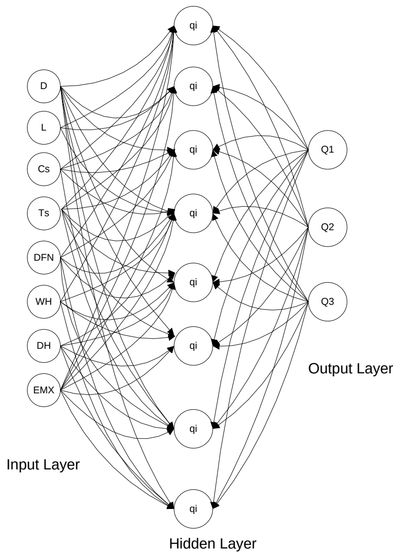

Figure 2. The architecture of the ANN Model.

3. Results and Discussion

Once the ANN model is evaluated in the training phase, the measured axial pile bearing capacities are compared with the capabilities obtained by BPNN. Then, the neural network models are capable of reproducing the target output values with minimal error. Furthermore, the result of the trained model is used for a new set of data is examined. Once the training, testing, and validation phases are accomplished, the neural network obtained can be used as a tool for predicting the axial bearing capacity of the single driven pile.

An ANN model (named HM) was developed to predict the axial bearing capacity of the driven pile. Figure 3 shows the comparison of Measured axial pile bearing Capacity and the prediction by HM model during the training Phase. From the 207 test piles used in the training set, the network HM was able to learn all the pattern presented with the high coefficients of correlation (R2) of 0.936. The mean square error of the neural network model was 0.0094, which is acceptable. The training process was determined after 15 (fifteen) iterations and then continued with testing phase. As shown in Figure 4, the model gives slightly lower coefficients of correlation (R2) of 0.916 after the completion of the testing phase

The model was used to predict the bearing capacity of three groups of piles (small, medium and large) and the results are shown in Figure 5, 6, 7. The figures indicate that the ultimate pile bearing capacity for spun piles predicted by HM model is in best agreement with the results of CAPWAP from PDA tests. Statistical analysis of the axial bearing capacity gives the R2 value of 0.811 for small piles, 0.911 for medium piles and 0.913 for large piles. The study indicates that the number of data is not always related to the quality of the prediction.

Artificial neural networks are used as a tool for predictive models on various geotechnical problems such as the piles bearing capacity. The primary idea behind this application is to develop optimal models using simple data. For example, some researchers [8] and [9] simulated data obtained from model pile load tests using in-situ pile load test. The output of the model for prediction of the ultimate bearing capacity while the input includes penetration depth of the pile, the diameter of the pile and the mean normal-stress. The result of the study shows that the ANN model gives a maximum error not more than 25%. Similarly, researcher [10] introduced a general regression neural network for predicting the capacity of a driven pile in cohesionless soil. The variables were selected as input data: angle of friction of soil, effective overburden pressure, pile length and cross-sectional pile area. The results show that the ANN model gives a better prediction when compared with analytical and empirical methods, given by researchers [11], [12] and [13]. Researchers [14] also studied a method for design and analysis of deep-foundation using artificial intelligence techniques. The inputs of the network for training and testing correspond to the N-SPT value and pile dimension. Back-propagation Neural Network (BPNN) models are used for predictions. During the training phase, the measured axial pile capacities were compared with the capabilities obtained by BPNN. The developed neural network models were capable of reproducing the target output values with minimal error.

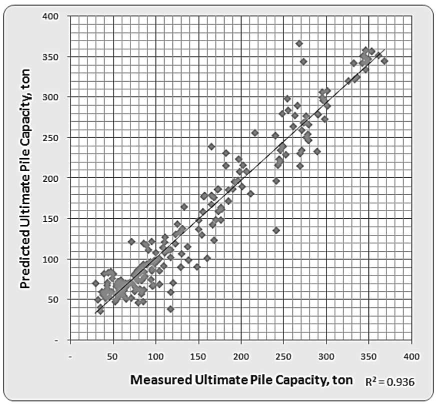

Figure 3. Predicting of axial bearing capacity. (training phase).

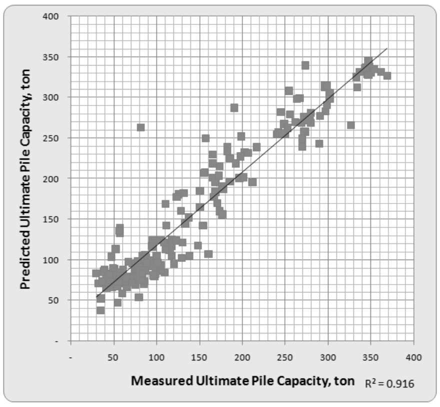

Figure 4. Predicting of axial bearing capacity. (testing phase).

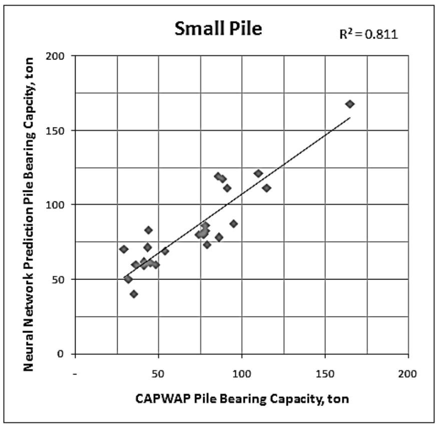

Figure 5. Predicted small pile capacity.

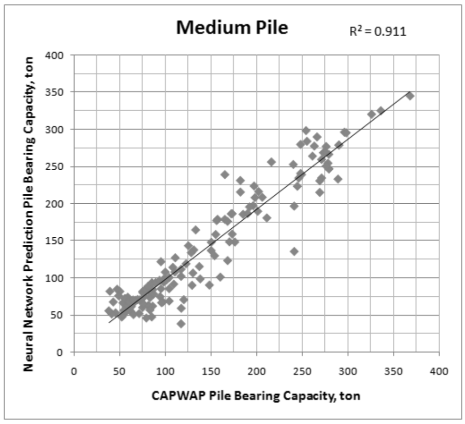

Figure 6. Predicted medium pile capacity.

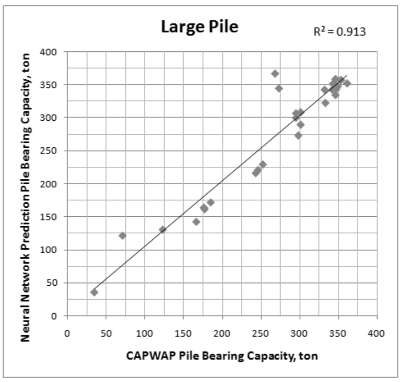

Figure 7. Predicted large pile capacity.

4. Conclusion

According to the simulation results, the technique that using artificial neural network can be applied to predict the ultimate pile capacity of the single driven pile. The ANN model gives a better prediction of the measured axial pile capacities. This model can be compared with the capabilities obtained by Back-propagation Neural Network (BPNN) models which are used for predictions model. It is easy to use, and the algorithm is easy to implement. However, it is hard to know how many neurons and layers are necessary, because of that factor the learning time may take longer.

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