Neural Network Application in Prediction of Axial Bearing Capacity of Driven Piles

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Abstract—**This paper presents the application of the Artificial Neural Network (ANN) for prediction of axial capacity of a driven pile by adopting data collected from several projects in Indonesia and Malaysia. As many as 300 data were selected for this study. In this study, ANN was set and trained to predict the axial bearing capacity from high strain dynamic testing, i.e. Pile Driving Analyzer (PDA) data. A system was developed by a computerized intelligent system for predicting the total pile capacity for various pile characteristics and hammer energy. The results show that the neural network models give a good prediction of axial bearing capacity of piles if both stress wave data and properties of both driven pile and driving system are considered in the input data. Verification of the model indicates that the numbers of data are not always related to the quality of the prediction.**

***Index Terms*— axial capacity, pile driving analyzer, artificial neural networks, driven pile.**

I. Introduction

ANALYTICAL and empirical prediction of axial bearing capacity of piles based on measured soil properties have improved considerably over the years. However, the results are still not reliable due to many factors such as: inherent soil variability, 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 driven pile, but the methods are inaccurate due to the simplicity in modeling the driving system, soil-pile-structure interaction, and the distribution of soil resistance along the pile. Therefore, most design codes require a number of Static Load Test (SLT), ASTM-D5780-10 [1] to be performed in construction sites to ensure the actual capacity of piles.

The SLT is not favored by practicing engineers because it is costly and time consuming. In some situations such as very soft near surface soil and offshore environment, the test is unmanageable due to the heavy setup. Alternatively, high strain dynamic pile test (HSDPT) was developed to provide data on strain or force and acceleration of a pile under an impact force. The data is used to evaluate the bearing capacity and the structural integrity of the pile as well as hammer performance, pile stresses and soil characteristics such as damping coefficients and quake values. The procedure is standardized in ASTM-D4945-08 [2].

Manuscript received December 28, 2012; revised January 29, 2013.

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Pile Driving Analyzer (PDA) combined with Case Pile Wave Analysis Program (CAPWAP) software is the most widely employed system for HSDPT due to its simplicity and quick handling of the data.

The ability of the high strain dynamic test to accurately predict static capacity from dynamic pile testing has been the subject of many studies. Based on [3] 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 in terms of design capacity. However, [4] indicated that the accuracy of HSDPT output relies mainly on the input parameters such as hammer efficiency and damping factor. Hence, many researchers still reluctant to adopt the prediction of pile bearing capacity based on the PDA test due to uncertainty parameters such as hammer system and estimation of soil damping factor and wave stress propagation theory. The use of the reduction factor was proposed in design codes (e.g. Australian Standard AS2159) when using CAPWAP simulated static load test.

Artificial neural networks (ANN) have been used by researchers as a tool for the development of predictive models on various geotechnical problems including bearing capacity of piles. The main idea behind this application is to develop optimal models using simple data. For example, [5] simulated data obtained from model pile load tests using in-situ pile load test. The target output of the model is a prediction the ultimate bearing capacity, while the input includes penetration depth of pile, diameter of 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, [6] introduced a general regression neural network for predicting the capacity of a driven pile in non cohesive soil. Five variables were selected as input data: angle of friction of soil, effective overburden pressure, piles length and cross sectional pile area. The results show that ANN model gives a better prediction when compared with analytical and empirical methods, given from [7]-[10]. Reference [11] also studied a method for design and analysis of deep foundation using an artificial intelligence technique. 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 capacities obtained by BPNN. The developed neural network models were capable of reproducing the target output values with minimal error.

Furthermore, [12] proposed a neural network for estimating the static pile capacity determined from dynamic stress-wave data (PDA) for precast reinforced concrete piles with a square section. The study was concerned with predicting the CAPWAP output rather than true bearing capacity of the pile. They used back-propagation neural networks (BPNN) for analysis and get the result between predicted and actual data gives a small error of about 10%. Reference [13] applied the ANN to predict the resistance of the driven pile in dynamic load test. One hundred and sixty five data from dynamic piles load test at various sites in Korea were selected to develop the model. The results indicate that the ANN model served as a reliable and simple predictive tool to predict the resistance of the driven pile with R2 values close to 0.9.

This paper presents the application of the ANN for prediction of axial capacity of the driven pile by adopting PDA data collected from several projects in Indonesia and Malaysia. As many as 182 load test records acquired from projects in Indonesia and 118 load test records collected in Malaysia are selected for the study. A system was developed by a computerized intelligent system for predicting the total pile capacity as a target output and many of the pile parameters as an input. Eight pile parameters were used as input parameters while the axial bearing capacity of the single pile (Q) is selected as the single target output variable for this study.

II. Overview of Artificial Neural Networks

ANN is mathematical inventions inspired by the function of the human brain and nervous system. The ANN must be trained by inputting data repeatedly together with corresponding target outcomes. After sufficient numbers of training iterations, the ANN learns to recognize patterns of the data, hence; creating an internal model of the governing data process. The ANN uses this internal model to make predictions for new input conditions. The input variables are called neurons, and neurons send signals to other neurons. Some inputs to the neuron may have greater importance than the other, and this is modeled by weighting the input to the neuron Fig.1. Thus, the neuron can be thought of as a small computing engine that takes in inputs, processes them, and then transmits an output. The output of the neuron is given by (1).

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

$$y_j = f(I_j)$$

where,

- I_j : the activation level of node j
- w_{ji} : connection weight between nodes j and i
- x_i : input from node 1, 1= 0,1,…n
- f() : transfer function
- n : number of iteration
- θ_j : bias value or threshold for node j
- y_j : the target output node j

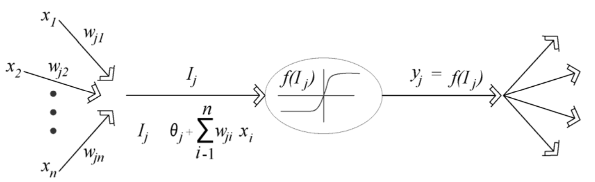


Fig.1. Neuron model with weighted inputs and embedded transfer function [14]

The most popular neural networks paradigm is the back-propagation neural networks (BPNN). BPNN consists of three inter-connected group of layers i.e. input layer, hidden layer and output layer as shown in Fig. 2. The purpose of BPNN training is to change iterative the weights between the neurons in a direction that minimizes the error.

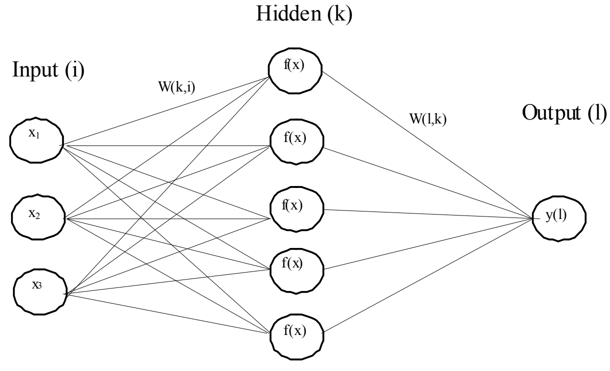


Fig.2. Artificial neuron with inputs and a single output

The number of hidden neurons is important in the back-propagation networks. However, there is no exact method for determining the number for hidden layer neurons. Too many hidden layers make the training time longer, but fewer hidden layers make learning algorithm be trapped in the local minimum, as described by [15]. Determining the suitable number of hidden layer requires the trial and error process. Reference [16] suggested that the rough estimations to find the best hidden layer size nodes on the hidden layer should be between average and the sum of the nodes in the input and output layers. Various transfer functions were investigated to achieve best performance in training as well as in testing. The optimal performance was obtained from tan sigmoid-log, sigmoid-log, sigmoid-linear activation functions in the first, second, third and output layers respectively.

III. Neural network Application in Pile Capacity Prediction

This study used the Neural Network Back Propagation (BPNN) algorithms. The best performances of BPNN depend upon the selection of suitable initial weight, learning rate, momentum, networks architecture model and activation function. The architecture model for this system has *n* number of input, one and two hidden layers with *n* neurons and one target output. The input networks consist of consists of a wide spectrum of variety in the pile equivalent diameter (D), embedment length (L), compression stress (CS), tension stress, (TS), vertical displacement (DFN), ram weight, (WH), drop height, (DH) and energy (EMX). Thus, eight parameters were used as input parameters while the axial bearing capacity of the single pile (Q) is selected as the single target output variable for this study. Therefore, the neural network model developed in this study uses 8(eight) nodes in the input layer (D, L, CS, TS, DFN, WH, DH, and EMX), 8(eight) nodes in the hidden layer (q1,q2,…..q8), and single node in the target output (Q). Fig.3 shows the architecture of the complete network for this study.

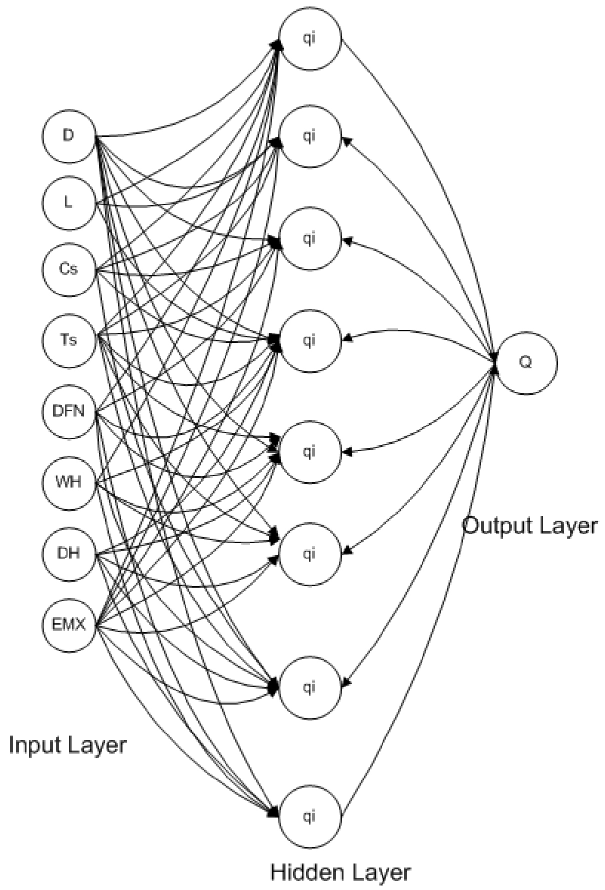


Fig. 3. The architecture model of the neural networks with 1 hidden layer in the system.

The function for training used Gradient Descent Back-propagation to minimize the error (MSE) as defined in (2).

$$E = \tfrac{1}{2}\sum_{j \in J}(t_j - a_j)^2 \qquad (2)$$

where t_j is target value, a_j is activation value of output layer, and J is set of training examples. The iteration in the process is necessary to find the minimum of the error.

The final output is generated by a non linear filter Φ caller activation function or transfer function. The transfer function used Log Sigmoid function with a range of [0,1]. The function is used in BPNN multilayer as shown in (3).

$$a_j = 1 \big/ (1 + e^{-a_{net,j}}) \qquad (3)$$

where

$$a_{net,j} = [\sum_{i=1}^{l} w_{ij} a_i] + \theta_j$$

Each i represents one of the units of layer l connected to unit j and θ_j represents the bias.

The updated weight on the link connection the i th and j th neuron between the layers is defined as,

$$\Delta W_{ij} = \eta(\partial E / \partial W_{ij}) \qquad (4)$$

where, η is the learning rate parameter with range 0 to 1 and $\partial E / \partial W_{ij}$ is the gradient of error with reference to the weight.

The normalized of data input used (5)

$$z_i' = (z_i - z_{\min}) \big/ (z_{\max} - z_{\min}) \qquad (5)$$

where z_i' is the normalized input values; z_i is the original data; z_{max} is the maximum and z_{min} is minimum values.

IV. A CASE STUDY

The prediction of axial pile bearing capacity using pile driving analyzer (PDA) test data has been examined by the previous researchers, such as [17], described a neural network to predict the friction capacity of the pile in clays soil.

For this study, the bearing capacity of the piles predicted based on PDA data ranges from 50 to 350 tons. An example of the measured stress wave signal is shown in Fig.4. The F and Z_v are the force and velocity multiplied by impedance measured near the pile head. The force and velocity reach maximum value at the certain time (tp) and then change within a period of 2L/c, which is the time taken for the wave to travel from the pile head to the pile toe and back to pile head. Thus, soil pile interaction occurs within the time interval from (t_p) to (t_p + 2L/c), then the force and velocity gradually decrease to zero. It means, the prediction of pile capacity usually based on this signal within this interval as the input data. Detail explanation of the analysis of pile driving formulas and wave equation based on PDA data can be found in Coduto [18].

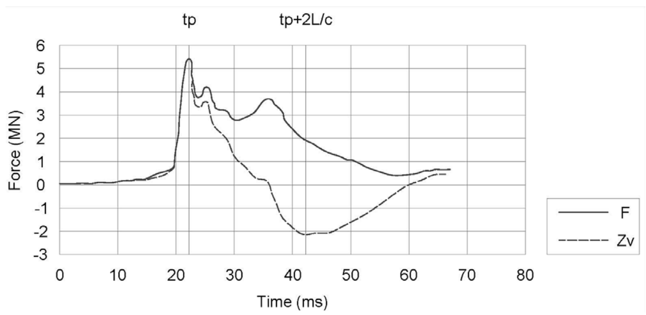


Fig. 4. Typical measured stress wave data from dynamic load test [4].

All databases are prepared for the training and testing procedure of the neural network. All of the input and target output variables were normalized to the values range between zero and one before training. In this study, all 300 test pile data were normalized between 0 – 1 value, then data are ready to be used for the training and testing with ANN model.

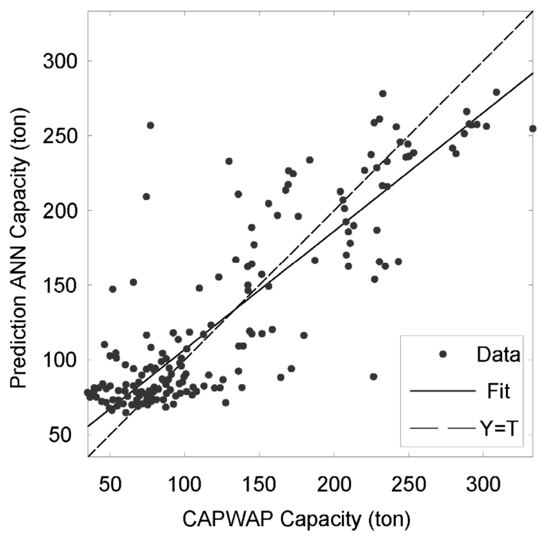
The target of ANN model is not the best training data, but the best responds of the training data to be used for testing data in a good manner. Reference [19] used Kolmogorov's theorem which any function of input (i) variables may be represented the required number of hidden nodes (h), whereas h = 2i + 1. The value of mean squared error (MSE) is a goal was varied based on the coefficient of determination R^2 of the testing result [13]. The R^2 value described the contribution of input value in predicting the

ISBN: 978-988-19251-8-3
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

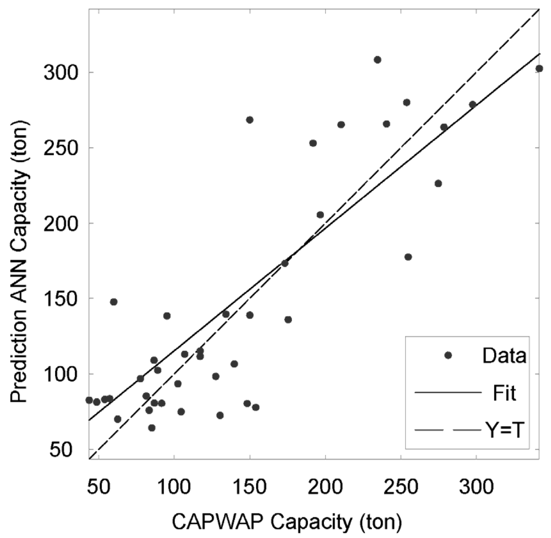
target output value, which means the lowest MSE value gives the better prediction of axial bearing capacity of the driven pile.

The neural network model was developed by MATLAB Ver 7.10.0.499 (R2010a) under Universiti Teknologi Malaysia (UTM) licensed. The computer model used in this study is Intel Core 2 Duo Processor, U7700-1.3GHz. The main parameter values using for training and testing the networks are the number of maximum iterations is 15,000; the learning rate is 0.2; and the target error is 0.001.

The following figures below show the performance of the ANN model both training and testing phase.



a. Training Phase



b. Testing Phase

Fig.5. Performance neural network model prediction axial pile bearing capacity

The result for the model with one hidden layer in Fig. 6 shows the neural networks model based on total axial pile capacity data domain provided reasonable prediction as well as training and testing phase.

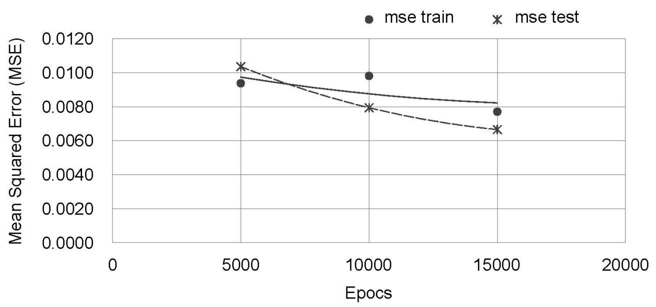


Fig. 6. The Means Square Error of neural network model for 1hidden layer

The best of mean regression (R) value at 15,000 epochs is shown in Table I. R-mean value of total axial pile capacity data domain for one hidden layer is a reasonable value. It is 0.9017 for training phase and 0.9577 for testing phase, but the CPU time is quite longer compared to the others. As shown in Table I, the training and testing phase achieved quite similar value of Mean Squared Error (MSE) , however testing phase provide the better results compare with training phase, especially with the epochs value more than 10,000.

TABEL I
Summary of ANN model performance

Epocs	Training Phase		Testing Phase		CPU time,s
	MSE Mean	R Mean	MSE Mean	R Mean	
5000	0.0094	0.8802	0.0104	0.9092	309
10000	0.0098	0.8759	0.0078	0.8396	622
15000	0.0076	0.9017	0.0067	0.9577	953

V. Conclusion

An ANN model is developed in this study to predict the axial bearing capacity of a single driven pile based on results of CAPWAP analysis from PDA test. The study showed that ANN gives a reasonable prediction of the pile bearing capacity. According to the results, the neural networks method based on axial pile bearing capacity data had the best performance since uses one hidden layer in the system.

Therefore, using ANN method to prediction of pile bearing capacity should consider both training and testing phase.

Acknowledgment

The authors would like to thank to Universiti Teknologi Malaysia for the financial support through International Doctoral Fellowship (IDF).

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ISBN: 978-988-19251-8-3
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

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ISBN: 978-988-19251-8-3
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)