Evaluation of Shaft Bearing Capacity of Single Driven Pile using Neural Network

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***Abstract*— Numerous methods have been developed for calculating the axial pile bearing capacity, including the shaft resistance of single driven piles in the last few decades. One of the proposed methods used the developed Neural Network (NN) model for prediction of the shaft bearing capacity of a driven pile based on the Pile Driving Analyzer (PDA) test data. As many as 200 sets of high quality test data from dynamic load tests performed at several construction projects in Indonesia were selected for this study. Inputs considered in the modeling are piling characteristics (diameter, length as well as compression capacity), pile set, and hammer characteristics (ram weight, drop height, and energy transferred). The NN modified model was developed in this study using a computerized intelligent system for predicting the shaft resistance for various pile and hammer characteristics. The results show that the NN modified model serves as a reliable prediction tools to predict the friction capacity of the driven pile with a coefficient of correlation (R) value close to 0.9 and Mean Squared Error (MSE) less than 1% over 15,000 numbers of iteration process.**

***Index Terms*— axial capacity, neural network, pile driving analyzer , shaft resistance**

I. INTRODUCTION

ARTICIAL neural networks (ANNs) are an alternative approach used by researchers to determine the structure and parameters of the model based on the data alone. The technique is well suited to model complex problems where the relationship between the model variables is unknown [1]. Like other statistical methods, ANNs have the ability to model nonlinear relationship between a set of input variables and the corresponding outputs without the need for predefined mathematical equations. Furthermore, unlike statistical methods, ANNs need neither prior knowledge nor the incorporation of any assumptions or simplifications about the nature of the relationship between the model inputs and corresponding outputs [2]. ANNs use the data alone to determine the structure of the model, as well as the unknown model parameters.

ANNs has been increasingly employed as an effective tool in civil engineering area, such as [3] used ANN method for monitoring the bridges construction and the alert of bridges monitoring system [4]. In geotechnical engineering since 1990's [5] presented a neural network for prediction of settlement of the homogeneous soil type on pile foundation. [6] presented the neural network model to predict the shaft resistance pile capacity in clay. Furthermore, [7] applied an ANN model to predict the resistance of driven pile in dynamic-load test.

This paper presents the application of the ANN for prediction of axial shaft capacity of driven piles by adopting PDA data collected from several construction projects in Indonesia involving PDA test with CAPWAP analysis. The PDA combined with CAPWAP software is the most widely employed system for high strain dynamic pile test (HSDPT) due to its simplicity and quick handling of the data. Detail explanation of the analysis of pile driving formulas and wave equation analysis adopted in PDA test and CAPWAP analysis can be found elsewhere (e.g. [8]).

An ANN system (named NN-HM) was developed by a computerized intelligent system based on these data for predicting the shaft resistance capacity (Qs) based on selected pile and hammer characteristics.

II. DATA COLLECTION

The data used for this study was collected from various projects involving dynamic pile tests in Indonesia. The tests were performed using PDA test based on ASTM D 4945-08 and CAPWAP software for analysis of bearing capacity. Only high quality data from on concrete pile were used in the study. Two hundred sets of high quality test data from the dynamic load test were selected for the subsequent study. The spun piles used in this study are circles with diameter between 300 and 500 mm and square with sides between 200 and 400 mm. In this study, the piles are grouped into small, medium, and large diameter piles. There are 24 (12%) small (diameter less than 200mm) piles, 126 (63%) medium sized (diameter between 200mm and 400mm) piles and 50 (25%) large piles (diameter > 400mm) (Table 1).

TABLE 1
GROUPING OF PILE DATA BASED ON DIAMETER

Group	Diameter	Number of piles	Percentage
Large pile	> 400 mm	50	25%
Medium pile	200 – 400 mm	126	63%
Small pile	< 200 mm	24	12%

III. MODELLING AND DATA PROCESSING

The development of NN-HM model in order to obtain more accurate estimate shaft resistance capacity of single Pile Driving Analyzer (PDA) test data. The architecture of the NN-HM model was developed based on the parameters

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and summarized in Fig. 1. There are five parameters were selected as input parameters for the subsequent study i.e. pile equivalent diameter (D), embedment length (L), ram weight, (WH), drop height, (DH) and energy transferred (EMX). The target output variance for this study is shaft resistance capacity (Qs). These target values were obtained from the output of CAPWAP analysis.

In the development of NN-HM model, it is important to divide the available data into three main groups, which are training (70% number of data), testing (15% number of data) and validation (15% number of data). The input and output variables are pre-processed by scaling down them to eliminate their dimension and to ensure that all variables receive equal attention during training. The scaling down or normalized data has to use with the limits of the transfer functions used in the hidden and output layers i.e, -1.0 to 1.0 for tanh transfer function and 0.0 to 1.0 for sigmoid transfer function. Rescaling is often accomplished by using a linear interpolation formula, as given by (1):

$$x_i' = \left[\frac{(x_i - min_{value})}{(max_{value} - min_{value})}\right] \quad (1)$$

where:

xi'	:	value of data normalization
xi	:	original data value
max value	:	maximum data value
min value	:	minimum data value

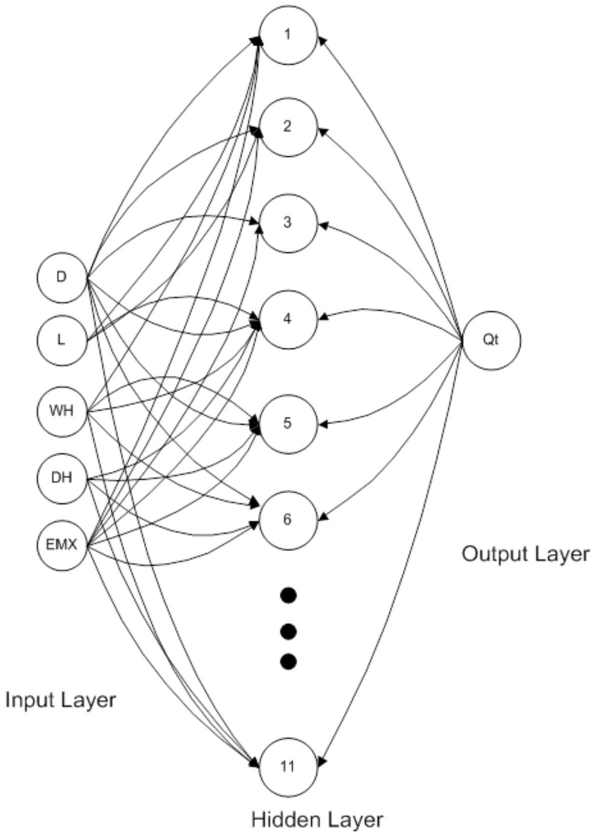

Fig.1 An Architecture ANN model

There are two evaluation criteria for the training of the ANN model to get the reasonable and optimal results. The criteria are the correlation of Regression (R) and Mean Square Error (MSE). [9] used error back propagation of neural network was utilized to predict the ultimate bearing capacity of pile. [10] used sum of correlation correlations and average sum squared error to predict the axial pile bearing capacity.

Relative important factor analysis was performed to recognize of each input variables on the shaft resistance capacity. For this reasons, the strength of the relations between the output parameters and the input parameters was evaluated using Cosine Amplitude Method (CAM). This method is one of the sensitivity analysis method which is used to find the Similarity relations between the input and output parameters..

All data pairs were expressed in common u-space to utilize Cosine Amplitude Method (CAM). The data pairs which are used to construct a data array u are defined as (2):

$$u = \{u_1, u_2, w_3, \ldots, u_n\} \quad (2)$$

The elements ui in the array u is a vector of lengths of m that is in (3):

$$u_i = \{u_{i1}, u_{i2}, w_{i3}, \ldots, u_{im}\} \quad (3)$$

Therefore, each data pairs can be considered as a point in m-dimensional space, where each point requires m-coordinates for a full description. The strength of relation between data pairs, u_i and u_j, is represented by the following (4):

$$r_{ij} = \frac{\sum_{k=1}^{m} u_{ik} u_{jk}}{\sqrt{\sum_{k=1}^{m} u_{ik}^2 \sum_{k=1}^{m} u_{jk}^2}} \quad (4)$$

The strength of the relation (r_{ij} value) indicates the influence of different input variables on one of the output variables. The larger the value of r_{ij} becomes, the greater is the effect on the output. For instance, if the output has no relation with the input, then the rij value is zero, while the value of r_{ij} closer to 1 expresses the further influence of the input parameter.

IV. Results and Discussions

The training, testing and validation processes were performed for 20,000 iterations with an interval of 5,000 iterations. Table 2 represents the performance of the NN-HM model to predict the shaft resistance of driven piles in terms of the coefficient of correlation (R) and mean squared error (MSE) for the different iteration number during the training, testing and validation process.

TABLE 2
NN-HM MODEL PERFORMANCE OF SHAFT PREDICTION

Iteration Number	Coefficient of correlation (*R*)			Mean squared error (*MSE*)		
	Training	Testing	Validation	Training	Testing	Validation
5,000	0.7292	0.5688	0.7937	0.0104	0.0111	0.0072
10,000	0.8268	0.8199	0.6399	0.0081	0.0096	0.0079
15,000	0.8615	0.8367	0.8852	0.0075	0.0059	0.0078
20,000	0.8655	0.7429	0.8589	0.0090	0.0076	0.0064

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Analysis of output indicates that the best results were obtained for the conditions given in Table 3.

TABLE 3
CHARACTERISTICS OF THE DEVELOPED ANN MODEL

Number of Iterations	15,000
Learning rate	0.15
Target error	0.005
Number of hidden layers	1
Number of hidden nodes	11

Based on (4), the value of r_{ij} is close to 1 for the ram weight variable. Comparison between each important variables are shown in Fig. 2 below:

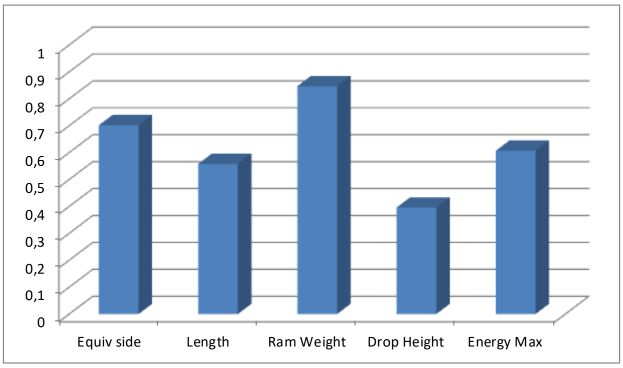


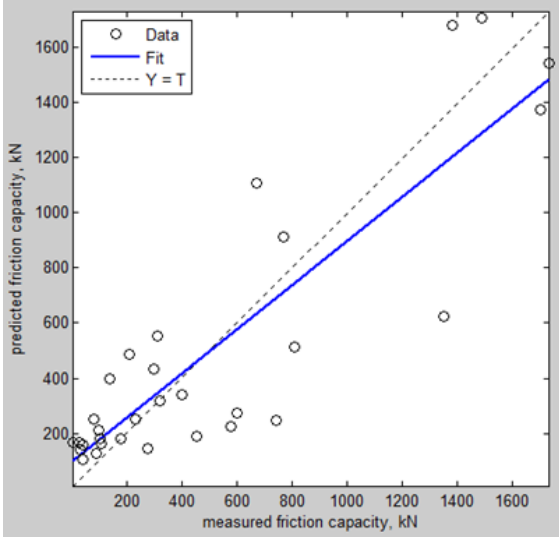
Fig.2 Important factor of each variable

V. Analysis and Performance

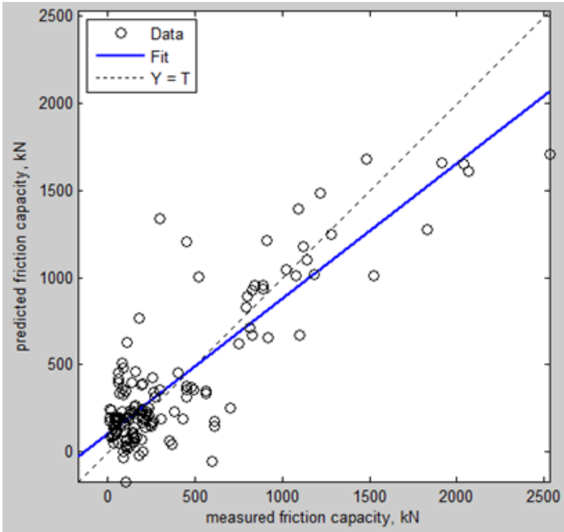
Comparison between the predicted values of shaft bearing capacity of piles by NN-HM model during the training, testing and validation phase and the measured bearing capacity using CAPWAP is presented in Fig.2. As shown in Table 2, coefficient of correlation R of the selected model was found 0.8615 for training, 0.8367 for testing, and 0.8852 for the validation process. The result of R still acceptable for prediction of shaft resistance capacity. On the other hands, the mean squared error, MSE, as shown in Table 2, was found 0.0075 for training, 0.0059 for testing and 0.0078 for the validation process.

VI. Conclusion

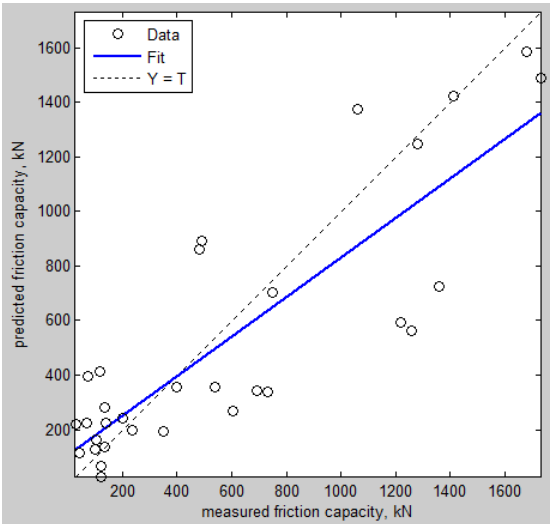
The Neural Network model (NN-HM) is developed in this study to predict the axial shaft bearing capacity of single driven piles based on the results of the CAPWAP analysis from PDA test. The model gives a good prediction of axial bearing capacity of driven piles which is implied by the higher coefficients of correlation (R) during the training, testing and validation phases. The mean squared error obtained during the three steps also acceptable. Results showed that the developed ANN-HM model gives more conservative value prediction of axial shaft bearing capacity compare with the result from CAPWAP analysis. Thus, the NN-HM serve as a reliable prediction tools to predict the resistance of the driven pile with a coefficient of correlation (R) values close to 0.9 and mean squared error (MSE) less than 1% after 15,000 numbers of iteration process. Note this model considers only pile and hammer characteristic while soil parameters are considered similar.



a. Training



b. Testing



c. Validation

Fig.3 Comparison of predicted & measured Shaft Resistance

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