Analysis of Ultimate Bearing Capacity of Single Pile Using the Artificial Neural Networks Approach: A Case Study

Analyse de la capacité portante ultime d'un pieu unique à l'aide de la méthode des réseaux de neurones artificiels : une étude de cas

Wardani S.P.R.
Civil Eng. Dept, Engineering Faculty, Diponegoro University & Indonesian Road Development Association, Indonesia
Surjandari N.S.
Civil Eng. Department, Engineering Faculty, Sebelas Maret University, Indonesia
Jajaputra A.A.
Professor Emeritus at Institut Teknologi Bandung & Visiting Professor at Diponegoro University, Indonesia

ABSTRACT: Degree of certainty, accuracy, complexity, and non-linearity are things that are adhere to geotechnical problems. Solutions using conventional approaches, although were still used in geotechnical problems require a large number of assumptions for the determination of geotechnical parameters. Currently new approaches emerge, including the "artificial intelligence", one of which is a neural network (NN).This study aims to apply NN model for prediction of ultimate bearing capacity of single pile foundation, was named NN_Qult model. The results of analysis model were then compared with Meyerhof, 1976 and Briaud ,1985 formulas. At the stage of modeling, data from full-scale pile load test and SPT were used. The selected input variables are: d (pile diameter), L (length of the pile embedded), the N60 (shaft) value, and the N60 (tip) value. The study generates design Charts that are expected to predict the ultimate bearing capacity of a single pile foundation. The results showed that neural networks can be used for prediction of ultimate bearing capacity of single pile foundation. This is particularly due to the sensitivity analysis results indicated the suitability of artificial neural network model with existing theories.

RÉSUMÉ : Degré de certitude, précision, complexité et non-linéarité sont des difficultés inhérentes aux problèmes géotechniques. Les approches conventionnelles, bien que toujours utilisées dans les problèmes géotechniques nécessitent un grand nombre d'hypothèses pour la détermination des paramètres géotechniques. Actuellement de nouvelles approches émergent, notamment « l'intelligence artificielle », dont l'une des formes est le réseau de neurones (NN). Cette étude vise à utiliser le modèle de réseau de neurones pour la prévision de la capacité portante ultime de fondation sur pieu unique, elle a été dénommée le modèle NN_Qult. Les résultats du modèle d'analyse ont ensuite été comparés avec les formules de Meyerhof, 1976 et de Briaud, 1985. Lors de l'étape de la modélisation, des données provenant d'essai de chargement de pieux grandeur nature et de données SPT ont été utilisées. Les paramètres retenus sont les suivants: d (diamètre du pieu), L (longueur du pieu), les valeurs N60 (frottement latéral et résistance de pointe). L'étude a abouti à des graphiques de conception prévus pour prédire la capacité portante ultime d'une fondation sur pieux unique. Les résultats ont montré que les réseaux neuronaux peuvent être utilisés pour la prédiction de la capacité portante ultime de fondation sur pieu unique. Cela est notamment dû aux résultats de l'analyse de sensibilité qui a indiqué la cohérence du modèle de réseau de neurones artificiel avec les théories existantes.

KEYWORDS: Ultimate bearing capacity, a single pile foundation, the neural network models, design Chart.

1 INTRODUCTION.

Mathematical model (white box model) is a form that has been established in the field of science. This model was created using the basic principles of physics and mechanics followed by a series of observations, used for simulation, prediction, and analyze the behavior of a system. Appropriate mathematical model when the underlying condition of a system are known, the measured uncertainty and inaccuracy did not reduce the accuracy of the model (Grima, 2000; Rahman and Mulla, 2005). Problems in geotechnical engineering are generally complex, so that its exact solution is the probability (Djajaputra, 1997; Griffith et al., 2002). Uncertainty and inaccuracy is almost always found as to seek geotechnical parameters. There are many factors that are not known with certainty because only a limited number of sampling used. This condition leads to the use of mathematical models for the solution in a difficult geotechnical problems (Rahman and Mulla, 2005; Prakoso, 2006).

Artificial neural network model has been started in the field of geotechnical engineering. The difference between neural network model and matematical model is the artificial neural network model does not require the initial assumption of physical laws (a priori any physical law) of a system, when new data are found, so the ability to predict can be upgraded with relative ease (Javadi et al., 2001; Hashash et al., 2004; Right and Faez, 2004).

The purpose of this study is to make an artificial neural network model for calculating the limit bearing capacity of a single pile foundation and then its ability is compared with some existing methods.

2. BASIC THEORY

2.1 Ultimate bearing capacity of single pile foundations.

The axial limit bearing capacity (ultimate) of the pile foundation (*Qult*) is assumed to be the result of 2 (two) mechanisms i.e. the side friction resistance of foundation (*Qs*) and end bearing resistance of foundation (*Qt*) so that the net ultimate bearing capacity due to the axial load pressure is as in Eq. 1 (Bowles , 1988).

$$Qult = Qt + Qs - W \tag{1}$$

by:
Qult = ultimate bearing capacity
Qt = end bearing resistance
Qs = friction resistance
W = weight of pile foundation.

2.1 Static Load Test Pile Foundations

Currently static load test yield in the most reliable way to determine the load capacity, but has some weakness i.e cost and time-consuming. Poulos and Davis (1980) stated that one of the usability of this test is its ability to compare between static load limit bearing capacity obtained from the dynamic and static formulas. Load test results in accordance with ASTM D-1143 shown as a load-movement curve. Prakash and Sharma (1990) described the full procedure for determining the limit bearing capacity of static load test results with some methods of interpretation.

2.3 Artificial Neural Network Model

Artificial Neural Network (ANN) is the information processing system that has performance characteristics such as human nerve network. Artificial neural network is a dynamic system (a system that can be changed) as it can be trained and have the ability to learn. Neural networks can work well even in the presence of confounding factors such as uncertainty, inaccuracy, and partial truth in the processed data (Fausett, 1994; Kurup and Dudani, 2002; Nugroho, 2003; Jeng et al., 2005; Wang et al., 2005).

Neural network consists of several interconnected neurons. Neurons transform information received via the connection to the discharge of other neurons. On artificial neural networks, this connection is called a weight. Information (input) is stored at a particular value on the corresponding weights are then sent to other neurons by the arrival of a certain weight. Input will be processed by the propagation function that will sum the values of all weights that come. The sum is then compared with a threshold value, usually through an activation function of each neuron. Neurons will be activated when the input is passed a certain threshold value, but if not and vice versa. Neurons that are activated will send the output via the output weights to all the neurons connected with it. This process is described in Figure 1 (Kusumadewi and Hartati, 2006).

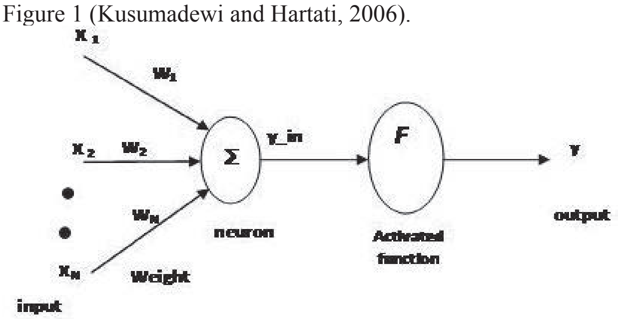


Figure 1. Tipical of an Artificial Neural Network (Kusumadewi dan Hartati, 2006)

Fausett (1994) and Kasabov (1998) classified models based on artificial neural networks i.e. network architecture (single layer, multi layer, competitive layer), presence or absence of feedback connections (feed-forward networks and feedback networks), the method of determining the connection weights/training/ algorithm (unsupervised and supervised), and activation function (Identity, Step Binary, Binary Sigmoid, Sigmoid Bipolar).

2.3.1 Evaluation of Precision, Accuracy, and Robustness ANN Modeling Results

Cooper and Emory (1997) in Somantri and Muhidin (2006) defined the precision as a measure of how much something means to give consistent results. Precision closely with a variety of data, measured by the coefficient standard errors. The smaller the standard error coefficient means higher precision. Accuracy is how well an instrument measures what it is supposed to be measured, therefore the level of accuracy is measured using the average. The closer the value 1 (one) indicates the more accurate.

3. RESEARCH METHODS

This study was conducted in several major stages i.e preliminary, model development, model verification, and calibration model. The resulting final model named NN_Qult.

In this study, the results of static load test was used as a reference for measuring the precision and accuracy of modeling results with the ANN approach. Some of the conventional formulas (Meyerhof, 1976 and Briaud,1985 in Coduto, 1994) were chosen for its performance compared with the results of ANN modeling approaches.

3.1 Preliminary Phase

Data was collected from the Final Report of Investigations and Axial Static Load Test Reports of load pile foundation. Datas taken at several building projects on the Java Island that use pile foundation.

To manufacture the artificial neural network model in this study, there are several things that need to be considered such as model input variable selection, data management, the determination of the model architecture, network criteria selected as the final model (Shahin et al.,2001). The selection of the model input variables was based on a prior knowledge (Maier and Dandy, 2000 in Shahin et al.,2001).

The available data was divided in to the proportion of 2/3 for the phase of training (i.e. training and testing) and 1/3 for the validation phase (Hammerstrom ,1993 in Shahin et al.,2001). Training set for adjusting the connection weights, testing set to check the ability of the model in several variations of the training phase, the validation set to estimate the ability of the model that has passed through phases of training to be applied. Another thing to note is the pattern of each sample data set used for training and validation phases were expected to represent the same population, then some random combination tried to obtain some consistency in the statistical value of the mean, standard deviation, minimum, maximum, range (Shahin et al., 2002b).

Because of the unavailability of the method for determining the optimum architecture, so in this study, fixing the number of hidden layers and choosing the number of nodes in each layer were conducted. Determination of a network was selected and some combinations of networks were trained. Observed output and predicted output were compared qualitatively by looking at a visual comparison of plot points of data and quantitative by statistical parameters test.

3.2 Model Verification

Model verification was conducted by sensitivity analysis. Sensitivity analysis is a method for extracting the influence of the relationship between input variables with output variables on the network. The first experiment with installing the first input variable values vary between the mean values ± standard deviation or between the minimum and maximum value while the other input variables fixed at the mean value of each. Similar experiments carried out at the other input variables. This process will generate a graph the relationship between each input variable versus network predicted output variables. The strength of the final model assessed the suitability of the final model with the existing theory (Shahin et al., 2002a; Samui and Kumar, 2006).

3.3 Calibration Model

Sensitivity analysis phase produces the final model i.e NN_Qult. The model was then tested with the full-scale static load test as a validation. Some selected conventional formulas were chosen and compared with the final model NN_Qult. The tools used to perform comparison were a few statistic parameters. Comparison of the ultimate bearing capacity predicted results and the measurement results (Qult_p / Qult _M) were used as a comparative analysis of variables. Comparison of Qult_p / Qult _M in the range of 0 to ∞ with optimum value equal to one. Mean (μ) and standard deviation (σ) of Qult_p /Qult_M was an indicator of the accuracy and precision of the method was analyzed.

4. RESEARCH FINDINGS

Final Model of NN_Qult have a 3 network configuration hidden nodes were trained on the 1000 epoch, learning rate = 0.5 and momentum = 0.5. Connection weights and bias values NN_Qult models are summarized in Table 1. Image network architecture shown in Figure 2 NN_Qult models, has 4 (four) input variables (d, L, N60 (shaft), and N60 (tip)) and 1 (one) variable output (Qult).

Tabel 1. Weight and bias for *NN_Q*$_{ult}$ Model

Node at the hidden layer	w_{ji} (weight of node i at input layer to node j at hidden layer				Bias at hidden layer (b_j)
	i = 1	i = 2	i = 3	i = 4	
j = 5	2,743	-3,124	-2,858	-0,124	0,326
j = 6	-5,600	2,146	-2,393	-0,841	0,767
j = 7	16,043	1,154	-6,541	-4,261	-0,456
Node at the output layer	**w_{ji} (weight of node i at hidden layer to node j at output layer**				**Bias at output layer (b_j)**
	i = 5	i = 6	i = 7		
j = 8	-2,644	-10,239	3,203		-0,838

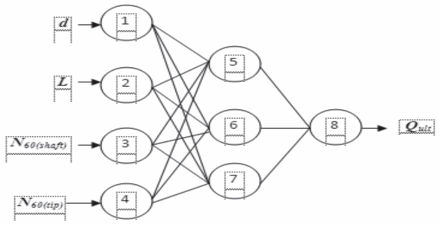
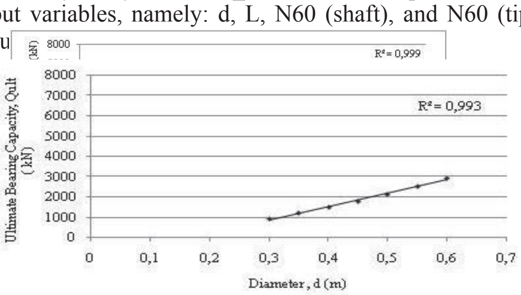


Figure 2. Network structure of *NN_Q*$_{ult}$ Model

4.1 Sensitivity Analysis of NN_Qult Model

Sensitivity analysis of NN_Qult model was performed on four input variables, namely: d, L, N60 (shaft), and N60 (tip). The resu



Figu

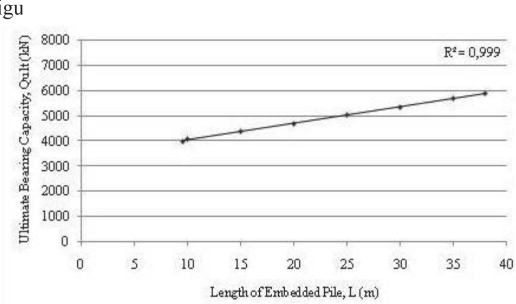


Figure 4. Graph of Relation of $N_{60(shaft)}$ versus Q_{ult} Variable

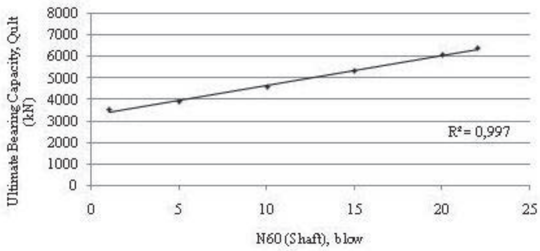


Figure 5. Graph of Relation of $N_{60(shaft)}$ versus Q_{ult} Variable

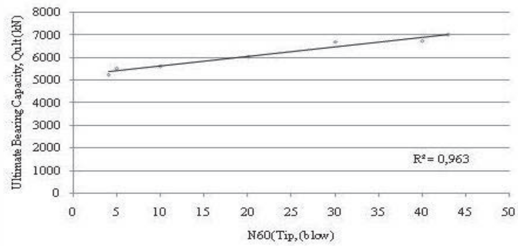


Figure 6. Graph of Relation of $N_{60(tip)}$ versus Q_{ult} Variable

4.2 Result of Model Calibration

4.2.1 *Graphically Method Evaluation*

Result of Model calibration by graphically method can be seen in Figure 7 until Figure 9.

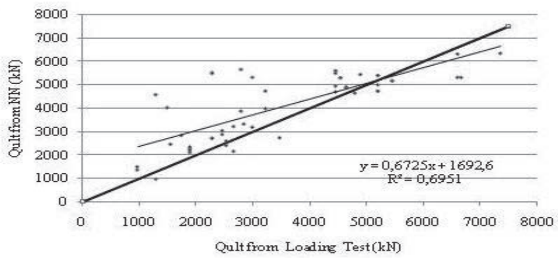


Figure 7. Calculation Result of Q_{ult} from *NN_Q*$_{ult}$ and Static Loading Test.

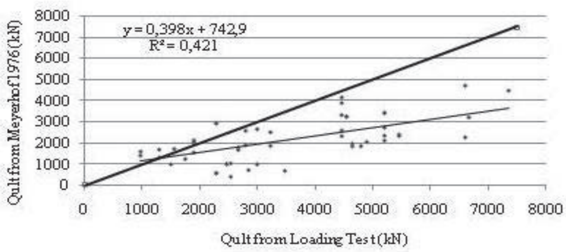


Figure 8. Q_{ult} from Meyerhof 1976 and Static Loading Test

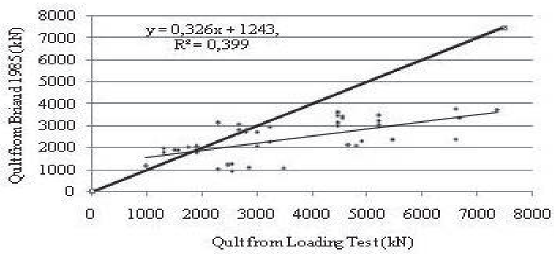


Figure 9. Q_{ult} from Briaud 1985 and Static Loading Test

Based on Graphically evaluation, there were two values reviewed, namely coefficient of determination (R^2) and the gradient/slope of the regression line (m). R^2 value close to 1 (one) means that the regression line closer to the data distribution. Value of *m* close to 1 (one) means that the regression line close to the best fit line, it is the line representing the distribution of data in which the predicted value equal to the measured value. R^2 for models NN_Qult, Meyerhof's formula (1976) and Briaud's formula (1985) respectively were 0.695: 0.421, and 0.399. *m* for the model NN_Qult, Meyerhof's formula (1976), Briaud's formula (1985) respectively were 0.673: 0.398, and 0.327.

The R^2 value from the regression line generated by NN_Qult closest to the data distribution when compared to the regression line generated by the Meyerhof 's formula (1976) and Briaud's formula (1985). Qult generated by NN_Qult closest Qult static loading test results of the test when compared with Qult that produced Meyerhof's formula (1976) and Briaud's formula (1985). This condition indicates that the predicted value of the research model most closely with observed value.

4.2.2 The Analytical Evaluation

In the evaluation of analytically there were 2 (two) values were reviewed to calculate the mean value and standard deviation. Mean (μ) for the model NN_Qult, Meyerhof's formula (1976), and Briaud's formula (1985) respectively were 1.27; 1.68, and 1.78. Standard deviation (σ) for the model NN_Qult, Meyerhof's formula (1976) and Briaud's formula (1985) respectively were 0.52; 0.34, and 0.33.

In this study, the statistical parameters used to evaluate the performance of the method are coefficient of determination (R^2), the gradient (m), mean (μ), and standard deviation (σ). The Rank Index (RI) was made to quantify the total performance of each method. RI is the algebraic sum of the ratings obtained from all of the criteria used (Titi and Farsakhs, 1999). RI values closest to 1 (one) is considered as a method that has the best performance. Table 4 is a recapitulation of all the statistical parameters obtained from the calculations that have been done. Three statistical parameters, namely R^2, m, and μ is considered best when approximately equal to 1 (one), while for σ is considered best when approximately equal to 0 (zero), so for consistency of the calculation, then the special statistic parameter σ, the value to be is the same compared with the absolute value (1 - σ).

Table 4. Perform Evaluation of Some Models

Method	NN_Q_{ult} Model					
	$R^2 - R_1$	$m - R_2$	$\mu - R_3$	σ	$(1-\sigma) = R_4$	RI $(R_1+R_2+R_3+R_4)$
NN_Q_{ult}	0,695	0,673	1,27	0,52	0,48	3,118
Meyerhof 1976	0,421	0,398	1,68	0,34	0,66	3,159
Briaud 1985	0,399	0,327	1,78	0,33	0,67	3,176

Referring to Table 4, it appears that for the model results (NN_Q_{ult}) provide RI value is the most closed to 1 (one) or the optimum value, so that it can be said that the model results of the research has the highest performance among the methods are comparable, despite differences in RI values is not too big.

4.2.3 Design Chart Based on Final Model

Based network architecture that has been verified by sensitivity analysis and has been calibrated with the results of static load, so that created a graph that is expected to be used for initial design purposes. Model NN_Qult produce design charts. One example of the design chart shown in Figure 10.

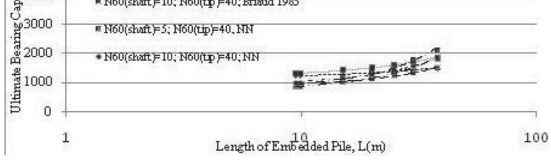


Figure 10. Example of *Design Chart* of NN_Q_{ult} Model

5. CONCLUSIONS

The new calculation of the ultimate bearing capacity by the artificial neural network model is given in chart form. The design chart is used as a tool to calculate the ultimate bearing capacity of a single pile in sand soil. This is particularly due to the sensitivity analysis results indicated the suitability of artificial neural network model with existing theories. The results of the model have the highest performance among the other methods, even though the difference is not too big.

6. REFERENCES

Bowles, J.E. (1988), *Foundation Analysis and Design*, Mc. Graw Hill Book Company, Singapore, xix+1004p.

Coduto, D.P. (1994), *Foundation Design, Principles and Practices*, Prentice Hall International, Inc., New Jersey, xx+796p.

Djajaputra, A.A (1997), Konsep Beban Terfaktor Dalam Perancangan Tiang Bor, *Proceeding Seminar PILE'97*, Bandung, pp.14-1s/d14-3.

Fausett, L.(1994), *Fundamentals of Neural Networks (Architectures, Algorithms, and Applications)*, Prentice Hall, xv+449p.

Griffith, D.V., G.A. Fenton, N. Manoharan (2002), Bearing Capacity of Rough Rigid Strip Footing on Cohesive Soil: Probability Study, *Journal of Geotechnical and Geoenvironmental Engineering*, pp. 743-755.

Grima, M.A. (2000), Neuro-Fuzzy Modeling in Engineering Geology: Applications to Mechanical Rock Excavation, Rock Strength Estimation, and Geological Mapping, *PhD thesis*, Delft University of Technology.

Hashash,Y.M.A., S. Jung, and J. Ghaboussi (2004), Numerical Implementation of a Neural Network Based Material Model in Finite Element Analysis, *International Journal for Numerical Methods in Engineering*, pp. 59:989-1005.

Jeng,D.K., S.M. Bateni, and E. Lockett (2005), Neural Network Assessment for Scour Depth Around Bridge Piers, *Research Report* No R855, Department of Civil Engineering Sydney NSW, Australia.

Kasabov, N.K. (1998), *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering*, The MIT Press, x+419p.

Kurup, P.U. and N.K. Dudani (2002), Neural Networks for Profilling Stress History of Clays from PCPT Data, *Journal of Geotechnical and Geoenvironmental Engineering*, pp. 569-579.

Nugroho, A.S. (2003), Pengantar Soft Computing, Kuliah umum ilmu komputer.com.

Prakash, S. and H.D. Sharma (1990), *Pile Foundations in Engineering Practice*, John Wiley & Sons, Inc., xxx+734p.

Prakoso, W.A. (2006), Desain Pondasi Dalam Berbasis Keandalan dan SNI 03-6747-2002, *Prosiding Pertemuan Ilmiah Tahunan – X (PIT – X) Himpunan Ahli Teknik Tanah Indonesia*, Jakarta, pp. 121-130.

Rahman, M.S., and M. Mulla (2005), *Fuzzy Neural Network Models for Geotechnical Problems* , NCDOT Research Project, USA.

Samui, P. and B. Kumar (2006), Artificial Neural Network Prediction of Stability Numbers for Two-Layered Slopes With Associated Flow Rule, *Electronic Journal Geotechnical Engrg*, http://geotech.civeng.okstate.edu/ejge/paper0626/index.html

Shahin,M.A., M.B. Jaksa, and H.R. Maier (2002a), *Artificial Neural Network-Based Settlement Prediction Formula For Shallow Foundations On Granular Soils*,Australian Geomechanics, pp.45-52.

Shahin,M.A., H.R. Maier, and M.B. Jaksa (2002b), Predicting Settlement of Shallow Foundations Using Neural Networks, *Journal of Geotechnical and Geoenvironmental Engineering*, pp. 785-793.

Shahin, M.A., M.B. Jaksa, and H.R. Maier (2005), Neural Network Based Stochastic Design Charts for Settlement Prediction, *Canadian Geotechnical Journal*, pp. 42:110-120.

Somantri, A. dan S.A. Muhidin (2006), *Aplikasi Statistika Dalam Penelitian*, Penerbit Pustaka Setia Bandung, 410p.

Wang, X., B. Li, D. Lockington, D. Pullar, and D.S. Jeng (2005), *Self-Organizing Polynomial Neural Network for Modeling Complex Hydrological Processes*, Research Report No. R861, Department of Civil Engineering Sydney NSW, Australia.