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ANALYSIS ULTIMATE BEARING CAPACITY ON BORED PILE WITH USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The issues that often arise within geotechnical engineering include uncertainty, complexity, and inaccuracies in planning. Therefore, this creates problems as relying on assumptions are the only way to determine parameters in design and construction. Recently, a new approach has emerged, inspired by the intelligence of the human brain, and it is called artificial neural network (ANN). This study aimed to utilize the ANN models with a back-propagation algorithm that feeds forward to predict the ultimate bearing capacity, namely NN_Q_{ult}. The total number of samples used are 375, and the input variables are d, Lp Le, A, K, f'c, N_{tip}, N_{shaft}, and P. According to Shahin (2001), the model was divided into two group: 2/3 training data and 1/3 validation data, processed in a modified ANN program. The prediction results of NN_Qult are then compared with the carrying capacity of pile driving analysis (PDA). It shows a good relationship, as evidenced by the value of R2> 0.8 and RMSE close to 0.1. The sensitivity analysis (AS) was also carried out to obtain the level of influence of the input compared to the output which are 12,367%; 10.255%; 14.576%; 8.323%; 15.870%; 5.154%; 8.218%; 14.314%; 10.923% respectively. The L_e, N_{tip} and P variables are the most influenced of the dataset.

Key words: geotechnical engineering, ANN, Back-propagation, PDA, Feed-forward.

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1. INTRODUCTION

Goh (1996) and Lee (1996) applied the Artificial Neural Networks (ANN) technique to their various studies. Furthermore, Niken (2012) analyzed the use of ANN in examining the capacity of bore piles and its reduction in sandy soil using static load (Kentledge).

The ANN method uses a working system similar to the human brain, which provides accuracy, completeness, and unreliability of one data with respect to another in predicting an analysis in the form of drill-pole-bearing capacity and its decline. ANN is composed of counter elements, known as neurons or nodes, that are interconnected with models similar to the human brain. This research is aimed at continuing that conducted by Niken (2012), i.e., using an ANN modeling approach to calculate the analysis of the bearing capacity of the boundary and elastic degradation of a pile driven into sandy soil with a static load.

The applications of *bored pile* and *Pile Driving Analyzer (PDA)* are extensively utilized in civil engineering projects that strictly require a load plan. Additionally, the use of a bored-pile foundation reduces vibration as well as noise and regulates the depth of the pile and its diameter. Some problems were associated with the implementation of load testing. The most common bore piles have the ability to settle at the bottom with a mixture of mud and concrete inadequate preparation, non-straight centralized relation between the load (hammer) and point of center pile foundation, use of unfit hammer with the load plan, and the incredible certification of human resources (HR) are some of the main aspects responsible for that inconsistency. With an immense degree of probability associated with analyzing the drill pillar capacity using data, inadequate and proficiency in analyzing Artificial Neural Network or variable inputs are not interconnected. Furthermore, ANN which ratifies the components of the human brain is perfect in examining the capacity of the bore pile. Additionally, N-SPT (a type of soil investigation) and Pile Driving Analyzer (PDA) are the data used in evaluating the bearing capacity of the support bored pile.

2. ARTIFICIAL NEURAL NETWORKS

The basic model of the artificial neural networks consists of inputs passing through a connection (relationship) that has a weight, with each nerve cell having a threshold value. The amount of weight from the input minus the threshold value will activate the nerve cell (postsynaptic potential, PSP, of the nerve cell). The activation signal becomes an activation/transfer function to produce the output of the nerve cell. This study analyzes the capacity of drill poles by utilizing the Back-Propagation Model with a feed-forward connection pattern, which is a simple network that has a feed-forward structure, in which the signal moves from the input to the hidden layer and finally reaches the output unit (has a stable behavior structure). The feed-forward tissue has nerve cells composed of several layers, with the input not classified as a nerve cell. Its ability is determined in the training process, as well as the level of accuracy of network modeling capabilities. A typical Back-Propagation algorithm model has two different layer directions, the forward direction/function signal and backward/error signal.

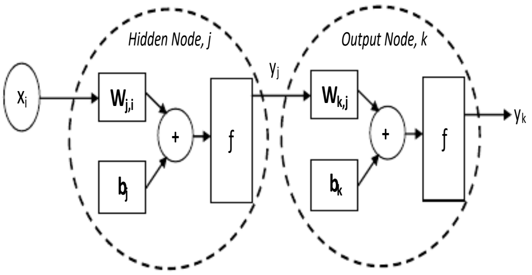

Figure 1 : *Neuron* Diagram and Transmission Process Scheme (Suwansawat, 2002)

Figure 1 shows the detail of the back-propagation algorithm process, where an investigation into the issues are conducted via the input values (xi), and the input neurons pass through to every neuron in the second layer. The weight of each line connection (wj, I) is multiplied by input to meet the hidden neuron-layer and is added to the bias value (bj) to correspond to a transformation function. The results in the hidden neuron-layer is transmitted to the output neuron-layer, which will be multiplied by the connection weight (wk, j) and coupled with the bias value (bk) to be performed on a transformation function. The input result is a signal produced by the output network neuron layer (yk). The variable input iterations in the ANN program also include goals, momentum, hidden layers and epochs.

2.1. Properties of Soil

Fenton & Griffiths (2002) described the importance of past data (empirical) using the dynamic properties of soil. When carrying out observation and testing, the properties of the soil only change within a few meter radius. As a result of the weathering of rocks, the land had changes in soil properties that are relatively far away. To get the mechanical properties of soils (soil engineering), testing should be conducted to find out the nature of the land when receiving loads, because the mechanical properties are important in planning the structure of the foundation.

2.2. In-Situ Testing and Pile Driving Analyzer

Situ testing is conducted in the form of the Standard Penetration Test (SPT), Cone Penetration Test, and PDA (Pile Driving Analyzer). The quality of test results is important in obtaining good results (Garbage In, Garbage Out). The factors are the types of tests, the influence of sample dependence (especially sand), Hammer Efficiency correction etc. Dynamic penetration testing SPT (Standard Penetration Test) is an in-situ often performed in addition to testing CPT. Dynamic pile foundation testing, using PDA with the Case - Goble et al. (1988) - provide important information relating to ground-pole foundation interaction under the axial loads provided. The results obtained from testing with PDAs are: pole capacity, hammer energy transfer to pole, compressive stress and pull, and integrity (integrity) of the pole. The PDA has 2 accelerometers that act as a measure of particle acceleration, which then integrates with time to obtain particle velocity (V) and two (2) strain transducers as measures of strain in the time function, which is converted to force (F) accelerometer, and the transducer is placed at 1.5 - 2D can be seen in Figure 2.

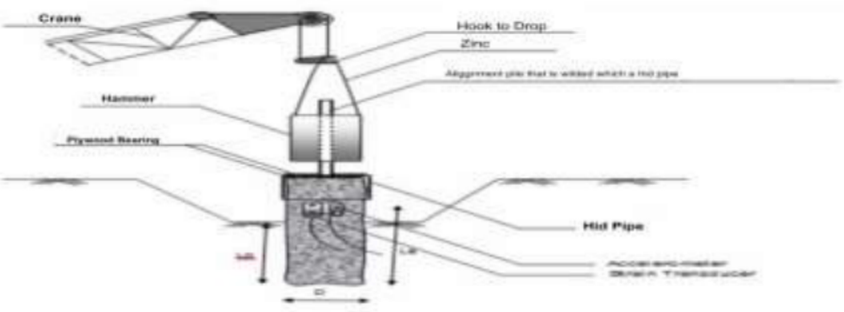

Figure 2 Concept of Loading Test PDA for Bored Piles

3. RESEARCH METHODS

The method used compared the capacity of pile supported by ANN with Back Propagation Feed Forward Algorithm with existing empirical formulas and secondary data studies. The data used in this research was the Final Report of Soil Investigation, the report of PDA collected throughout Indonesia, and the created algorithm that includes data variables from bored pile foundation, field test and N-SPT dynamic load test (tip and shaft), interpretation of soil properties, soil engineering and PDA testing (Pile Driving Analysis) for analysis by artificial neural networks with backpropagation feed-forward. The results of the analysis in reviewing the bore pile capacity were the ultimate bearing capacities, and the elastic decrease was compared with the empirical conventional formulas from the PDA test results.

3.1. Data and Collection

The type of data used was based on field testing obtained from a soil mechanics laboratory that have good credibility, consultants, and contractors. The data used in this study included a Final Report of Soil Investigation in the form of Boring Testing (SPT), soil profile, groundwater surface, laboratory data (Soil Properties and Soil Engineering), and the PDA Test Report.

3.2. Model Making Database

The foundation type information in the form of drill piles and foundation geometry (Length, L and diameter, D) was obtained from the PDA test report of each project. In general, the soil conditions in the field are layered with various types of soil that are not restricted to sandy layers or any other layer types.

3.3. Selection of Model Input Variables

In the modeling phase, one should pay attention to input variables, data processing, model architecture, and network criteria. Selection of good input variables can improve the ability of the model by producing better results. The choice of excessive inputting the variable model into the network model will cause the size of the network to increase and will reduce the speed of training and efficiency of existing networks, so it will be difficult to apply.

3.4. Model NN_Q_{ult}

The input variables in the artificial neural network model were pole length (Lp, Le) diameter, cross-sectional area, A (m2), Concrete Quality, f'c (MPa) and soil property variable, represented by Nshaft and Ntip value, i.e., N-SPT value at pole end area is taken 8d up and 3d down the pole end. The International Standards recommendation for actual energy received is 60% of the theoretical energy, so it was necessary to use the N60 value (Jefferies & Davies, 1993). The N60 value is derived from the theoretical N values using Equation 1 (Bowles, 1988).

$$Er1 \times N1 = Er2 \times N2 \qquad (1)$$

where:

Er1 x N1 = energy ratio 1 with energy ratio 2

Er2 x N2 = N value for energy ratio 1 and energy ratio 2

The model input variable for the calculation of carrying capacity of pile foundation limit (Qult) used in this study can be seen in Table 1.

Table 1. Variable Input Model for calculation

Categories	Input Variables
Foundation	Circumference of Pile (K)
	Diameter of pile, d (m)
	A (m^2)
	Hammer (Ton)
	Le (meter)
	Lp (meter)
	f'c (MPa)
Soil	$N_{60(shaft)}$ (Blow)
	$N_{60(tip)}$ (Blow)

3.5. Data Analysis

Using more samples provide better information for learning the network artificial model and its relationship between the data input and output targets; it can be used to minimize the ambiguity or data error and to obtain the potential accuracy that can (only) be achieved by the network to avoid *overfitting*. Moreover, there are several approaches to avoid overfitting, such as increasing the size of the training sample, limiting the number of hidden nodes as well as the number of epoch trainings.

The separation between the validation and the training phase is essential, particularly in ensuring the network model's ability within the range of data used. Furthermore, for the management of the model, it is divided into 2/3 training phases (i.e., training and testing) and l/3 for validation (Shahin et al., 2001).

3.6. Architecture and Final Model Network Criteria

Shahin et al. (2001) reported the existence of a network with a hidden layer by using a sigmoid type activation function, which was thought to be enough to resolve a problem. The results of the measurements and outputs generated by the network was compared qualitatively and quantitatively. Testing statistical parameters using quantitative analysis is by calculating the root mean squared error (RMSE) and the coefficient of correlation "r". Shahin et al. (2001) used the RMSE approach as the error measuring tool to determine the performance of a model and used the coefficient of correlation (r) to measure whether trend performances were good, comparing the prediction value with a trend that is happening.

The "r" value constraints suggested by Smith (1986) in Shahin et al. (2000) are as follows: $|r| > 0.8$: the relationship between two sets of variables is very strong; $0, 2 < r < 0, 8$: there is a relationship between two sets of variables; $|r| \leq 0, 2$: the relationship between two sets of variables is very weak.

3.7. MODEL TESTING

The stages of sensitivity analysis yielded the final model for NN_Qult. The model was then used for testing (matching) the dynamic load test results as well as the empirical formulas

The tool used for the comparison is a parameter of statistical science to provide an overview of the problems in the study.

3.8. DESIGN RESEARCH NETWORK

The research design model of the ANN is the ultimate bearing capacity, named NN_Q_{ult}. There are two ways to make the model: the first method is carried out so that each model is made separately by the training process on separate networks that produce one (1) output, and the second is validation model where both are made via the training process simultaneously on the same network to produce an ultimate bearing capacity. The determination of network architecture was made by considering the following parameters:

1. The number of hidden layers (i.e., 1 and 2).
2. Number of hidden nodes: trying or choosing (i.e., 1 until 10),
3. Activation function: using logsing.

The training process is stopped by selecting the criteria of the epoch number with the value set between 1000 and 10,000.

4. DISCUSSION AND MODEL RESULTS

The number of samples used in this research was 375, and the data spread throughout the territory of Indonesia. In addition, the PDA data for soil properties will increase following the completion of this research. The data was also classified based on the diameter of the bore piled. Figure 3 shows the planned design network model with one hidden Layer, 2 hidden Nodes, and 1 Output Q_{ult}.

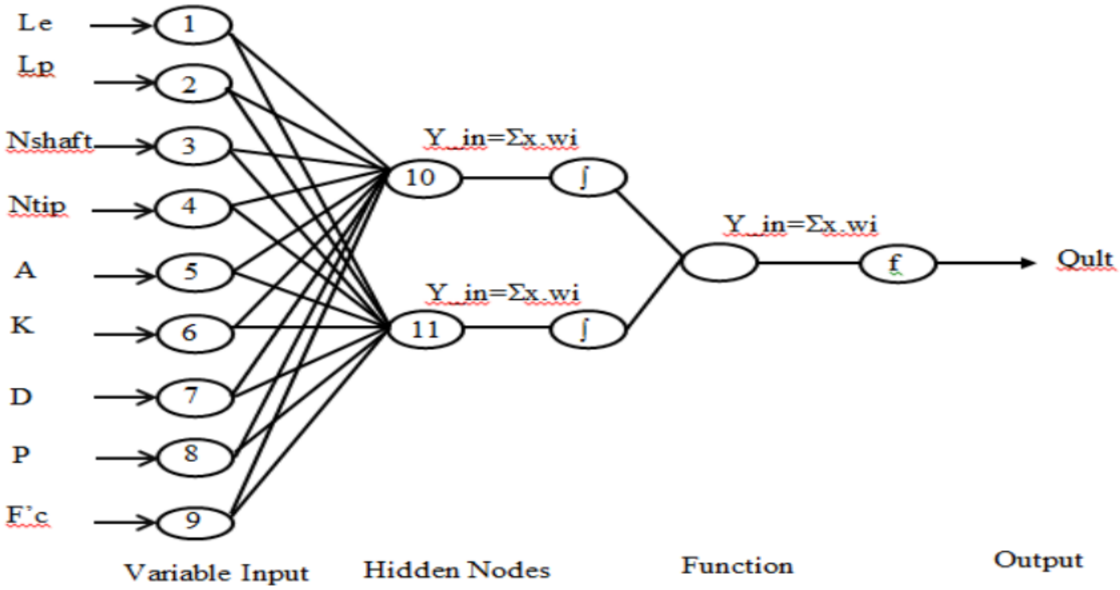

Figure 3. Design Network Model with one Hidden Layer, 2 Hidden Nodes, and 1 Output Q_{ult}.

The ANN modified model used the variable inputs L_e, L_p, D, A, K, P, f (c), N_{shaft}, N_{tip}, hidden nodes, momentum, goal and epoch to generate an output in the form of ultimate bearing capacity. The creation, investigation, and validation process of the program is still running to date, and it is expected that the results will be better than that of the conventional formula already existing.

4.1. Influence of Input Variables on Model NN_Qult

The steps in the calculation of the influence of each input variable in influencing the output of NN_Q_{ult} are each hidden node i, calculating the P_{ij} value obtained by multiplying the absolute value of weight between hidden-output with the absolute value of hidden-output connections for each variable j. The calculation of results sensitivity testing using Equation 2.

$$y_{in} = \sum_{i=1}^{N} xi\, wi + b$$

4.2. Result

The result of this study used in forecasting the capacity value of the support bore pile foundation with nine variables using the input and back-propagation algorithm made up of feed forward produced a coefficient of correlation greater than 0.8.

Figure 4 shows the network model selected in the NN_Q_{ult} model with the Back Propagation Feed-Forward Algorithm.

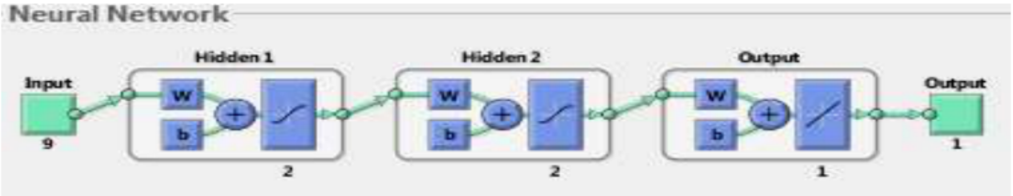

Figure 4 Selected network on NN_Qult modeling

As for the results of the iteration, analysis of artificial neural networks using the back propagation feed forward algorithm was made by entering the number of hidden layers between 2, 3, 4, 5, 6, 7, 8, 9, and 10 at epoch 1000; epoch 10,000, goal 0.01; 0.001 with a constant momentum value that can be seen in Table 2.

Table 2 Result of recapitulation coefficient of correlation (r) and RMSE training and validation

Hidden Layer	Epoch	Goal	Momentum	r		RMSE	
				Training	Validation	Training	Validation
2 ; 2	1.000	0,01	0,5	0,5207	0.2984	0.1374	0.2694
	10.000	0,001		0.3956	0.7035	0.1475	0.1171
3 ; 3	1.000	0,01	0,5	0,7817	0.6901	0.099	0.1916
	10.000	0,001		0.8617	0.9297	0.0812	0.1171
4 ; 4	1.000	0,01	0,5	0,7824	0.9109	0.099	0.1289
	10.000	0,001		0.8546	0.9205	0.0831	0.1112
5 ; 5	1.000	0,01	0,5	0.3816	0.8193	0.1481	0.2205
	10.000	0,001		0.8709	0.6569	0.0787	0.1909
6 ; 6	1.000	0,01	0,5	0.7863	0.8389	0.099	0.1922
	10.000	0,001		0.9021	0.9151	0.0691	0.1317
7 ; 7	1.000	0,01	0,5	0.7848	0.8531	0.009	0.1423
	10.000	0,001		0.8808	0.8808	0.8973	0.1451
8 ; 8	1.000	0,01	0,5	0.7828	0.6965	0.099	0.1730
	10.000	0,001		0.9121	0.7772	0.0656	0.1560
9 ; 9	1.000	0,01	0,5	0.7489	0.9148	0.1061	0.1265
	10.000	0,001		0.9291	0.4333	0.0592	0.2170
10 ; 10	1.000	0,01	0,5	0.7855	0.9007	0.099	0.2201
	10.000	0,001		0.8959	9148	0.0711	0.1170

The hidden neuron value, the number of epochs, and the goal were able to attain good modeling results, with 3 hidden neurons, epoch 10,000, goal 0.001, momentum 0.5 with the value r = 0.8617 and rmse = 0.081. This showed that the model was very good at r > 0.8, and the input variables were very strongly related, as seen in Figure 5 and Figure 6 which describes the results of regression modeling (the best fit line models).

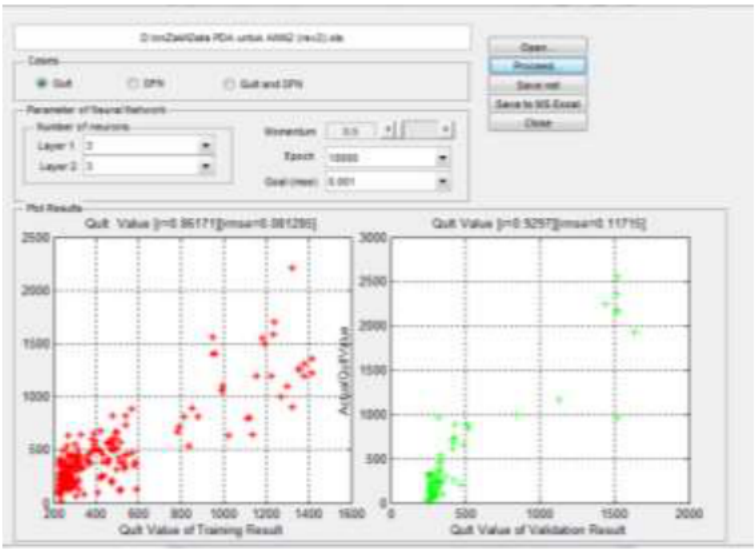

Figure 5. Output value of r and RMSE for hidden 3in networks model of NN_Q_{ult}

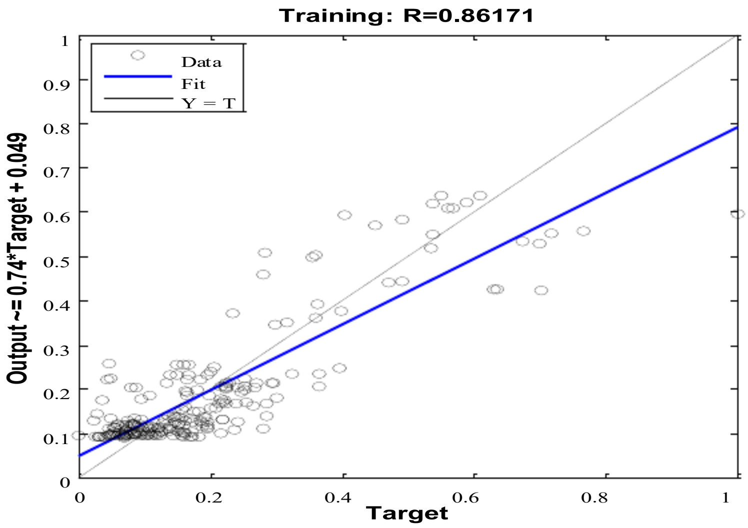

Figure 6. Regression value for hidden 3and hidden 3 for the networks model NN_Q_{ult}

The best results of the neural network model were determined by looking at the coefficient of correlation > 0.8, which highlights the relationship between epoch and sse and the graph of the relationship between the results of calculations with the suitability of network models that have a strong relationship. The network criteria for the structure chosen as the final model must be the primary focus. Distribution of data points that approach the line connecting the x and y coordinates (best fit line) between the results of calculations and predictive results that will be used between epoch and sse is taken with the smallest sse value and the graph tended to be flat. This shows that there was no change in the error value of the training. In addition, the results of the weights or biases can be seen in Table 3 and Table 4 with the influence of each input variable in the NN_Q_{ult} modeling.

Table 3 Weight and Bias for model NN_Q_{ult}

Network Weight and Network NN_Qult Value										
Hidden layer node	**Wji (the weight of node I on the input layer to node j on the hidden layer**									**Bias on layer (bj)**
	I = 1	I = 2	I = 3	I = 4	I = 5	I = 6	I = 7	I = 8	I = 9	
j = 10	0,37	0,49	0,52	0,51	0,48	0,53	0,65	0,27	0,60	1,604
j = 11	0,35	0,66	0,40	0,05	0,44	0,00	0,82	0,61	0,37	0,188
j = 12	0,78	0,61	0,34	0,11	0,07	0,51	0,44	0,41	0,78	1,567
Node on the output layer	Wji (the weight of node I on the input layer to node j at the output									The bias on the output layer (bj)
	I = 10	I = 11	I = 12							
j = 13	0,268	0,690	0,93							0,78

Table 4 Influence Weight for model NN_Q_{ult}

	Pij									
A	**D**	**Le**	**Lp**	**A**	**K**	**N_{shaft}**	**N_{tip}**	**f'c**	**P**	**Total**
hidden node 10	0,099	0,132	0,139	0,136	0,130	0,144	0,174	0,073	0,161	1,189
hidden node 11	0,244	0,456	0,276	0,033	0,305	0,005	0,566	0,424	0,260	2,569
hidden node 12	0,734	0,569	0,318	0,104	0,069	0,482	0,416	0,386	0,734	3,813
B	Qij									
hidden node 10	0,083	0,111	0,117	0,115	0,109	0,121	0,147	0,061	0,136	
hidden node 11	0,095	0,178	0,107	0,013	0,119	0,002	0,220	0,165	0,101	
hidden node 12	0,193	0,149	0,084	0,027	0,018	0,126	0,109	0,101	0,193	
	D	Le	Lp	A	K	N_{shaft}	N_{tip}	f'c	P	
Total of Weight (Rj)	0,371	0,437	0,308	0,155	0,247	0,250	0,476	0,328	0,429	3,000
	Prosentase Variabel									
	D	Le	Lp	A	K	N_{shaft}	N_{tip}	f'c	P	
Influence	12,367	14,576	10,255	5,154	8,218	8,323	15,870	10,923	14,314	100

Table 4 shows the results of the weights obtained from hidden layer 3, epoch 10,000 iterations, 0.001 goals, and 0.5 constant momenta on the ANN of the back-propagation algorithm feed-forward. Table 3 shows the level of influence of each input variable on the ultimate bearing capacity of the bored-pile being D = 12.376%, Le = 14.576%, Lp = 10.255, A = 5.154%, K = 8.218%, N_{shaft} = 8.323%, N_{tip} = 15.870%, f'c = 10.923%, and P = 14.314%. The biggest results that affect the ultimate bearing capacity of the bored-pile are L_e = 14.576%, N_{tip} = 15.870% and weight of hammer (P) = 14.314%.

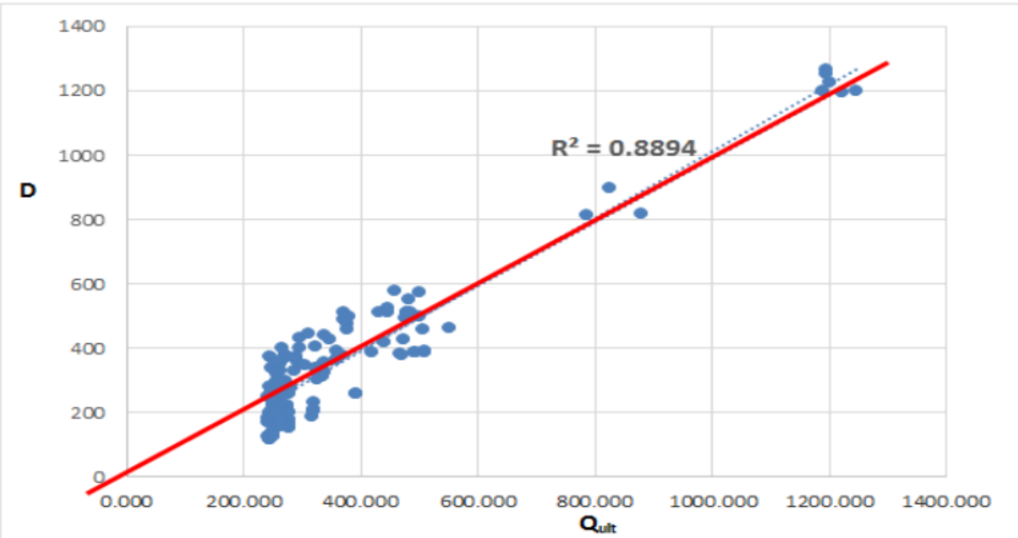

Figure 7 Results of NN_Qult Graph Analysis with PDA

Figure 7 suggests that the results of the ultimate bearing capacity analysis on bored pile foundation using the artificial neural network method with the back propagation feed forward algorithm had a value of R2 is 0.8894, indicating that the spread of the NN_Q_{ult} has a correlation to the spread bearing capacity testing with PDA.

5. CONCLUSIONS

Using ANN to obtain the ultimate bearing capacity of the bored-pile is a new method that can be used in geotechnical engineering, particularly if there is a lack of data or variable input. The coefficient of correlation (r) is more than 0, concluding that this model has a correlation to a validation model. The significance and weight of the influence of input variables P (hammer) on the PDA testing is 14.314%.

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