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Estimation of standard penetration test value on cohesive soil using artificial neural network without data normalization

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ABSTRACT

Artificial neural networks (ANNs) are often used recently by researchers to solve complex and nonlinear problems. Standard penetration test (SPT) and cone penetration test (CPT) are field tests that are often used to obtain soil parameters. There have been many previous studies that examined the value obtained through the SPT test with the CPT test, but the research carried out still uses equations that are linear. This research will conduct an estimated value of SPT on cohesive soil using CPT data in the form of end resistance and blanket resistance, and laboratory test data such as effective overburden pressure, liquid limit, plastic limit and percentage of sand, silt and clay. This study used 242 data with testing areas in several cities on the island of Sumatra, Indonesia. The developed artificial neural network will be created without data normalization. The final results of this study are in the form of root mean square error (RMSE) values 3.441, mean absolute error (MAE) 2.318 and R^2 0.9451 for training data and RMSE 2.785, MAE 2.085, R^2 0.9792 for test data. The RMSE, MAE and R^2 values in this study indicate that the ANN that has been developed is considered quite good and efficient in estimating the SPT value.

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1. INTRODUCTION

Soil investigation is the first step that must be taken when building a construction. The soil investigation method depends on the soil condition and the function of the building. The standard penetration test (SPT) and the cone penetration test (CPT) are frequently used test methods at field sites. Usually investigations with soil investigations in the laboratory to obtain further parameters of the mechanical and physical properties of the soil. The SPT and CPT tests have their respective advantages and disadvantages. In the CPT test, only soil pressure data were obtained in the form of qc and fs values but no visual soil was obtained and the maximum depth of the test was 20 m. While the SPT data obtained soil samples and the depth of the test can be tens of meters, but the test data obtained is only soil hardness (number of blows for penetration of 30 cm). Therefore, this study was conducted to obtain the concept of a formula approach to be able to see the correlation of the SPT value from CPT data so that it can predict the soil strength (shear strength) at a depth of more than 20 m.

In recent years, artificial neural networks have attracted a lot of research interest in solving a problem that is complex and has a nonlinear nature. An artificial neural network (ANN) is an information processing system that has characteristics similar to a biological neural network [1]. Therefore, this study will estimate the value of SPT using artificial neural network capabilities. The artificial neural network architecture consists of an input layer, an output layer and a hidden layer. Commonly used activation functions are binary sigmoid, bipolar sigmoid and linear functions. The learning algorithm that is most often used and effective in solving complex problems is the backpropagation algorithm. To find the best performing network, trial and error is carried out on the network architecture, activation functions and training parameters. The best artificial neural network model is obtained based on the smaller the error rate and the correlation coefficient value is close to 1. Until the time this paper was published, ANN still received extensive attention by researchers and continues to be developed. In the geotechnical field, there have been many studies using the capabilities of this ANN. Related researches such as soil composition [2], soil classification [3], soil compaction [4], bearing capacity [5], unit weight [6], shallow foundation bearing capacity [7]–[9], estimated settlement in shallow foundations [10]–[12], preconsolidation stress [13], electrical resistivity of soil [14], deformation of geogrid-reinforced soil structures [15], tunnel boring machine performance [16], estimating cohesion of limestone samples [17] and many other related studies.

In estimating the value of SPT, artificial neural networks have also been widely used by previous researchers such as predicting the value of N-SPT using the general regression neural network [18] method at a location in Izmir, Turkey. In this study using input data in the form of the percentage of gravel, sand, silt and clay. From the research, it was found that the value of R^2 was 0.9738, root mean square error (RMSE) 0.04, mean absolute error (MAE) 0.01 in the training data, while the test data obtained the values of R^2 0.9348, RMSE 0.08 and MAE 0.05. Another similar study is predicting N-SPT values based on CPT data at study locations in Dubai and Abu Dhabi, United Arab Emirates [19]. In this study, using input data in the form of end resistance value (qc), blanket resistance (fs) and soil effective pressure. From this study, the results obtained in the form of R value 0.95 and MAE 2.88.

The research conducted by [18], [19] had several shortcomings that could be complemented by other researchers. In research [19], estimating the value of SPT is only based on the percentage of gravel, sand, silt and clay, while in research [18] only estimates the value of SPT based on the values of qc, fs and overburden effective pressure. In fact, the value of soil density is influenced by many variables both from the mechanical and physical properties of the soil. Due to the large number of variables that affect soil density, conventional correlation is considered less effective in estimating SPT values. This problem is what prompted the author to conduct research to estimate the value of SPT using the ability of ANNs by combining the thoughts of previous researchers, namely using input variables in the form of tip resistance (qc), sleeve resistance (fs) obtained from CPT and laboratory data in the form of effective overburden pressure, liquid limit, plastic limit, percentage of sand, silt and clay on the cohesive soil.

In general, the data used in artificial neural networks will normalize the data or transform the data into a range of values according to the activation function used. For example, if you use the binary sigmoid activation function, then the data must be normalized by transforming the data into a range of 0 to 1 or if use the bipolar sigmoid activation function, the data will be normalized by transforming the data into the range -1 to 1. This method sometimes experiences difficulties because at times perform normalization, the data is not normalized to normal. Therefore, this research will carry out the process of developing an artificial neural network without normalizing the data. This research is expected to develop an artificial neural network without normalizing data with a low error rate, thus facilitating further research.

2. RESEARCH METHOD

2.1. Research model

In this study, the method used is to conduct direct research in the field and then process the research results using ANN software. Field tests carried out are SPT and CPT. The UDS sample obtained from the SPT test was carried out in the laboratory to obtain data on soil properties, both physical and mechanical properties of the soil. All data that has been obtained is then processed in Microsoft Excel software first for grouping data based on training data and test data. After grouping the data, the next step is to develop an artificial neural network using the ANN application. The research was conducted to obtain ANN with a smaller error value. In general, the research methodology can be seen in Figure 1.

2.2. Data collection

Data collection is an activity that aims to find the data needed in the research process in order to achieve the research objectives. In this study, the data needed is data on SPT, CPT and laboratory tests results. In SPT testing, the data required is the SPT value. In the CPT test, the data required is the value of end resistance (qc) and sleeve resistance (fs). In laboratory testing, the data required is the value of effective overburden pressure ($\sigma'0$), the percentage of sand and fine grains. These data were obtained from the Laboratory of Soil and Rock mechanics, Civil Engineering department, University of Riau. The data obtained are the results of testing in several areas on the island of Sumatra, Indonesia, including the provinces of Riau,

Riau Islands, Jambi, South Sumatra, West Sumatra and North Sumatra from 2005 to 2020. Statistics of all data can be seen in Table 1.

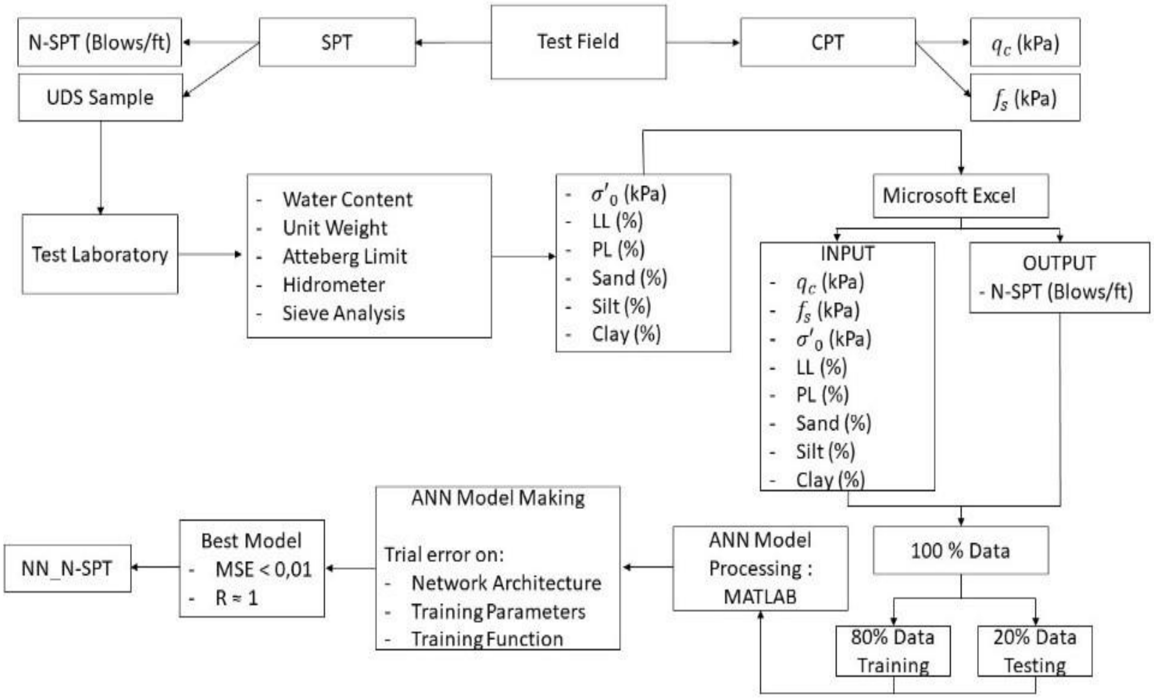


Figure 1. Research flow chart

Table 1. Collected data statistics

Variable	q_c (kPa)	f_s (kPa)	(σ'_0)(kPa)	Liquid Limit (%)	Plastic Limit (%)	Sand (%)	Silt (%)	Clay (%)	N-SPT (blows/ft)
Max	24525	426.106	422.105	87.210	51.700	71.440	96.050	95.630	60
Min	98.100	0.100	23.490	16.940	12.650	0.070	2.970	0.010	1
Mean	3028.281	83.289	157.609	48.976	27.271	11.920	36.512	51.399	11.612

2.3. Design of artificial neural network (ANN) model

The process of making ANNs is done by dividing the data into training data and test data. As much as 80% of the data is used as training data and 20% of the data will be used as test data. Training data is the data used to train the network by entering input data and output data. While the test data is data used to test the performance of the network being developed.

The design of the neural network model to be developed is adjusted to the purpose and nature of the data used. To predict the value of SPT that requires a relatively large amount of data input, the most appropriate method used is to create a network with a multilayer and backpropagation algorithm and supervised learning methods. Multilayer network architecture is the most appropriate solution for network models with large amounts of data and relatively complex problems. Multilayer network architecture consists of 3 layers, that is:

a. Input layer, this layer consists of several neurons whose number is adjusted according to the input pattern or variable.
b. Output layer, this layer consists of neurons whose number is in accordance with the desired output pattern or variable.
c. Hidden layer, this layer is between the input layer and the output layer, one or more hidden layers is determined based on a trial process and the number of neurons in the hidden layer is also determined based on a trial process to find the best performing network.

To get the network with the best performance, several trial variations can be carried out, that is:

a. Variations in network architecture (number of hidden layers and number of neurons in hidden layers).

b. Variations on training functions (trainlm, traincgb, traingd, traingdm, traingda, traingdx, trainrp, traincgf, traincgp, or other training functions that have been provided).
c. Variations in the activation function (bipolar sigmoid, binary sigmoid or linear function).
d. Variations in training parameters (number of epochs, learning rate, goals, and validation checks).

The training process can be stopped if you have found a network with the best performance, namely a network with a smaller error value and an R value that is closer to 1.

2.4. Testing the artificial neural network (ANN) model

To measure the accuracy and performance of the neural networks developed in producing SPT values, this study uses the RMSE and MAE values and the R^2 value. The best performance is indicated by the small RMSE and MAE values and the R^2 value that is close to 1. To calculate the RMSE and MAE values, the following equation is used:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - y_i)^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| \tag{2}$$

Where, RMSE is root mean square error, MAE is mean absolute error, f_i is original value, y_i is forecast result value, and n is amount of data.

2.5. Comparison of ANN with conventional equations

The best artificial neural network model that has been obtained is then compared with conventional equations by several previous studies in determining the SPT value. Several previous studies in determining the value of the SPT can be seen in Table 2. Where Kc is the ratio between qc and N-SPT or Kc=qc/NSPT (in MPa), N is the SPT value, D50 is the grain diameter that passes 50% filter while FC is the fines content.

Table 2. The value of Kc is based on several studies

Reference	Kc (MPa)	Notes
[20]	0.77	Sand
	0.70	Silty Sand
	0.58	Sandy Silt
[21]	0.438	Sand (Canada, Japan, Norwagia, China and Italy): D50=0.35+-0.23 mm
[22]	0.508	Clean Sand dan sandy silt, FC=3%-35%
[23]	0.568	Sweden Sand
	0.367	Clay, Silty Clay and Silt
	0.423	Sandy Silt, silt-sand
	0.529	Clean Sand dan Clayey Sand
	0.374	Sandy Clay, Silty Sand, Silty Clayey Sand
	0.572	Gravelly Sand, Coarse Sand and Sand-Gravel
[24]	0.37	Clay dan silty sand (Tanzania): D50=0.38 mm
[25]	0.43	Victoria Sand
[26]	0.427	Silty Sand
	0.337	Sandy Silt
	0.319	Silty Clay
	0.291	Clay

3. RESULTS AND DISCUSSION

3.1. Results of the model making stage

From the research process, it was found that the best performance artificial neural network in estimating SPT values was a network with 2 hidden layer network architecture, 16 neurons in 1st hidden layer and 8 neurons in 2nd hidden layer. The training function used was traincgb. Network architecture can be seen in the Figure 2. In Figure 3 you can see the accuracy value of the network performance. The value of R training is 0.97053, R validation is 0.99052, R Test is 0.95974 and R All is 0.97216.

3.2. Weights and bias

Based on the best ANN model obtained, then the weight and bias values are also obtained. This value can be used as a multiplier of a network. Tables 3 to 7 are the weight and bias values of the developed network model.

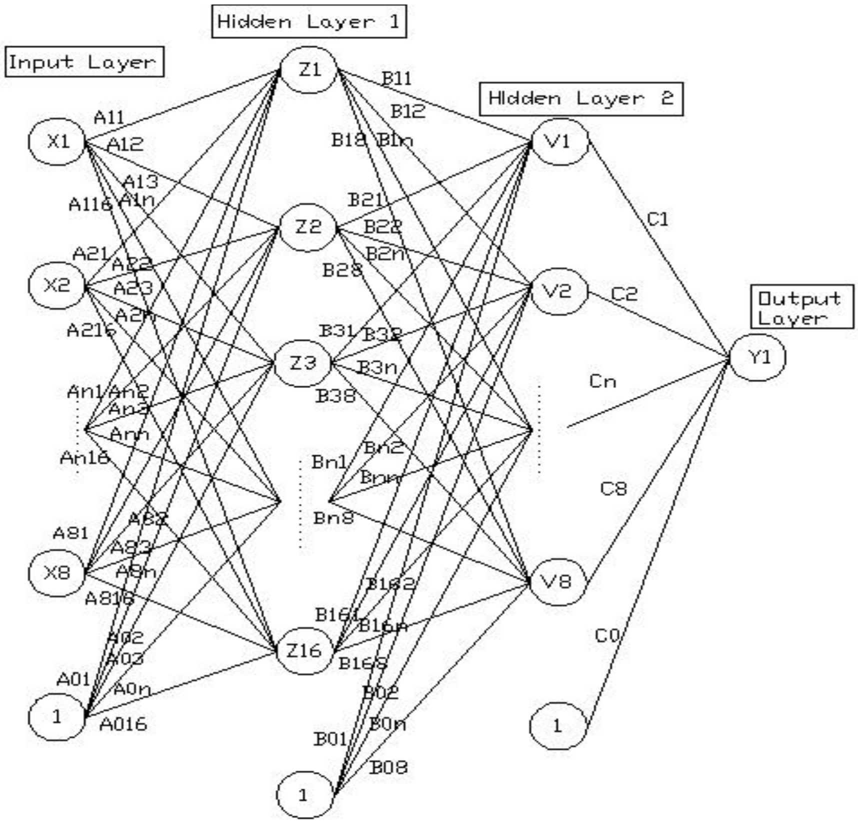


Figure 2. ANN architecture

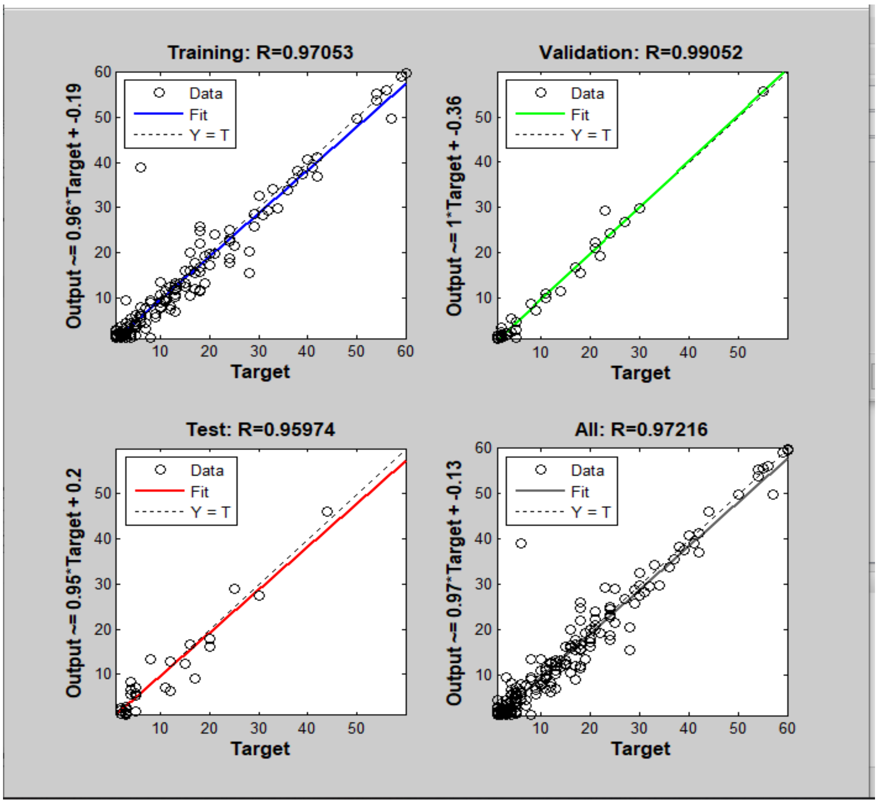


Figure. 3. ANN regression

Table 3. Weights (A11-A816) from input layer to 1st hidden layer, as shown in Figure 2

A11	-1.321	A21	-0.543	A31	0.870	A41	-0.437	A51	0.207	A61	0.849	A71	-0.88	A81	0.778
A12	0.216	A22	-1.091	A32	-0.952	A42	0.541	A52	1.337	A62	-0.75	A72	0.752	A82	0.692
A13	-0.861	A23	0.067	A33	-0.556	A43	0.869	A53	-1.087	A63	0.893	A73	-0.819	A83	1.204
A14	-2.197	A24	-1.088	A34	0.532	A44	-0.365	A54	0.594	A64	1.970	A74	-1.584	A84	-0.600
A15	-0.308	A25	0.844	A35	-1.050	A45	0.438	A55	1.413	A65	-0.10	A75	-0.576	A85	0.810
A16	-0.183	A26	-0.920	A36	0.154	A46	0.381	A56	1.215	A66	-0.57	A76	0.364	A86	0.448
A17	-1.637	A27	-0.267	A37	2.367	A47	-2.290	A57	-1.130	A67	0.393	A77	-0.731	A87	-0.449
A18	-0.158	A28	0.744	A38	-0.923	A48	-0.089	A58	-0.387	A68	-0.14	A78	-1.479	A88	1.244
A19	-0.360	A29	1.173	A39	1.561	A49	-0.841	A59	-0.768	A69	-1.34	A79	-1.062	A89	-0.317
A110	-0.263	A210	1.563	A310	0.784	A410	0.667	A510	1.613	A610	0.602	A710	-0.002	A810	1.000
A112	-0.354	A212	2.228	A312	0.030	A412	-0.330	A512	0.996	A612	0.220	A712	-0.151	A812	1.957
A113	0.461	A213	-0.301	A313	1.092	A413	-0.798	A513	1.720	A613	-0.27	A713	-0.892	A813	0.633
A114	1.028	A214	0.596	A314	1.156	A414	-0.510	A514	-0.416	A614	0.543	A714	-1.501	A814	0.628
A115	1.117	A215	-0.110	A315	0.785	A415	-0.442	A515	-1.692	A615	-0.67	A715	-0.790	A815	0.380
A116	1.486	A216	-0.873	A316	0.369	A416	-0.216	A516	-0.524	A616	-0.86	A716	0.516	A816	-0.943

Table 4. Bias (A01-A016) from input layer to 1st hidden layer, as shown in Figure 2

A001	A002	A003	A004	A005	A006	A007	A008
1.819	-1.805	1.816	1.245	0.960	-1.559	1.158	-0.763
A009	A010	A011	A012	A013	A014	A015	A016
0.109	0.111	0.185	0267	-1.091	0.931	1.828	1.561

Table 5. Weights (B11-B168) from 1st hidden layer to 2nd hidden layer, as shown in Figure 2

B11	-0.103	B12	-0.040	B13	-0.839	B14	0.664	B15	-0.387	B16	-0.58	B17	-0.680	B18	-0.143
B21	0.232	B22	1.031	B23	-0.241	B24	-0.168	B25	0.505	B26	0.277	B27	0.464	B28	-0.299
B31	-0.425	B32	0.107	B33	-0.536	B34	1.112	B35	0.335	B36	0.920	B37	-0.291	B38	0.585
B41	0.380	B42	0.230	B43	-0.835	B44	-0.079	B45	-0.277	B46	-1.19	B47	-0.542	B48	-2.204
B51	0.658	B52	-0.309	B53	-0.958	B54	-0.531	B55	0.224	B56	1.203	B57	0.480	B58	0.098
B61	-0.237	B62	1.157	B63	-0.292	B64	0.543	B65	0.292	B66	-0.39	B67	0.216	B68	0.783
B71	-0.290	B72	1.169	B73	-0.555	B74	0.120	B75	-0.083	B76	0.465	B77	-0.227	B78	0.508
B81	-0.166	B82	0.612	B83	0.420	B84	-0.152	B85	0.589	B86	0.938	B87	-0.282	B88	0.533
B91	-0.183	B92	0.763	B93	0.763	B94	0.792	B95	-0.407	B96	-0.41	B97	0.439	B98	1.688
B101	-0.143	B102	-1.310	B103	-0.207	B104	0.311	B105	1.616	B106	0.524	B107	-0.384	B108	-1.572
B111	0.557	B112	-0.874	B113	0.178	B114	-0.887	B115	-0.175	B116	-0.42	B117	0.502	B118	-1.304
B121	-0.212	B122	-0.035	B123	-0.706	B124	1.606	B125	0.172	B126	-0.69	B127	-0.900	B128	0.067
B131	-0.549	B132	-0.208	B133	0.378	B134	-0.593	B135	1.056	B136	-0.06	B137	0.697	B138	-0.171
B141	-0.432	B142	-0.617	B143	0.176	B144	-0.695	B145	0.294	B146	0.45	B147	-0.091	B148	1.183
B151	-0.031	B152	-0.641	B153	0.143	B154	0.011	B155	0.544	B156	-0.48	B157	-0.030	B158	0.966
B161	-0.491	B162	-0.336	B163	-0.383	B164	-0.679	B165	0.548	B166	-0.57	B167	-0.115	B168	2.041

Table 6. Bias (B01-A08) from 1st hidden layer to 2nd hidden layer, as shown in Figure 2

B01	B02	B03	B04	B05	B06	B07	B08
1.789	-1.458	0.769	-0.520	-0.257	-0.664	-1,019	-1.286

Table 7. Weights (C1-C8) and bas (C0) from 2nd hidden layer to output layer, as shown in Figure 2

C1	C2	C3	C4	C5	C6	C7	C8	C0
-0.231	-2.029	-1.121	-1.783	1.209	-1.206	0.497	1.823	0.134

3.3. Results of the model testing stage

The ANN that has been developed is then simulated to estimate the SPT value. This simulation is done using input data on training data and input data on test data. Furthermore, the SPT output value from the artificial neural network is compared with the original SPT value to obtain the RMSE and MAE values. RMSE and MAE values from the simulation results can be seen in Table 8. To get the R^2 value, the predicted SPT value data compared with the original SPT value is displayed in a linear regression graph. This linear regression graph can be seen in Figure 4. In Figure 4(a) is a linear regression line on the training data and in Figure 4(b) is a linear regression line on the test data.

Table 8. Measure of accuracy ANN

Observation	Training data	Testing data
RMSE	3.278	2.012
MAE	1.783	1.328

The next step to compare the effectiveness of using artificial neural networks in estimating SPT values, estimation using conventional correlation by [23], [24], [26] was also carried out. The use of this correlation results in the RMSE and MAE values in Table 9. The R^2 value can be seen in the Figures 5(a) and (b) to Figures 7(a) and (b).

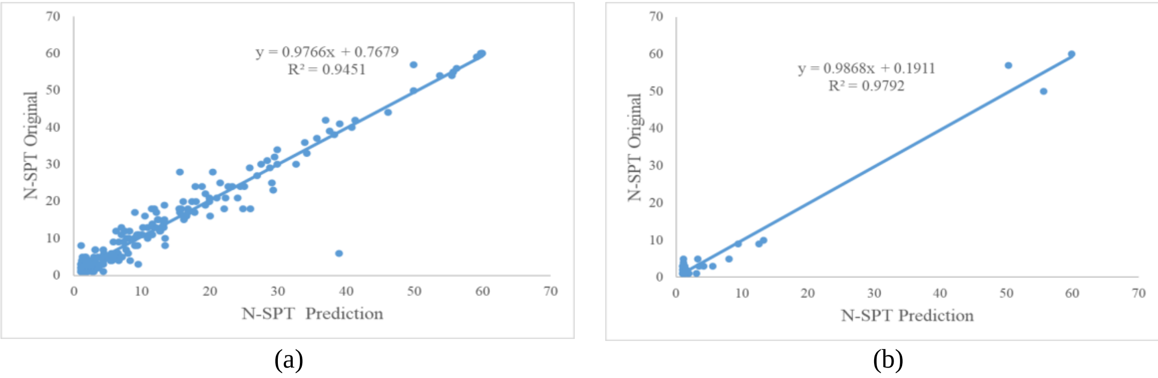


Figure 4. N-SPT prediction using ANNs (a) training data and (b) testing data

Table 9. Prediction of SPT value using conventional correlation

Research	Training data		Testing data	
	RMSE	MAE	RMSE	MAE
[23]	9.005	5.001	7.964	2.936
[24]	8.787	4.928	7.833	3.001
[26]	8.327	4.908	7.658	3.259

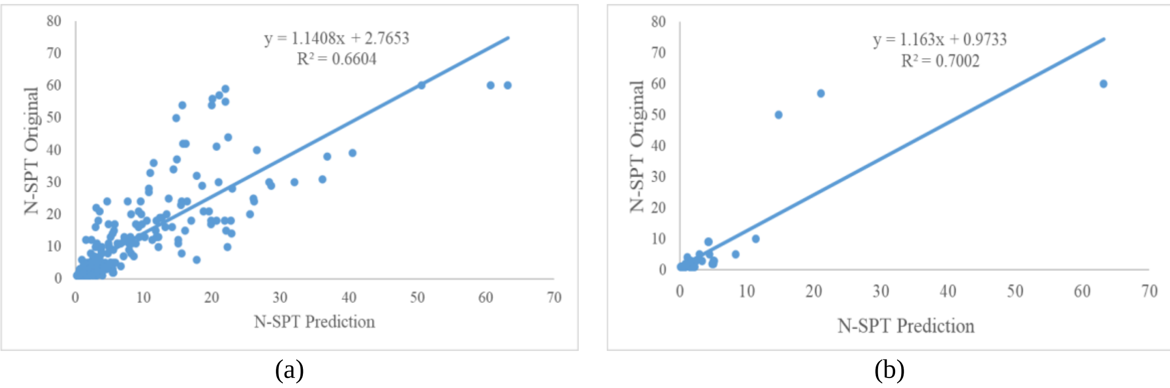


Figure 5. SPT value estimation using correlation by [23] (a) training data and (b) testing data

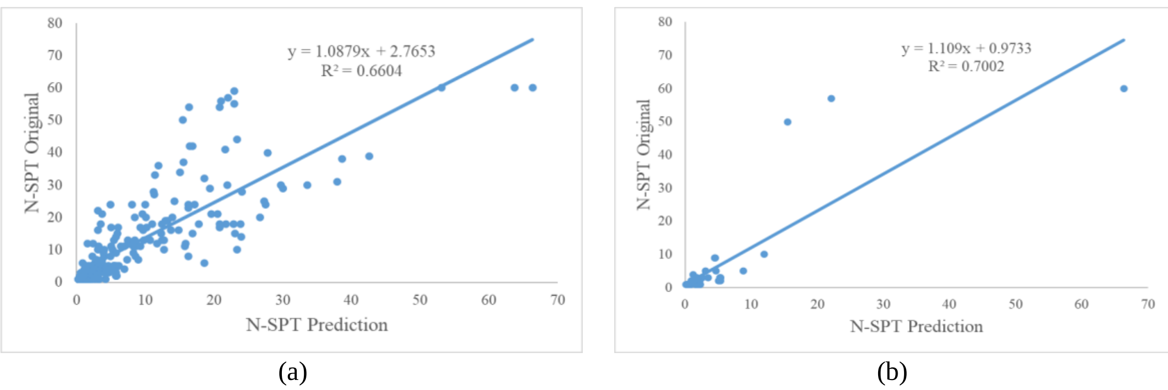
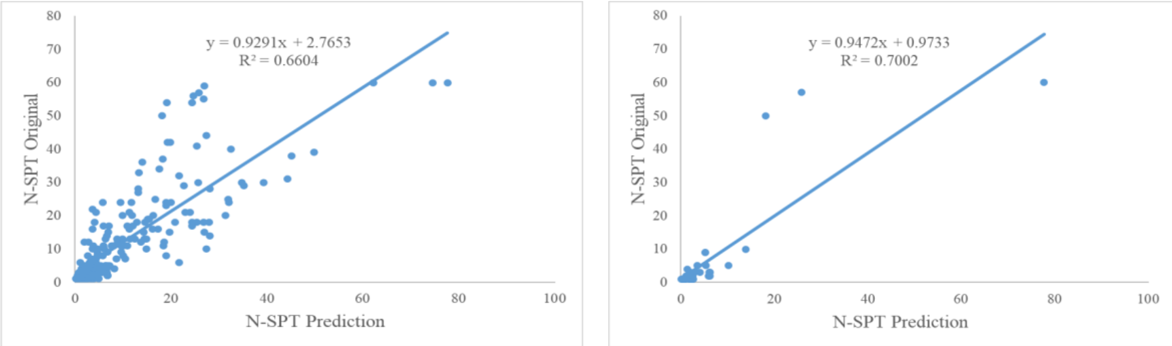


Figure 6. SPT value estimation using correlation by [24] (a) training data and (b) testing data

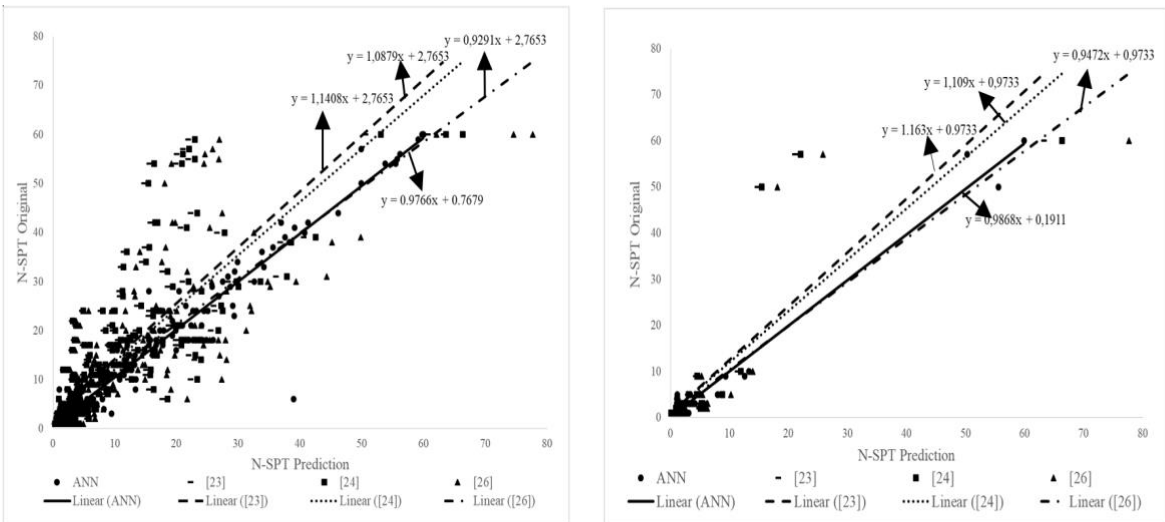


(a) (b)

Figure 7. SPT value estimation using correlation by [26] (a) training data and (b) test data

3.4. Design chart based on the best model

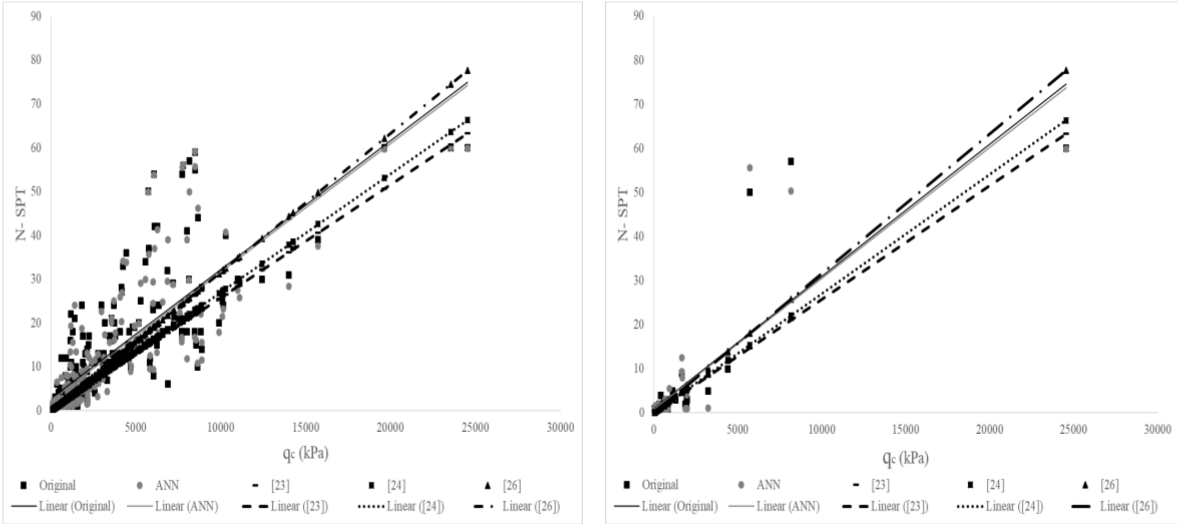
Figures 8(a) and (b) are a design chart between the estimated SPT value and the original SPT value. On this graph, a linear regression line is drawn between the estimated SPT value and the original SPT value through calculations with artificial neural networks or calculations using conventional correlation by [23], [24], [26]. Based on this graph, it can be seen that the estimation results of SPT values using ANNs give better results than the other three conventional correlations. Estimating the value of SPT using ANN produces a correlation coefficient (R^2) that is closer to 1 (red linear regression line) compared to the other three correlations, that is the R^2 value on the training data 0.9451 and on the 0.9792 test data.



(a) (b)

Figure 8. Design chart N-SPT predicition VS N-SPT original (a) training data (b) testing data

Figures 9(a) and (b) are design chart between tip resistance (q_c) value and SPT value (N-SPT). In this graph, a combination of the relationship between qc and SPT values is displayed in the original data, the estimated data using an artificial neural network and the estimated data using conventional correlation by [23], [24], [26]. From this graph, it is clear that the linear regression line of the correlation between the q_c value and the SPT value estimated by ANN almost coincides with the linear regression line of the relationship between the q_c value and the SPT value in the original data. This means that the estimation results using ANN are almost close to the original value. Table 10 is a verification of the estimated data using an artificial neural network and using conventional correlation by [23], [24], [26]. It can be seen that the estimation results using an artificial neural network are almost close to the original value or have a small error value compared to using conventional correlation.



(a) (b)

Figure 9. Design chart q_c VS N-SPT (a) training data and (b) test data

Table 10. Verification of SPT value estimation data with ANN and conventional correlation

	INPUT								OUTPUT				
No	qc (KN/m2)	fs (KN/m2)	σ'0 (KN/m2)	Liquid Limit (%)	Plastic Limit (%)	Sand (%)	Silt (%)	Clay (%)	Original N-SPT (blows/ft)	ANN N-SPT (blows/ft)	[23] N-SPT (blows/ft)	[24] N-SPT (blows/ft)	[26] N-SPT (blows/ft)
1	837.623	63.388	199.150	60.90	39.10	0.080	49.48	50.440	1	1.003	2.159	2.264	2.651
2	2256.300	135.939	86.870	42.520	22.510	54.660	8.540	36.800	5	4.867	5.815	6.098	7.140
3	8632.800	303.920	302.100	49.540	27.460	0.800	12.850	86.350	10	10.797	22.249	23.332	27.319
4	5477.250	179.850	171.250	58.500	27.600	0.560	28.480	70.960	16	16.497	14.117	14.803	17.333
5	5165.341	74.455	252.900	18.500	15.200	53.140	29.890	16.970	20	19.832	13.313	13.960	16.346
6	6005.121	153.456	271.185	71.270	32.570	2.020	18.260	79.720	24	24.404	15.477	16.230	19.004
7	8115.545	98.100	319.755	58.200	30.380	1.900	11.830	86.270	30	29.832	20.916	21.934	25.682
8	4227.218	420.046	328.755	49.140	29.020	3.420	46.320	50.260	33	34.153	10.895	11.425	13.377
9	10277.862	237.955	131.170	73.170	33.420	0.240	9.850	89.910	40	40.741	26.486	27.778	32.525
10	8647.892	426.106	131.215	75.070	30.350	3.360	8.860	87.780	44	46.131	22.288	23.373	27.367
11	5715.162	157.960	185.430	76.530	32.960	0.120	94.350	5.530	50	49.850	14.730	15.446	18.086
12	7776.446	183.372	138.305	61.890	34.400	2.180	90.380	7.440	56	56.127	20.042	21.017	24.609
13	23544.00	98.100	176.500	72.000	42.400	1.180	49.690	49.690	60	59.931	60.680	63.632	74.506

4. CONCLUSION

ANN without data normalization is well developed in this study. The data used in this study were obtained from several locations on the island of Sumatra, Indonesia with a total of 244 data consisting of SPT, CPT and laboratory test data. This study uses input variables consisting of the value of tip resistance (q_c), blanket resistance (f_s), effective soil overburden pressure, liquid limit, plastic limit and percentage of sand, silt and clay. Meanwhile, the output variable is the SPT value. Based on the results of the research conducted, the network with the best performance is a network using network architecture with 2 hidden layers, 16 neurons in 1st Hidden Layer and 8 neurons in 2nd hidden layer, training function is traincgb, activation function is bipolar sigmoid and learning algorithm is backpropagation algorithm. This ANN model is said to be more effective in estimating the SPT value because it has a smaller error value than using conventional correlation. In the training data, the RMSE value for ANN was 3.278, MAE 1.783 and R^2 0.9451, while in the test data, the RMSE for ANN was 2.012, MAE 1.328, R^2 0.9792. Therefore, based on this research, artificial neural networks without data normalization can be applied to other studies that have complex and nonlinear equations both in the geotechnical field and in other fields.

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