Prediction of SPT value on cohesive soil using artificial neural networks

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ABSTRACT

Soil investigation is the main key in starting a construction. Standard Penetration Test (SPT) and Cone Penetration Test (CPT) are field tests that are often used in estimating soil parameters for foundation design purposes. The SPT value shows a correlation with the CPT value and other soil parameters. At present, there have been many conventional correlations examining these correlations, but the nonlinear nature of the soil due to very complex soil formations means that this correlation cannot be used in all situations. Artificial neural networks (ANN) are often used to estimate a complex and nonlinear value. In this study, that will predict the value of SPT on cohesive soil based on CPT test data and soil physical properties using artificial neural network capabilities using the Backpropagation algorithm and the activation function is bipolar sigmoid. This study uses 284 data from several places in Sumatra Island, Indonesia with data input are tip resistance (q_c), shaft resistance (f_s), effective overburden pressure (σ'_0), percentage of liquid limit, plastic limit, sand, silt and clay. This study shows that the artificial neural network is able and effective in predicting the N-SPT value with a small error value and a strong regression equation. In this study, RMSE 3,441, 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. This model is hereinafter referred to as NN_Nspt(C).

KEYWORDS
Standard Penetration Test
Cone Penetration Test
Cohesive Soil
Artificial Neural Networks
Backpropagation

1. Introduction

Planning a construction requires data on the physical and mechanical properties of the soil obtained from the results of soil investigations in the field and in the laboratory. The physical and mechanical properties of the soil in various locations vary, therefore soil investigations need to be carried out for each construction site. Standard Penetration Test (SPT) and Cone Penetration Test (CPT) are often used in initial soil investigations to determine soil parameters that are useful in foundation analysis and design.

The SPT value shows a correlation with soil parameters, both the results of field testing such as CPT and the physical and mechanical properties of the soil through laboratory research. There have been many studies that have discussed the correlation between N-SPT, CPT data and physical and mechanical properties of soil. The correlation can be seen in Table 1.

Table 1. Summarize of Literature Review

Refrence	Kc (Mpa)	Note
[1]	0.77	Sand
	0.70	Silty Sand
	0.58	Sandy Silt
[2]	0.438	Sand (Canada, Japan, Norwagia, China and Italy): D50 = 0.35+-0.23 mm
[3]	0.508	Clean Sand dan sandy silt, FC =3% - 35%
[4]	0.37	Clay dan silty sand (Tanzania) : D50 = 0.38 mm
	0.427	Silty Sand
[5]	0.337	Sandy Silt
	0.319	Silty Clay

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Refrence	Kc (Mpa)	Note
	0.291	Clay
[6]	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
[7]	0.43	Victoria Sand

Where Kc is the ratio between qc and N-SPT or Kc = q_c / NSPT (in MPa), N is the SPT value, D50 is the grain diameter that passes 50% filter while FC is the fines content.

In general, soil from one place to another has varying properties with great uncertainty, this is due to very complex soil formations [8]. This complex soil characteristic causes conventional correlation which tends to be linear in nature which is considered less efficient in predicting the SPT value. Artificial Neural Network (ANN) is a network of a group of small processing units that are modeled based on the human nervous system. ANN is an adaptive system that can change its structure to solve problems based on external and internal information flowing through the network. Artificial neural networks are considered effective in this study because of their ability to process complex and nonlinear data so that later it is expected to obtain a model that can predict N-SPT values with smaller error values so that they are closer to the values in the field. ANN can be described as a "massively parallel distributed processor" which can store information extracted from data sets supplied from the network [9]. The ANN system consists of three or more layers. The first layer contains input neurons while the last layer contains output. Between the input and output layers are one or more hidden layers, which serve to describe and study patterns that govern network data. In developing the ANN model, things that need to be considered are the determination of the input and output models, data sharing, pre-processing of available data, determining the appropriate network architecture and the appropriate training parameters. In the geotechnical field, the backpropagation algorithm is the most frequently used by researchers [10].

In recent years, ANN has become one technique that is widely used by researchers and has received considerable attention in its development. Until now, there have been many researches, especially in the field of geotechnical engineering, using this artificial neural network capability. Several related studies such as in determining foundation behavior like prediction of shallow foundation reliability [11], pile raft foundation [12], axial capacity of pile foundation [13], shaft resistance [14], elastic settlement [15], settlement shallow foundation [16] and loading-unloading pile static load [17]. Other related research such as predicting soil physical and mechanical properties like prediction of CBR value [18], uniaxial compressive strength [19], undrained shear strength [20]-[21], bearing capacity [22]-[23], unit weight [24], compression index & compression ratio [25], classification [26], compression coefficient [27], liquefaction [28], and electrical resistivity of soil [29]. ANN is also used in prediction of dynamic compaction [30] and slope stability [31].

In predicting the value of SPT, artificial neural networks have also been widely used by previous researchers. Related research, such as predicting the value of N-SPT using the General Regression Neural Network [32] location in Izmir, Turkey with input data in the form of a percentage of gravel, sand, silt and clay. The results of the study were R^2 value in training was 0.9738 and R^2 value on testing 0.9348, MAE in training is 0.01 and MAE on testing is 0.05 and the RMSE value in training is 0.04 and on testing is 0.08. Research conducted by [32] only predicts SPT values based on the percentage of gravel, sand, silt and clay, while there are many other variables that affect soil density such as plasticity, moisture content, overburden effective pressure and others. Similar research has also been conducted, namely research predicting the value of N-SPT based on CPT data with input data in the form of tip resistance (q_c), skin resistance (f_s) and effective overburden pressure at study locations in Dubai and Abu Dhabi, United Arab Emirates [33] with the results of research with R = 0.95 and MAE = 2.S88. RMSE and MAE are a measure of the accuracy of a relationship where the smaller the value, the better the accuracy, whereas for R, the closer to 1 it shows the better the accuracy. Then the research conducted by [33] only used the CPT data input parameter and the effective soil pressure without using other soil physical properties. Both of these studies show good results which can be seen as small errors. Therefore, in this study the author tries to combine the thoughts that have been carried out by previous researchers. In this research, will predict the SPT value using the CPT test parameters are tip resistance (q_c), skin resistance (f_s) and laboratory tests are effective overburden pressure, liquid limit, plastic limit, percentage of sand, silt and clay. This research is expected to increase the use of artificial neural networks in solving complex equations and predicting equations with complex variables. This research is also expected to increase the interest of researchers to continue to develop the capabilities of artificial neural networks in all fields.

2. Method

In general, the research procedure can be seen in Fig. 1 following.

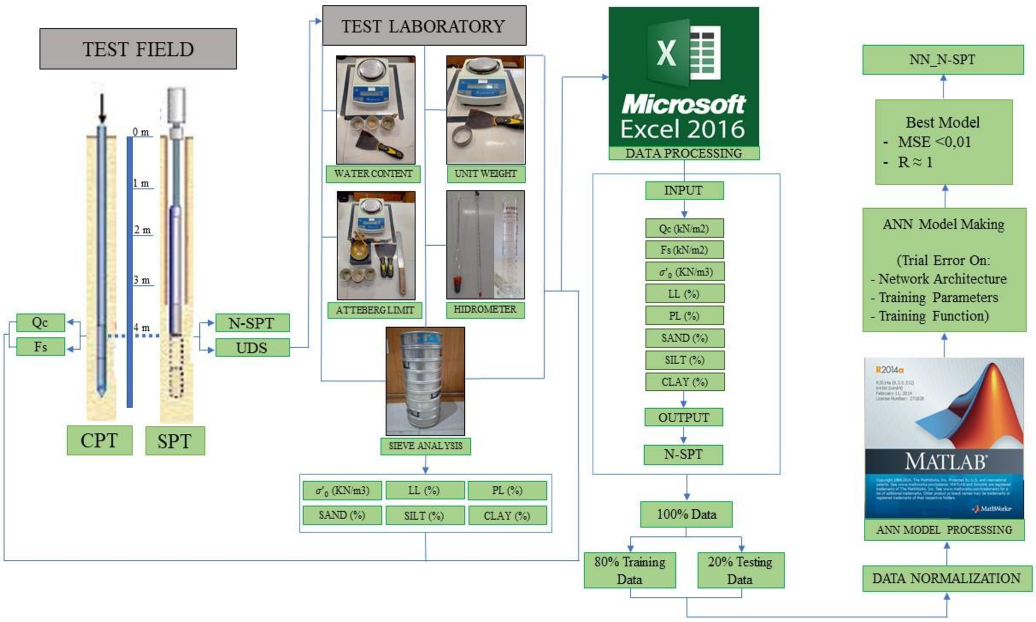

Fig. 1. (a) Original and (b) Gaussian noise image

Fig. 1 is a research procedure which in general consists of 5 stages, namely the collection of data both from the field and from the laboratory, then the data normalization stage uses Microsoft Excel software, then divides the data into training data and test data. The next stage of ANN architecture development uses ANN software, in this case using Matlab and the last stage is the testing phase of the network model that has been developed. This procedure can be described as follows.

2.1. Data Collection

Data collection is an activity that aims to obtain and complete the data needed to conduct research, in this case, in the form of SPT, CPT and laboratory testing data. The data is in the form of tip resistance (q_c) and skin friction (f_s) data obtained from the CPT test, the N-SPT value obtained from the SPT test, as well as data on soil effective overburden pressure (σ'_0), liquid limit (LL), plasticity limit (PL), percentage of sand (S), silt (M) and clay (C) obtained from laboratory testing. This data was obtained from 2005 - 2020 in various locations on the island of Sumatra, Indonesia namely Riau, West Sumatra, North Sumatra, Riau Islands, South Sumatra and Jambi provinces. Statistics of all data can be seen in Table 2.

Table 2. Decomposition to lower resolution

Variable	q_c *(kPa)*	f_s *(kPa)*	(σ'_0) *(kPa)*	LL *(%)*	PL *(%)*	S *(%)*	M *(%)*	C *(%)*	N-SPT *(blows/ft)*
Max	24525	426.106	422.105	87.21	51.7	71.44	96.05	95.63	60
Min	98.1	0.1	23.49	16.94	12.65	0.07	2.97	0.01	1
Mean	3028.281	83.289	157.609	48.976	27.271	11.920	36.512	51.3985	11.6115
SD	3809.434	81.605	92.376	16.328	6.664	17.884	25.704	27.539	13.558

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2.2. Data Normalization

Data normalization is needed in order to simplify the calculation process, namely by transforming data values into a certain range of values. For example, the data range is transformed between 0 and 1, meaning that the minimum data is 0 and the maximum data is 1. This is adjusted to the needs or the activation method applied to the developed ANN model. In this study using the bipolar sigmoid activation function which has a value range of -1 to 1, therefore the data needs to be transformed into a range of -1 to 1. The formula used to perform this normalization is the normalization min-max method with the equation (1).

$$Xnormalized = \frac{Xcurrent - (\frac{Xmax+Xmin}{2})}{\frac{Xmax-Xmin}{2}} \quad (1)$$

2.3. Data Training and Testing

After normalizing the data, then dividing the data into 2 (two) parts, for training and testing purposes so that it becomes data as input (input vector) and as a target (output) in accordance with the developed ANN model. In this study there were 284 data which were divided into 80% as training data and 20% as test data. The training data aims to train the network with the input and target given to the network and to get the weight for each input while the test data aims to measure the performance of the ANN model developed.

2.4. Design of Artificial Neural Network Model

The design of the N-SPT Prediction model is carried out by building an artificial neural network (ANN) with the backpropagation learning method, then making variations on the network architecture, namely the number of hidden layers and the number of neurons in the hidden layer by trial and error, with the hope that convergence occurs. faster. In addition, variations on the training function and activation function were also made.

The architectural design of the ANN model to be developed is adjusted to the application to be developed. To make N-SPT predictions or Predictions that require relatively large data or load or input patterns, a network with many layers (multilayer net) with backpropagation algorithms and supervised learning methods is a good choice. The network (ANN model) is given a pair of patterns consisting of the input pattern and the desired pattern or target.

An example of creating a network pattern by varying the training function, the number of hidden layers and the number of neurons in the hidden layer.

• Model 1 (trainlm_1HL_8N) :
Activation function = tansig
Training function = Trainlm
Hidden layer = 1
Neuron Hidden layer = 8

• Model 2 (trainlm_1HL_16N) :
Activation function = tansig
Training function = Trainlm
Hidden layer = 1
Neuron Hidden layer = 16

If by using the trainlm training function you have not got the best performance network, then it can be continued by varying the training functions traincgb, traingd, traingdx and other functions that have been provided by Matlab.

For each variation pattern running several times, the goal is to provide training on the network and changes in weight on the network. The repeated running process will reduce the error rate on the network because of the weight adjustment on the network. This repetitive running process can be done by experimenting with existing parameters, for example by changing the number of epochs, validation checks, gradients, performance, learning rates and other indicators according to the training function.

2.5. Testing the Artificial Neural Network Model

Testing on the ANN model is carried out to determine the accuracy or accuracy of the results or outputs of the Prediction model built, compared to the actual N-SPT value. After obtaining the network with the best results, perform a simulation using the test data that has been prepared and then compare the Prediction results with the original data. To measure the level of accuracy of an ANN model in predicting the SPT value, this study uses parameters such as the coefficient of correlation

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(R), root mean squared error (RMSE), and mean absolute error (MAE). The RMSE and MAE values can be generated using the following formula (2) and (3).

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| \tag{3}$$

Where:
RMSE = Root Mean Square Error
MAE = Mean Absolute Error
f = original value
y = Prediction result value
n = amount of data

3. Results and discussion

3.1. Results of the Model Making Stage

In this study, the best performance artificial neural network model was obtained, that is an artificial neural network with 1 hidden layer, 20 neurons in the hidden layer and the training function traincgb. The network architecture can be seen in Fig. 2. In this model, the R training value was 0.96306, R validation 0.99263, R Test 0.96177 and R All 0.96723 which we can see in Fig. 3.

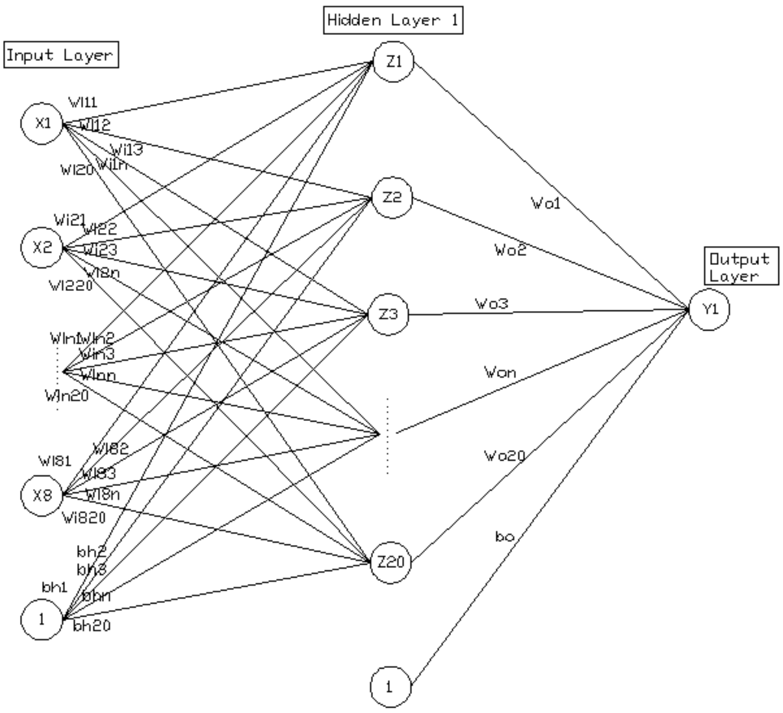

Fig. 2. NN_Nspt(C) Network Architecture

Fig. 2 is an architectural design of an artificial neural network that has been developed. X1-X8 are neurons in the input layer. Z1-Z20 are neurons in the hidden layer and Y1 are neurons in the output layer. The number of neurons in each layer is obtained based on the results of trial and error in the network training process and choosing the best network architecture design based on the smaller error value. Neurons in the input layer are connected to neurons in the hidden layer based on network weight, the weight in Fig. 2 is symbolized by W while the bias is symbolized by b and so on from the hidden layer to the output layer.

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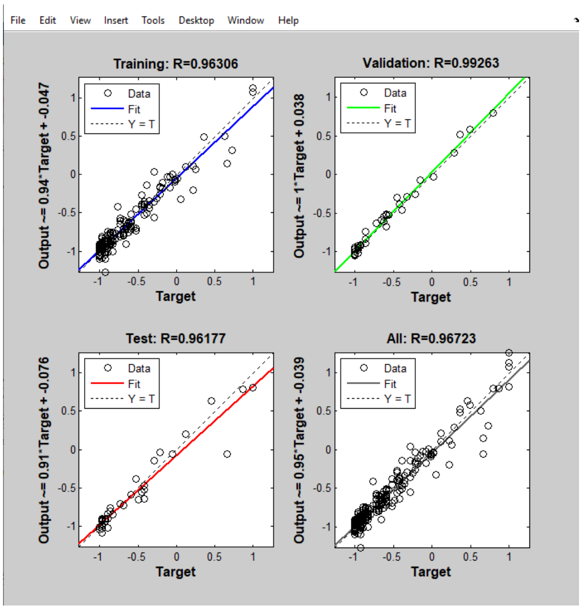

Fig. 3. ANN Regression Model NN_Nspt(C)

Fig. 3 is a graph between the target and output values obtained based on the network architecture that has been developed, namely the network architecture in Fig. 2. In this figure, you can see a good trendline graph between the target value and the network output where the R value is close to 1. In Fig. 3 there are 4 graphs, the first graph is from the training results, the second graph is the validation result, the third graph is the test result and the fourth graph is the average of the whole process.

3.2. Weight and Bias

Table 3 to Table 6 are the weight and bias values of the developed network model.

Table 3. Weight from input layer to hidden layer [W1]

W_{i11}	0.141	W_{i12}	1.365	W_{i13}	0.601	W_{i14}	0.161	W_{i15}	0.441
W_{i21}	-0.272	W_{i22}	-0.246	W_{i23}	-0.174	W_{i24}	1.868	W_{i25}	-1.522
W_{i31}	0.317	W_{i32}	0.258	W_{i33}	0.670	W_{i34}	-0.605	W_{i35}	-0.875
W_{i41}	0.957	W_{i42}	0.036	W_{i43}	-0.021	W_{i44}	0.294	W_{i45}	-0.143
W_{i51}	-0.398	W_{i52}	-0.582	W_{i53}	1.322	W_{i54}	0.312	W_{i55}	0.301
W_{i61}	0.909	W_{i62}	-0.011	W_{i63}	1.003	W_{i64}	-0.159	W_{i65}	0.172
W_{i71}	-1.067	W_{i72}	1.264	W_{i73}	0.851	W_{i74}	-0.425	W_{i75}	-0.784
W_{i81}	-1.172	W_{i82}	-1.436	W_{i83}	0.624	W_{i84}	-0.779	W_{i85}	0.135
W_{i16}	0.395	W_{i17}	0.675	W_{i18}	1.675	W_{i19}	0.486	W_{i110}	0.812
W_{i26}	0.019	W_{i27}	0.254	W_{i28}	2.520	W_{i29}	-0.189	W_{i210}	0.460
W_{i36}	-0.658	W_{i37}	-0.003	W_{i38}	1.339	W_{i39}	0.125	W_{i310}	-0.273
W_{i46}	-0.066	W_{i47}	1.652	W_{i48}	0.226	W_{i49}	-0.595	W_{i410}	-0.138
W_{i56}	0.946	W_{i57}	1.580	W_{i58}	-0.620	W_{i59}	0.337	W_{i510}	0.792
W_{i66}	0.596	W_{i67}	0.696	W_{i68}	-1.159	W_{i69}	1.939	W_{i610}	0.934
W_{i76}	1.363	W_{i77}	-1.014	W_{i78}	1.478	W_{i79}	-0.509	W_{i710}	1.038
W_{i86}	0.766	W_{i87}	0.499	W_{i88}	-0.481	W_{i89}	-0.920	W_{i810}	0.591
W_{i111}	-0.195	W_{i112}	-0.819	W_{i113}	-0.447	W_{i114}	0.411	W_{i115}	-0.255
W_{i211}	0.953	W_{i212}	-0.883	W_{i213}	0.206	W_{i214}	-0.469	W_{i215}	0.704
W_{i311}	0.777	W_{i312}	0.058	W_{i313}	-0.323	W_{i314}	-0.380	W_{i315}	1.968
W_{i411}	-0.730	W_{i412}	-0.772	W_{i413}	1.003	W_{i414}	0.795	W_{i415}	0.926
W_{i511}	-1.197	W_{i512}	-0.966	W_{i513}	-0.862	W_{i514}	-0.029	W_{i515}	-0.418
W_{i611}	0.274	W_{i612}	-0.584	W_{i613}	0.153	W_{i614}	0.657	W_{i615}	1.790
W_{i711}	-0.760	W_{i712}	0.566	W_{i713}	-0.218	W_{i714}	-0.916	W_{i715}	-0.031
W_{i811}	-0.072	W_{i812}	0.557	W_{i813}	-0.824	W_{i814}	1.164	W_{i815}	1.770
W_{i116}	-0.162	W_{i117}	1.194	W_{i118}	1.481	W_{i119}	0.424	W_{i120}	0.424
W_{i216}	0.422	W_{i217}	0.962	W_{i218}	0.596	W_{i219}	-1.195	W_{i220}	-0.758
W_{i316}	0.640	W_{i317}	-0.528	W_{i318}	-0.215	W_{i319}	0.591	W_{i320}	-0.246
W_{i416}	0.888	W_{i417}	1.147	W_{i418}	0.290	W_{i419}	-1.177	W_{i420}	-0.182

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W_{i516}	0.662	W_{i517}	-2.069	W_{i518}	-0.290	W_{i519}	-0.180	W_{i520}	0.459
W_{i616}	0.765	W_{i617}	-1.423	W_{i618}	0.833	W_{i619}	-0.236	W_{i620}	-0.593
W_{i716}	-0.282	W_{i717}	0.864	W_{i718}	0.571	W_{i719}	1.283	W_{i720}	-1.223
W_{i816}	0.850	W_{i817}	0.292	W_{i818}	0.673	W_{i819}	-1.221	W_{i820}	-1.066

Table 4. Bias from the input layer to the hidden layer [B1]

bh_1	-1.972	bh_2	-1.950	bh_3	-1.321	bh_4	-1.998	bh_5	-1.202
bh_6	-1.127	bh_7	-0.740	bh_8	-0.284	bh_9	-0.385	bh_{10}	-0.660
bh_{11}	-0.074	bh_{12}	0.202	bh_{13}	-1.254	bh_{14}	0.402	bh_{15}	-2.010
bh_{16}	1.626	bh_{17}	-1.412	bh_{18}	2.245	bh_{19}	1.879	bh_{20}	2.112

Table 5. Weight from hidden layer to output layer [W2] (Matrix 1x20)

W_{o1}	0.330	W_{o2}	1.313	W_{o3}	-1.248	W_{o4}	0.656	W_{o5}	0.518
W_{o6}	-0.620	W_{o7}	0.660	W_{o8}	-0.574	W_{o9}	-0.246	W_{o10}	-0.107
W_{o11}	0.159	W_{o12}	0.155	W_{o13}	-0.509	W_{o14}	-0.612	W_{o15}	1.624
W_{o16}	0.442	W_{o17}	0.810	W_{o18}	0.719	W_{o19}	0.548	W_{o20}	0.171

Table 6. Bias from hidden layer to output layer [B2] (Matrix 1x1)

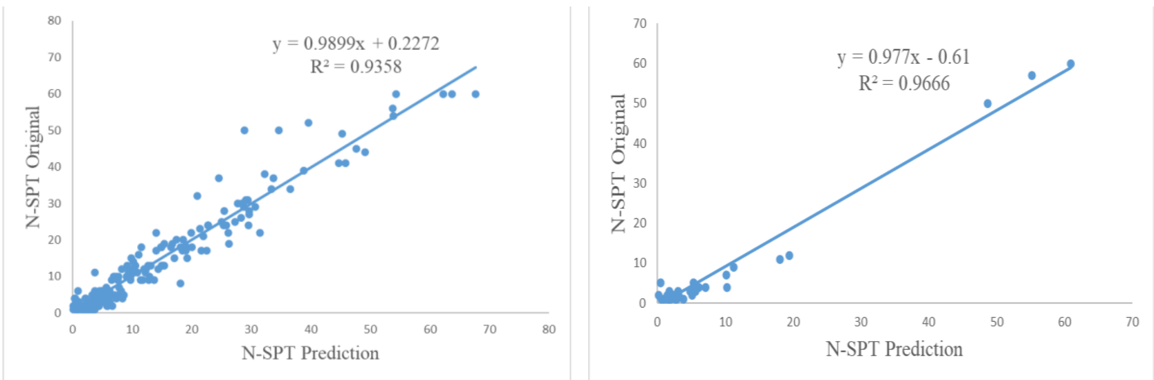
b_0	0.63075

3.3. Results of the Model Testing Stage

At this stage, the ANN model that has been developed is simulated against the existing data then the RMSE and MAE are calculated as a measure of predictioning accuracy. Furthermore, the correlation coefficient (R^2) between the output data and the target is also calculated. Table 7 is the RMSE and MAE values based on the developed neural network model and Fig. 4 is a graph showing the R^2 value based on the developed network model.

Table 7. Measure of Accuracy NN_Nspt(C)

Observation	Training Data	Testing Data
RMSE	3,441	2,785
MAE	2,318	2,085



(a) (b)

Fig. 4. N-SPT Prediction Using Artificial Neural Networks (a) Training Data (b) Test Data

Fig. 4 (a) and (b) shows the relationship between the predicted N-SPT and the original N-SPT results from the field. On the linear line, it can be seen that the R value is close to 1 which shows the results of the prediction of the SPT value using ANN close to the original SPT value in the field.

The steps for calculating the N-SPT using the ANN model that have been developed manually are as follows:

1. The first step is to transform the original input data into normalized input data (Xn). In this study using the bipolar sigmoid activation function which has a range of -1 to 1, therefore the input data must be transformed into a range of -1 to 1. Input data are shown in matrix [Xn] (1x8)i, where i is the amount of data.

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2. The second step is to calculate the operations on the hidden layer. The weight values from the input layer to the hidden layer are displayed in the form of an 8x20 matrix and the bias values from the input layer to the hidden layer in the 1x20 matrix and the hidden layer in the 1x20 matrix. Furthermore, the matrix multiplication is carried out using equations:

   [HL](1x20)i = [Xn](1x8)i*[W1](8x20)i+[B1](1x20)i

3. The third step is to activate the hidden layer in accordance with the activation function. For the bipolar sigmoid activation function, the activation function formula is:

   $f(x) = \frac{1-e^{-x}}{1+e^{-x}}$

4. The fourth step is to calculate the operations at the output layer. The calculation process uses a multiplication matrix where the output layer is displayed in a 1x1 matrix, the hidden layer values are displayed in a 1x20 matrix, the weight from the hidden layer to the output layer in the 1x20 matrix, and the bias value in the 1x1 matrix.

   [OL](1x1)i = [HL](1x20)i*[W2](1x20)i+[B2](1x1)i

5. The activation function used in the output layer is a linear function with a formula

   F(x) = x

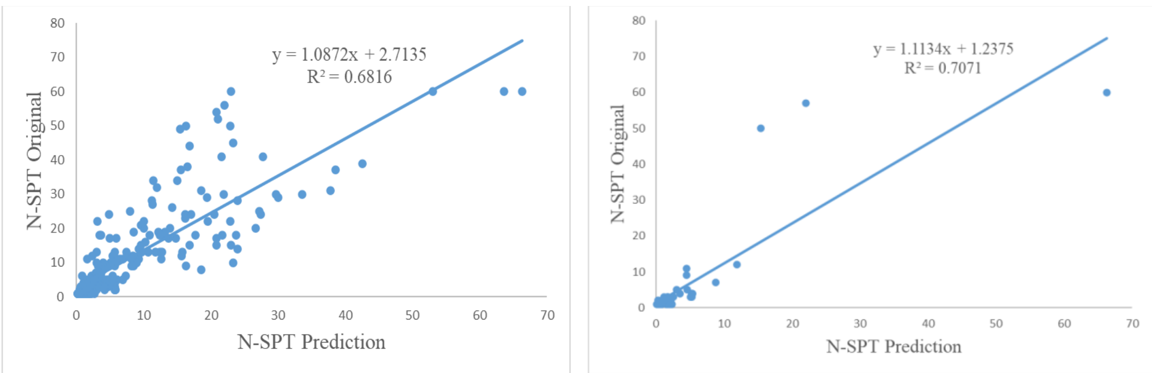
6. The final step is to denormalize the activated output value.

3.4. N-SPT Prediction Using Conventional Correlation

At this stage, N-SPT Predictions are carried out using conventional correlations that have been developed by previous researchers. The following estimates are made using the correlation value based on research by [4], [5], [6]. This N-SPT Prediction uses the Kc value as described in the introduction. Table 8 displays the RMSE and MAE values and Fig. 5 to Fig. 7 shows a graph showing the R^2 value obtained through conventional correlation by [4], [5], [6].

Table 8. N-SPT Prediction Using Conventional Correlation

Research	Training Data		Testing Data	
	RMSE	*MAE*	*RMSE*	*MAE*
[4]	8,417	4,733	7,808	2,841
[5]	7,947	4,643	7,591	3,068
[6]	8,641	4,813	7,951	2,810



(a) (b)
Fig. 5. N-SPT Prediction Using [4] Correlation (a)Training Data (b) Test Data

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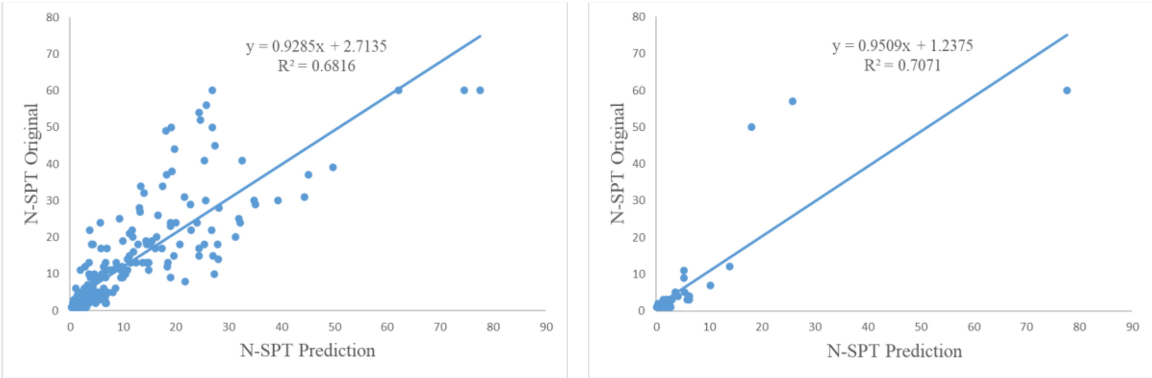
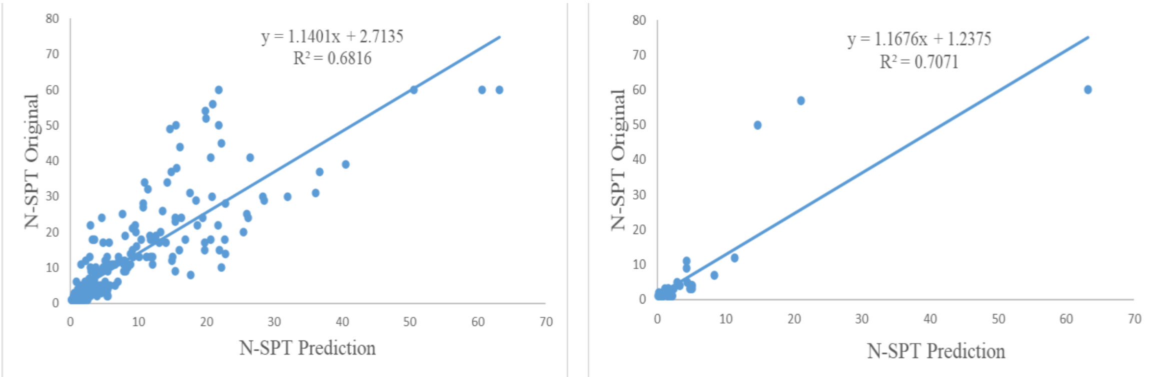


(a) (b)

Fig. 6. N-SPT Prediction Using [5] Correlation (a)Training Data (b) Test Data



(a) (b)

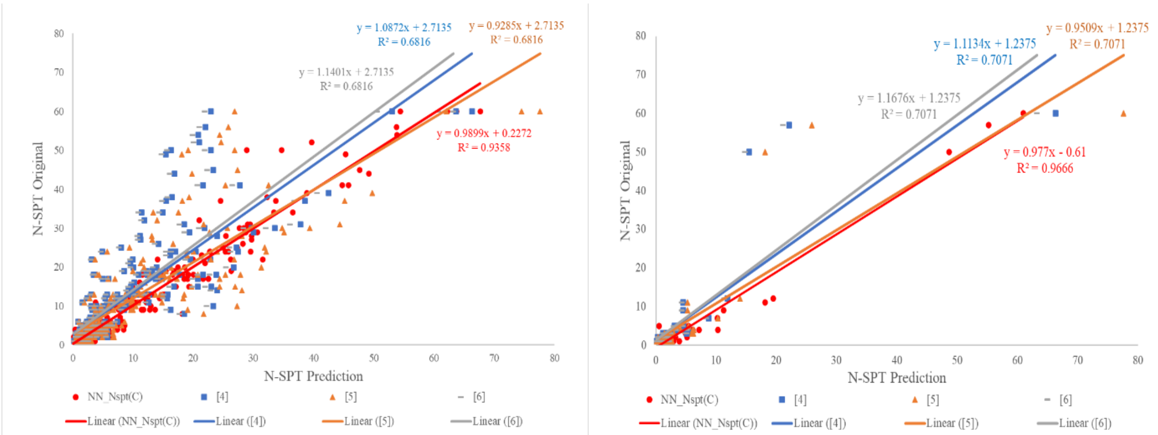
Fig. 7. N-SPT Prediction Using [6] Correlation (a)Training Data (b) Test Data

Table 9. Comparison of N-SPT Predictions using ANN and Conventional Correlation

Research	Training Data		Testing Data	
	RMSE	*MAE*	*RMSE*	*MAE*
NN_Nspt(C)	3,441	2,318	2,785	2,085
[4]	8,417	4,733	7,808	2,841
[5]	7,947	4,643	7,591	3,068
[6]	8,641	4,813	7,951	2,810

Based on Table 9, it can be seen that the prediction of the SPT value using ANN shows much better results than using conventional correlation. This can be seen from the RMSE and MAE values in both the training data and the test data showing smaller results.

3.5. Design Chart Based on the Best Model



(a) (b)

Fig. 8. Design Chart N-SPT Prediction VS N-SPT Original (a)Training Data (b) Test Data

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Fig. 8 (a) and (b) are a design chart based on the best network model. The N-SPT Prediction using artificial neural networks provides more accurate and effective results than other conventional correlations, this can be seen through the estimated R^2 value using the artificial neural network (in red) which is greater or closer to 1 than other Predictions. In the training data, $R^2 = 0.9358$ and the test data $R^2 = 0.9666$.

Furthermore, to determine the effectiveness of the estimated SPT value using artificial neural networks with the estimated SPT value using conventional correlation, in Table 10, several examples of comparison of the estimated SPT value using artificial neural networks and conventional correlation by [4], [5], [6] are shown.

Table 10. Verification of N-SPT Prediction using NN_Nspt(C) with Conventional Correlation by Previous Researchers

	INPUT								OUTPUT				
NO	qc (KN/m2)	fs (KN/m2)	σ'_o (KN/m2)	Liquid Limit (%)	Plastic Limit (%)	Sand (%)	Silt (%)	Clay (%)	Original N-SPT(A) (blows/ft)	NN_Nspt(C) N-SPT(P) (blows/ft)	[4] N-SPT(P) (blows/ft)	[5] N-SPT(P) (blows/ft)	[6] N-SPT(P) (blows/ft)
1	958.362	36.976	237.845	37.110	16.110	1.740	12.260	86.000	5	5.486	2.590	3.033	2.470
2	8632.800	303.920	302.100	49.540	27.460	0.800	12.850	86.350	10	9.810	23.332	27.319	22.249
3	8866.731	49.050	82.665	18.662	14.352	49.440	12.231	38.329	14	14.889	23.964	28.059	22.852
4	9885.462	49.050	108.190	23.983	19.583	57.040	14.746	28.214	20	20.409	26.717	31.283	25.478
5	10077.545	98.100	247.345	27.940	23.700	51.620	26.720	19.980	25	24.995	27.237	31.891	25.973
6	7183.938	387.118	169.900	60.000	37.600	0.760	44.560	54.680	29	28.775	19.416	22.734	18.515
7	5553.969	247.514	261.760	53.460	26.880	1.720	77.990	20.290	34	33.414	15.011	17.576	14.314
8	15728.700	179.033	67.025	25.840	21.370	47.880	45.140	6.980	39	38.888	42.510	49.774	40.538
9	8647.892	426.106	131.215	75.070	30.350	3.360	8.860	87.780	45	47.647	23.373	27.367	22.288
10	5715.162	157.960	185.430	76.530	32.960	0.120	94.350	5.530	49	45.289	15.446	18.086	14.730
11	7714.227	197.984	351.440	74.250	34.810	0.980	6.930	92.090	54	53.862	20.849	24.412	19.882
12	19620.000	392.400	327.900	49.010	29.000	3.420	46.320	50.260	60	62.227	53.027	62.089	50.567

4. Conclusion

The backpropagation network model with a tansig activation function is well developed in this study. The data used are 242 data on training data and 42 data on test data. Input parameters used are tip resistance (q_c), skin resistance (f_s), effective overburden pressure, liquid limit, plastic limit, percentage of sand, silt and clay with the output is N-SPT. The NN_Nspt(C) model was developed with a network architecture of 1 hidden layer and 20 neurons in the hidden layer. The artificial neural network has proven to be able and effective in predicting SPT values. In this study, the artificial neural network proved to be better at predicting SPT values compared to conventional correlation. This can be proven by the RMSE, MAE value of N-SPT estimates with the artificial neural network is smaller than the conventional correlation and the R^2 value in the artificial neural network is closer to 1 compared to conventional correlation. This can be proven by the RMSE, 3.441, MAE 2.318 and R^2 0.9358 for training data and RMSE 2.785, MAE 2.085, R^2 0.9666 for test data.

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