International Journal Of Artificial Intelegence Research
Vol 5, No 2, December 2021, pp 123-131
ISSN: 2579-7298

Prediction of SPT value based on CPT data and soil physical properties using ANN with and without data normalization

Hendra Fernando[a,1,*], Soewignjo Agus Nugroho[b,,2], Reni Suryanita[b,3]Mamoru Kikumoto[c,4]

[a] *Department of Civil Engineering, Riau University, HR. Subrantas KM 12.5, Pekanbaru, 28293, Indonesia*
[b] *Department of Civil Engineering, Riau University, HR. Subrantas KM 12.5, Pekanbaru, 28293, Indonesia*
[c]*Department of Civil Engineering Yokohama National University, Japan*
[1] *hendra.fernandoo@gmail.com*; [2] nugroho.sa@eng.unri.ac.id; [3] reni.suryanita@lecturer.unri.ac.id*
** corresponding author*

ARTICLE INFO

Article history:
Received 28-12-2020
Revised 19-05-2021
Accepted 28-06-2021

Keywords:
Artificial Neural Network
Normalization Data
Cohesive Soil
SPT Value
Cone Penetration Test

ABSTRACT

Artificial neural networks (ANN) are now widely used and are becoming popular among researchers, especially in the geotechnical field. In general, data normalization is carried out to make ANN whose range is in accordance with the activation function used. Other studies have tried to create an ANN without normalizing the data and ANN is considered capable of making predictions. In this study, a comparison of ANN with and without data normalization was carried out in predicting SPT values based on CPT data and soil physical properties on cohesive soils. The input data used in this study are the value of tip resistance, sleeve resistance, effective soil overburden pressure, liquid limit, plastic limit and percentage of sand, silt and clay. The results showed that the ANN was able to make predictions effectively both on networks with and without data normalization. In this study, it was found that the ANN without data normalization showed a smaller error value than the ANN with data normalization. In the network model without data normalization, RMSE values were 3.024, MAE 1.822, R^2 0.952 on the training data and RMSE 2.163, MAE 1.233 and R^2 0.976 on the test data. Whereas in the ANN with data normalization, the RMSE values were 3.441, MAE 2.318, R^2 0.936 in the training data and RMSE 2.785, MAE 2.085 and R^2 0.963 in the test data. ANN with normalization provides a simpler architecture, which only requires 1 hidden layer compared to ANN without normalization which requires 2 hidden layer architecture.

I. Introduction

The mechanical properties of soil and rock in general have significant non-linearity, this is due to the very complex composition of soil and rock [1]. Therefore, conventional methods in geotechnical engineering cannot predict nonlinearity properties accurately. Soil and rock which are the basic materials in geotechnical engineering have varying properties which are very complex and uncertain, this happens because the physical processes of material formation vary widely and are influenced by many factors [2]. The modeling of the behavior of these geotechnical materials is very complex and is sometimes beyond the capabilities of most forms of engineering methods using conventional equations [3]. Along with the times, the pressure on the need for geotechnical engineering facilities is increasing with an increasing frequency, the industry urgently needs an effective method to analyze the properties of soil and rock, therefore a method is needed that can compensate for these pressure needs [4].

Machine learning techniques are methods that are able to effectively solve complex and non-linear problems and avoid the drawbacks that might arise when using conventional methods. In machine learning, the computer can do its own learning to understand and identify trends in a broad data set and then use these trends to form models to predict unknown characteristics. The essence of machine learning is algorithms and many algorithms have been developed to date. Each algorithm has its advantages and disadvantages in solving a problem. Artificial neural network (ANN) is a popular algorithm among researchers these days, especially in geotechnical problems. ANN has three main advantages: first, the counting speed is high. Second, a strong fault-tolerant ability. Third, proficient in dealing with problems with complex solving rules [4].

The approach to using ANN can be a recommendation for forecasting, especially in cases where theoretical modeling does not give the expected results [5]. Artificial neural networks (ANN) aim to model the behavior of the nervous system in the human brain. ANN is the most effective solution in solving complex and nonlinear data modeling. In the geotechnical field, the problems that develop generally have many variables which make it difficult for modeling using conventional mathematics.

An artificial neural network can be defined as a group of processing elements in a group that specifically makes its own calculations and gives the results to the second or next group. Each sub-group according to its turn must make its own calculations and provide the results for the subgroup or group that has not done the calculation. In the end, a group of one or more processing elements produces output (output) from the network. the basis of the ANN learning rules is the variation on neural connections. the point is that if two neurons are activated at the same time, the synaptic link between them is strengthened [6]. The basic characteristics of an ANN are (1) Precise precision of any nonlinear equation, this is possible as long as the network structure and the appropriate transfer function are given. By studying sample data, the network can solve any nonlinear equation. (2) Fault tolerance: each neuron will store the information provided by the network. Each piece of network information has an equipotential distribution in the information storage so that the network can still recover lost information. This makes the memory function associative and fault-tolerant of network errors (3) Learning adaptability: the connections between neurons in the network are malleable and diverse. Networks can be set up through instructional training according to information processing needs. (4) Parallel processing: at the same time, each unit on the network can perform similar processing and large-scale information processing methods are carried out on the entire parallel network. This massive parallel network processing capability allows the network to solve complex problems.

The artificial neural network architecture consists of an input layer, in which this layer consists of neurons that are designed according to the model of the problem to be solved. The second is the output layer, where this layer consists of neurons that are the desired output or result from training or simulation results on the network. Between the input layer and the output layer there is a hidden layer, where increasing the number of hidden layers can increase accuracy and reduce errors, but also complicate the network as it increases network training time. By increasing the number of neurons in the hidden layer is also one way to improve network performance. Increasing the number of neurons in this hidden layer makes the training effect easier to observe and adjust than by increasing the number of hidden layers.

In recent years, ANN has become a popular method among researchers in solving geotechnical modeling problems. Several related studies such as predictions on foundation problems, that is prediction settlement of shallow foundation [7], axial capacity of pile foundation [8], pile drivability [9], pile bearing capacity [10], shaft and tip resistance concrete piles [11]. ANN has also been widely used to predict several physical and mechanical properties of soil such as prediction of soil classification [12], compaction [13], soil deformation [14], Compression coefficient value [15], compression index and compression ratio [16], bearing capacity [17], unit weight [18], compressive strength [19][20], recompression index [21], elastic settlement [22], soil layers [23], clay sensitivity [24], and electrical resistivity of soil [25]. In soil improvement, ANN has also been widely used such as slope stability [26][27] and soil stabilization [28]. Other related research such as prediction on liquefaction potential [29][30] and ground vibrations [31]and also prediction SPT value [32][33][34].

One of the basic elements of ANN is the activation function. The activation functions commonly used are the binary sigmoid and bipolar sigmoid activation functions. The activation function will carry an infinite range of input values to a finite output. To bring a range of output values into the input range, input data is normally normalized, that is, converting the data into a range of its activation function. The binary sigmoid activation function has a value range between 0 to 1 and the bipolar sigmoid activation function has a value range between -1 to 1. Previous research has made ANN models to predict SPT values on cohesive soils based on CPT data and soil physical properties data by doing data normalization. In subsequent studies, Fernando et al. (unpublished) have also conducted a similar study using the same data without normalizing the data. The results of this study indicate that ANN is still capable of modeling the given equation. In this article, we will compare the making of an artificial neural network model using the same data in research by Nugroho et al. (unpublished) and Fernando et al. (unpublished) comparing the results between normalizing the data and without normalizing the data.

II. Research Metodology

A. *Literature Review*

Research by Nugroho et al. (unpublished) regarding the prediction of SPT values based on CPT data and soil physical properties by normalizing the data shows that ANN is the best solution in predicting SPT values with a small error value compared to predictions using conventional correlation. This study uses 244 data from SPT testing, CPT testing and laboratory testing. This data is a test conducted with study locations in several areas on the island of Sumatra, Indonesia. The input data used in this study are the value of tip resistance (q_c), sleeve resistance (f_s), effective soil overburden pressure, liquid limit, plastic limit and percentage of grains of sand, silt and clay. The output data in this study is the SPT value. In this study, the values of 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 were obtained. The neural model was developed with a network architecture of 1 hidden layer and 20 neurons in the hidden layer with Backpropagation algorithm and the bipolar sigmoid activation function.

Fernando et al. (unpublished) also conducted a study to predict the value of SPT based on CPT data and soil physical properties using the same test data as research by Nugroho et al. But in this study, an artificial neural network was created without normalizing the data. The results showed that ANN was still able to predict SPT values with a small error value compared to predictions using conventional correlation. In the training data, the RMSE value 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. The best performing artificial neural network model in this study is an artificial neural network with backpropagation algorithm, bipolar sigmoid activation function, traincgb training function, network architecture with 2 hidden layers, 16 neurons in hidden layer 1 and 8 neurons in hidden layer 2. Will However, in making an artificial neural network model without normalizing the data, it requires increasing the number of hidden layers to 2 hidden layers, while in making artificial neural networks with data normalization only one hidden layer is needed to get the best performance network.

B. *Data Collection*

The data used in this study are data obtained from previous studies by Nugroho et al. (unpublished) and Fernando et al. (unpublished). The input variable used is also equated with the research, which consists of 8 input variables, namely value of tip resistance (q_c), sleeve resistance (f_s), effective soil overburden pressure, liquid limit, plastic limit and percentage of grains of sand, silt and clay.

C. *Making Neural Network Model*

The process of creating an artificial neural network is carried out using the Matlab application. In this article, it will create an artificial neural network by normalizing data and without normalizing data. The network model to be developed will be created using the same data as previous research by Nugroho et al. (unpublished) and Fernando et al. (unpublished). Then the results of the artificial neural network were compared with data normalization and without data normalization. The network creation aims to prove previous research using the same algorithm, that is the Backpropagation algorithm and the same activation function, that is the bipolar sigmoid activation function, as well as the same training function namely traincgb, but variations will be made on the network architecture. Determining the network architecture is done by varying the number of hidden layers and also the number of neurons in the hidden layer. The reference number of hidden layers is between 1 and 2 hidden layers and the number of neurons in the hidden layer is between 8, 16 and 20 hidden layers according to previous research by Nugroho et al. (unpublished) and Fernando et al. (unpublished). The network with the best performance is the network that has the smallest error value and the correlation coefficient value that is close to 1. In this study we will use the RMSE and MAE values to see the network error rate and the R2 value to see the correlation strength value between the predicted results and the original value. To calculate the RMSE value you can use (1) and to calculate the MAE value using (2).

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

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

Where RMSE is Root Mean Square Error, MAE is Mean Absolute Error, f_i is original value, y_i is predictive value, n is amount of data.

III. Result and Discussion

The results and discussion of the networks that have been developed are as follows:

A. ANN with Data Normalization

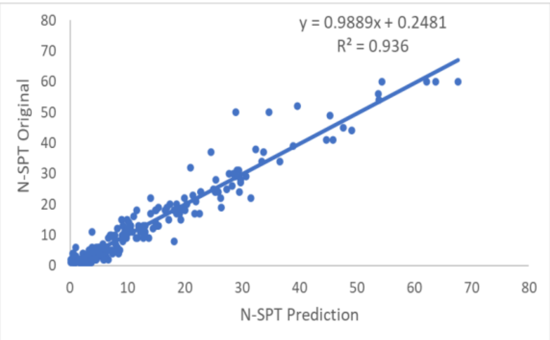
Table 1. ANN Architecture with 1 Hidden Layer in ANN with data normalization

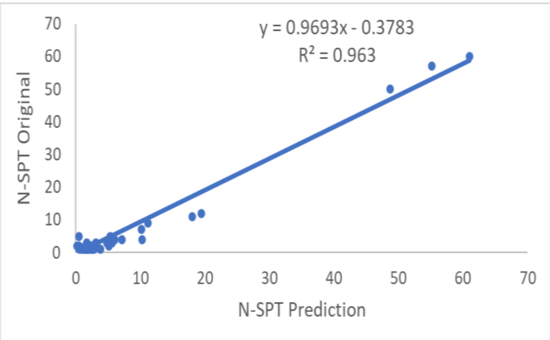
Neurons	Training Data			Testing Data		
	RMSE	MAE	R^2	RMSE	MAE	R^2
8	4.356	2.752	0.897	4.756	3.038	0.909
16	4.691	2.655	0.883	4.431	3.125	0.899
20	3.441	2.318	0.936	2.785	2.085	0.963

Table 2. ANN architecture with 2 hidden layers in ANN with data normalization

Neurons		Training Data			Testing Data		
Hidden Layer 1	Hidden Layer 2	RMSE	MAE	R^2	RMSE	MAE	R^2
8	8	4.046	2.622	0.912	1.982	1.573	0.983
16	8	3.962	2.530	0.916	2.506	1.850	0.971
16	16	4.553	3.116	0.889	2.534	1.837	0.970
20	8	5.511	3.354	0.835	5.982	2.753	0.825
20	16	4.590	3.016	0.885	2.566	1.607	0.973
20	20	4.889	3.215	0.870	3.177	1.997	0.954

The network with the best performance is the network that has smaller errors and regression correlation whose value is getting closer to 1. Based on Table 1 and Table 2, the best performing network is the network that has 1 hidden layer architecture with 20 neurons in hidden layer.





(a) (b)

Fig. 1. N-SPT prediction VS N-SPT original on ANN with data normalization
(a)Training Data (b) Test Data

Fig. 1 and Fig. 2 are graphs of the relationship between the predicted SPT values and the original SPT values on the training data and on the test data. In this graph it can be seen that ANN has a strong regression equation which is indicated by the R^2 value which is getting closer to 1, where the training data shows R^2 0.936 and the test data gets R^2 0.963.

Furthermore, in Table 3, the prediction of the SPT value will be carried out using input data taken randomly from the data held.

Table 3. Example of prediction results of SPT value using ANN with data normalization

No	Input Data								Output Original	Output ANN	Difference
	q_c[a] (kPa)	f_s[b] (kPa)	σ'_0[c] (kPa)	LL[d] (%)	PL[e] (%)	S[f] (%)	M[g] (%)	C[h] (%)	N-SPT[i] (blows/ft)	N-SPT (blows/ft)	
1	98.10	9.81	35.25	43.67	31.97	4.92	91.11	3.97	1	1.19	0.19
2	1695.73	88.99	96.54	25.33	20.43	43.40	46.69	9.91	5	3.82	1.18
3	8632.80	303.92	302.10	49.54	27.46	0.80	12.85	86.35	10	8.86	1.14
4	3783.86	38.54	309.18	45.35	32.35	6.34	45.63	48.03	16	16.04	0.04
5	3561.78	153.94	70.25	85.70	51.70	2.80	53.41	43.79	21	19.23	1.77
6	6005.12	153.46	271.19	71.27	32.57	2.02	18.26	79.72	24	25.85	1.85
7	5275.30	67.41	49.78	73.30	30.98	7.88	6.90	85.22	26	25.62	0.38
8	14006.50	245.25	186.30	74.40	39.60	0.52	25.60	73.88	31	32.33	1.33
9	11097.56	106.68	422.11	36.25	16.53	3.16	21.80	75.04	29	29.95	0.95
10	4227.22	420.05	328.76	49.14	29.02	3.42	46.32	50.26	34	34.64	0.64
11	15728.70	179.03	67.03	25.84	21.37	47.88	45.14	6.98	39	36.86	2.14
12	8647.89	426.11	131.22	75.07	30.35	3.36	8.86	87.78	45	48.51	3.51
13	5715.16	157.96	185.43	76.53	32.96	0.12	94.35	5.53	49	49.38	0.38
14	8158.65	163.50	356.78	50.64	25.86	37.82	6.74	55.44	56	52.00	4.00
15	19620.00	392.40	327.90	49.01	29.00	3.42	46.32	50.26	60	59.84	0.16

[a] Tip resistance

[b] Sleeve resistance

[c] Effective soil overburden pressure

[d] Liquid limit

[e] Plastic limit

[f] Percentage of grains of sand

[g] Percentage of grains of silt

[h] Percentage of grains of clay

[i] SPT value

B. *ANN Without Data Normalization*

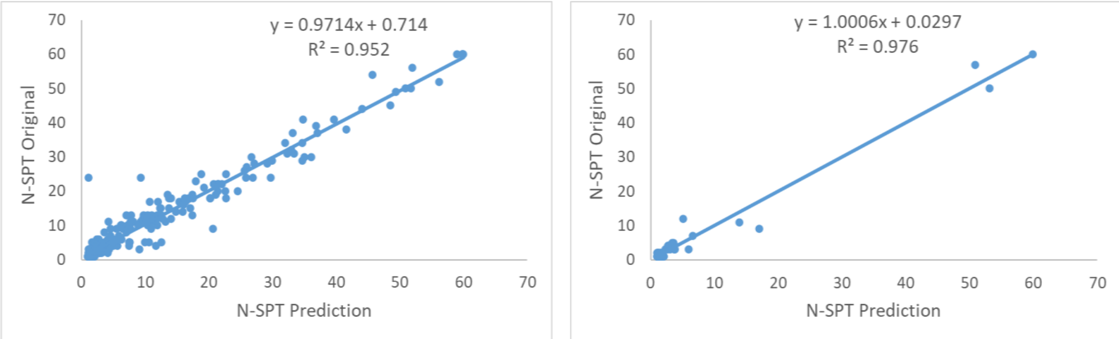
Table 4. ANN Architecture with 1 Hidden Layer in ANN without data normalization

Neurons	Training Data			Testing Data		
	RMSE	MAE	R^2	RMSE	MAE	R^2
8	5.954	3.774	0.807	4.235	2.247	0.938
16	4.035	2.397	0.911	4.306	2.384	0.925
20	5.615	3.537	0.829	2.840	2.316	0.972

Table 5. ANN architecture with 2 hidden layers in ANN without data normalization

Neurons		Training Data			Testing Data		
Hidden Layer 1	Hidden Layer 2	RMSE	MAE	R^2	RMSE	MAE	R^2
8	8	5.14	3.226	0.857	2.453	1.828	0.982
16	8	3.194	1.772	0.947	2.212	1.514	0.975
16	16	4.984	3.125	0.866	3.665	2.019	0.951
20	8	5.806	3.915	0.817	4.797	2.790	0.933
20	16	3.446	2.267	0.936	2.186	1.603	0.978
20	20	3.024	1.822	0.952	2.163	1.233	0.976

Based on Table 4 and Table 5, it is found that the network with the best performance is a network that has 2 hidden layer architecture with 20 neurons in hidden layer 1 and 20 neurons in hidden layer 2. In this network model, the RMSE values were 3.024, MAE 1.822, R^2 0.952 on the training data and RMSE 2.163, MAE 1.233 and R^2 0.976 on the test data.



(a) (b)

Fig. 2. N-SPT prediction VS N-SPT original on ANN without data normalization
(a)Training Data (b) Test Data

Fig. 1 and Fig. 2 are the relationship between the predicted SPT values using ANN and the original SPT values on the training data and test data. Based on this figure, it can be seen that ANN is able to predict the SPT value without normalizing the data efficiently. This can be seen based on the value of the regression equation R^2 which is close to 1 where the training data obtained the value of R^2 0.952 and the R^2 test data was 0.976.

Table 6. Example of prediction results of SPT value using ANN without data normalization

No	Input Data								Output Original	Output ANN	Difference
	q_c (kPa)	f_s (kPa)	σ'_0 (kPa)	LL (%)	PL (%)	S (%)	M (%)	C (%)	N-SPT (blows/ft)	N-SPT (blows/ft)	
1	98.10	9.81	35.25	43.67	31.97	4.92	91.11	3.97	1	0.99	0.01
2	1695.73	88.99	96.54	25.33	20.43	43.40	46.69	9.91	5	5.17	0.17
3	8632.80	303.92	302.10	49.54	27.46	0.80	12.85	86.35	10	9.81	0.19
4	3783.86	38.54	309.18	45.35	32.35	6.34	45.63	48.03	16	11.13	4.87
5	3561.78	153.94	70.25	85.70	51.70	2.80	53.41	43.79	21	21.95	0.95
6	6005.12	153.46	271.19	71.27	32.57	2.02	18.26	79.72	24	22.75	1.25
7	5275.30	67.41	49.78	73.30	30.98	7.88	6.90	85.22	26	28.27	2.27
8	14006.50	245.25	186.30	74.40	39.60	0.52	25.60	73.88	31	29.47	1.53
9	11097.56	106.68	422.11	36.25	16.53	3.16	21.80	75.04	29	30.67	1.67
10	4227.22	420.05	328.76	49.14	29.02	3.42	46.32	50.26	34	36.57	2.57
11	15728.70	179.03	67.03	25.84	21.37	47.88	45.14	6.98	39	38.89	0.11
12	8647.89	426.11	131.22	75.07	30.35	3.36	8.86	87.78	45	47.65	2.65
13	5715.16	157.96	185.43	76.53	32.96	0.12	94.35	5.53	49	45.29	3.71
14	8158.65	163.50	356.78	50.64	25.86	37.82	6.74	55.44	56	53.78	2.22
15	19620.00	392.40	327.90	49.01	29.00	3.42	46.32	50.26	60	62.23	2.23

IV. Conclusion

Based on the research results, it was concluded that ANN was able to solve modeling problems in predicting SPT values using CPT data and soil physical properties either by normalizing data or without data normalization. In the network model with data normalization, the best performance network is a network with 1 hidden layer architecture with 20 neurons in hidden layer. In the training data, the RMSE values were 3.441, MAE 2.318, R^2 0.936, and the test data obtained were RMSE values 2.785, MAE 2.085 and R^2 0.963. In the network model without data normalization, the best performance network is a network with 2 hidden layers, hidden layer 1 consists of 20 neurons and hidden layer 2 consists of 20 neurons. In the training data, the RMSE values were 3.024, MAE 1.822, R^2 0.952, and the test data obtained were RMSE values 2.163, MAE 1.233 and R^2 0.976.

Both of these methods, that is ANN with data normalization and without data normalization, can be selected when modeling an artificial neural network by taking into account the advantages and disadvantages of each method. Based on the smallest error value, ANN without normalization gives a smaller error value than ANN with normalization. If based on network architecture, ANN with normalization provides a simpler architecture, which only requires 1 hidden layer compared to ANN without normalization which requires 2 hidden layer architecture. Both methods can be used which can be adjusted according to the objectives and approach you want to use.

Acknowledgment

The authors would like to thank the Soil Mechanics Laboratory, Faculty of Engineering, Riau University and also to CV. Geotechnical Multi Services which has provided data on the results of field testing and laboratory testing. These data are very useful for writers in the research process until this research is completed.

References

[1] M. B. Jaksa, "The influence of spatial variability on the geotechnical design properties of a stiff, overconsolidated clay," *Ph.D. Thesis, Univ. Adelaide, Aust.*, no. December, 1995, [Online]. Available: https://www.researchgate.net/publication/238346452.

[2] J. K. Mitchell and K. Soga, *Fundamentals of Soil Behavior*, vol. 158, no. 1. 2005.

[3] Z. yu Yin, Y. fu Jin, and Z. qiang Liu, "Practice of artificial intelligence in geotechnical engineering," *J. Zhejiang Univ. Sci. A*, vol. 21, no. 6, pp. 407–411, 2020, doi: 10.1631/jzus.A20AIGE1.

[4] Z. Chao, G. Ma, Y. Zhang, Y. Zhu, and H. Hu, "The application of artificial neural network in geotechnical engineering," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 189, no. 2, 2018, doi: 10.1088/1755-1315/189/2/022054.

[5] M. J. Sulewska, "Applying artificial neural networks for analysis of geotechnical problems," *Comput. Assist. Mech. Eng. Sci.*, vol. 18, no. 4, pp. 231–241, 2011.

[6] K. Cui and X. Jing, "Research on prediction model of geotechnical parameters based on BP neural network," *Neural Comput. Appl.*, vol. 31, no. 12, pp. 8205–8215, 2019, doi: 10.1007/s00521-018-3902-6.

[7] T. Gnananandarao, R. K. Dutta, and V. N. Khatri, *Application of artificial neural network to predict the settlement of shallow foundations on cohesionless soils*, vol. 13. Springer Singapore, 2019.

[8] A. Benali, M. Hachama, A. Bounif, A. Nechnech, and M. Karray, "A TLBO-optimized artificial neural network for modeling axial capacity of pile foundations," *Eng. Comput.*, no. 0123456789, 2019, doi: 10.1007/s00366-019-00847-5.

[9] W. Zhang and A. T. C. Goh, "Multivariate adaptive regression splines and neural network models for prediction of pile drivability," *Geosci. Front.*, vol. 7, no. 1, pp. 45–52, 2016, doi: 10.1016/j.gsf.2014.10.003.

[10] H. Maizir, R. Suryanita, and H. Jingga, "Estimation of Pile Bearing Capacity of Single Driven Pile in Sandy Soil Using Finite Element and Artificial Neural Network Methods," *Int. J. Appl. Phys. Sci.*, vol. 2, no. 2, 2016, doi: 10.20469/ijaps.2.50003-2.

[11] E. Momeni, R. Nazir, D. J. Armaghani, and H. Maizir, "Application of artificial neural network for predicting shaft and tip resistances of concrete piles," *Earth Sci. Res. J.*, vol. 19, no. 1, pp. 85–93, 2015, doi: 10.15446/esrj.v19n1.38712.

[12] C. Reale, K. Gavin, L. Librić, and D. Jurić-Kaćunić, "Automatic classification of fine-grained soils using CPT measurements and Artificial Neural Networks," *Adv. Eng. Informatics*, vol. 36, no. April, pp. 207–215, 2018, doi: 10.1016/j.aei.2018.04.003.

[13] J. Jayan and D. N. Sankar, "Prediction of Compaction Parameters of Soils Using Artificial Neural Network," vol. 03, no. October, pp. 368–375, 2016.

[14] J. Lai, J. Qiu, Z. Feng, J. Chen, and H. Fan, "Prediction of Soil Deformation in Tunnelling Using Artificial Neural Networks," *Comput. Intell. Neurosci.*, vol. 2016, 2016, doi: 10.1155/2016/6708183.

[15] B. T. Pham *et al.*, "Development of artificial neural networks for prediction of compression coefficient of soft soil," *Lect. Notes Civ. Eng.*, vol. 54, pp. 1167–1172, 2020, doi: 10.1007/978-981-15-0802-8_187.

[16] A. J. AL-TAIE, A. F. AL-BAYATI, and Z. N. M. TAKI, "Compression Index and Compression Ratio Prediction by Artificial Neural Networks," *J. Eng. [S.l.]*, vol. 23, no. 12, pp. 96–106, 2017, doi:

<https://jcoeng.edu.iq/index.php/main/article/view/406.

[17] R. Kumar Dutta, R. Rani, and T. Gnananandarao, "Prediction of Ultimate Bearing Capacity of Skirted Footing Resting on Sand Using Artificial Neural Networks ARTICLE INFO ABSTRACT," *J. Soft Comput. Civ. Eng.*, vol. 2, no. 4, pp. 34–46, 2018, doi: 10.22115/SCCE.2018.133742.1066.

[18] G. Straz and A. Borowiec, "Estimating the unitweight of local organic soils from laboratory tests using artificial neural networks," *Appl. Sci.*, vol. 10, no. 7, 2020, doi: 10.3390/app10072261.

[19] R. A. Mozumder and A. I. Laskar, "Prediction of unconfined compressive strength of geopolymer stabilized clayey soil using Artificial Neural Network," *Comput. Geotech.*, vol. 69, pp. 291–300, 2015, doi: 10.1016/j.compgeo.2015.05.021.

[20] V. C. Moussas and K. Diamantis, "Predicting uniaxial compressive strength of serpentinites through physical, dynamic and mechanical properties using neural networks," *J. Rock Mech. Geotech. Eng.*, 2020, doi: 10.1016/j.jrmge.2020.10.001.

[21] A. Kordnaeij, F. Kalantary, B. Kordtabar, and H. Mola-Abasi, "Prediction of recompression index using GMDH-type neural network based on geotechnical soil properties," *Soils Found.*, vol. 55, no. 6, pp. 1335–1345, 2015, doi: 10.1016/j.sandf.2015.10.001.

[22] E. Díaz, V. Brotons, and R. Tomás, "Use of artificial neural networks to predict 3-D elastic settlement of foundations on soils with inclined bedrock," *Soils Found.*, vol. 58, no. 6, pp. 1414–1422, 2018, doi: 10.1016/j.sandf.2018.08.001.

[23] A. J. Choobbasti, F. Farrokhzad, S. R. Mashaie, and P. H. Azar, "Mapping of soil layers using artificial neural network (case study of Babol, Northern Iran)," *J. South African Inst. Civ. Eng.*, vol. 57, no. 1, pp. 59–66, 2015, doi: 10.17159/2309-8775/2015/v57n1a6.

[24] A. Abbaszadeh Shahri, "An Optimized Artificial Neural Network Structure to Predict Clay Sensitivity in a High Landslide Prone Area Using Piezocone Penetration Test (CPTu) Data: A Case Study in Southwest of Sweden," *Geotech. Geol. Eng.*, vol. 34, no. 2, pp. 745–758, 2016, doi: 10.1007/s10706-016-9976-y.

[25] B. Alsharari, A. Olenko, and H. Abuel-Naga, "Modeling of electrical resistivity of soil based on geotechnical properties," *Expert Syst. Appl.*, vol. 141, p. 112966, 2020, doi: 10.1016/j.eswa.2019.112966.

[26] S. Kostic, N. Vasovic, K. Todorovic, and A. Samcovic, "Application of artificial neural networks for slope stability analysis in geotechnical practice," *2016 13th Symp. Neural Networks Appl. NEUREL 2016*, 2016, doi: 10.1109/NEUREL.2016.7800125.

[27] A. Chakraborty and D. D. Goswami, "Slope Stability Prediction using Artificial Neural Network (ANN)," *Int. J. Eng. Comput. Sci.*, vol. 6, no. 6, pp. 21845–21848, 2017, doi: 10.18535/ijecs/v6i6.49.

[28] I. Taleb Bahmed, K. Harichane, M. Ghrici, B. Boukhatem, R. Rebouh, and H. Gadouri, "Prediction of geotechnical properties of clayey soils stabilised with lime using artificial neural networks (ANNs)," *Int. J. Geotech. Eng.*, vol. 13, no. 2, pp. 191–203, 2019, doi: 10.1080/19386362.2017.1329966.

[29] A. Abbaszadeh Shahri, "Assessment and Prediction of Liquefaction Potential Using Different Artificial Neural Network Models: A Case Study," *Geotech. Geol. Eng.*, vol. 34, no. 3, pp. 807–815, 2016, doi: 10.1007/s10706-016-0004-z.

[30] X. Xue and E. Liu, "Seismic liquefaction potential assessed by neural networks," *Environ. Earth Sci.*, vol. 76, no. 5, 2017, doi: 10.1007/s12665-017-6523-y.

[31] K. Ram Chandar, V. R. Sastry, and C. Hegde, "A Critical Comparison of Regression Models and Artificial Neural Networks to Predict Ground Vibrations," *Geotech. Geol. Eng.*, vol. 35, no. 2, pp. 573–583, 2017, doi: 10.1007/s10706-016-0126-3.

[32] M. A. Benbouras, R. Mitiche Kettab, H. Zedira, F. Debiche, and N. Zaidi, "Comparing nonlinear regression analysis and artificial neural networks to predict geotechnical parameters from standard penetration test," *Urban. Archit. Constr.*, vol. 9, no. 3, pp. 275–288, 2018.

[33] B. Tarawneh, "Predicting standard penetration test N-value from cone penetration test data using artificial neural networks," *Geosci. Front.*, 2017, doi: 10.1016/j.gsf.2016.02.003.

[34] Y. Erzin and Y. Tuskan, “Prediction of standard penetration test (SPT) value in Izmir, Turkey using radial basis neural network,” *Celal Bayar Üniversitesi Fen Bilim. Derg.*, pp. 37–41, 2017, doi: 10.18466/cbayarfbe.319912.