International Journal of GEOMATE, June 2023, Vol. 24, Issue 106, pp.46-53
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2023.106.g12133
Geotechnique, Construction Materials and Environment

ESTIMATION OF THE ALLOWABLE BEARING CAPACITY OF SOIL IN SOME MUNICIPALITIES OF THE PROVINCE OF PAMPANGA USING ARTIFICIAL NEURAL NETWORK

Carmela Marie A. Lingad[1] and Erica Elice S. Uy[2]

[1,2] Civil Engineering Department, De La Salle University, Philippines

*Corresponding Author, Received: 12 June 2022, Revised: 16 Aug. 2022, Accepted: 19 Nov. 2022

ABSTRACT: Urbanization is evident in some municipalities of Pampanga specifically in San Fernando and Santo Tomas. Those municipalities being developed, requires an information of the load-bearing capacity of soil. Predicting the soil bearing capacity provides an estimation of how much loads can the soil carry. The bearing capacity was calculated using the local shear failure equation of the Terzaghi's bearing capacity formula. Also, the bearing capacity was predicted using Artificial Neural Network for those locations which has available data with the N_{60} value, friction angle, unit weight, and footing width as dependent parameters. The results show a coefficient of correlation of approximately equal to 1 and a mean squared error of at least 0 for a hidden layer of 10 which proves that ANN is an efficient way in predicting the bearing capacity. Based on the sensitivity analysis, it was found out that the unit weight is the most significant parameter affecting the value of the bearing capacity. A relationship between the N_{60} value, soil classification, and the bearing capacity was observed. It was concluded that the N_{60} value and soil classification are the two determining factors on how the value of the bearing capacity will be, because it affects the consistency of the soil and most of the parameters are dependent on those two variables. The value of the bearing capacity ranges from a minimum of 20 kPa to a maximum of 630 kPa for a specific area.

Keywords: Allowable bearing capacity, Artificial neural networks, Geographic information system, SPT-N

1. INTRODUCTION

Urbanization starts to arise in the Philippines. Also, some of the provinces being near to Metro Manila start to get urbanized and be developed. One of the provinces that are starting to get urbanized is the province of Pampanga.

According to Das and Sobhan [6], bearing capacity are usually analyzed when it comes to designing foundations. Bearing capacity is the load-carrying capacity with respect to the shear failure of soil of shallow foundations. A wrong estimation of the bearing capacity often leads to a wrong design of the foundation.

The analysis of soil depends on its failure mechanism. Figure 1 provides the failure mechanism of a footing when induced with a load. With this failure mode, the analysis of the bearing capacity of soil is derived [1].

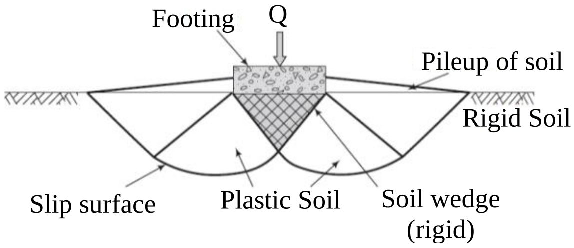


Fig. 1 Failure Mechanism obtained from Budhu [1]

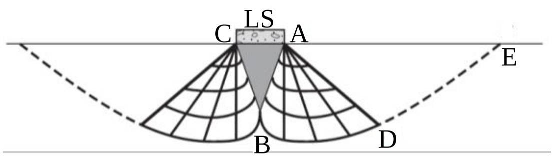


Fig. 2 Local shear failure of soil obtained from Budhu [1]

This study considered the local shear failure of footing. Refer to Figure 2 for the failure mechanism of local shear failure of footing [1]. Dungca [7] have provided a bearing capacity estimation using borehole data as well for Quezon City, Philippines way back 2019. This study adapted the same study but for San Fernando and Santo Tomas, Pampanga. In addition, this research used Artificial Neural Network to estimate the bearing capacity of the said locations.

Previous research done by Dungca, Concepcion, Limyuen, See, and Vicencio [8] provided an estimation of the soil bearing capacity of soil in Metro Manila, Philippines. In the research, it was found out that the areas that are near a body of water projects a lower bearing capacity than those being surrounded by purely land. It was recommended in the study that since most areas in Metro Manila comprises of high-rise buildings, the use of shallow foundation is not recommended. Those areas that has a geological feature of rock projects the highest value of the bearing capacity.

Chao, Zhang, Zhu, and Hu [2] stated that artificial Neural Network (ANN) is the duplication of the physiological structure and mechanics of human brain. They stated that ANN is mostly used in computing some geotechnical engineering problems. It was also said that using ANN for solving is beneficial because of the following factors: a) it has high speed when it comes to calculation; b) it has strong ability when it comes to fault-tolerance; and, c) it has dexterous capability when it comes with dealing with convoluted solving rules [2].

Hanandeh, Alabdullah, Aldawhi, Obaidat, and Alqaseer [11] used the same software, which is the artificial neural network in determining the bearing capacity of piles using cone penetration test results. The study also used the mean squared error and the coefficient of correlation in validating the results estimated using artificial neural network. On contrary, the ANN is incapable of generating empirical equations that can be used for future calculation; still, ANN provides an accurate estimation of the bearing capacity of bored piles. The researchers in the said study recommended to use other models in predicting such values for a variety of ways in estimating the bearing capacity of bored piles.

The determination of the allowable bearing capacity allows the easier design of the proper dimension of a footing that can carry such loadings. In addition, the use of artificial neural network for the estimation of the bearing capacity provides a more accurate value because it also provides a validation value in the means of the mean square error and the coefficient of correlation.

Section 2 describes the significance of this study. Sections 3 and 4 provides the methodology and results of the study. Section 5 provides the conclusion, and Section 6 and 7 gives the acknowledgement and references, respectively.

2. RESEARCH SIGNIFICANCE

This study was technically and academically significant because this study provided another way of estimating the allowable soil bearing capacity of soil. Artificial neural network was used to estimate the allowable bearing capacity. This gave additional knowledge of ways in computing values.

This study provided a reference map of the allowable bearing capacity to the local government and private developers of the municipalities of San Fernando and Santo Tomas to help lessen the risk of structural failure due to improper design of shallow foundations for a more economical and safer design of foundation that can resist failures.

3. METHODOLOGY

For the study, 52 borehole data was used to estimate the bearing capacity. The borehole data was obtained from the municipalities of San Fernando and Santo Tomas, Pampanga. Most areas in the said location are sand. 52 borehole data was obtained because of the availability of the borehole data. The borehole data was plotted to provide an estimation of the bearing capacity of the area within 1 km radius. The standard penetration test – N (SPT – N) value was obtained in the borehole data provided by the local government units and some private testing companies. The SPT–N value was corrected using Eq. 1 which was provided by Das and Sobhan [6].

$$N_{60} = \frac{N\eta_H\eta_B\eta_S\eta_R}{60} \tag{1}$$

3.1 Input Parameters/Independent Parameters

The input parameters for the calculation of the bearing capacity are the following: SPT-N values, friction angle, unit weight of soil, and footing width. The friction angle and unit weight of soil was calculated according to the corresponding corrected SPT-N value. The value of the friction angle was interpolated using Table 1 which was proposed by Kulwahy and Mayne [12]. The value of the footing width was considered as 1 m for all embedment depths considering the limitations of the Terzaghi's bearing capacity equation [6].

Table 1. SPT-N value vs. Friction angle relationship from Kulhawy and Mayne [12]

SPT – N value	Friction angle
0 – 4	< 28
4 – 10	28 – 30
10 – 30	30 – 36
30 – 50	36 – 41
> 50	> 41

A study done by Puri, Prasad, and Jain [17] provided a prediction of the geotechnical parameters using machine learning, one of which is the density of soil using SPT-N value. The following equations (Eq's 2-a to 2-e) were used for the calculation of the density of soil which is then multiplied to the acceleration due to gravity to obtain the unit weight of the soil which will be used for Eq. 3.

a) For Coarse Grained soil,

a.1) Dry Density with $1 \leq N \leq 50$,

$$\rho_d = 0.0068(N) + 1.5554 \tag{2-a}$$

a.2) Bulk Density with $1 \leq N \leq 39$,

$$\rho_b = 0.0096(N) + 1.5001 \quad (2\text{-b})$$

a.3) Bulk Density with $40 \leq N \leq 50$,

$$\rho_b = 0.0141(N) + 1.3726 \quad (2\text{-c})$$

b) For Fine Grained soil,

b.1) Dry Density with $1 \leq N \leq 50$,

$$\rho_d = 0.0114(N) + 1.2488 \quad (2\text{-d})$$

b.2) Bulk Density with $1 \leq N \leq 50$,

$$\rho_b = 0.0080(N) + 1.7202 \quad (2\text{-e})$$

3.2 Output Parameter/Dependent Parameter

The ultimate bearing capacity was calculated using the Terzaghi's bearing capacity equation (Equation 3) considering local shear failure [6].

$$q_{u(GS)} = 1.3cN_c + qN_q + 0.4\gamma BN_\gamma \quad (3)$$

where B is the width or diameter of the base of the footing, L is the length of the footing, q is the vertical effective stress from the natural ground level to the bottom of the footing, γB is the effective vertical stress from the bottom of the footing to the *'B'* projection, N_c, N_q, and N_γ are the Terzaghi's bearing capacity coefficient, and c is the cohesion in which according to Kulhawy and Mayne [12] can be expressed as $c = \frac{1}{2}[0.06(\mathrm{N})(\mathrm{P_a})]$, where N is the SPT-N value, and P_a is the atmospheric pressure. The allowable bearing capacity was computed using a factor of safety of 3.

3.3 Artificial Neural Network

Artificial Neural Network was used to predict the allowable bearing capacity with the independent parameters (SPT-N value, friction angle, unit weight, footing width) as input values and the dependent parameter (allowable bearing capacity computed using Terzaghi's bearing capacity equation) as output value. For the simulation of training of artificial neural network, the dataset was trained using a different number of hidden layers such as 5, 10, 15, and 20. The value of the coefficient of correlation and the mean square error was obtained to validate the efficiency of ANN in predicting the dependent parameter.

A sensitivity analysis was done to determine which independent parameter is highly significant and greatly affects the accuracy of the dependent parameter. According to Mrzyglod, Hawryluk, Janik, and Olejarczyk-Wozenska [15] to know the significance of one parameter to the desired output, a sensitivity analysis should be done. Sensitivity analysis can be computed by obtaining the error of the measured and predicted outputs. The equation of the error is presented in Eq. 4 and can be denoted as,

$$Error = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2 \quad (4)$$

$$W = \frac{Error_i}{Error} \quad (5)$$

where n is the number of output values, y_i is the measured/computed values, $\hat{y_i}$ is the predicted values from ANN. Eq. 5 represent the value of W. W is the ratio (sensitivity of the parameter), $Error_i$ is the computed error without the specific parameter, and $Error$ is the total error including all parameters. If the value of W is less than or equal to 1, hence, the parameter is insignificant; in other words, it does not affect the value of the output.

3.4 Artificial Neural Network Validation

According to Rezaei, Nazir, and Momeni [19] to validate the predicted values for ANN, the coefficient of correlation and the mean square error should be obtained. Both the coefficient of correlation and mean square error are displayed upon the ANN simulation. An article written by Elcicek, Akdogan, and Karagoz [9] provided an equation for the mean square error and coefficient of correlation. It can be computed as,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(x_{ob} - x_{pr}\right)^2 \quad (6)$$

$$R^2 = \left[\sum_{i=1}^{N}(x_{ob} - \bar{x}_{ob})^2 - \sum_{i=1}^{N}\left(x_{ob} - \bar{x}_{pr}\right)^2\right] \times \left[\sum_{i=1}^{N}(x_{ob} - \bar{x}_{ob})^2\right]^{-1} \quad (7)$$

where MSE is the mean square error, R^2 is the coefficient of correlation, N is the total number of data, x_{ob} are the actual computed values, x_{pr} are the predicted values using ANN, $\bar{x}_{ob}$ is the mean of the actual computed values, and $\bar{x}_{pr}$ is the mean of the predicted values using ANN.

4. RESULTS AND DISCUSSION

From the borehole data, refer to Table 2 for the data in one of the borehole logs obtained from a bridge in Bulaon, San Fernando City. The table comprises of the standard penetration test N (number of blows) value, the corrected N value, and the soil classification for each layer of test. Table 3 represents the values of the input parameters. The input parameters used are the following: the corrected N value (N_{60}), the friction angle, the unit weight of the soil, and the width of the foundation.

Table 2. Sample borehole analysis of a bridge in barangay Bulaon, San Fernando City

Depth		SPT N-value	N_{60}	Soil Classification
1st	2nd			
0	1	22	12.375	SM
1	2	22	12.375	SM
2	3	15	8.4375	SM
3	4	21	11.8125	SM
4	5	21	11.8125	SM
5	6	18	10.125	SM

Table 3. Input parameters for the calculation of the bearing capacity

Depth		N_{60}	Ø' (°)	δ (kN/m^3)	B width
1st	2nd				
0	1	12.375	21.61	16.08	1
1	2	12.375	21.61	16.08	1
2	3	8.4375	20.65	15.82	1
3	4	11.8125	21.47	16.05	1
4	5	11.8125	21.47	16.05	1
5	6	10.125	21.08	15.93	1

4.1 Bearing Capacity Calculation

From the obtained data, refer to Table 3 for the calculated ultimate bearing capacity equation using Eq. 3 and the allowable bearing capacity using a factor of safety of 3 [7]. All the values of the parameters required for the ultimate bearing capacity equation was computed first such as the cohesion, unit weight, q, and N_c, N_q, N_λ.

Table 4. Sample Calculation of the Bearing Capacity in a school in Bulaon, San Fernando City

Depth (m)		N_{60}	Soil Class	Ultimate Capacity (kPa)	Allow Capacity (kPa)
1st	2nd				
0	1	12.38	SM	171.04	51.65
1	2	12.38	SM	312.30	93.38
2	3	8.44	SM	406.89	119.63
3	4	11.81	SM	585.04	173.67
4	5	11.81	SM	724.28	214.73
5	6	10.13	SM		

To validate the results of the computed allowable bearing capacity, the computed values were compared to the allowable foundation pressure provided in the National Structural Code of the Philippines 2015 [16]. Observing all the computed allowable bearing capacity for different embedment depths, it satisfies all the limitations within the code. Hence, the values computed are acceptable.

4.2 ANN Validation

The values of the coefficient of correlation were obtained for all hidden layers (HL) (5, 10, 15, 20) in both locations, hence different values of hidden layers were used. The mean squared error and the coefficient of correlation provides the accuracy of the estimated value in the artificial neural network.

The lowest value of the mean square is found when there are 10 hidden layers. Though all the other 3 returns a value of mean square error of approximately 0, yet the lowest value of MSE is found at 10 hidden layers. Table 5 and 6 represents the value of the MSE and R of all the hidden layers (5, 10, 15, 20) with their corresponding embedment depths (1m, 2m, 3m, 4m, and 5m).

Table 5. Summary of validation results in ANN with 5 and 10 hidden layers

Df	HL = 10		HL = 5	
	MSE	R	MSE	R
1	0	1	0.067	1
2	0.0003	0.986	0.001	0.997
3	0.002	0.991	0.009	0.994
4	0.0017	0.98	0.0018	0.995
5	0.003	0.995	0.011	0.956

Table 6. Summary of validation results in ANN with 15 and 20 hidden layers

Df	HL = 15		HL = 20	
	MSE	R	MSE	R
1	0.069	0.98	0.051	1
2	0.002	0.995	0.013	0.991
3	0.009	0.954	0.004	0.996
4	0.023	0.994	0.0021	0.943
5	0.003	0.985	0.003	0.977

Figure 3 shows the regression fit graph of the training, validation, and testing of the data in both locations with their corresponding coefficient of correlation with a hidden layer of 10. As it can be seen in Figure 3, the regression fit line and data lies on the fitting line which explains the accuracy of the output values predicted using ANN with 10 hidden layers. The regression fit line also provided the values of the coefficient of correlation which shows that it is approximately equal to 1.

There are 52 available borehole data. The dataset was divided into a 70% – 15% – 15% distribution for the training, validation, and testing, respectively; hence, 36 data was used for the training, 8 data for validation and testing.

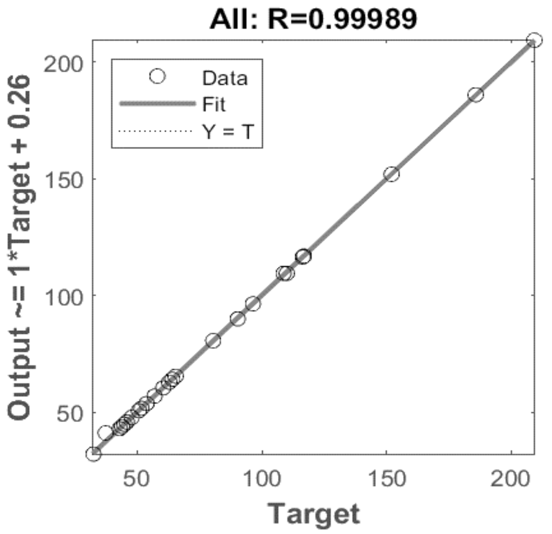


Fig. 3. Regression fit curve considering all analysis (training, validation, and testing) of both municipalities for Df = 1 m with 10 hidden layers

Figure 4 shows the comparison of the computed values of the allowable bearing capacity using the Terzaghi's bearing capacity equation and the estimated allowable bearing capacity using Artificial Neural Network. It shows how close the values are from each other. The figure also proves that the estimated values using ANN are close enough to the computed values. The estimated values compared here are the ones estimated using 10 hidden layers. With the figure, it is seen that it provides the most accurate estimated values compared to the calculated values.

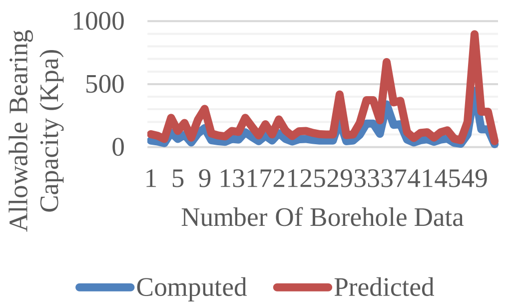


Fig. 4. Comparison of results of the computed and estimated allowable bearing capacity at Df=1m

4.3 Sensitivity Analysis

A summary of the weights for both locations is provided in Table 7. The sensitivity analysis provided an idea of who is the most significant parameter amongst the independent parameters such as the SPT-N value, friction angle, unit weight, and the footing width. As it can be seen, the unit weight is the most significant parameter as it returns the highest value of the weight, second is the SPT-N value, and the third is the friction angle. For the footing width, two embedment depth returns a value of weight of less than 1, but the rest provides a value of more than 1. In conclusion, it can then be said that the footing width is still a significant parameter. In contradiction, it can also be concluded that it is the least significant because it has the lowest value of the weight.

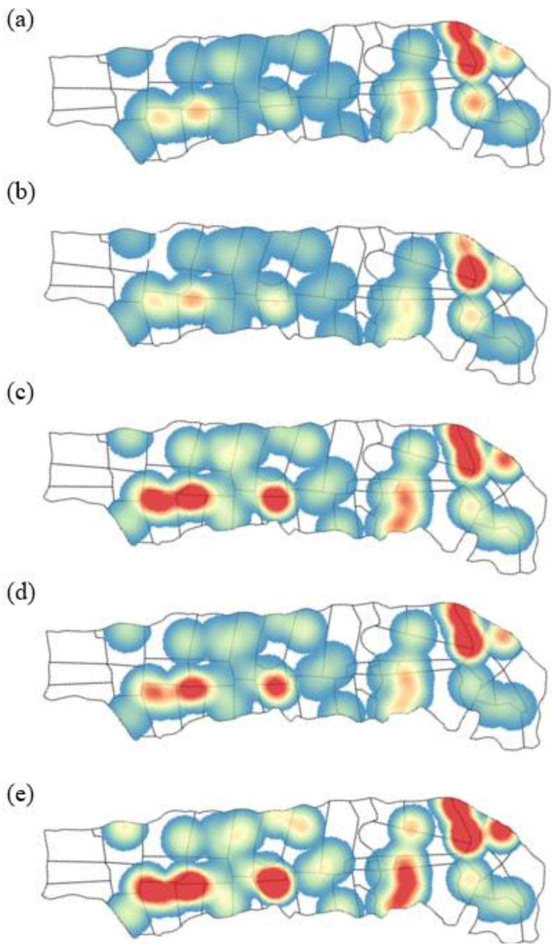
Table 7. Summary of the dependent parameters' weights for both locations

Df (m)	Weights			
	SPT – N value	Friction angle	Unit weight	Footing Width
1	25.464	2.057	748.984	0.929
2	21.452	1.306	224.052	0.794
3	4.863	4.236	209.623	2.307
4	29.043	18.131	382.678	9.210
5	61.387	9.709	158.060	7.500

4.4 Allowable Bearing Capacity Map

The allowable bearing capacity distribution map for the municipalities of San Fernando and Santo Tomas are shown in Figure 5a to Figure 5e. The values of the bearing capacity were mapped using Geographic Information System (GIS). The values of the allowable bearing capacity are within a range of minimum of 20 kPa to a maximum of at least 635 kPa. The values estimated in the ANN are all ultimate bearing capacities. A factor of safety of 3 is used [7] to calculate for the allowable bearing capacity of soil. The bearing capacity are estimated from 1 m embedment depth to a 5-m embedment depth. The width of the footing used is 1m for all embedment depths to lessen the scope of the study. The values are for both San Fernando and Santo Tomas, Pampanga, from left to right of the map, respectively. Kindly refer to Figure 5a – 5e for the allowable bearing capacity maps.

Another factor that contributes to the different values of the bearing capacity at different embedment depth is the relationship between the N_{60} value, soil classification, and allowable bearing capacity which will be further explained in Section 4.5. The maps represented by Figures 5a to 5e can be used as reference for the allowable bearing capacity because it provided a conservative estimation of the allowable bearing capacity of San Fernando and Santo Tomas. This can help the municipality of both locations to have a bird's eye view of each location's bearing capacity.



The values for the bearing capacity values are as follows:

- 0 to less than 100 kPa
- 100 to less than 200 kPa
- 200 to less than 300 kPa
- 300 to less than 400 kPa
- 400 to less than 500 kPa
- 500 to less than 600 kPa
- greater than 600 kPa

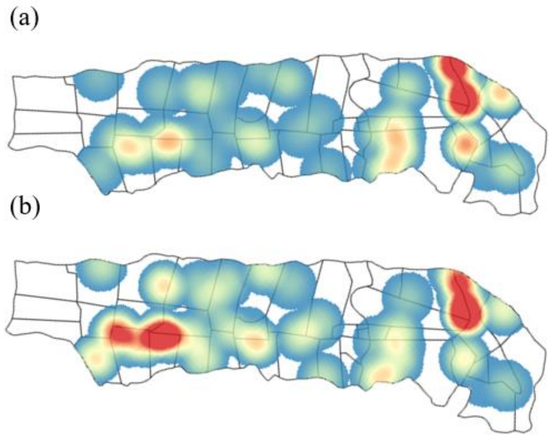
Fig. 5. Allowable Bearing Capacity Map at (a) Df = 1m; (b) Df = 2m; (c) Df = 3m; (d) Df = 4m; and, (e) Df = 5m

4.5 Relationship between the Allowable Bearing Capacity, N_{60} value, and the Soil Classification

Relating the two parameters and the allowable bearing capacity, it can be observed that both N_{60} value and soil classification are directly related to the value of the allowable bearing capacity. It can be observed that if the soil is classified as coarse-grained, if the N_{60} value is greater than 11, the soil is already considered as dense; hence, it can have a greater value of the bearing capacity. It is notable that the N_{60} value and soil classification affects the consistency of the soil. It is notable that a coarse-grained soil with a higher value of N_{60} provides a higher value of the bearing capacity. It is because it is denser. The denser the soil, the higher the value of the friction angle.

Also, a dense soil shows a lower void ratio which also helps in the higher value of the bearing capacity. The lesser the voids, the stronger the soil is because there will be a lower pore pressure and at the same time, settlement can be greatly minimized. In contradiction, if the soil is considered as fine-grained (which is considered as weak soil), yet the N_{60} value is more than 10, the soil still projects a higher value of bearing capacity. Since the research is limited to allowable bearing capacity only, the susceptibility to liquefaction should be considered which is recommended for future researchers to study.

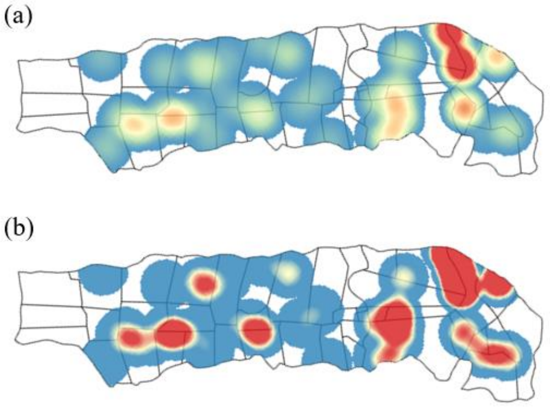
Therefore, even if the soil is cohesive, yet has a higher value of the N_{60}, it still does not possess a higher value of bearing capacity. Hence, it can be concluded that both the N_{60} value and soil classification should be considered as the greatest contributing factor in the value of the allowable bearing capacity. Based on the sensitivity analysis as well (Refer to Section 4.3), the unit weight and friction angle contribute greatly to the value of the bearing capacity of soil. Refer to Figures 6 and Figures 7 for a side-by-side comparison of the N_{60} value map and the soil classification map plotted using GIS.



Legend for the SPT – N_{60} value map:

- 0 to less than 5
- 5 to less than 10
- 10 to less than 15
- 15 to less than 20
- 20 to less than 25
- 25 to less than 30
- 30 to less than 35

Fig. 6. Side-by-side comparison of (a) Bearing Capacity Map and (b) SPT – N_{60} value map for Df = 1m for both San Fernando and Santo Tomas, Pampanga



Legend for the soil classification map:
- Sand
- Silt
- Clay

Fig. 7. Side-by-side comparison of (a) Bearing Capacity Map and (b) Soil classification map for Df = 1m for both San Fernando and Santo Tomas, Pampanga

5. CONCLUSION

Urbanization starts to arise in most of the provinces in the country and one of which is the province of Pampanga. Pampanga is one of the provinces that is just a few hours away from Manila; hence, developments are evident there. Some of the highly urbanized municipalities in the province of Pampanga is San Fernando (the province's capital) and Santo Tomas just below San Fernando. An estimation of the allowable bearing capacity was provided for both locations using artificial neural network.

The SPT-N value and soil classification was obtained from the borehole data and those data were used to obtain the bearing capacity using the Terzaghi's bearing capacity equation. The values of the allowable bearing capacity are within a range of a minimum of 20 kPa to a maximum of at least 635 kPa. It is notable as well that as the value of the embedment depth of footing increases, the values of the bearing capacity increase, respectively.

Upon obtaining the actual values of the bearing capacity, the values were trained using the artificial neural network where the N_{60} value, friction angle, unit weight, and footing width are the input values, and the bearing capacity is the output value. 10 hidden layers was used because it yields to a more acceptable value of the allowable bearing capacity. The results were validated by obtaining the mean square error and coefficient of correlation. It is observed that all the values of the coefficient of correlation for all embedment depths yields to a value of approximately equal to 1, which proves the efficiency of the artificial neural network in predicting the values of the bearing capacity. After training the data using ANN, the independent parameters have undergone a sensitivity analysis to determine its significance in the prediction of the bearing capacity. The sensitivity analysis has provided an observation that the most significant parameter is the unit weight, followed by the N_{60} value, and lastly is the friction angle.

The authors recommend the use of other models to determine the allowable bearing capacity of soil. It is also recommended to study other locations and consider susceptibility to liquefaction.

6. ACKNOWLEDGMENTS

The author would like to thank the Department of Science and Technology-Engineering Research and Development for Technology (DOST-ERDT) for funding the research. This will not be possible without the help of the aforementioned.

7. REFERENCES

[1] Budhu, M., Soil Mechanics and Foundation, 3rd Ed., Hamilton Printing Company, John & Wiley Sons, Inc., USA, pp. 422 – 434.

[2] Chao, Z., Ma. G., Zhang, Ye., Zhu, Y. & Hu, H, The Application of Artificial Neural Network in Geotechnical Engineering, 2018 International Conference on Civil and Hydraulic Engineering, 2018, pp. 3 – 5.

[3] Chen, W. F. & McCarron, W., Bearing Capacity of Shallow Foundations, 1991, pp. 3.

[4] Das, B. M., Shallow Foundations – Bearing Capacity and Settlement, 2nd Ed., CRC Press, Taylor & Francis Group, USA, 2009, pp. 11 – 23.

[5] Das, B. M., & Larbi-Cherif, S., Soils and Foundations: Bearing Capacity of Two Closely-Spaced Shallow Foundations on Sand, Japanese Society of Soil Mechanics and Foundation Engineering, Volume 23, Issue 1, 1983, pp. 1 – 2.

[6] Das, B. M., & Sobhan, K., Principles of Geotechnical Engineering, 8th Ed., Cengage Learning, Stamford, USA, 2014, pp 644 – 653.

[7] Dungca, J., A Reference for the Allowable Soil Bearing Capacities in Quezon City, Philippines, International Journal of GEOMATE, 2020, Volume 19, Issue 71, pp. 1 – 5.

[8] Dungca, J. R., Concepcion, I. Jr., Limyuen, M. C. M., See, T. O. & Vicencio, M. R., Soil Bearing Capacity Reference for Metro Manila, Philippines, International Journal of GEOMATE, April 2017, Volume 12, Issue 32, pp. 5 – 11.

[9] Elcicek, H., Akdogan, E. & Karagoz, S., The Use of Artificial Neural Network for Prediction of Dissolution Kinetics: Research Article, The Scientific World Journal, 2014, pp. 2 – 5.

[10] Fatehnia, M. & Amirinia, G., A Review of Genetic Programming and Artificial Neural Network Applications in Pile Foundations, International Journal of Geo-Engineering, 2018, Volume 9, Issue 2, pp. 1 – 5.
[11] Hanandeh, S., Alabdullah, S. F., Aldahwi, S., Obaidat, A. & Alqaseer, H., Development of a Constitutive Model for Evaluation of Bearing Capacity from CPT and Theoretical Analysis using ANN Techniques, International Journal of GEOMATE, October 2020, Volume 19, Issue 74, pp. 229 – 235.
[12] Kulhawy, F. H. & Mayne, P. W. Manual on Estimating Soil Properties for Foundation Design, Research Project, Volume 4, Issue13, 1990, pp 2-17 – 2-28.
[13] Moayedi, H., Kalantar, B., Dounis, A., Bui, D. T. & Foong, L. K., Development of Two Novel Hybrid Prediction Models Estimating Ultimate Bearing Capacity of the Shallow Circular Footing, Applied Sciences, 2019, pp. 1 – 18.
[14] More, J. J., The Levenberg-Marquardt Algorithm: Implementation and Theory, U.S. Energy Research and Development Administration, 2006, pp. 105 – 106.
[15] Mrzyglod, B., Hawryluk, M., Janik, M. & Olejarczyk-Wozenska, I., Sensitivity Analysis of the Artificial Neural Networks in a System for Durability Prediction of Forging Tools to Forgings Made of C45 Steel, The International Journal of Advanced Manufacturing Technology, Issue 109, 2020, pp. 1385 – 1395.
[16] National Structural Code of the Philippines (NSCP) 2015, 7th Ed., Association of Structural Engineers of the Philippines, Inc., Volume 1, Issue 1, 2015, pp. 3-13.
[17] Puri, N., Prasad, H. D. & Jain, A., Prediction of Geotechnical Parameters Using Machine Learning Techniques, 6th International Conference on Smart Computing and Communications, 2017, pp. 509 – 517.
[18] Ramesh, S., Suman, R. V., Yashwanth, M. & Prasad, S. K., Evaluation of Bearing Capacity of Ground in Transition Zone, Proceedings of the Indian Geotechnical Conference 2019, IGC – 2019, Volume 1, 2019, pp. 451.
[19] Rezaei, H., Nazir, Rm. & Momeni, E., Bearing Capacity of Thin-Walled Shallow Foundations: An Experimental and Artificial Intelligence-Based Study, Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering), Volume 17, Issue 4, 2016, pp. 273 – 276.
[20] Skempton, A. W., Standard penetration test procedures and the effects in sands of overburden pressure, relative density, particle size, ageing and overconsolidation, Geotechnique, Volume 36, Issue 3, 1986, pp. 425 – 447.