Migration Letters

Volume: 20, No: 6, pp. 930-940

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)
www.migrationletters.com

Development of New Correlation Fines Content, NSPT and CPT Using Neural Network Approach and Multilinear Regression to Support Liquefaction Hazard Analysis

Akhmad Muktaf Haifani[1], Hadi Suntoko[2], Adi Gunawan Muhammad[3], Siti Alimah[4]

Abstract

Identification and characterization of constituent soil types in the form of Fines Content (FC) values are essential in analyzing the potential of soils to be liquefaction. Multiple Linear Regression is one of the fundamental statistical models used to determine the causality between target and predictor geotechnical parameters. The study used multilinear regression approaches and artificial neural networks to get optimal results from FC predictions. The study considers the correlation between the SBT Index and FC and several other parameters such as NSPT, Depth, Totally Overburden Stress, Initially Overburden Stress, and Sleeve Friction. The coefficient of determination resulting from the regression process shows a reasonably strong relationship between the independent and target parameters, as much as 61.4%. In comparison, the Neural Network is 96.928%, which indi-cates a nonlinear influence.

Keywords: *Linear Regression; Neural Network; Fines Content; NSPT*

1. INTRODUCTION

Liquefaction occurs in an area characterized as water-saturated sandy soil that experiences earthquakes. Liquefaction events describe the process of transforming a granular material from solid to liquid due to increased pore pressure and reduced effective stress (Division, 1978). Liquefaction is more likely to occur in water-saturated, unconsolidated soils with low porosity, such as sandy loam, sand, and fine gravel. During an earthquake, the unconsolidated sand layer tends to experience volume shrinkage (Ni & Fan, 2002) states that several factors could affect the liquefaction potential, such as relative density (or void ratio), adequate confining pressure, soil characteristics, and fines content. (Uyeno, 1976) Mentioned that muddy sand is resistant to liquefaction due to increased FC by 20%. (Cetin et al., 2004) used FC, resistance corrected SPT 60 % ((N1)_60), cyclic stress ratio (CSReq), moment magnitude (Mw), and initially effective overburden stress (〖σ^'〗 _v) to calculate Probabilistic Liquefaction Hazard Analysis.

Geotechnical investigation in the form of a Sieve Test is a critical procedure for characterizing the types of constituent soil in FC values based on the soil grain of the soil sample (ASTM, n.d.). Soil type is determined established on the percentage of grain size

[1] Research Centre for Nuclear Reactor Technology- National Research and Innovation Agency (BRIN), Bld 80, KST BJ Habibie, Serpong, South Tangerang, Indonesia, https://orcid.org/0000-0002-7652-6303, akhm020@brin.go.id
Faculty of Engineering, Department of Civil Engineering, University of Indonesia, Depok, West Java, Indonesia
[2] Research Centre for Nuclear Reactor Technology- National Research and Innovation Agency (BRIN), Bld 80, KST BJ Habibie, Serpong, South Tangerang, Indonesia. hadi004@brin.go.id
[3] Research Centre for Nuclear Fuel Cycle and Radioactive Waste Technology, National Research and Innovation Agency (BRIN), Bld 20, KST BJ Habibie, Serpong, South Tangerang, Indonesia, adig001@brin.go.id
[4] Research Centre for Nuclear Reactor Technology- National Research and Innovation Agency (BRIN), Bld 80, KST BJ Habibie, Serpong, South Tangerang, Indonesia, siti012@brin.go.id

(FC) retained by sieve No. 200. (Boulanger & Idriss, 2014) Considered FC as a parameter that could trigger liquefaction created by the correlation between FC and the Soil Behavior Type Index (SBT-Ic). This index explains a parameter determined from the end resistance of the Cone Penetration Test (CPT) (Qc) and sleeve friction (fs).

Researchers currently use a linear regression approach by considering various variables to FC. Researchers also often rely on Bayesian classification (BC), Artificial Neural Networks (ANN), and adaptive neuro-fuzzy inference systems (ANFIS) to predict an independent parameter (Šapina, 2016). These methods are an alternative because it takes into account the non-linearity of the soil (Abdipour et al., 2018); (Farjam et al., 2014); (Mansouri et al., 2016); (Sabzalian et al., 2014). Several researchers have formulated the nonlinear approaches have a higher level of accuracy than other methods. This relationship can predict better than the linear-based method (Khairunniza-Bejo et al., 2014) (Safa et al., 2016). The ANN method can demonstrate this phenomenon, which provides less error rate and is more proficient than Multiple Linear Regression (MLR) or other liner-based models to find the best variable (Odabas et al., 2014).

The liquefaction probability analysis incorporates the error factor into the uncertainty in the model parameter (ε). The analysis considers the term "load" and the uncertainty of the factor parameters of the NSPT correction factor (N1.60), Cyclic Stress Ratio (CSR), Grain Size (FC), Moment Magnitude (Mw), and Effective Stress (σ′v) (Cetin, 2000). The analysis can then be estimated by summing the probabilities of all potential sequences of parameters that determine the liquefaction, which involves combination in the liquefaction domain. The grain size parameter taken from the CPT data is important to determine accomplishment in calculating the liquefaction probability (Tabrizi-Zarringhabaei et al., 2019). This study uses the MLR and ANN approaches to obtain the good quality assessment of the FC value from several available geotechnical parameters. This study aims to produce a new equation based on a statistical gradation approach (Haifani, 2021) using the MLR method to predict FC values through a combination of NSPT and CPT data. The results of this formulation were then validated using the ANN method.

2. METHODS

In the following, the development of FC model is presented using both MLR and ANN methods. The FC model was developed based on the NSPT-CPT dataset of geotechnical investigation.

2.1. Geotechnical Investigation of the NSPT-CPT Method

The procedure to identify geotechnical procedures applied in in-situ site investigations are The Cone Penetration Test (CPT) and Standard Penetration Test (NSPT) which describe geotechnical foundation designs and establish soil properties. CPT is trustworthy for carrying out field investigations and carrying out geotechnical designs. CPT examination expresses soil stratigraphy and records rapid and constant parameters such as cone end resistance (QC) and sleeve friction (fs) (Guen, 2014). The advantages of CPT are the process of repeatability, incessant measurement, and ease of usage (Robertson et al., 1983). CPT analyses explain the soil characteristics of bearing capacity, pore water pressure, and sleeve friction ((Peixoto et al., 2000); (Guen, 2014) ; (Lingwanda et al., 2015)). NSPT is used to obtain the desired soil profile per depth, soil properties, identify soil stratigraphy, and its lateral circulation and find untenable soil profiles due to liquefaction ((Guen, 2014)7; (Tsukamoto et al., 2004)). NSPT is broadly employed in determining soil parameters based on empirical correlation (Davidson et al., 1999). NSPT signifies the influence of historical stresses and strains, soil structure, effective horizontal stresses, and combined relative and vertical stresses (Seed, 1979). NSPT provides an overview of in-situ soil characteristics under earthquake stress conditions, is exciting to conceal under laboratory examinations and envisages natural soil liquefaction for upcoming earthquakes (Tokimatsu & Yoshimi, 1983). The combination of CPT and NSPT can properly characterize soil grain size in the form of Fines Content (FC) in the site area.

Geotechnical investigation used dataset covers 44 boreholes in locations where there is evidence of liquefaction (Figure 1-2). The depth of boreholes was relatively uniform, ranging from 4 to 20 m depth, with the groundwater depth between 0.3 to 7 m, hence relatively shallow (TRS-PVMBG, 2012). NSPT analysis provides information on soil classification, index parameters such as water content, density, and some geotechnical applications through semi-empirical procedures, such as evaluating shallow foundation settlement and the pile's bearing capacity and evaluating the potential for sand liquefaction. The SPT examination used a split tube dropped from a height of 75 cm, using a 63.5 kg hammer, to press down the pipe to a total depth of 45 cm. NSPT data estimates every 15 cm step, with no more than 50 hammer blows for every 15 cm step (Akin et al., 2011).

Subsurface information, such as geological profiles, NSPT, Vs., and CPT (Figure 2), were obtained from the borehole data and seismic reflection investigations. It is necessary to develop a geotechnical subsurface model using bore logs representing typical soil profiles in the area. Based on the soils' nature, they have been classified into general groups to identify the respective layers. The study uses a frequency distribution approach to tell how each soil type frequencies. As with all methods, SPT investigations have uncertainties that will affect the analysis results. Experts agree that there is a tolerance for NSPT ranging from at best 1.4% and at worst 100% (Kulhawy & Mayne, 1990), (Kulhawy & Trautmann, 1996), (Schmertmann, 1975), (Youd & Idriss, 2001).

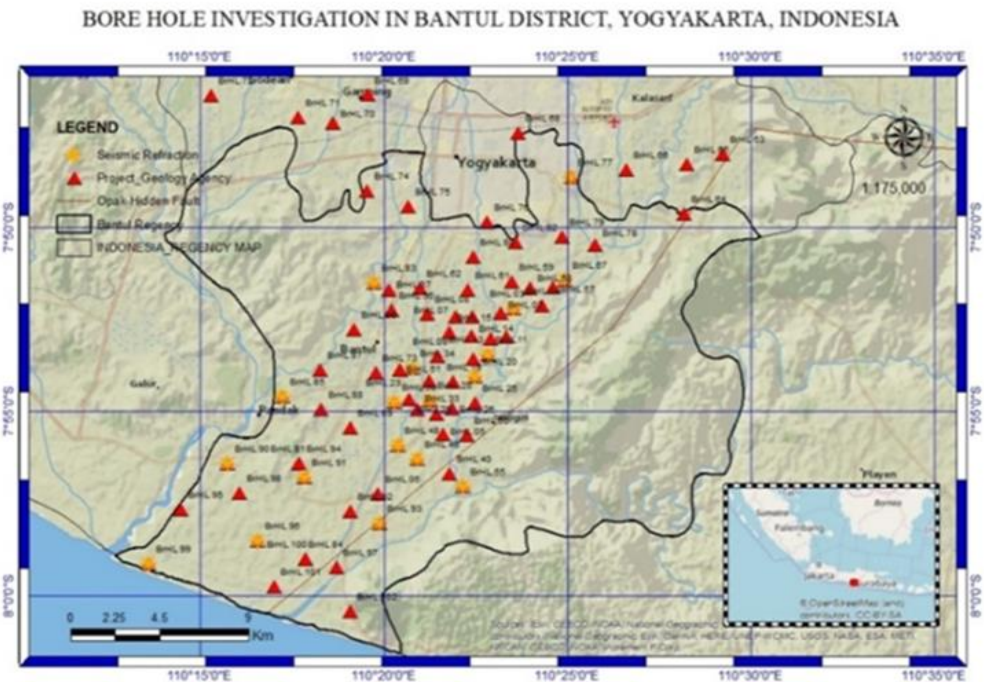
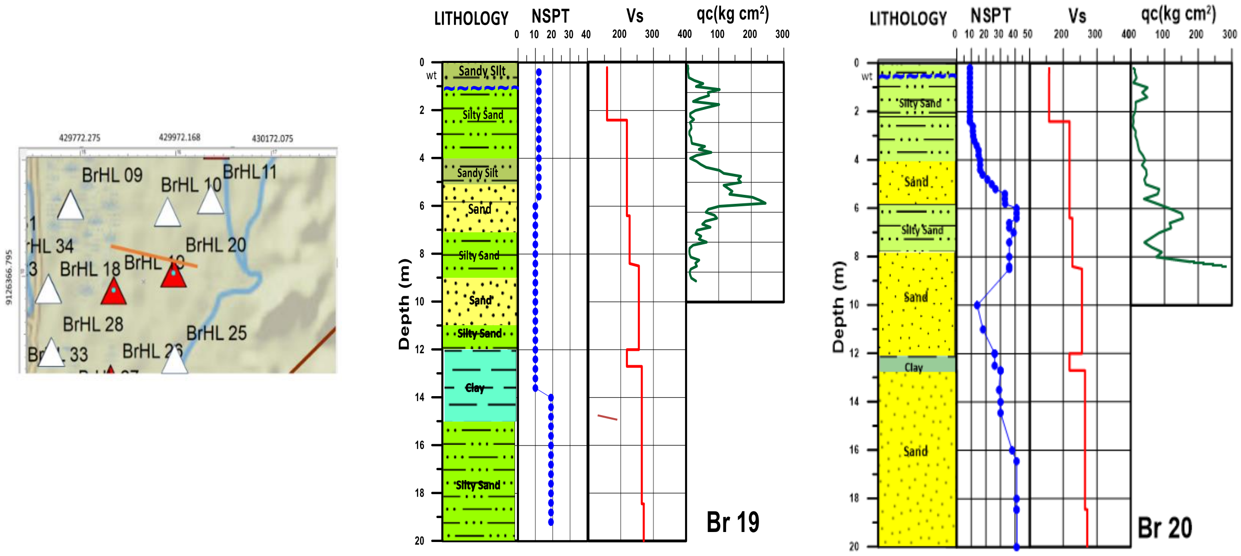


Fig. 1. Boreholes locations of NSPT, CPT, and seismic measurements in the vicinity of the study area (Muktaf & TAMPUBOLON, 2022)



(a) (b) (c)

Fig. 2: (a) Borehole 19 and 20 locations; (b) NSPT-Vs profile of Borehole 19 (Br 19); (c) NSPT-Vs profile of Borehole 20 (Br 20

2.2. Multi Linear Regression (MLR)

Multiple Linear Regression (MLR) study is an analysis that has more than one predictor variable. Multiple Linear Regression analysis techniques determine the significant effect of two or more in-dependent variables (X1, X2, X3, Xk) on the target variable (Y). In MLR analysis, the least square method is used, including estimating the regression coefficient, the Sum Square Error (SSE), and Sum Square Total (SST). The regression reduces the quantity of the squared upright spaces from each data position on the line to get the best fit. The regression coefficient describes each predictor variable's unrelated contribution in predicting the target variable in multi linear regression analyses. In contrast to simple linear regression, a description of each independent variable's degree of inter-action or correlation is necessary.

The least-squares method, commonly known as Least Square, estimates model parameters in multi-ple regression analyses. This method's concept is that the regression coefficient β has a minimum er-ror (Weisberg, 2005).

2.3. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a processing data system that imitates the human neural net-work system. ANN consists of connected contribution and yield. Each connection has a unique weight to get the best prediction estimation results. The ANN arrangement includes Input Layer as the initial layer that connects data sources with the processing network. The obscure layer becomes the connecting layer for input variables to produce yield, the Yield Layer, by describing ANN pro-cessing's yield. This yield is generated based on the weight, several concealed layers, and the activa-tion function. The Initiation function is used to get the yield and input value. The equation used in the Neural Network is given in Equation 1 as follows:

$$y = \emptyset\left(\sum_{i=1}^{n} W_i X_i + b\right) \qquad (1)$$

Where are: y – Output, $\emptyset$ – initiation function, $\sum_{i=1}^{n} W_i X_i$ – Input accumulation with weight, b – refraction.

The backpropagation algorithm repeatedly performs learning on a multilayer feed-forward Neural Network to study the weighting for predictions on the label class in a data set or attribute representing an entity (Han et al., 2012). A multilayer feed-forward neural Network comprises one contribution layer, one or more concealed layers, and one yield layer.

Feed-Forward Backpropagation occurs because the input unit goes to the obscure layer and later goes to the yield layer, producing yield. However, if the yield does not match expectations, the contribution will spread backward on the obscure layer and be forwarded to the yield layer. In the backpropagation process for each training, the analysis will modify the weight to reduce the mean square error between the estimated response quantity ($\hat{y}_i$) and the observed response quantity (y_i).

The following steps describe an artificial neural network's modelling utilizing the backpropagation algorithm: The first step is to initiate weighting and bias on the Network. The weights and biases are random numbers between -1 to one or -0.5 to 0.5. The second stage is to spread the input forward. Every j_{th} output is the input value for each obscure layer or output layer. It can be written as $O_j = I_j$. Then the net input is calculated from unit j to the previous layer i can be formulated given in Equation 2 as follows:

$$I_j = \sum_i^n w_{ij} O_i + \theta_j \quad (2)$$

Where are:

w_{ij}– the connecting weight of the i_{th} unit in the previous-j unit layer,

O_i – the i_{th} unit output of the previous layer,

θ_j – the j_{th} unit's bias.

Then the output is calculated, namely O_j using the logistic, sigmoid, or function. This function is a squashing function to map input with a large domain into a smaller range, from 0 to 1 using the Equation 3 as follows:

$$O_i = \frac{1}{1 + e^{-I_j}} \quad (3)$$

The third stage is the Back propagate error process, namely the weighting and bias update process, to get the best error in the network prediction results. This process is performed using the Equation 4-7 as follows:

$$Err_j = O_j \left(1 - O_j\right) \sum_i^n Err_i w_{ij} \quad (4)$$

$$\Delta w_{ij} = (l) Err_j O_j \quad (5)$$

$$w_{ij} = w_{ij} + \Delta w_{ij} \quad (6)$$

$$\Delta\theta = (l) Err_j \quad (7)$$

$$\theta_j = \theta_j + \Delta\theta \quad (8)$$

Where are:

Err_j – an error in the next layer,

Δw_{ij} – weight addition,

w_{ij} – weight update results,

l – the percentage of learning between 0 and 1,

$\Delta\theta$ – added bias,

θ_j – updated bias.

3. RESULTS

Based on the previous study of (Yi, 2014), (Suzuki, 1998)and (Boulanger & Idriss, 2014), we developed FC linear model using three independent variables shown in Equation 9-12 (Haifani, 2021) as follows:

$$X_1 = (\mathrm{NSPT} + Qc) \quad (9)$$

$$X_2 = \left(\frac{fs}{Qc}\right) \quad (10)$$

$$X_3 = (\mathrm{Depth}) \quad (11)$$

$$X_4 = \left(\frac{\sigma 0}{\sigma' 0}\right) \quad (12)$$

Where are:

Qc – measured tip resistance, fs – sleeve friction, $\sigma 0$ – total overburden stress, $\sigma' 0$ – effective overburden stress.

3.1 Multiple Linear Regression Analysis

For the hypothesis test we used the coincident assessment (F-assessment) and partial assessment (t-test). The F-assessment is applied to simultaneously assessment the predictor variable's effect on the target variable (Ghozali, 2016). This assessment's hypothesis is H_0: No predictor variables significantly affect the target variable, and H_1: At least one independent variable significantly affects the target variable. Table 1 shows the results of the F-assessment using the R Studio software. Based on the results in Table 1, the model produces a decision to reject H_0 which indicated by the p-value of the F-assessment of $1.42e^{-114}$, which is still lower than the significance probability 0.05. It means there was one independent variable that significantly affects the target variable.

Table 1. The result of F-assessment

Model	p-value F Assessment	Decision
Model 1	$1.42e^{-114}$	Reject H_0

Afterward, we performed the t-assessment to determine the result of every unconstraint variable on the target variable. Table 2 shows the outcome of the t-assessment. From the results of Table 2, with a substantial level of 5%, it can be concluded that the variables substantially influence the target variable are X_1 and X_2. Based on the t-assessment result, this study formulated empirical formulation for FC as shown in Equation 13.

Table 2. The result of t-assessment

Coefficient	Model 1				
	Estimate	Standard Error (SE)	tStat	P-Value	Decision
Intercept	1.10520	0.025766	42.896	$2.9282e^{-179}$	Reject H_0
$X_1(\mathrm{NSPT} + Qc)$	-0.24105	0.009786	-24.631	$2.336e^{-91}$	Reject H_0
$X_2\left(\frac{fs}{Qc}\right)$	-0.04046	0.005262	-7.6898	$6.6475e^{-14}$	Reject H_0
$X_3(\mathrm{Depth})$	0.026618	0.007836	3.3970	0.00072956	Reject H_0
$X_4\left(\frac{\sigma 0}{\sigma' 0}\right)$	-0.03171	0.010663	-3.7386	0.00020403	Reject H_0

$$FC = 1.1052 - 0.241 * \log(\text{NSPT} + Qc) - 0.040 * \log\left(\frac{fs}{Qc}\right) + 0.027 * \log(\text{Depth}) - 0.031\left(\frac{\sigma_0}{\sigma'_0}\right) \quad (13)$$

Equation 13 describes that FC will be worth 1.1052, assuming no influence from other variables. Every one-unit increase of the variable X_1 (log (NSPT + *Qc*)) will decrease the FC value by 0.241, assuming the other variables are considered constant. Every one-unit increase of the X_2 variable will decrease the FC value by 0.04, assuming the other variables are considered constant. Every one-unit increase in the X_3 variable will increase the FC value by 0.027, assuming the other variables are considered constant. Every one-unit increase of the X_4 variable will decrease the FC value by 0.031, assuming the other variables are considered constant. This equation can be applied in an area with conditions including depth (0.2 - 20 m), *Vs* (112.7484-483.5294 m/sec), NSPT (3 - 56), and *Qc* (0.26-35.19 MPa).

From the calculation, we also gained the coefficient of determination, *R-Square*, for the model which was 61.4%. It means that the independent variable can explain the target variable, FC, by 61.4%, and the rest is explained by other variables not included in the model.

3.2. Artificial Neural Network (ANN)

The algorithm employed in this study is the Multi-layer Neural Network, namely 64 obscure layers, one obscure layer processing, and 1000 epoch (iterations) learning process to form a linear equation model. The results of data processing using the Neural Network produced 385 weights factor.

The multi-layer neural network model produces an *R-Square* of 0.96928 (96.928%). It means the model explains the Y variable by 96.928%, and the balance is explained by other variables which are not part of the model. Meanwhile, the value of Adjusted R Square is 0.96906 (96.906%).

3.3. Validity Assessment based on Performance Work

It is essential to estimate model prediction errors with accuracy because (a) it gives understanding into its precision, (b) permits comparison of numerous simulations, and (c) ones are used to determine threshold warnings (Salazar et al., 2017), (Swanepoel et al., 2016). To promote the evaluation of the ultimate computation results, the analysis implements distinct execution calculation purposes, namely, the mean absolute error (*MAE*), mean square error (*MSE*), maximum absolute error (*S*), and the coefficient of determination (*RSq*), using Equation 14-16. The analysis has to calculate approximately the indecision correlated with prototype simulation; the remainder of the prediction set is calculated and analysed (Kang et al., 2017). Table 3 shows the result of the performance evaluation functions of MAE, MSE, S and Rsq between MLR and ANN methods.

$$MAE = \frac{1}{N}\sum_i^N \left|Y_{obs} - Y_{pred}\right| \quad (14)$$

$$MSE = \frac{1}{N}\sum_i^N \left(Y_{obs} - Y_{pred}\right)^2 \quad (15)$$

$$S = \max\left|Y_{obs} - Y_{pred}\right| \quad (16)$$

Where are:

Y_{obs} – Fines Content data from proposed equation 18 (Multiple Linear Regression)

Y_{pred} – Fines Content data from Artificial Neural Network calculation.

Table 3. Comparison between MAE, MSE, S, and R-Square between MLR and ANN

Type Analysis	MAE	MSE	S	R-Square
Multiple Linear Regression	0.0824	0.0118	0.4558	0.614
Artificial Neural Network	0.0504	0.0071	0.4149	0.96928

The study uses graphs and box plots to show comparisons between predicted and actual FC values in order to understand the distribution of data and the ability of the selected model to predict FC. As described in Figures 3 and **4**, the FC value predicted by the ANN model and by the MLR model has a tendency to resemble and great accuracy with the actual FC value

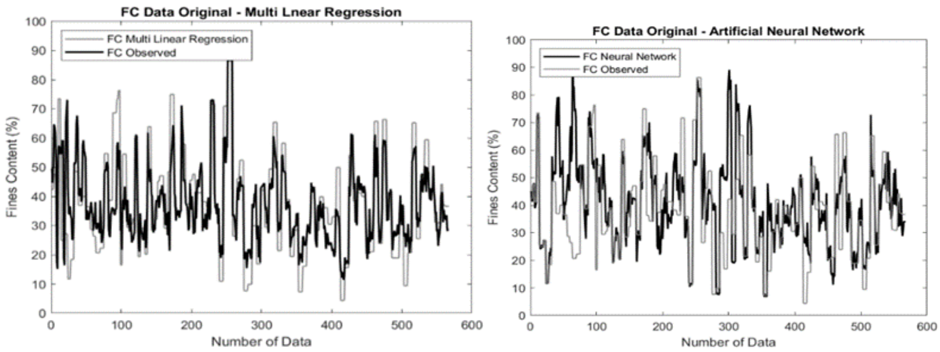


Fig. 3. Performance of the (a), MLR for the Fines Content (b), ANN for the Fines Content (FC): fitting of observed FC values and predicted values

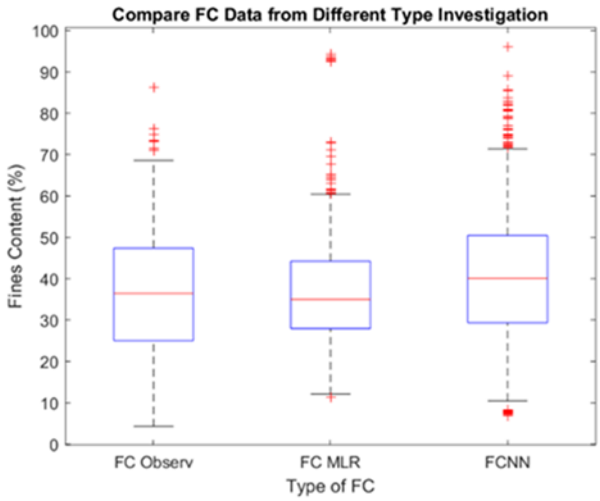


Fig. 4. Comparison of boxplot between FC observed, FC from MLR, and FC from ANN

4. DISCUSSION

In general, all ANN models have greater effectiveness in expecting FC than the multilinear regression models. In this study, the calculations show a substantial quantity of the relationship among the input parameter and FC because of a nonlinear relationship, which can be the primary justification for the differences between the ANN and MLR models' performance. Nevertheless, the variance in operation between the two models for predicting FC shows the significance of selecting the appropriate model. The high-level capability of the ANN modelling method associated to the MLR method to predict output variable because this method captures a particularly nonlinear and a complex correlation between output and input variables ((Gholipoor et al., 2013)**;** (Khairunniza-Bejo et al., 2014)**,** (Mansourian et al., 2017)**,** (Singh et al., 2003)).

Based on the interpretation of the pack plot (Figure 4), it also shows relatively the same results, namely the maximum, minimum, *Q1*, median, and *Q3* values between the predicted FC and the actual FC using the ANN method when compared with the FC produced by the MLR approach. The *MAE*, *MSE*, and S calculations for the FC ANN results show lower values than the FC results from MLR. Also included in this case, the value of the coefficient of determination shows that the *R-Square* value of ANN (96.928%) is higher than the MLR (61.4%).

5. CONCLUSIONS

The analysis results using two methods, linear regression with the Least Square approach and Artificial Neural Network, appear that the R-Square and Adjusted R-Square are 61.4% 61.1% 96.928%, 96.906%, respectively. Artificial Neural Network shows a better model for estimating FC based on comparing the results of the two calculation methods. Artificial Neural Networks in this study can produce the best results because Neural Networks can learn by themselves, learn from examples, and apply to the same events. Besides, the Neural Network's adaptive and flexible nature explains the soil's nonlinear characteristics from each regression parameter used in the study.

Acknowledgements

The funding for this research was provided by Ministry Research of Research Technology and Higher Education of Indonesia. This support is gratefully acknowledged. We are also thankful to PVMBG for providing the necessary data.

Conflict of Interest

The authors declare no conflict of interest.

References

Abdipour, M., Ramazani, S. H. R., Younessi-Hmazekhanlu, M., & Niazian, M. (2018). Modeling oil content of sesame (Sesamum indicum L.) using artificial neural network and multiple linear regression approaches. Journal of the American Oil Chemists' Society, 95(3), 283–297.

Akin, M. K., Kramer, S. L., & Topal, T. (2011). Empirical correlations of shear wave velocity (Vs) and penetration resistance (SPT-N) for different soils in an earthquake-prone area (Erbaa-Turkey). Engineering Geology, 119(1–2), 1–17.

ASTM, B. (n.d.). 214: standard test method for sieve analysis of metal powders. ASTM Int, 1, 1–4.

Boulanger, R. W., & Idriss, I. M. (2014). CPT and SPT based liquefaction triggering procedures. Report No. UCD/CGM.-14, 1.

Cetin, K. O. (2000). Reliability-based assessment of soil liquefaction initiation hazard. Ph. D. Thesis, Department of Environmental Engineering, University of California Berkeley.

Cetin, K. O., Seed, R. B., Der Kiureghian, A., Tokimatsu, K., Harder Jr, L. F., Kayen, R. E., & Moss, R. E. S. (2004). Standard penetration test-based probabilistic and deterministic assessment of seismic soil liquefaction potential. Journal of Geotechnical and Geoenvironmental Engineering, 130(12), 1314–1340.

Davidson, J. L., Maultsby, J. P., & Spoor, K. B. (1999). Standard Penetration Test Energy Calibrations. Final Report and Appendices.

Division, C. on S. D. of the G. E. (1978). Definition of terms related to liquefaction. Journal of the Geotechnical Engineering Division, 104(9), 1197–1200.

Farjam, A., Omid, M., Akram, A., & Fazel Niari, Z. (2014). A neural network based modeling and sensitivity analysis of energy inputs for predicting seed and grain corn yields. Journal of Agricultural Science and Technology, 16(4), 767–778.

Gholipoor, M., Rohani, A., & Torani, S. (2013). Optimization of traits to increasing barley grain yield using an artificial neural network.

Ghozali, I. (2016). Aplikasi Analisis Multivariete Dengan Program IBM SPSS 23 (VIII). Badan Penerbit Universitas Diponegoro.

Guen, O. (2014). Correlation between SPT and CPT. NTNU.

Haifani, A. M. (2021). Developing New Relationship between Standard Penetration, Cone Penetration Test and Sleeve Friction in Various Soil Type. Journal of Hunan University Natural Sciences, 48(4).

Han, J., Kamber, M., & Pei, J. (2012). Data mining concepts and techniques third edition. University of Illinois at Urbana-Champaign Micheline Kamber Jian Pei Simon Fraser University.

Kang, F., Liu, J., Li, J., & Li, S. (2017). Concrete dam deformation prediction model for health monitoring based on extreme learning machine. Structural Control and Health Monitoring, 24(10), e1997.

Khairunniza-Bejo, S., Mustaffha, S., & Ismail, W. I. W. (2014). Application of artificial neural network in predicting crop yield: A review. Journal of Food Science and Engineering, 4(1), 1.

Kulhawy, F. H., & Mayne, P. W. (1990). Manual on estimating soil properties for foundation design. Electric Power Research Inst., Palo Alto, CA (USA); Cornell Univ., Ithaca ….

Kulhawy, F. H., & Trautmann, C. H. (1996). Estimation of in-situ test uncertainty. Uncertainty in the Geologic Environment: From Theory to Practice, 269–286.

Lingwanda, M. I., Larsson, S., & Nyaoro, D. L. (2015). Correlations of SPT, CPT and DPL data for sandy soil in Tanzania. Geotechnical and Geological Engineering, 33, 1221–1233.

Mansouri, A., Fadavi, A., & Mortazavian, S. M. M. (2016). An artificial intelligence approach for modeling volume and fresh weight of callus–A case study of cumin (Cuminum cyminum L.). Journal of Theoretical Biology, 397, 199–205.

Mansourian, S., Darbandi, E. I., Mohassel, M. H. R., Rastgoo, M., & Kanouni, H. (2017). Comparison of artificial neural networks and logistic regression as potential methods for predicting weed populations on dryland chickpea and winter wheat fields of Kurdistan province, Iran. Crop Protection, 93, 43–51.

Muktaf, H. A., & TAMPUBOLON, B. D. (2022). New Approach for Developing Correlation of NSPT and Shear-Wave Velocity (Vs): Bantul Case Study. Indonesian Journal on Geoscience, 9(3).

Ni, S., & Fan, E. (2002). Fines content effects on liquefaction potential evaluation for sites liquefied during Chi-chi earthquake, 1999. Journal of the Chinese Institute of Engineers, 25(5), 533–542.

Odabas, M. S., Leelaruban, N., Simsek, H., & Padmanabhan, G. (2014). Quantifying impact of droughts on barley yield in North Dakota, USA using multiple linear regression and artificial neural network. Neural Network World, 24(4), 343.

Peixoto, A. S. P., Albuquerque, P. J. R. de, & Carvalho, D. de. (2000). Utilization of SPT-T, CPT and DMT tests to predict the ultimate bearing capacity of precast concrete pile in Brazilian unsaturated residual soil. In Advances in unsaturated geotechnics (pp. 32–39).

Robertson, P. K., Campanella, R. G., & Wightman, A. (1983). Spt-Cpt Correlations. Journal of Geotechnical Engineering, 109(11), 1449–1459.

Sabzalian, M. R., Khashei, M., & Ghaderian, M. (2014). Artificial and hybrid fuzzy linear neural network-based estimation of seed oil content of safflower. Journal of the American Oil Chemists' Society, 91, 2091–2099.

Safa, M., Nejat, M., Nuthall, P., & Greig, B. (2016). Predicting CO_2 emissions from farm inputs in wheat production using artificial neural networks and linear regression models-Case study in Canterbury, New Zealand.

Salazar, F., Toledo, M. Á., González, J. M., & Oñate, E. (2017). Early detection of anomalies in dam performance: A methodology based on boosted regression trees. Structural Control and Health Monitoring, 24(11), e2012.

Šapina, M. (2016). A comparison of artificial neural networks and ordinary kriging depth maps of the lower and upper Pannonian stage border in the Bjelovar Subdepression, Northern Croatia. Rudarsko-Geološko-Naftni Zbornik, 31(3), 75–86.

Schmertmann, J. H. (1975). Measurement of in situ shear strength, SOA Report. Proceedings, ASCE Spec. Conference on In Situ Measurement of Soil Properties, Raleigh, NC, 1975, 2, 57–138.

Seed, H. B. (1979). Soil liquefaction and cyclic mobility evaluation for level ground during earthquakes. Journal of the Geotechnical Engineering Division, 105(2), 201–255.

Singh, T. N., Kanchan, R., Verma, A. K., & Singh, S. (2003). An intelligent approach for prediction of triaxial properties using unconfined uniaxial strength. Min Eng J, 5(4), 12–16.

Suzuki, Y. (1998). Correlation between SPT and seismic CPT. Proc. of the First International Conference on Site Characterization, 2, 1375–1380.

Swanepoel, A., Barnard, S., Recknagel, F., & Cao, H. (2016). Evaluation of models generated via hybrid evolutionary algorithms for the prediction of Microcystis concentrations in the Vaal Dam, South Africa. Water SA, 42(2), 243–252.

Tabrizi-Zarringhabaei, S., Ejlali, R. G., Fard, M. Y., & Sayyedfattahi, S. (2019). A new approach for particle size characterization of soil based on dynamic image analysis (DIA). Rudarsko-Geološko-Naftni Zbornik, 34(4).

Tokimatsu, K., & Yoshimi, Y. (1983). Empirical correlation of soil liquefaction based on SPT N-value and fines content. Soils and Foundations, 23(4), 56–74.

Tsukamoto, Y., Ishihara, K., & Sawada, S. (2004). Correlation between penetration resistance of Swedish weight sounding tests and SPT blow counts in sandy soils. Soils and Foundations, 44(3), 13–24.

Uyeno, C. K. (1976). Liquefaction of Ottawa sand with fines. University of California, Davis.

Weisberg, S. (2005). Applied linear regression (Vol. 528). John Wiley & Sons.

Yi, F. (2014). Estimating soil fines contents from CPT data. Proc. 3rd International Symposium on Cone Penetration Testing, Huntington Beach, Las Vegas, Nevada, USA, 949–955.

Youd, T. L., & Idriss, I. M. (2001). Liquefaction resistance of soils: summary report from the 1996 NCEER and 1998 NCEER/NSF workshops on evaluation of liquefaction resistance of soils. Journal of Geotechnical and Geoenvironmental Engineering, 127(4), 297–313.