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# PREDICTING GEOTECHNICAL AXIAL CAPACITY OF REINFORCED CONCRETE DRIVEN PILE USING MACHINE LEARNING TECHNIQUE

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**Graphical abstract**

**Abstract**

Modified Meyerhof method is a popular method to calculate pile geotechnical axial capacity in Malaysia currently. From past experience, pile design based on empirical and analytical method produce variability of predicted capacity, in which, there is a wide scatter of predicted capacities and tendency for the predictions to be conservative, i.e. to underestimate the load capacity. This study provides options of machine learning and statistical approach for prediction of pile capacity based on soil investigation and dynamic pile load test result. It serves as an additional checking for engineer during design of pile based on conventional empirical method. It also helps to provide deeper insights of non-linear variables related to pile capacity through machine learning and statistical approach. This study helps engineer to design pile foundation optimally, economically and safely. The prediction of pile geotechnical axial capacity with machine learning technique and statistical approach for local marine clay soil in Penang, Malaysia is proposed in this study. The information from soil investigation report and dynamic pile load test report are gathered from six projects at Batu Kawan and Nibong Tebal located in Penang state that contributed 439 numbers of data. The skin friction factor, end bearing factor and pile geotechnical axial capacity are computed and predicted using empirical method, machine learning model and statistical model. Support Vector Machine illustrate best fit model for predicting skin friction factor with $R^2$ of 0.517 while Random Forest seems to be the best fit model for predicting end bearing factor with $R^2$ of 0.264. Random Forest is found to be the best model in predicting the geotechnical pile axial capacity compare to other models as it explains 96.2% of the variability of pile capacity.

*Keywords*: Pile geotechnical axial capacity, machine learning, skin friction factor, end bearing factor, statistics

**Abstrak**

Kaedah Meyerhof yang diubahsuai adalah kaedah yang popular untuk mengira kapasiti paksi geoteknikal cerucuk di Malaysia pada masa ini. Daripada pengalaman lepas, reka bentuk cerucuk berdasarkan kaedah empirikal dan analitikal menghasilkan kapasiti yang berbeza. Terdapat serakan luas kapasiti ramalan dan kecenderungan untuk ramalan itu konservatif, iaitu kapisiti cerucuk rendah diramalkan. Kajian ini menyediakan pilihan pembelajaran mesin dan pendekatan statistik untuk ramalan kapasiti cerucuk berdasarkan penyiasatan tanah dan keputusan ujian beban cerucuk dinamik. Ia berfungsi sebagai pemeriksaan tambahan untuk jurutera semasa reka bentuk cerucuk berdasarkan kaedah empirikal konvensional. Ia juga membantu untuk memberikan pandangan yang lebih mendalam tentang pembolehubah bukan linear yang berkaitan dengan kapasiti cerucuk melalui pembelajaran mesin dan pendekatan statistik. Kajian ini membantu jurutera mereka bentuk asas cerucuk secara optimum, menjimatkan dan selamat. Satu kaedah baru untuk meramal kapasiti paksi geoteknikal cerucuk dengan teknik pembelajaran mesin dan pendekatan statistik untuk tanah liat marin tempatan di Batu Kawan, Pulau Pinang, Malaysia dicadangkan. Sebanyak enam projek di Batu Kawan dan Nibong Tebal yang terletak di negeri Pulau Pinang menyumbang kepada 439 bilangan data. Maklumat daripada laporan penyiasatan tanah dan laporan ujian beban cerucuk dinamik dikumpulkan. Faktor geseran kulit, faktor galas hujung dan kapasiti paksi geoteknikal cerucuk dikira dan diramal menggunakan kaedah empirikal, model pembelajaran mesin dan model statistik. Mesin Vektor Sokongan menggambarkan model kesesuaian terbaik untuk meramalkan faktor geseran kulit dengan $R^2$ sebanyak 0.517 manakala Random Forest nampaknya model paling sesuai untuk meramalkan faktor galas akhir dengan $R^2$ sebanyak 0.264. Random Forest ialah model terbaik untuk meramalkan kapasiti paksi geoteknik cerucuk berbanding model lain kerana ia menerangkan 96.2% kebolehubahan kapasiti cerucuk.

*Kata kunci:* Kapasiti paksi geoteknik cerucuk, pembelajaran mesin, faktor geseran kulit, faktor galas hujung, statistik

## 1.0 INTRODUCTION

Reinforced Concrete (RC) pile is a common construction material for building and infrastructure foundation in Malaysia because of its material availability and economical application. There are numerous approaches of designing reinforced concrete (RC) pile. Modified Meyerhof method is the most popular method to calculate pile geotechnical axial capacity in Malaysia currently. This method correlates SPT-N value to skin friction factor, $K_s$ and end bearing factor, $K_b$. Standard Penetration Test (SPT) is a very common and economical way of soil investigation in Malaysia. Skin friction factor and end bearing factor varies from place to place depends on the local soil characteristics.

However, foundation design using piles based on empirical approaches to soil profile, interaction between soil and pile structure, and distribution of soil resistance along the pile do not produce really quantitative data (Shooshpasha et al., 2013). While analytical method has it disadvantages such as the difficulty of determining the appropriate geotechnical parameters. Proper geotechnical modelling of a site remains the most challenging task facing the pile designer. From past experiment and study, pile design based on empirical and analytical method produce variability of predicted capacity. There is a wide scatter of predicted capacities and tendency for the predictions to be conservative, i.e. to underestimate the load capacity. It is therefore alarming to consider that even for the reasonably well-understood element of axial load capacity, there is significant room for prediction difference across different prediction methods and between individual predictors employing the same methodologies (Poulos, 1988). The majority of piling contracts include load tests to confirm capacity, which is typical given the high level of uncertainty in forecast techniques (Randolph, 2003).

This study aims to propose alternative method of predicting geotechnical axial capacity of reinforced concrete (RC) driven pile based on soil investigation report and dynamic pile test conducted at Batu Kawan, Penang, Malaysia by training, validating and testing four (4) machine learning models and develop statistical model prediction equation for pile geotechnical axial capacity.

### 1.1 Pile Design

The design and analysis of pile foundations can be divided into three categories whereby category 1 is known as empirical method while category 2 and 3 are known as analytical method (Poulos, 1988).

Empiricism has been a mainstay of pile foundation design for a long time. Between the 1950s and the 1980s, significant advancements in pile design techniques based on good theoretical assumptions were made. According to prior research and experimentation, pile designs that rely on empirical and analytical methods have unpredictable anticipated capacities. The anticipated capacities are widely dispersed, and there is a propensity for the estimates to be cautious, or to underestimate the load capacity. It is therefore alarming to consider that even for the reasonably well-understood element of axial load capacity, there is significant room for prediction difference across different prediction methods and between individual predictors employing the same methodologies (Poulos, 1988).

Even while scientific approaches to pile design have made significant strides in recent years, such as correlation with static cone resistance, unconfined strength, rock classification, total stress, effective stress and cavity expansion, the most fundamental component of pile design—estimating axial capacity—remains mainly dependent on empirical correlations (Randolph, 2003).

To date, Modified Meyerhof formula is still the most popular pile design method in Malaysia. The formulae are derived based on empirical study on relationship between SPT-N value, pile geometry and pile capacity. The formulae are shown in following Equation (Eq. 1, 2 & 3):

$$\text{Ultimate Skin Friction} = N_{av} \times A_p \times L \times K_s \quad (1)$$

$$\text{Ultimate End Bearing} = K_b \times N_b \times A_b \quad (2)$$

Pile Allowable Axial Capacity

$$= (\text{Ultimate Skin Friction})/\text{FOS} + (\text{Ultimate End Bearing})/\text{FOS} \quad (3)$$

Where $N_{av}$ is the average SPT-N value along pile shaft, $N_b$ is the SPT-N value at pile base, $A_p$ is pile shaft area, $A_b$ is pile base area, $K_s$ is the friction factor of 2.0 (sand), 2.5 (silt) and 3.0 (clay), $K_b$ is the ending bearing factor of 400 (sand), 300 (silt) and 200 (clay). For design norm, the maximum skin friction stress, $f_s$ is 100 kN/m$^2$ and maximum end bearing stress, $f_b$ is 10,000 kN/m$^2$. Whereas FOS is factor of safety normally in a combination of FOS = 2 for both shaft friction and end bearing or FOS = 1.5 for shaft friction and FOS = 3.0 for end bearing. Lower FOS combination shall be selected. Skin friction stress, $f_s$ and end bearing stress, $f_b$ can be computed following Equation (Eq. 4 & 5).

$$f_s = K_s \times N_{av} \quad (4)$$

$$f_b = K_b \times N_b \quad (5)$$

As we can see from above equations, the type of soil (sand, silt, clay) plays a very important role in determining the pile allowable axial capacity. However, tropical residual soils such as in Malaysia are generally complex in soil characteristics, its properties change over short distance.

### 1.2 Standard Penetration Test

Engineering properties and soil profiles are developed using the Standard Penetration Test (SPT). The SPT is thought to be the most traditional in situ soil testing method and is still the common testing methodology currently to explore the soil profile at a site. Its first iteration stems from the start of the 19$^{th}$ century. In 1902, open-end pipe of 25mm diameter during wash-boring process was introduced in United States. This is the beginning of dynamic testing and sampling of soils. Between the late 1920s and early 1930s, the test was standardized using a 51mm outside diameter split-barrel sample, driven into the soil with a 63.5kg weight having a free fall of 760mm (Shooshpasha et al., 2013).

The fundamental SPT implementation process involves providing an external driving force to a thick, hollow tube in order to press it into the soil while measuring the soil resistance in terms of blow count. Soil samples and data on groundwater are also gathered while the SPT goes forward. The number of strikes needed to penetrate each 150mm section into the earth is recorded. This is carried out up until 450 mm in length or till penetration refusal. In most cases, the first 150mm of the first record of progress (seating) is deleted, while the second and third increments are recorded and added to yield the number of blows N per 300mm.

Research conducted by Toh et al. (1989) concluded that design of piles based on empirical relationship between pile capacities and SPT-N value by adopting international practice and further developed to local experience due to economic cost of SPT compare to relatively high cost of pressure meter or any other instrument in Malaysia (Toh et al., 1989). However, there are disadvantages for using SPT for recovery of suitable sample for laboratory testing.

### 1.3 Dynamic Pile Load Test

A dynamic load test tracks how a pile responds to hammer strikes delivered at the pile head. The observations are then examined using the stress wave theory to forecast the soil resistance that would be mobilised by the pile under static load circumstances. Due to the extremely high rate of applied loading, dynamic load tests are unable to account for time-related effects like consolidation, relaxation, and creep. Dynamic load tests occasionally need to be calibrated with static load tests. The pile has electronic gauges attached to it. With known pile parameters, the gauges measure the acceleration of the pile and subsequently, indirectly, the velocity and displacement. As the hammer impacts the pile, the gauges also detect strain in the pile slightly below the head.

Amongst static analysis, dynamic analysis, dynamic testing, pile load testing and in-situ testing, the pile load test is considered as the best method to determine the pile bearing capacity. However, such a method is time-consuming, and the costs are often difficult to justify for ordinary or small projects, whereas other methods have lower accuracy (Pham et al., 2020).

### 1.4 Machine Learning

Machine learning is a field of computer science that involves the development of algorithms and statistical models that enable computer systems to automatically improve their performance on a particular task by learning from data, without being explicitly programmed. The goal of machine learning is to enable computers to automatically learn and adapt to new information without human intervention. This is done by creating algorithms and models that analyse and interpret data, identify patterns and trends, and make predictions or decisions based on the information learned.

There are three different kinds of machine learning: reinforcement learning, unsupervised learning, and supervised learning. Supervised machine learning involves the provision of both the desired input and output. Unsupervised machine learning is the process of teaching an algorithm to operate on data that has not been categorised or labelled while enabling the system to make decisions on its own. Reinforcement machine learning enables a computer to automatically decide the appropriate conduct within a particular situation.

### 1.5 Machine Learning for Predicting Pile Capacity

There are many machine learning techniques being employed to predict pile capacity such as support vector machine, neural network, iterative technique, gradient boosted tree technique, genetic algorithm, etc. In the field of geotechnical engineering, machine learning has been applied to various aspects of pile design, including the prediction of pile capacity, the determination of the pile-soil interaction behaviour, and the optimization of pile design parameters.

Goh was one of the first, if not the first, proponents of ANNs in geotechnical engineering, and he released a study in 1994 that used ANNs to evaluate the possibility for seismic liquefaction (Jaksa and Liu, 2021).

The ultimate capacity of driven piles was predicted using ANNs (Abu-Kiefa, 1998; Lee and Lee, 1996). However, only a small quantity of data was used to create their models, and none of them were built utilising the more precise measurements of soil characteristics obtained from the CPT results (Shahin, 2010). Numerous geotechnical engineering applications have used ANNs.

Mahesh and Surinder (2008) modelled the total pile capacity using dynamic stress-wave data using radial basis function and polynomial kernel-based support vector machines, and the outcomes were contrasted with a generalised regression neural network approach. The results indicate that generalised regression neural network-based approaches perform better than support vector machines, while polynomial kernel-based SVMs may forecast total pile capacity using stress-wave data linearly (Mahesh and Surinder, 2008).

Maizar et al. (2013) utilized Artificial Neural Network (ANN) for prediction of axial capacity of a driven pile by adopting high strain dynamic testing i.e. Pile Driving Analyzer (PDA) data from Indonesia and Malaysia. Pile characteristics and hammer energy are two examples of the parameters recorded. The findings demonstrate that when stress wave data, driven pile characteristics, and driving system characteristics are taken into account in the input data, neural network models can accurately forecast the axial bearing capacity of piles. The model's validation shows that the quantity of data is not always correlated with the accuracy of the forecast (Maizar et al., 2013).

Based on the results of the cone penetration test (CPT), Kordjazi et al. (2014) created SVM models to forecast the ultimate axial load-carrying capacity of piles. The data includes details on the geometry of the piles, the outcomes of full-scale static pile load tests, and CPT results. According to the comparison (Kordjazi et al., 2014), the SVM models created in this research perform better than the conventional techniques.

In order to predict the axial pile capacity, Benali et al. (2017) proposed Artificial Neural Networks (ANN) and Principal Component Analysis (PCA). The Back-Propagation Multi-Layer Perceptron (BPMLP) with Bayesian Regularisation (BR) is the technique used in the model. The created model has appealing characteristics and advantages that make it a promising tool, according to an evaluation of the novel method's prediction performance versus a number of conventional SPT-based approaches (Benali et al., 2017).

Pham et al. (2020) used random forest (RF) and artificial neural network (ANN) methods to forecast the eventual axial bearing capacity of driven piles. The outcomes revealed that RF performed better than ANN and other techniques. The diameter of the pile, the length of the pile segments, the natural ground elevation, the pile top elevation, the guide pile segment stop driving elevation, the pile tip elevation, the average standard penetration test (SPT) value along the embedded length of the pile, and the average SPT blow counts at the tip of the pile were collected from driven pile static load test reports. The output variable was the ultimate load on the pile top. The average SPT value and pile tip elevation was shown to be the most crucial variables in determining the axial bearing capacity of piles by sensitivity analysis (Pham et al., 2020).

Six machine learning algorithms with different biases were taught by Gomes et al. (2021) and validated using a leave-one-out cross validation method. Using the Décourt-Quaresma dataset, random forest (RF) was the approach that performed the best. The study also included a case study that demonstrated the top performing models outperformed semi-empirical approaches in two of the three piles taken into consideration (Gomes et al., 2021).

Systematic literature review and mapping done by Carvalho et al. (2023) has shown the machine learning has become predominant in the prediction of pile bearing capacity in the past twenty-five years and has surpassed the most traditional regression-based methods both in number and performance. In comparison to other methods, ANN has shown to be a very efficient tool when compared to classic empirical methods that are consolidated. ANNs have performed better, and, in most cases, results are much closer to the bearing capacities measured by pile load tests (Carvalho et al., 2023).

Overall, using machine learning to improve the precision and effectiveness of pile design has showed promise and future study in this area is likely to progress the industry. Numerous researchers have started investigating the disciplinary or thematic applications of ML methods in recent years as a result of the rapid growth of ML and its dissemination across numerous engineering fields. In fact, deep learning (DL) and machine learning (ML) are particularly useful in and relevant to geotechnical engineering, where measurements—especially in situ—are influenced by measurement and model uncertainties, data are frequently sparse, and soil and rock variability can frequently be highly variable.

## 2.0 METHODOLOGY

In overall, the procedures are divided into 3 phases, i.e., Phase 1 – data collection and pre-processing, Phase 2 – calibration of $K_s$ and $K_b$ value and Phase 3 – prediction of geotechnical pile axial capacity.

### 2.1 Study Sites

Total of six projects at Batu Kawan and Nibong Tebal located in Penang State contributed 439 numbers of data. The sites are chosen based on location of similar geological formation, i.e. Quaternary age marine and continental alluvial deposits: clay, silt, sand, peat with minor gravel. The site location is as shown in Figure 1.

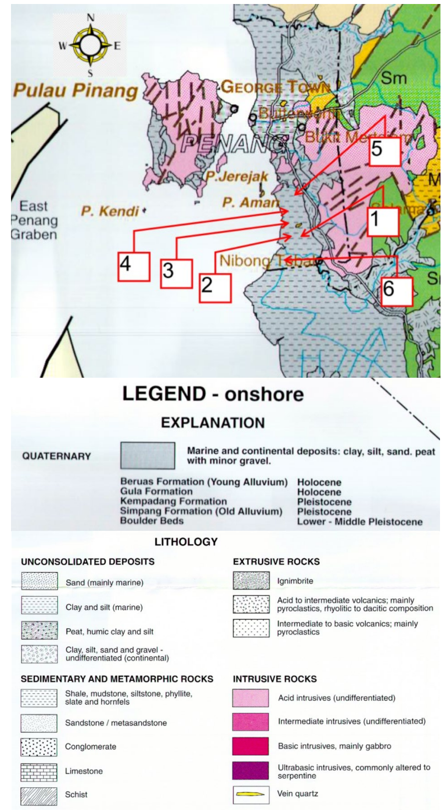


**Figure 1** Location of study area in geological map

### 2.2 Data Collection

Throughout this study, Excel spreadsheet with data analysis add-on software, XLSTAT, were utilised to perform data compilation, data pre-processing, data visualization, statistical interpretation, statistical modelling, machine learning training, validation and testing. The qualitative and quantitative parameters used in this study are tabulated in Table 1.

**Table 1** Summary of data source

| Source | Data | Unit |
|---|---|---|
| Soil Investigation Report | Pile penetration depth | m |
| | Pile shaft and base area | $m^2$ |
| | Pile shape | - |
| | Average SPT-N along pile shaft and SPT-N at pile base | - |
| | Soil type along pile shaft and soil type at pile base | - |
| Dynamic Pile Load Test Report | Pile shaft and base stress | $kN/m^2$ |
| | Pile shaft and base resistance | kN |

### 2.3 Detail Procedure

The detail procedure is outlined below:

1) Data collection and pre-processing (pile penetration depth, pile shaft area, pile base area, pile shape, SPT-N along pile shaft, SPT-N at pile base, soil type, skin friction stress, end bearing stress, skin friction resistance, end bearing resistance, total pile resistance) from soil investigation report and dynamic pile load test report

2) Calibration of skin friction factor, $K_s$ and end bearing factor, $K_b$ value for empirical method (Modified Meyerhof)
   a) $K_s$ and $K_b$ were back calculated from the pile stress and pile resistance obtained from dynamic load test
   b) Machine learning and statistical model were developed for comparison with manual back calculation
3) Prediction of geotechnical pile axial capacity using machine learning models and statistical model
   a) Develop machine learning models by partitioning dataset for training, validation and testing: 80% for training and validation, 20% for testing
   b) Develop statistical model by perform Analysis of Covariance (ANCOVA) with same dataset for machine learning model to propose statistical model prediction equation
   c) Setup model performance indicators comparison amongst machine learning model and statistical model
   d) Compute pile geotechnical axial capacity with empirical method
   e) Compare pile geotechnical axial capacity between empirical method, machine learning models and statistical model

Figure 2 shows the flow chart of research methodology.

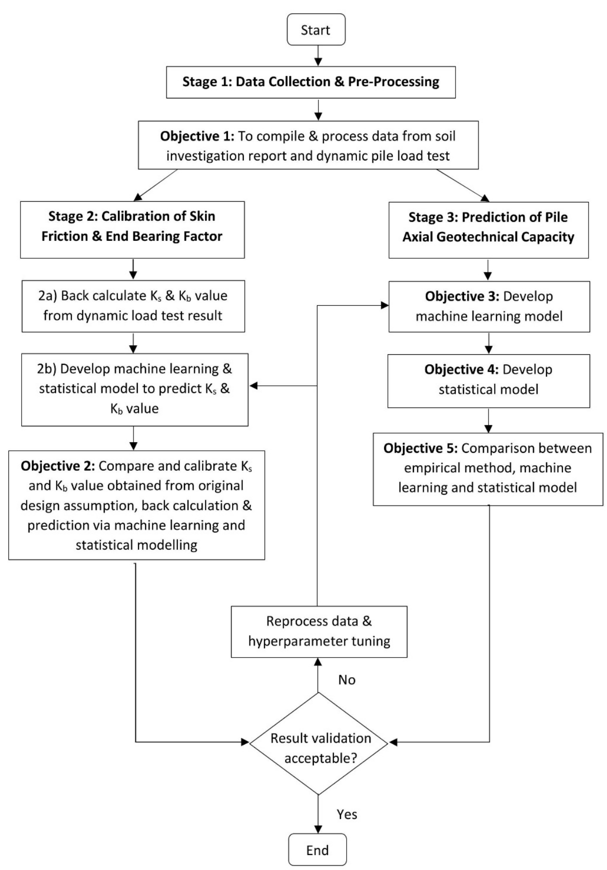


**Figure 2**: Flow Chart

## 3.0 RESULTS AND DISCUSSION

### 3.1 Data Compilation

The first objective of this study is to compile data from soil investigation report and dynamic pile load test report. Skin friction factor ($K_s$) and end bearing factor ($K_b$) were computed via following equation (Eq. 6 & 7):

$$K_s = f_s/N_{av} \qquad (6)$$

$$K_b = f_b/N_b \qquad (7)$$

where $K_s$ is the skin friction factor, $f_s$ is the average skin friction stress (kN/m$^2$), $N_{av}$ is the average SPT-N value along pile shaft, $K_b$ is the end bearing factor, $f_b$ is the end bearing stress (kN/m$^2$), $N_b$ is the SPT-N value at pile base.

Table 2 shows range of actual pile capacity and pile penetration depth with respect to pile size for six numbers of projects. It gives an overview on the minimum and maximum actual pile capacity and pile penetration depth.

### 3.2 Skin Friction and End Bearing Factor

The second objective of this study is to compare actual skin friction factor, $K_s$ and end bearing factor, $K_b$ value back calculated from dynamic pile test with $K_s$ and $K_b$ value in original design assumption, i.e. modified Meyerhof empirical method. Mean value of $K_s$ and $K_b$ was back calculated based on dynamic pile load test result and tabulated in Table 3. Generally, there is no change suggested for design value of skin friction factor, $K_s$ of 2.5 and 2 for silt and sand respectively as they are quite consistent with findings of Meyerhof (1976), Gue (2007) and Tan et al. (2009). However, it is worth to mention that most of the previous findings proposed $K_s$ value of 2.5 for skin friction factor of clay. Whereas the end bearing factor $K_b$ for sand, silt and clay, the results attest to corroborate with Decourt (1995), Gue (2007) and Tan et al. (2009) with downgraded value of 250, 200 and 100 respectively.

Though $K_s$ and $K_b$ value have been calibrated as shown in above table, it only makes the pile capacity prediction more conservative and challenging as the current Modified Meyerhof empirical method predicted a scatter wide range of pile capacity compare to load test result, i.e. from 5.76% to 94.96%. Neither downgrade nor upgrade of skin friction factor and end bearing factor will help in minimise the wide gap of predicted pile capacity. The empirical method of pile design, which oversimplified the complexities of soil response such as reduction in effective stresses, degree of remoulding during pile installation, relaxation of radial total stress during consolidation, and reduction in radial effective stress during loading, does not reflect the design of piles based on science and theory (Randolph, 2003). It is notable that skin friction factor and end bearing factor of silt is on very high side. For sand and clay, the percentage difference between designed and back calculated value is between -42% to 32%. However, silt shows a vast difference of 102% to 181%. This makes the calibration more prone to error.

**Table 2:** Range of Actual Pile Capacity and Pile Penetration Depth With Respect to Pile Size

| Pile Size | Minimum Actual Pile Capacity (kN) | Maximum Actual Pile Capacity (kN) | Minimum Actual Pile Depth (m) | Maximum Actual Pile Depth (m) |
|---|---|---|---|---|
| 150mm x 150mm | 334 | 461 | 22.5 | 23.0 |
| 200mm x 200mm | 265 | 1422 | 28.0 | 29.4 |
| 250mm x 250mm | 1354 | 1815 | 38.3 | 44.0 |
| 250mm x 250mm | 1141 | 1307 | 29.0 | 29.4 |
| 300mm x 300mm | 1007 | 1293 | 27.0 | 39.0 |
| 300mm x 300mm | 1469 | 1886 | 23.0 | 35.0 |
| 300mm x 300mm | 1720 | 1732 | 35.5 | 35.5 |
| 350mm x 350mm | 2158 | 4385 | 28.7 | 56.0 |
| 400mm x 400mm | 2526 | 4131 | 35.5 | 47.0 |
| 450mm diameter | 2106 | 3177 | 22.2 | 35.4 |
| 500mm diameter | 2325 | 2806 | 33.0 | 47.0 |

**Table 3**: Summary of Skin Friction and End Bearing Factor

| Factor | Soil | Design Assumption | Mean Value Based on Back Calculation of Pile Load Test | % Difference | Suggested Design Assumption | Remarks on Suggested Design Assumption |
|---|---|---|---|---|---|---|
| Skin Friction Factor, $K_s$ | Clay | 3.0 | 3.97 | 32% | 3.0 | Most of the previous findings suggested value of 2.5 |
| | Silt | 2.5 | 7.04 | 181% | 2.5 | Aligned with Meyerhof (1976), Gue (2007), Tan et al. (2009) |
| | Sand | 2.0 | NA | NA | 2.0 | Aligned with Meyerhof (1976), Gue (2007) |
| End Bearing Factor, $K_b$ | Clay | 200 | 116.48 | -42% | 100 | Aligned with Decourt (1995) |
| | Silt | 300 | 605.11 | 102% | 200 | Aligned with Decourt (1995) |
| | Sand | 400 | 281.37 | -30% | 250 | Aligned with Gue (2007), Tan et al. (2009) |

In addition, the machine learning and statistical model are adopted to predict skin friction factor and end bearing factor as shown in Table 4.

Table 5 and 6 shows performance metrics of machine learning and statistical model on prediction of $K_s$ and $K_b$.

**Table 4**: Skin Friction and End Bearing Factor Prediction using Machine Learning and Statistical Model

| Factor | Soil | Design Assumption | Mean Value Based on Back Calculation of Pile Load Test | SVM Mean Value | KNN Mean Value | DT Mean Value | RF Mean Value | ANCOVA Mean Value |
|---|---|---|---|---|---|---|---|---|
| Skin Friction Factor, $K_s$ | Clay | 3.0 | 3.97 | 4.06 | 4.82 | 4.25 | 4.12 | 4.10 |
| | Silt | 2.5 | 7.04 | 7.42 | 8.17 | 7.24 | 7.24 | 7.30 |
| | Sand | 2.0 | NA | NA | NA | NA | NA | NA |
| End Bearing Factor, $K_b$ | Clay | 200 | 116.48 | 116.25 | 154.94 | 125.02 | 137.35 | 152.15 |
| | Silt | 300 | 605.11 | 417.94 | 479.69 | 542.46 | 521.30 | 496.21 |
| | Sand | 400 | 281.37 | 244.32 | 210.82 | 242.03 | 282.16 | 277.73 |

**Table 5:** Machine Learning and Statistical Models Performance Metrics on Prediction of Skin Friction Factor

| Performance Metrics | SVM | KNN | DT | RF | ANCOVA |
|---|---|---|---|---|---|
| MAE | 1.151 | 1.407 | 1.191 | 1.208 | 1.185 |
| MSE | 2.452 | 3.635 | 2.524 | 2.535 | 2.515 |
| $R^2$ | 0.517 | 0.284 | 0.503 | 0.501 | 0.505 |
| MAPE | 22.19% | 29.79% | 22.48% | 22.41% | 22.37% |

**Table 6**: Machine Learning and Statistical Models Performance Metrics on Prediction of End Bearing Factor

| Performance Metrics | SVM | KNN | DT | RF | ANCOVA |
|---|---|---|---|---|---|
| MAE | 294.822 | 286.577 | 273.398 | 253.609 | 278.467 |
| MSE | 192402.562 | 178086.356 | 162408.256 | 151718.245 | 164092.596 |
| $R^2$ | 0.067 | 0.136 | 0.213 | 0.264 | 0.204 |
| MAPE | 64.37% | 68.84% | 81.27% | 59.17% | 83.41% |

From Table 5, SVM illustrates the best fit model for predicting skin friction factor with $R^2$ of 0.517. Meanwhile, other machine learning model such as DT and RF and statistical model appear to have very close, yet lower $R^2$ compare to SVM. From Table 6, RF seems to be the best fit model for predicting end bearing factor with $R^2$ of 0.264. DT and ANCOVA have $R^2$ close to RF but the SVM and KNN demonstrated lower $R^2$ compare to other models. It is also notable to mention that $R^2$ generally is about 0.5 or less than 0.5 which implies only 50% or less that the models built are able to predict $K_s$ and $K_b$ value. Thus the machine learning have advantages in the capability of predicting the $K_s$ and $K_b$ in a range of value (continuous data), instead of discrete value found in most of the literature. This lends support to more comprehensive and meaningful prediction in future whereby limited soil investigation data and pile load test report are available.

### 3.3 Machine Learning Model for Pile Axial Geotechnical Capacity

Third objective of this study is to train, validate and test four (4) machine learning models for prediction of pile geotechnical axial capacity. The data consists of information from six (6) project sites. The dataset is partitioned and divided into 80% for training and validation, whereas 20% for testing.

The hyperparameter of each machine learning is listed as below:

1) Support Vector Machine
   C = 1
   Tolerance = 0.001
   Epsilon = 0.1
   Pre-processing = Standardisation
   Cross-validation = 10 folds
   Kernel = Radial Basis Function (RBF)
   Gamma = 0.5

2) K-Nearest Neighbours
   Model = Metric
   Distance = Euclidean Distance
   Number of Neighbours = √351=19
   Cross-validation = 10 folds

3) Decision Trees
   Method = Chi-Squared Measurement (CHAID)
   Tree Parameters (minimum parent size, minimum son size, maximum depth) = Automatic
   CP = 0.0001
   Bonferroni Correction – Number of Intervals = 10
   Bonferroni Correction – Significance Level = 5%
   Validation = 35 nos (10% of 351) chosen randomly from training set

4) Random Forest
   Sampling = Random with replacement
   Method = Bagging
   Sample size = 316
   Number of trees = 100
   Stop conditions – Construction time = 300
   Tree parameters – Minimum node size = 2
   Tree parameters – Minimum son size = 1
   Tree parameters – Maximum depth = 20
   CP = 0.0001

Generally, the smaller the error i.e. MAE, MAPE, MSE, RMSE, MSLE, RMSLE, the better is the machine learning model performance. $R^2$, an indicator with a range of 0 to 1. It is equivalent to the model's determination coefficient and is understood as the percentage of the response variable's variability that the model is responsible for explaining. The model performs better the closer $R^2$ is to 1. The more closely a model matches the data, the closer the residuals are to 0. Following Table 7 shows the model performance indicator for 4 machine learning models.

Table 7: Machine Learning Model Performance Indicator for Predicting Pile Axial Geotechnical Capacity

| | **MSE** | **$R^2$** | **MAE** |
|---|---|---|---|
| **Support Vector Machine** | 55,824.957 | 0.956 | 183.976 |
| **K-Nearest Neighbours** | 103,575.971 | 0.919 | 219.599 |
| **Decision Trees** | 52,508.261 | 0.959 | 181.957 |
| **Random Forest** | 49,203.432 | 0.962 | 172.887 |

From the Table 7, Random Forest is found to be the best prediction model as it has the least error and highest R-Squared (49,203.432, 0.962), followed by Decision Trees, Support Vector Machine and K-Nearest Neighbours.

Figures 3 to 6 shows the graph of Actual Total Resistance versus Predicted Total Resistance for all four machine learning models.

Comparison of predictions and observed values is possible using a response variable versus predictions graphic. The points will be nearer to the regression line the more variance is explained by the model. Response variable versus Standardized residuals chart induce following findings:

1) A larger variability of errors on the model using K-Nearest Neighbours compare to predictions made by Support Vector Machine, Decision Trees and Random Forest model.
2) Good performance (small residuals) of the Random Forest model on the bigger pile capacity value and poorer performance for the smaller pile capacity value
3) Generally, the observations concentrated on top right and bottom left of the chart for all models.

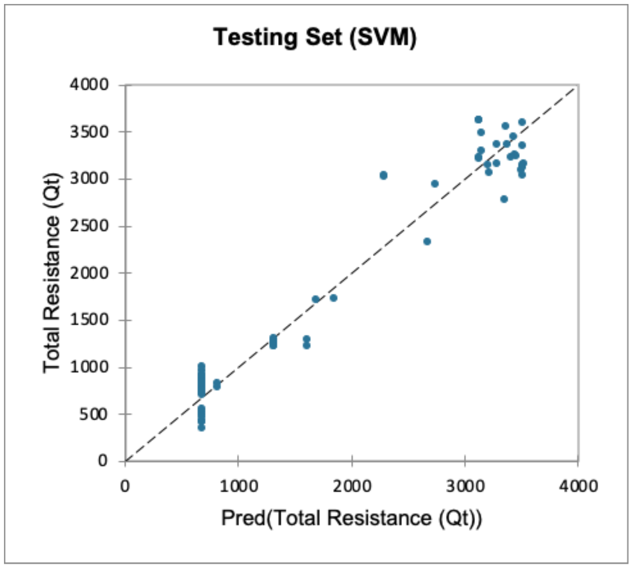


**Figure 3**: Actual Total Resistance vs Predicted Total Resistance for Support Vector Machine

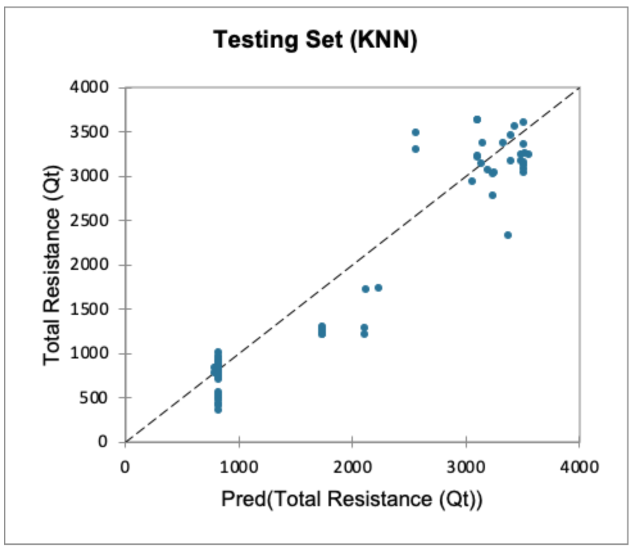


**Figure 4:** Actual Total Resistance vs Predicted Total Resistance for K-Nearest Neighbours

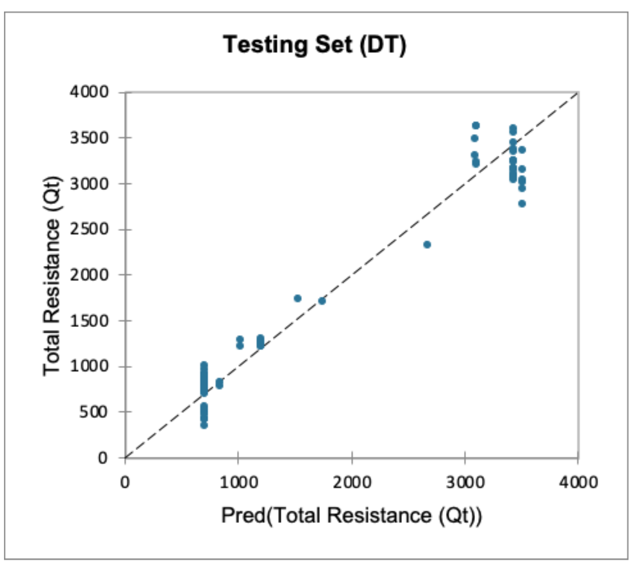


**Figure 5**: Actual Total Resistance vs Predicted Total Resistance for Decision Trees

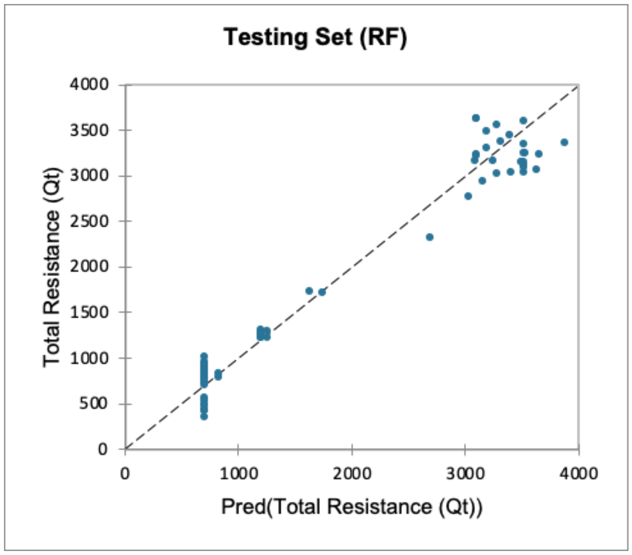


**Figure 6**: Actual Total Resistance vs Predicted Total Resistance for Random Forest

### 3.4 Statistical Model Prediction for Pile Axial Geotechnical Capacity

The fourth objective is to develop statistical model prediction equation for pile geotechnical axial capacity. Table 8 shows the model performance indicator for statistical model prediction equation. It shows the accuracy and reliability of the statistical model prediction equation.

Table 8: Model Performance Indicator for Statistical Model Prediction Equation

| **Statistics** | **Training Set** | **Validation Set** | **Testing Set** |
|---|---|---|---|
| MSE | 94616.318 | 47177.079 | 62389.249 |
| $R^2$ | 0.943 | 0.977 | 0.951 |
| MAPE | 15.309 | 9.858 | 15.65 |

Figure 7 shows the graph of Actual Total Resistance versus Predicted Total Resistance for statistical model.

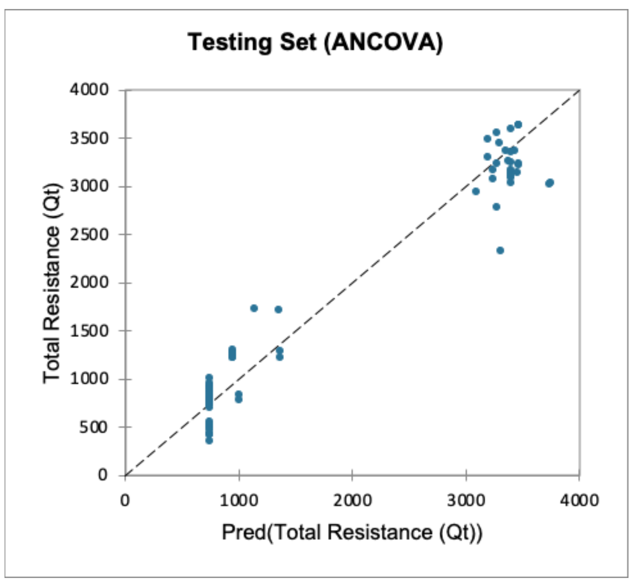


**Figure 7:** Actual Total Resistance vs Predicted Total Resistance for statistical model

**Table 9:** Type I Sum of Square table

| Source | DF | Sum of squares | Mean squares | F | Pr > F | p-values signification codes |
|---|---|---|---|---|---|---|
| Pile Depth | 1.000 | 393611582.273 | 393611582.273 | 4160.081 | **<0.0001** | *** |
| Pile Shaft Area | 1.000 | 64394296.254 | 64394296.254 | 680.583 | **<0.0001** | *** |
| Pile Base Area | 1.000 | 484984.405 | 484984.405 | 5.126 | **0.024** | * |

| | | | | | | |
|---|---|---|---|---|---|---|
| Pile Shape | 1.000 | 2309903.555 | 2309903.555 | 24.413 | **<0.0001** | *** |
| Average Shaft SPT-N (Nav) | 1.000 | 1937555.120 | 1937555.120 | 20.478 | **<0.0001** | *** |
| Base SPT-N (Nb) | 1.000 | 47945.941 | 47945.941 | 0.507 | 0.477 | ° |
| Soil Along Pile Shaft | 1.000 | 15499468.917 | 15499468.917 | 163.814 | **<0.0001** | *** |
| Soil At Pile Base | 1.000 | 1069782.752 | 1069782.752 | 11.307 | **0.001** | *** |

*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*

**Table 10**: Type III Sum of Square table

| Source | DF | Sum of squares | Mean squares | F | Pr > F | p-values signification codes |
|---|---|---|---|---|---|---|
| Pile Depth | 1.000 | 52913.390 | 52913.390 | 0.559 | 0.455 | *** |
| Pile Shaft Area | 1.000 | 58724.127 | 58724.127 | 0.621 | 0.431 | *** |
| Pile Base Area | 1.000 | 1143034.851 | 1143034.851 | 12.081 | **0.001** | * |
| Pile Shape | 1.000 | 1687601.808 | 1687601.808 | 17.836 | **<0.0001** | *** |
| Average Shaft SPT-N (Nav) | 1.000 | 385160.433 | 385160.433 | 4.071 | **0.045** | *** |
| Base SPT-N (Nb) | 1.000 | 41297.232 | 41297.232 | 0.436 | 0.509 | ° |
| Soil Along Pile Shaft | 1.000 | 3109108.364 | 3109108.364 | 32.860 | **<0.0001** | *** |
| Soil At Pile Base | 1.000 | 1069782.752 | 1069782.752 | 11.307 | **0.001** | *** |

*Signification codes: 0 < *** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1 < ° < 1*

From Table 9 (Type I Sum of Square table) and Table 10 (Type III Sum of Square table), the lower the F probability corresponding to a given variable, the stronger the impact of the variable on the model as it is before the variable is added to it. From the results, SPT-N at pile base brings the least information to the model. The following variables bring significant information to explain the variability of the dependent variable Total Resistance ($Q_t$): Pile Base Area, Pile Shape, Average Shaft SPT-N ($N_{av}$), Soil Along Pile Shaft and Soil at Pile Base. From the table of model parameter, the higher the p-value, the weaker impact of the parameter on the model. From the results, SPT-N at pile base gives least impact to the model. Generally, where pile is installed at clay soil, most of the contribution of pile bearing capacity comes from skin friction. End bearing of pile did provide some capacity but is lesser compare to skin friction. Thus, the SPT-N at base ($N_b$) does not bring significant impact on pile geotechnical axial capacity, identical to the results from ANCOVA. Among the explanatory variables, based on the Type III sum of squares, variable Soil Along Pile Shaft is the most influential. This is in agreement of different type of soil resulted in different bearing capacity of pile. This also in line with the design of friction pile at soft clay area as skin friction contribute majority of the pile geotechnical axial capacity.

The equation of the model is shown in Eq.8:

Total Resistance ($Q_t$)
= 2990.39523274356 - 26.1675743180599*Pile Depth
+ 20.0768144662322*Pile Shaft Area
+ 20719.2449341038*Pile Base Area
- 1123.37776845147*Pile Shape
+ 60.4988187721365*Average Shaft SPT-N ($N_{av}$)
+ 4.70421602126417*Base SPT-N ($N_b$)
- 732.904175636292*Soil Along Pile Shaft
- 209.510814409674*Soil At Pile Base (8)

Where;
Pile Shape – Square = 1
Pile Shape – Circular = 2
Soil Along Pile Shaft – Sand = 1
Soil Along Pile Shaft – Silt = 2
Soil Along Pile Shaft – Clay = 3
Soil at Pile Base – Sand = 1
Soil at Pile Base – Silt = 2
Soil at Pile Base – Clay = 3

### 3.5 Comparison Between Empirical Method, Machine Learning Model and Statistical Model for Pile Axial Geotechnical Capacity

The fifth objective is to compare results between empirical method, machine learning models and statistical model. Table 12 shows the testing set performance metrics of each empirical, machine learning and statistical model.

**Table 11**: Performance Metrics of Empirical Method, Machine Learning Model and Statistical Model for Pile Axial Geotechnical Capacity

| Performance Metrics | Modified Meyerhof | SVM | KNN | DT | RF | ANCOVA |
|---|---|---|---|---|---|---|
| MAE | 1031.309 | 183.976 | 219.599 | 181.957 | 172.887 | 182.748 |
| MSE | 1651282.733 | 55824.957 | 103575.971 | 52508.261 | 48203.432 | 62389.249 |
| $R^2$ | -0.293 | 0.956 | 0.919 | 0.959 | 0.962 | 0.951 |
| MAPE | 72.49% | 15.88% | 18.27% | 15.31% | 14.61% | 15.65% |

From Table 11, Random Forest is the best model to predict geotechnical pile axial capacity compare to other models as it explains 96.2% of the variability of pile capacity, followed by Support Vector Machine, Decision Trees, ANCOVA, K-Nearest Neighbours and empirical Modified Meyerhof method. Negative R2 value of Modified Meyerhof indicates that the underestimation of pile capacity compares to actual pile capacity obtained from field.

Figure 8 shows the graph of Actual Total Resistance vs Predicted Total Resistance for empirical method (modified Meyerhof).

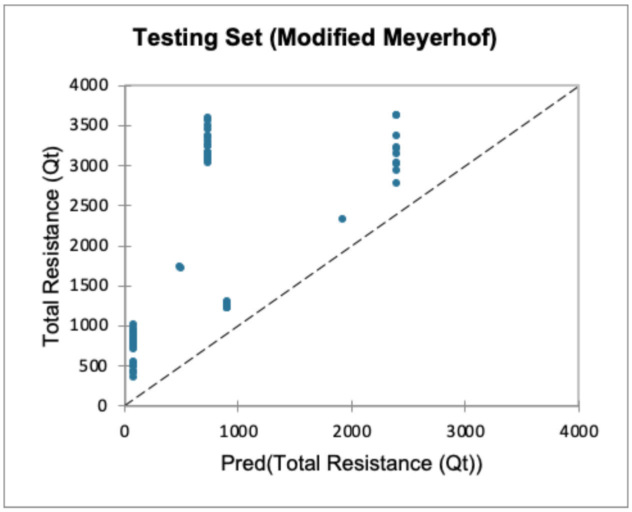


**Figure 8:** Actual Total Resistance vs Predicted Total Resistance for empirical method (modified Meyerhof)

## 4.0 CONCLUSION

Total of six projects at Batu Kawan and Nibong Tebal located in Penang state contributed 439 numbers of data to this study. The data are chosen based on location of similar geological formation, mainly consists of unconsolidated alluvial deposits. The calculated pile capacity / actual pile capacity had a wide scatter range of 5.76% to 94.96%. All 439 numbers of pile tested actual capacity is more than capacity calculated via empirical method. This shows that empirical method predicts pile capacity conservatively with wide range of values. These findings signify the importance to reduce gaps in pile capacity prediction via calibration of empirical design value, machine learning and statistical models. For machine learning, prediction shall be generated based on best fit model.

$K_s$ and $K_b$ were back calculated from dynamic pile load test results and further calibrated. Generally, there is no changes suggested for design value of skin friction factor, with $K_s$ of 2.5 and 2 for silt and sand respectively as they are quite consistent with findings of Meyerhof (1976), Gue (2007) and Tan et al. (2009). However, it is worth to mention that most of the previous findings proposed Ks value of 2.5 for skin friction factor of clay. Whereas the end bearing factor $K_b$ for sand, silt and clay, the results attest to corroborate with Decourt (1995), Gue (2007) and Tan et al. (2009) with downgraded value of 250, 200 and 100 respectively.

Though $K_s$ and $K_b$ value have been calibrated as shown in above table, it only makes the pile capacity prediction more conservative and challenging as the current Modified Meyerhof empirical method predicted a scatter wide range of pile capacity compare to load test result, i.e. from 5.76% to 94.96%. Neither downgrade nor upgrade of skin friction factor and end bearing factor will help in minimise the wide gap of predicted pile capacity because empirical method (SPT-N based) over simplifies the science and theory of pile design.

Next, the data is partitioned into 80% (351 numbers) for training and validation while 20% (88 numbers) for testing. Four machine learning models, i,e, Support Vector Machine, K-Nearest neighbours, Decision Trees and Random Forest are chosen.

From statistical modelling, SPT-N at pile base brings the least information to the model while Pile Base Area, Pile Shape, Average Shaft SPT-N ($N_{av}$), Soil Along Pile Shaft and Soil at Pile Base bring significant implication to pile capacity.

From the comparison of testing set performance metrics of each empirical, machine learning and statistical models, Random Forest machine learning method is the best model to predict geotechnical pile axial capacity. Random Forest explains 96.2% of the variability of pile capacity, followed by Support Vector Machine, Decision Trees, ANCOVA, K-Nearest Neighbours and empirical Modified Meyerhof method. Negative R2 value of Modified Meyerhof indicates that the underestimation of pile capacity compares to actual pile capacity obtained from field. Most of the machine learning model predicts better than statistical method except K-Nearest Neighbours. Empirical method performs poorest amongst all pile capacity prediction models.

Machine learning model possess advantages compare to empirical method. Machine learning model is capable of solving non-linear problem, in the other hand, empirical method usually formulates and solves problem in linear relationship. Furthermore, machine learning model also display pros over analytical and theoretical method. Though analytical and theoretical method is able to define non-linear relationship between pile capacity and variable parameters, the soil and its properties remain vastly heterogenous at field. Analytical and theoretical method might be able to predict pile capacity accurately based on parameters that are well defined and tested properly in laboratory. However, it would be almost impossible to identify the complete range of soil properties over a site especially when the project is in big scale. There is possibility of different actual pile capacity though given similar pile penetration depth, SPT-N, pile size and pile shape due to heterogenous soil properties within a project site. Machine learning method can assist to predict pile capacity based on locality.

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