RESEARCH ON DETERMINING THE PILES BEARING CAPACITY USING A RANDOM FOREST MODEL CONSIDERING THE RANDOMNESS OF THE SOIL DATA

NGHIÊN CỨU XÁC ĐỊNH SỨC CHỊU TẢI CỦA CỌC BẰNG MÔ HÌNH RỪNG NGẪU NHIÊN CÓ XÉT ĐẾN TÍNH NGẪU NHIÊN CỦA SỐ LIỆU ĐẤT NỀN

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Abstract: *Bearing capacity is one of the most important parameters when designing piles. However, determining the exact bearing capacity of piles is a difficult job due to the influence of many parameters. The traditional methods of calculating the axial load capacity of piles all use a predefined problem, that is, determining only a single load capacity value, which is not entirely consistent with the actual working of the piles, where the input parameters affecting the bearing capacity of the piles are random. In this study, an advanced machine learning model based on artificial intelligence, the Random Forest, was developed and applied to predict the bearing capacity of piles. This model is used as a predefined model applied in the Monte-Carlo simulation method to determine the reliability of the pile-bearing capacity. The results show that the Random Forest model very well predicts the bearing capacity of piles on both training and testing data. In addition, the Monte-Carlo simulation results with random soil data show that there is still the possibility of unsafe pile operation even when the pile top load is lower than the expected average bearing capacity of the pile. Furthermore, the maximum load to the top of the pile should not exceed 99.2% of the mean load value, to achieve a high probability of safe working, on this data set.*

Keywords: *Axial bearing capacity of piles, machine learning, random forest, reliability, Monte Carlo simulation.*

Tóm tắt: *Sức chịu tải là một trong những tham số quan trọng nhất khi thiết kế cọc. Việc xác định chính xác giá trị sức chịu tải cọc trong quá trình thiết kế giúp giảm nhiều chi phí và công sức. Tuy vậy, việc xác định đúng sức chịu tải của cọc là một việc khó khăn do bị ảnh hưởng bởi rất nhiều tham số. Các phương pháp tính toán sức chịu tải dọc trục của cọc hiện nay đều sử dụng bài toán tiền định, tức là chỉ xác định một giá trị sức chịu tải duy nhất, điều đó chưa hoàn toàn phù hợp với sự làm việc thực tế của cọc, khi mà các tham số ảnh hưởng đến sức chịu tải cọc đều mang tính ngẫu nhiên.Trong nghiên cứu này, mô hình máy học tiên tiến là rừng ngẫu nhiên được phát triển và ứng dụng để dự đoán sức chịu tải của cọc. Mô hình này được sử dụng như là mô hình tiền định ứng dụng trong phương pháp mô phỏng Monte-Carlo để từ đó xác định được độ tin cậy của sức chịu tải cọc. Các số liệu tính toán được lấy từ kết quả thí nghiệm nén tĩnh cọc tại Việt Nam. Các thông số đầu vào về đất nền và cọc được đo đạc tại hiện trường và mang tính ngẫu nhiên, phân tán. Việc dự đoán sức chịu tải có xét đến độ tin cậy đang trở thành một xu hướng nghiên cứu nhằm phản ánh sát thực hơn sự làm việc của kết cấu móng và giải quyết các vấn đề trong kỹ thuật xây dựng.*

Từ khóa: *Sức chịu tải dọc trục của cọc, máy học, rừng ngẫu nhiên, độ tin cậy.*

1. Introduction

A pile foundation is a type of structure that is widely used as a support structure in civil works, bridges and roads, irrigation and specially used in high-rise buildings. Pile foundation has the advantage of large load capacity, and diverse construction methods (boring, driving, and static jacking). Piles are usually designed to work in compression and the maximum compressive force the pile can withstand without failure is called the ultimate pile load capacity. In favor of safety, the ultimate bearing capacity of the pile is usually taken by the destructive compressive force according to the ground soil, but not according to the pile material. During the working process, the bearing capacity of the pile depends on two components, which are lateral friction and the pile's tipping force in the extreme state.

To determine the bearing capacity of piles, field test methods are considered to have higher reliability, some of which can be mentioned as follows: (1) Field static compression method [1]; (2) method of dynamic load test PDA [2]; self-balancing method using load box Osterberg [3], [4]. The methods give reliable results but have the disadvantage of being time-consuming and expensive, making it impossible to mass-produce on a large number of piles. Therefore, several methods have been proposed to calculate the bearing capacity of piles, using semi-empirical formulas. These methods are built from empirical formulas, mainly based on the geometrical parameters of the piles and geological parameters obtained from the results of the SPT (Standard Penetration Test), and CPT test (Cone Penetration Test) [5]–[7]. With the development of the finite element method, many authors have calculated the bearing capacity of piles and soil simulating the working of piles-soil and approximating it by software such as Abacus, Plaxis, and Ansys [8], [9]. However, these methods have the disadvantage that the model is relatively sensitive to the input parameters and the calculation results still need to be adjusted relative to converge with the pile load test results. In addition, the parameters affecting the pile bearing capacity, especially the parameters of the foundation, are random and distributed [10], [11]. For example, the SPT and CPT values of the soil are not constant but change continuously within a soil layer, or the thickness of the soil layer at different locations is not the same. That has not been considered much in previous studies, leading to the results of the calculation of the pile-bearing capacity are still subjective and not general. Also, from a random point of view, the pile still has some probability of failure. Therefore, considering the working reliability of piles is of great practical significance.

In recent years, along with the development of the 4th industrial revolution, machine learning models based on large databases have achieved great success [12]–[16]. In many cases, machine learning models give more impressive results and are much closer to experimental results than traditional models [17]. Therefore, the application and development of advanced machine learning models in the pile-bearing capacity problem is a scientific and practical issue. However, Machine Learning models are all based on a set of random parameters. Some studies have mentioned the influence of these random parameters on the stability of the model. For example, Some works of literature [18]–[20] take into account the effect of random data division on the stability of machine learning models. Pham and Tran (2022) [13] consider the effect of random initialization of weights on the results of pile-bearing capacity analysis, by a random forest model optimized with a genetic algorithm. Pham et al (2021) [16], Menz et al (2020) [21]used the Monte-Carlo simulation method to evaluate the importance of the input variables to the model accuracy.

The research on the application of machine learning in solving the pile foundation problem mentioned above only stops at predefining the model or assessing the influence of the randomness of the model's parameters on the stability of the model. Furthermore, studies have not clarified the effect of the randomness of soil data, a very important input parameter for pile load capacity analysis. In essence, the characteristics of the soil around the piles are not the same, even large changes are in the same soil layer [22], [23]. Therefore, the stability assessment when determining the bearing capacity of piles with random soil data should be considered specifically.

In this study, a method of calculating the pile-bearing capacity of piles is presented by combining a machine learning model named Random Forest and a Monte Carlo simulation method for evaluation. The initial research results show that the model can estimate relatively accurately the pile-bearing capacity and determine the dispersion of the load capacity parameter when the ground soil parameter is random, thereby calculating the reliability of the pile-bearing capacity.

2. Research methods

2.1 Random Forest model

2.1.1 Decision Tree model

The decision tree model is a supervised learning model that can be applied to both classification and regression problems. This model is the basis of several more advanced machine learning models, for example, Random Forests, gradient-enhanced trees, etc.

In the decision tree model, the architecture of the decision tree model can be thought of as a sequence of *if_then_else* functions, depending on the input data set, the complexity of the tree, and the depth of the if the function is calculated and optimized. In addition, each internal node corresponds to an input variable (*e.g* x_1, x_2, x_3, *etc.*); the line connecting it and its children represent a specific value for that variable. Each leaf node represents the predicted output of the model (*e.g* R_1, R_2, R_3, *etc.*), given the values of the variables represented by the path from the root node to that leaf node.

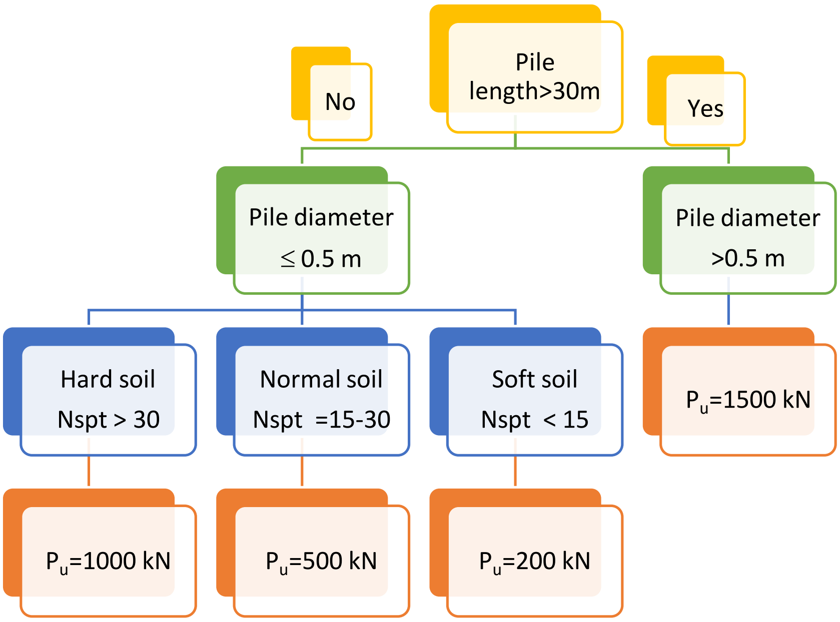

Figure 1. *A typical decision tree model used in pile load forecasting*

The machine learning technique used in decision trees is known as decision tree learning, or simply called a decision tree for short. A typical regression decision tree model is presented above. Decision tree models are widely used in practice because of their fast training and prediction speed. The training of a decision tree is to determine the hierarchies of nodes, branches and leaves on the tree. Since only logical conditional functions (if_then) are used, no arithmetic computation is required, so decision trees have the advantage of fast mining and prediction speed. However, this model often suffers from overfitting, when the nodes of the model cover the training data set, it will have low performance when used to predict the test set or the new model data. That spurs the development of more advanced models based on decision trees, random forest models, gradient enhancement trees being one of them. Another disadvantage of the decision tree model is that it only allows predictions in the range [min; max] of the learning data and will give false results when the input variables are out of range of that learning data

2.2.2 Random Forest - RF

Random Forest (RF) is a Machine learning model based on a decision tree, which can be used flexibly and easily for both classification and regression. RF model is also a type of ensemble model, in which, the decision tree is considered a member model of this ensemble model. In essence, RF creates a decision tree on randomly selected data samples, called a random sample encapsulation process (Bootstrap technique). This randomization process will: (1) Generate a random dataset based on the original data set; (2) Generate several trees with random parameters to learn those datasets. This technique will help the RF model avoid overfitting problems from the decision tree model.

Predictions from each tree are generated and the best solution is selected by polling (with classification) or averaging (with regression). If in a single decision tree algorithm, when building a decision tree to an arbitrary depth, the tree will correctly classify all the data in the training set, leading to a poor prediction model on the test dataset. control, then the model is overfitting (the model is overfitting when it predicts well on the training data, but poorly on the test data). Meanwhile, the Random Forest algorithm consists of many decision trees, each of which has random elements of sampling. Because each decision tree does not use all the training data, as well as the attributes of the data to build the tree, each tree can make bad predictions, then each decision tree model is not overfitting but can be underfitting (the model has high bias). However, the final result of the Random Forest algorithm is aggregated from many decision trees, so the information from the trees will complement each other, leading to the model having "low bias" and "low variance", or The model having good predictive results.

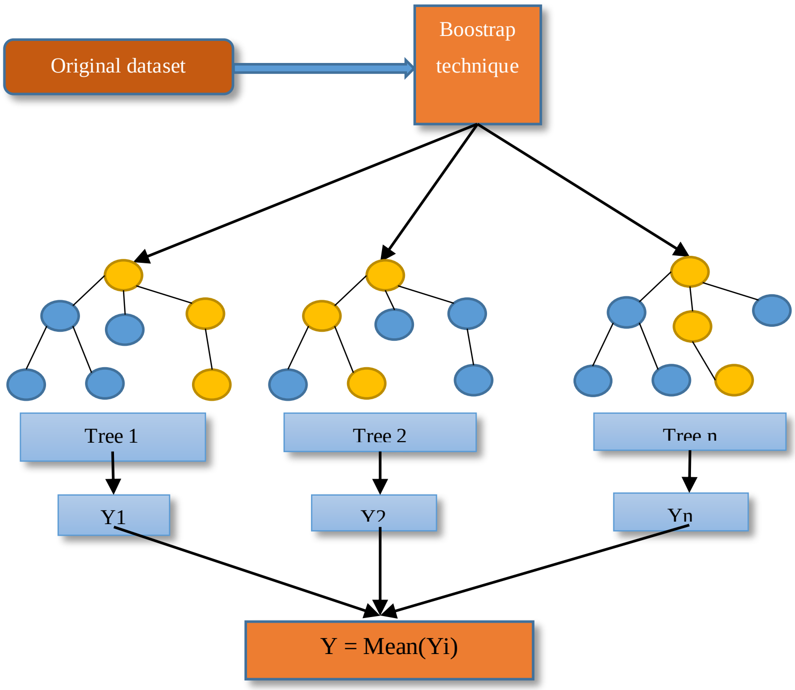

Figure 2. *Random Forest model*

The general formula of the model is written in the following form:

$$F(x) = \sum_{i=1}^{M} \gamma_i(x) \qquad (1)$$

Where F(x) is the predicted value of the output model, $\gamma_i(x)$ is the i^{th} decision tree and M is the total number of trees.

Because the decision trees are built independently, the training process can be carried out in parallel, so the random forest model is one of the combinatorial models that need the shortest training time due to the use of computer's multithreading.

2.2 Data used

In problems using machine learning models, the training data is considered the most important parameter. Usage data needs to be collected and processed to eliminate unusual variables. Existing studies on the determination of pile load capacity often suggest including the parameters of the geometric dimensions of the pile as well as the soil parameters to be included in the calculation. Meyerhof (1963) [5], Shioi (1982)[6], and Decourt (1995)[24] propose to use parameters related to the geometric dimensions of the pile and the average SPT indexes along the pile body and at the pile tip to calculate the pile bearing capacity. The soil SPT index is one of the most popular tests, so soil properties are characterized through SPT results. In this study, the average SPT value along the pile body and pile tip is taken as the main parameter to determine the bearing capacity of the pile. In addition, the parameters of the pile shape, size, and thickness of the soil layers were also collected and statistically evaluated to evaluate the bearing capacity of the pile.

Therefore, this study proposes the parameters of geological conditions, size, shape, and size of piles [25]. Specifically, the data were collected from a published study [13], in which pile tests were conducted in a neighborhood to evaluate the effect of the randomness of soil data on the bearing capacity of piles. The input parameters include (i) the Diameter of the pile (Y_1); (ii) the Thickness of soil layer 2 (Y_2); (iii) the Thickness of soil layer 4 (Y_3); (iv) the Thickness of soil layer 4(Y_4); (v) pile top elevation (Y_5); (vi) natural ground elevation (Y_6); (vii) driving stop height of guide pile section (Y_7); (viii) pile tip height (Y_8); (ix) average SPT value along the pile body length (Y_9) and (x) average SPT value at pile tip (Y_{10}). Diagrams of parameters are shown in Figure 3. These parameters are random statistics in Table 1. The bearing capacity of the pile is the output parameter (Pu).

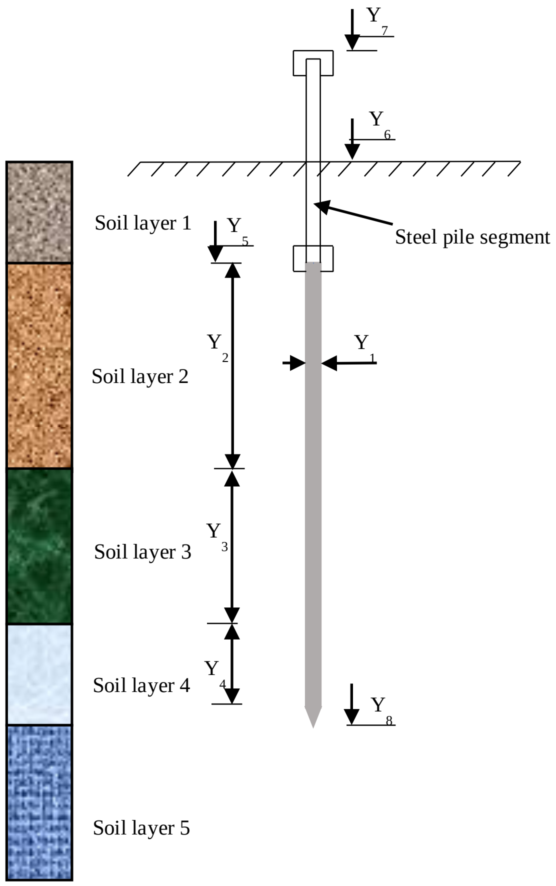

Figure 3. *Diagram of pile parameters [13]*

The dataset is divided into 2 sets of training and testing data. The number of training samples is 80% and the test sample is 20% of the total. The training random statistics must be large enough to ensure the efficiency and reliability of the model. The training data consisting of 10 input parameters and 1 output parameter is normalized to ensure that the variables have the same influence. To ensure that the input parameters have the same significance and importance for the random forest model in determining the pile bearing capacity, the input data are normalized in the interval [0,1], The normalized formula for the value of X_i is written as follows:

$$X_i^{norm} = \frac{X_{max} - X_i}{X_{max} - X_{min}} \quad (2)$$

Where X_i^{norm} is the normalized value of X_i; X_{max}, X_{min} are the maximum and minimum values of the variable X.

Table 1. *Inputs and output of the present study*

No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Pu
Unit	m	m	m	m	m	m	m	m	-	-	MN
1	0.40	4.35	8.00	1.00	2.05	3.48	2.08	15.40	13.35	7.50	1.40
2	0.30	3.40	5.25	0.00	3.40	3.47	3.42	12.05	8.65	6.75	0.56
3	0.30	3.40	5.30	0.00	3.40	3.52	3.42	12.10	8.70	6.76	0.51
4	0.40	4.25	8.00	0.90	2.15	3.56	2.26	15.30	13.15	7.61	1.40

5	0.40	3.40	7.30	0.00	3.40	3.49	3.39	14.10	10.70	7.28	1.07
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
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471	0.30	3.40	5.26	0.00	3.40	3.49	3.43	12.06	8.66	6.75	0.51
472	0.40	3.85	7.60	0.00	2.95	3.67	3.27	14.40	11.45	7.15	1.43
Min	0.30	3.40	1.50	0.00	0.68	3.04	1.03	8.30	5.60	4.38	0.41
Max	0.30	3.40	1.50	0.00	0.68	3.04	1.03	8.30	5.60	4.38	1.551
Average	0.36	3.83	6.58	0.33	2.80	3.50	2.92	13.54	10.74	7.06	0.98
SD*	0.00	0.35	0.28	0.71	0.64	0.13	0.84	0.71	1.34	0.25	0.02

* Standard deviation

2.3 Performance evaluation

In this study, three statistical criteria, namely the correlation coefficient (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are used to evaluate the performance of models [26]. In which, the correlation between the actual value and the predicted value is expressed by R^2. Conversely, a higher R^2 value means better model performance. The R^2 value varies between -∞ and 1, and the closer R^2 is to 1, the more accurate the model is. A value of R^2 less than 0 represents a negative correlation between the forecast results and the actual results of the data. RMSE and MAE are used to evaluate the error between the actual value and the predicted value. Specifically, the criteria related to the mean error such as RMSE, and the lower the MAE, the higher the accuracy of the model and the better the performance of the model.

The formula to determine R^2, RMSE, and MAE is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{k}\sum_{i=1}^{k}\left(y_i - \overline{y}_i\right)^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{k}\left(y_i - \overline{y}_i\right)^2}{\sum_{i=1}^{k}\left(y_i - \overline{y}\right)^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{k}\sum_{i=1}^{k}\left|y_i - \overline{y}_i\right| \tag{5}$$

Where: k is the number of tuples, y_i and $\overline{y}_i$ is the actual data measured and the data predicted by the model; $\overline{y}$ is the mean value of y_i .

2.4 Reliability analysis

To calculate the reliability of the works, these include: collecting data about the work, statistical analysis, generating random variables, setting up the confidence function, analyzing the relationship between the works in the system, reliability of the works, and the reliability of the system of works [27], [28]. Depending on the complexity, the calculation requirements, the importance level, and the ability to provide observation data and design data about the building to be able to solve the problem of calculating the reliability of the work and construction system at different levels. When considering the geometrical parameters of the pile and the soil parameters as random quantities, the value of the bearing capacity of the piles and the pile group is also a random quantity. Therefore, this study selects the parameters related to the geometrical dimensions of the pile and the characteristic parameters for the ground soil to use in the simulation problem to determine the reliability of the pile-bearing capacity.

The iterative calculation is performed on the analytical model of the pile, based on the statistical characteristics and the distribution rules of input parameters using Monte-Carlo simulation [27], [29]. The basic idea behind the Monte Carlo method is to use random sampling to obtain numerical solutions to problems that are too difficult or impossible to solve analytically. The method involves generating a large number of random samples or simulations of a system or process and analyzing the results to obtain estimates of the system's behavior. Therefore, with each iteration of the Monte-Carlo simulation progress, random values of the input variables are generated according to the distribution law and within the allowed range. Based on the obtained data set, the statistical characteristics of the results as follows:

$$\overline{S} = \frac{1}{M}.\sum_{i=1}^{M} S_i \tag{6}$$

$$\sigma_x = \sqrt{\frac{1}{M-1}\left[\sum_{i=1}^{M} S_i^2 - \frac{1}{M}\left(\sum_{i=1}^{M} S_i\right)^2\right]} \tag{7}$$

Where, M – is the number of iterations (number of input trials); $\overline{S}$ – is the mathematical expectation of S; σ_x – is the standard deviation of S; S_i – is the value of S obtained in the calculation with the i^{th} solution of the input data.

The reliability of the value of internal force S is determined by the formula:

$$P = \Phi\left(\frac{S_{tk} - S}{\sigma_x}\right) \tag{8}$$

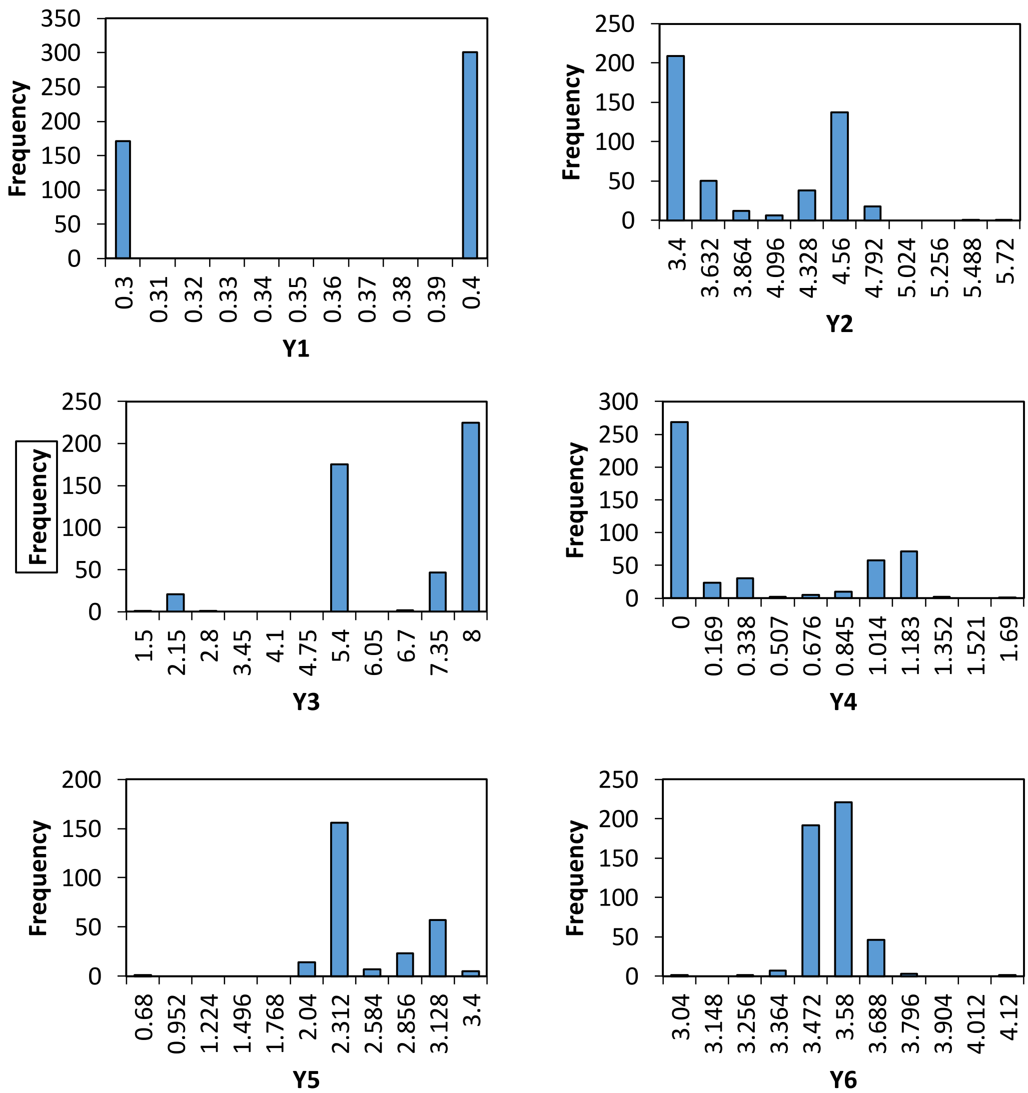
Where: $\Phi(x)$ – In this study, it is assumed that the pile-bearing capacity follows the normal distribution, so $\Phi(x)$ is a normal distribution function; S_{tk} – is the design value of S.

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{z^2}{2}} dz \tag{9}$$

3. Results and Discussion

3.1 Input data

Before analysis, input data needs to be analyzed and processed. The distribution of the data is shown in Figure 4. The distribution characteristics of the input parameters include the geometrical dimensions of the pile, the soil characteristics determined according to the normal distribution, and the calculation of the parameters. the number of standard deviations. It can be seen that the data variables are distributed in a relatively wide and general range, while the parameter of pile diameter (Y_1) shows that the amount of pile D400 seems to be larger than that of pile D300, although So the number of piles in each group is also large enough to serve the training of the model. The bearing capacity of piles D300 and D400 can be approximated according to the Gauss distribution.



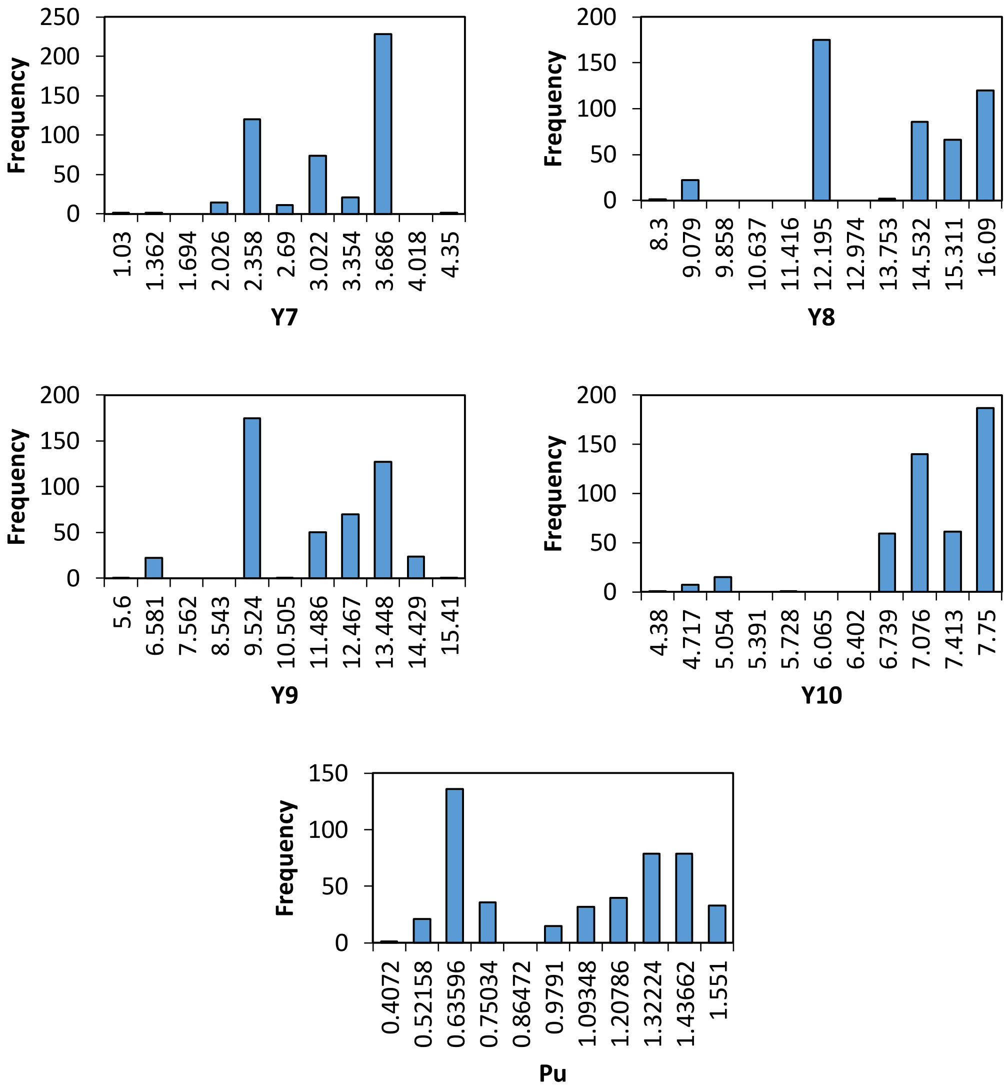


Figure 4. *Histogram of all input and output variables*

In addition, the correlation of the variables is shown Table 2. It can be seen that most of the variables have a small correlation with each other (below 0.8), showing that the variables have a linearly independent relationship. Some variables have a greater correlation (above 0.8) showing that they have a linear dependent relationship, this study temporarily does not consider that issue but will continue to be interested in future studies. The formula for calculating the correlation coefficient between variables is written as follows:

$$r_{x,y} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{X})(y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{X})^2 \sum_{i=1}^{n}(y_i - \overline{Y})^2}}} \quad (10)$$

where: $\overline{X}, \overline{Y}$ - are the average values of the two variables x, y; n - is the number of samples of the variable x, y;

The correlation coefficient is in the range [0,1], The closer this coefficient is to zero, it means that the variables have a linearly self-sufficient relationship and vice versa is linearly self-sufficient.

Table 2. *Correlation matrix of input and output variables*

	Y1	*Y2*	*Y3*	*Y4*	*Y5*	*Y6*	*Y7*	*Y8*	*Y9*	*Y10*	*Pu*
Y1	1.00										
Y2	0.67	1.00									
Y3	0.62	0.45	1.00								
Y4	0.55	0.74	0.63	1.00				**sym**			

Y5	-0.73	-0.96	-0.59	-0.85	1.00						
Y6	0.31	0.20	0.31	0.14	-0.20	1.00					
Y7	-0.63	-0.79	-0.51	-0.91	0.87	-0.08	1.00				
Y8	0.63	0.53	0.99	0.74	-0.67	0.30	-0.61	1.00			
Y9	0.70	0.69	0.95	0.81	-0.81	0.30	-0.73	0.98	1.00		
Y10	0.36	0.23	0.93	0.62	-0.41	0.23	-0.42	0.93	0.84	1.00	
Pu	0.84	0.68	0.85	0.61	-0.76	0.34	-0.59	0.85	0.88	0.66	1.00

3.2 Results model of training

In this study, the Random Forest model is built and trained based on the Sklearn library in the Python programming language platform [30]. The model is put into development against the training dataset and then retested against the test dataset with default model hyper-parameters. The results of training and testing the model are shown in Figure 5 và Table 3. It can be seen that the predictive capacity of the model is perfect when the correlation coefficient R^2 is above 0.95 for both training and testing datasets. In addition, the error criteria such as RMSE and MAE on both data sets are small and the difference is not much, showing that the model has high generalizability and avoids overfitting. This is further confirmed by the model's error chart on the train and test sets in Figure 6, where the errors are mostly in the range[-4%, 6%].

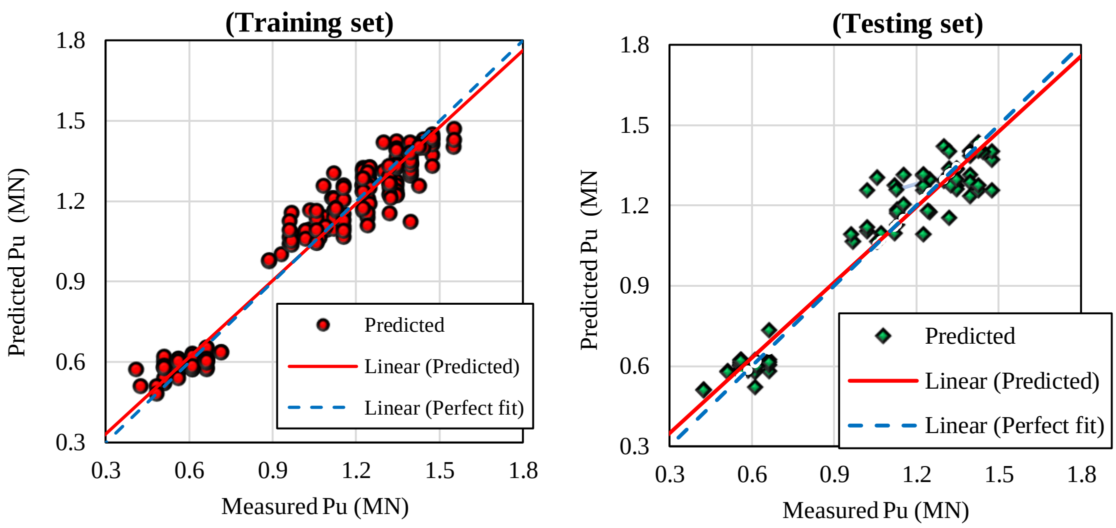


Figure 5. *The regresion chart predicts the bearing capacity of piles*

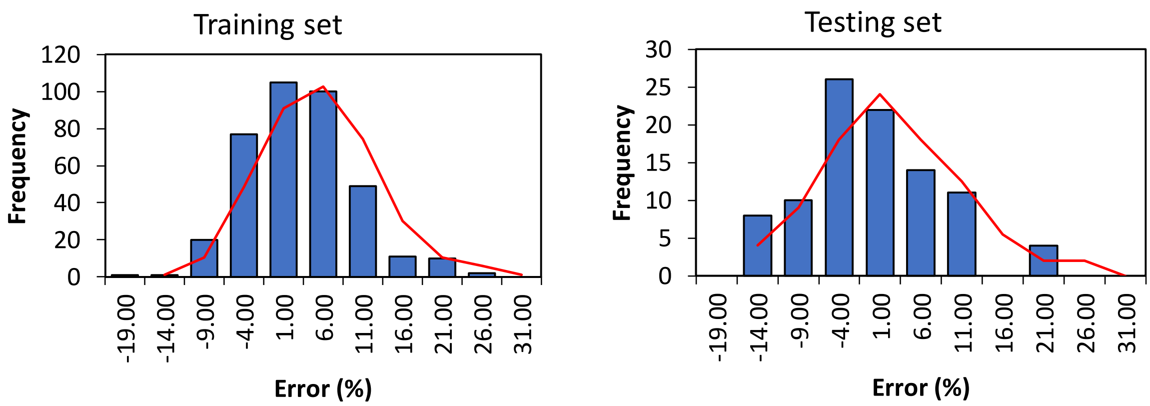


Figure 6. *Histogram of errors on the Training set and Testing set*

Table 3. *Calculation results of the pile-bearing capacity of the model*

Training set			Testing set		
R^2	RMSE (MN)	MAE (MN)	R^2	RMSE (MN)	MAE (MN)
0.967	0.055	0.045	0.950	0.073	0.056

3.3 Calculation of reliability of pile-bearing capacity

As analyzed above, the calculation of pile load capacity based only on fixed parameters of pile shape, size, and foundation parameters is not completely consistent with reality. On the construction site, the parameters related to the soil thickness are not the same at all locations, in addition, even within a soil layer, the SPT value fluctuates within a certain range. Therefore, when calculating the pile bearing capacity, random parameters of the ground soil will make the pile load capacity not completely constant but will change in a certain range. That would make the design of piles less secure and although this is partly addressed through reliability coefficients, detailed analysis of the probability of safety or danger in a particular area is also something to consider carefully. Therefore, in this section, it is proposed to use the Monte Carlo simulation method to calculate the pile-bearing capacity, considering the randomness of the soil data. The soil parameters selected for use in the simulation are shown in Table 4. A note is that in each simulation iteration, the values of the input variables are generated according to the normal distribution to be included in the calculation of the pile-bearing capacity.

Table 4. *Calculation results of the pile-bearing capacity of the model RF*

Input parameter	Mean value	Standard Deviation (SD)	Percentage of (SD/Mean) (%)
Y_2	3.83	0.482	13
Y_3	6.58	1.638	25
Y_5	2.80	0.616	22
Y_6	3.50	0.080	2
Y_7	2.92	0.599	21
Y_8	13.54	1.798	13
Y_9	10.74	2.264	21
Y_{10}	7.06	0.660	9

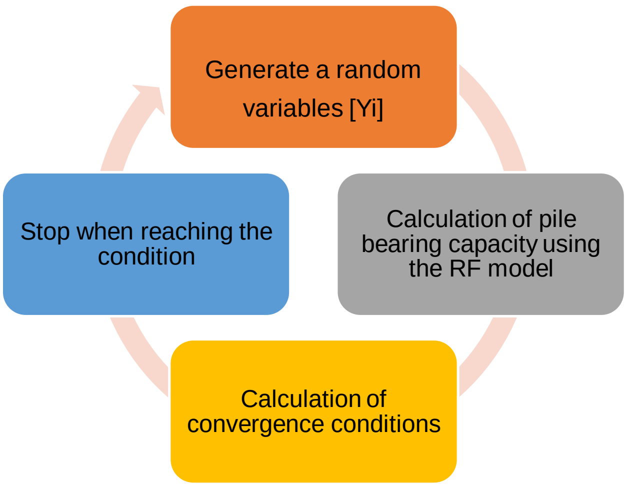


Figure 7. *Cycle diagram of simulation*

In this study, because the data set has 2 types of piles D300, and D400 because each type of pile has only a different reliability, the simulation needs to be conducted separately for each type. In this study, type D400 was selected for simulation. The number of simulation iterations is determined according to the convergence condition. When the convergence criterion function is almost unchanged after a certain number of simulation iterations, the simulation problem can be considered to be stable and stop the iteration. The convergence condition is defined as:

$$f_{MC} = \frac{1}{\overline{G}}\frac{1}{n}\sum_{i=1}^{n} G_i \rightarrow 1 \qquad (11)$$

Where: $\overline{G}$ - is the expected value of pile load capacity; n - is the number of simulations.

The results of the Monte-Carlo simulation to calculate the pile load capacity are shown in Figure 8. It can be seen that after about 300 iterations, the simulation converged.

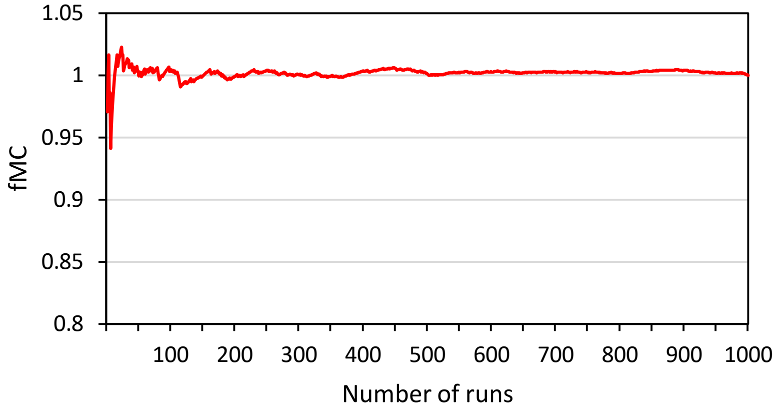


Figure 8. *Statistical convergence analysis*

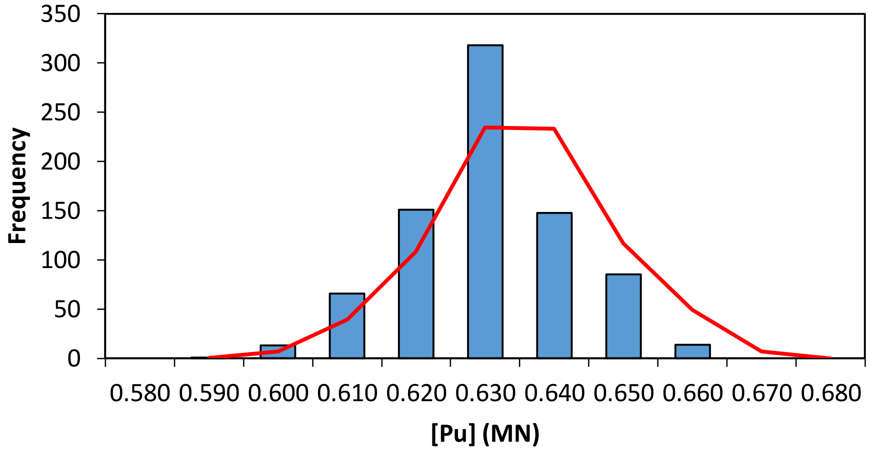


Figure 9. *Histogram of piles bearing capacity from Monte-Carlo simulation*

Figure 9 shows the pile design load distribution chart, with the safety factor F_S=2, the analysis shows that the mean expected value of the pile-bearing capacity is $\overline{Pu} = 0.63(MN)$ with standard deviation $\sigma = 0.069$.

To make sure a reliability level of at least X%, the load on the top of the pile should not exceed P_{max}, where P_{max} is determined such that:

$$P = \Phi\left\{\frac{\overline{Pu} - P_{max}}{\sigma}\right\} \geq 0.01X \quad (12)$$

Therefore, an investigation of some typical reliability is conducted and the results are shown in Figure 10.

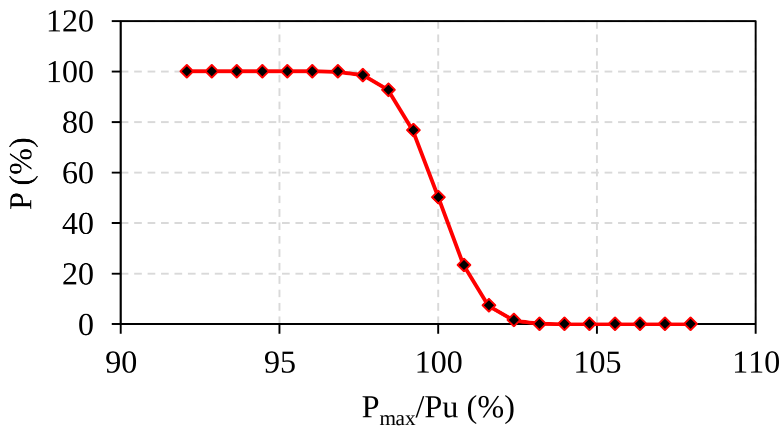


Figure 10. *Probability of safe working of piles according to P_{max}*

It can be seen that, if P_{max} lower than 98.5% of $\overline{Pu}$, the probability of safe working of piles is almost maximally above 92%, and when the pile top load is greater than 101.6% of $\overline{Pu}$, the remaining stop reliability is determined to be less than 7.36%. The probability of safe working threshold of the pile is P_{max} less than 99.2% of $\overline{Pu}$, then the safe working probability of the pile reaches at least 76.5%.

4. Conclusion

The study shows that the machine learning-based random forest model is a great tool for predicting pile-bearing capacity. The accuracy of the model on both the existing training and test data is excellent, demonstrating that the model is highly generalizable to the data.

The use of a Random Forest model to calculate the working reliability of the piles considering the randomness of the soil data shows that the pile still has a certain probability of failure, even when the pile top load does not exceed the mean value of the pile load capacity. To achieve high pile working reliability [76.5÷100]%, the maximum load to the top of the pile should be less than 99.2% of the mean pile-bearing capacity.

The method of calculating the bearing capacity of piles using the random forest model can be considered reliable. This model can be used in calculating the reliability of piles, thereby evaluating pile performance more objectively when considering the randomness of the input parameters.

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