Prediction of the uplift capacity of helical piles using machine learning

Previsão da capacidade de carga à tração de fundações por estacas helicoidais usando aprendizagem de máquina

Caio C. S. Oliveira[1], Cristina H. C. Tsuha[1] and José A. Schiavon[2]

[1]Dept. of Geotechnical Engineering, University of São Paulo at São Carlos School of Engineering, Brazil, caio.cesar.oliveira@usp.br and chctsuha@sc.usp.br

[2]Aeronautics Institute of Technology, Civil Engineering Division, 50 Marechal Eduardo Gomes Sq., São José dos Campos, SP, 12228-900, Brazil, schiavon@ita.br

ABSTRACT: Helical piles have been widely used as foundations for guyed towers in power transmission lines in Brazil to resist tensile loads. However, in the Brazilian context, predictions are based on the torque method that often do not provide accurate predictions for the small diameter multi-helix piles commonly used in that country. At the same time, tensile load capacity prediction methods based on the Standard Penetration Test (SPT) and Cone Penetration Test (CPT) are rare in the literature and also present predictions with considerable variability. Given the need for more accurate methods for helical piles design, this paper evaluates the application of Artificial Intelligence through Machine Learning methods for predicting tensile load-displacement curves and load capacity. In this study, a database was composed of 33 tensile load tests conducted at different sites in Brazil, including SPT tests results, installation torque and pile geometry was evaluated. Three ML methods were applied: Cubist, Random Forest and Stochastic Gradient Boosting Machine. Additionally, the performance of the best method was compared with an analytical method based on the SPT data.

KEYWORDS: Helical Piles, load capacity prediction, machine learning, artificial intelligence, SPT.

1 INTRODUCTION

For pile foundations, Terzaghi (1943) proposed a theoretical solution for predicting load capacity, and Meyerhof (1951) also developed a theoretical calculation based on plasticity theory. Seeking a better fit for predictions for conventional piles, Meyerhof (1956) suggested a semi-empirical approach based on the Standard Penetration Test (SPT), where the pile load capacity is related to the number of blows/300mm obtained in the test.

In this context, several semi-empirical correlations have been developed over the years based on *in situ* tests. In the Brazilian scenario, numerous SPT-based methods have been calibrated through back-analyses of load tests and are extensively employed for predicting pile load capacity. However, in the case of helical piles (or anchors when submitted to tensile loads), equations for uplift capacity prediction based on the SPT data are rare in the literature. Tsuha et al. (2024), utilizing a database of helical piles installed in Brazil, examined the methods proposed by Kanai (2007) and Perko (2009), both based on SPT data. The authors concluded that these methods yield unreliable predictions and exhibit high variability in Brazilian soils, highlighting the necessity of a new SPT-based method for helical piles in these soils.

On the other hand, with the advancement of technology and the dissemination of Artificial Intelligence (AI), a new horizon of analysis opens up to improve the accuracy of predictions of geotechnical variables through Machine Learning (ML) algorithms. In this sense, predictions based on the observation of historical data from different variables (or features) combinations related to the problem have become increasingly attractive.

The purpose of this study is to evaluate the capability of Machine Learning methods to predict the load-displacement curves of the load tests on the helical piles of the database and to compare the measured values of uplift capacity with the predicted values obtained by the SPT method proposed in Perko (2009). The tests used in the current paper are part of the database published by Tsuha et al. (2024).

This study was conducted using a relatively small database, consisting of 33 tension load tests on 4-helix helical piles carried out at 20 sites in Brazil. Despite the limited size of the database, the approach presented in this paper represents an initial point towards the use of ML techniques in predicting the load-displacement curves of helical piles.

For this purpose, 28 load tests were subjected to three supervised ML methods for load-displacement curve prediction, namely: Cubist, Random Forest (RF), and Stochastic Gradient Boosting Machine (SGB). The remaining 5 curves, not used in the Machine Learning analysis, were applied as a case study to verify the performance of the best-trained model and compare the predicted tension loads with those measured in the field. The values of uplift capacity of measured curves were obtained using the modified Davisson criterion, defined as the applied load that caused a net deflection of the pile head equal to 10% of the average helix diameter, and compared with those calculated by the method of (Perko 2009).

The ML methods were applied using *Rstudio software* (v. 2023.06.2 Build 561), which includes the *R* language provided and freely available by the *CRAN Team* (v. 4.3.1). The study was conducted using the *Caret* package, which offers a wide range of tools and methods for artificial intelligence and statistical analysis.

In the first stage, the main objective was to evaluate the individual performance (training and testing) of each machine learning algorithm with different hyperparameters and interpret them based on the R^2 (coefficient of determination), MAE (Mean Absolute Error), and RMSE (Root Mean Squared Error) metrics. The model with the best overall performance (in both training and testing) will be the one that presents the lowest sum of RMSEs in these two phases.

2 LOAD-DISPLACEMENT CURVES AND DATABASE CHARACTERISTICS

2.1 Tension load-tests and test sites

The tension load-tests used in this study refer to the 4-helix piles data published by Tsuha et al. (2024), which achieved a net displacement (total minus elastic) equal to 10% of the average helix diameter (AC358 failure criterion). The uplift capacity of the piles was defined by the modified Davisson method, where the failure load corresponds to a net displacement of 10%D (Souissi, 2020):

Table 1. Characteristics of the 33 helical piles in 20 different sites used in the current work

CHARACTERISTIC	N. of piles	Min value	Max value
Installation soil of the pile helices			
sand	5	-	-
sandy soil	9	-	-
clay	6	-	-
clayey soil	12	-	-
structured lateritic soil	1	-	-
Shaft diameter (mm)			
73	2	-	-
88.9	8	-	-
101.6	23	-	-
Pile dimension			
shaft diameter, d (mm)	-	73	101.6
helix diameter, D (mm)	-	254	406.4
embedment length, L (m)	-	6	22
Pile verticality			
vertical	18	-	-
Inclined (vertical inclination angle (°)	15	32	42
Torque and uplift capacity measured results			
*final avg. torque, T_f (kN.m)	-	6.8	23.4
**uplift capacity, Q_u (kN)	-	107.4	596.3
K_T factor (m^{-1})	-	8.5	36.1
SPT N60-value			
N_{60} at the bottom helix (blows/30cm)	-	2	83

* Averaged for the final penetration equal to three times the diameter of the largest helix (D_{max})
** load leading to a net settlement (total minus elastic) equal to 10% of the averaged helix diameter

$$Net\ displacement = Total\ displacement - \frac{PL}{EA} \tag{1}$$

In the equation above, P corresponds to the load applied at the top of the pile, L is the total length of the pile shaft, E is the modulus of elasticity of the material, and A is the net area of the cross-section of the shaft.

Defining the failure load in terms of net displacement is important because, typically, Brazilian helical piles are installed at deep depths (with 15 meters length or more) and small cross-sectional areas. In these situations, the elongation or shortening of the shafts becomes crucial in determining the failure load. Table 1 describes the characteristics of the tests in the database related to the four-helix piles.

2.2 Brief overview of ML in the Geotechnics

Puri et al (2017) applied the methods of Linear Regression, Artificial Neural Network, Support Vector Machine, Random Forest, and M5 Tree to predict geotechnical parameters, and the authors showed that the trained models performed well compared to the measured values.

Recently, Peres (2021) employed machine learning techniques using a dataset composed of helical piles installed in Brazilian soils to predict the installation torque along the depth. The study addressed nine algorithms, of which Cubist, Boosting, and Random Forest stood out for their effectiveness in analyzing the dataset.

Li et al. (2022) used a database comprising 2197 data points from the literature to estimate soil thermal conductivity using six machine learning algorithms. In their study, the authors noted that the AdaBoost method exhibited the best prediction performance.

Wang et al. (2022) studied machine learning models to predict the behavior of helical piles in dense sands for wind energy tower purposes. The authors applied two methods in their study: Gradient Boosting Decision Tree (GBDT) and Particle Swarm Optimization (PSO). The results showed that the GBDT model accurately predicted the anchor mobilization distance and the tensile capacity of the piles. They also observed that the embedment ratio was the most significant variable in the model, while the relative density of the soil, the helix spacing ratio, and the number of helices had relatively minor influence. In particular, it was found that the helix spacing ratio does not influence the capacity of adjacent helices when S/D > 6.

The lack of studies employing artificial intelligence to predict the behavior of helical piles is evident. However, existing research demonstrates that such techniques show promise in this context, and therefore, this study aims to expand the application of machine learning to predict the behavior of these piles through their load-displacement curve.

3 Review of APPLIED ML ALGORITHMS

3.1 Cubist

Cubist is a hybrid algorithm that combines decision trees with linear regression, used for regression and classification tasks. The algorithm creates a series of rules based on decision trees, which connect various combinations of subsets of predictor variables with the target variable, based on patterns identified in the data. From these trained trees, the algorithm extracts rules that, when satisfied, are capable of predicting the target variable. Additionally, weights are assigned to the rules according to their predictive accuracy, prioritizing those that provide more accurate predictions.

Simultaneously, Cubist establishes multi-variate linear relationships associated with each compartment (or rule) defined by the regression trees. Finally, the prediction is made by combining predictions derived from the rules of decision trees and linear regressions, through weighted averages of individual predictions.

3.2 Random Forest

The Random Forest, like Cubist, is widely used in regression and classification tasks. This method is based on the technique of regression trees, differing from conventional methods by generating multiple trees with distinct subsets of instances. Using the Bootstrap technique with replacement, the algorithm randomly selects data subsets for each tree. This allows the same instance to appear multiple times in a subset, while others may be left out. This approach promotes the creation of diverse trees, reducing the model's sensitivity to the original dataset.

An advantage of Random Forest is the Out of Bag (OOB) technique, in which the model is evaluated with instances left out of the training process. This allows them to be used to test the model without the need for a separate validation set.

Upon completion of the testing process, the model employs ensemble aggregation to calculate the result for each instance based on the results of each tree. For classification tasks, the mode is used, while for regression cases, the average is used.

3.3 Stochastic Gradient Boosting Machine

Stochastic Gradient Boosting Machine (SGB) is a powerful variant of the Gradient Boosting Machine (GBM) algorithm. Unlike traditional GBM, which utilizes the entire training dataset for each iteration, SGB introduces a random sampling technique similar to Random Forest. In SGB, it selects a subset of the training data randomly for each iteration, a process known as stochastic gradient descent.

Moreover, SGB incorporates another form of randomness by employing random feature sampling. This means that at each node of the decision tree, SGB randomly selects a subset of features (columns). This introduces further variability and aids in preventing overfitting by reducing the correlation between trees.

Furthermore, SGB includes a shrinkage parameter, known as the learning rate, to control the contribution of each weak learner to the ensemble. A lower learning rate necessitates more iterations but can enhance generalization.

Similar to GBM, SGB employs gradient descent optimization to minimize a loss function. It calculates the gradient of the loss function concerning the predictions of the current ensemble model. Then, it adjusts the predictions of the new weak learner (decision tree) in the direction that minimizes the loss.

The gradient boosting process in SGB involves adding the new weak learner to the ensemble to reduce the overall error of the model iteratively. Each new weak learner works on correcting the errors of the previous ensemble, refining the model with each iteration.

Similar to GBM, the training process in SGB continues until a predefined stopping criterion is met. The final prediction of the SGB model is the sum of the predictions from all the weak learners, weighted by the learning rate.

4 SPT-based method

Perko (2009) proposed an equation using the SPT data for calculating the tensile capacity of helical piles. In this equation the author applies the concept of the individual bearing method, where each helix contributes individually to the total capacity:

$$Q_u = \sum_n q_{ult} . A_n + \alpha H_{eff} (\pi d) \quad (2)$$

In the equation above, An represents the effective area of the n^{th} helix, q_{ult} is the ultimate resisting pressure of the n^{th} helix and depends on the surrounding soil, α is the coefficient of adhesion between the shaft and the soil, H_{eff} is the total length of the shaft above the upper helix, considering the disturbance effect due to installation and the ground surface, and d is the external diameter of the shaft.

Table 2 indicates the values of qult as a function of Nspt for different materials. The method was calibrated for an efficiency of 70% (N70).

Perko (2009) did not propose a correlation for the contribution

Table 2 Correlations between ultimate bearing pressure and NSPT value (Perko 2009)

Primary Soil Condition	*Approximate bearing pressure (kPa/blows/300mm)*
Fine-grain soil	68 N_{70}
Coarse-grain soil	74 N_{70}
Weathered bedrock	81 N_{70}

of the shaft resistance to the pile capacity. In the present study, it was chosen to ignore this portion because it is insignificant for the total pile capacity, due to the small diameter of the shafts of Brazilian helical piles, as observed by Tsuha et al. (2024).

5 COMPARISON BETWEEN ML ALGORITHMS AND SPT-BASED METHOD

The 28 load-displacement curves from the database, a total of 336 instances (points of the load-displacement curves), with 80% (270) arbitrarily allocated to the model training set and the remaining 20% (66) designated for the testing phase. For the analyses, 7 variables to predict the curves were adopted:

- shaft diameter;
- wing ratio (average diameter of the helices divided by the diameter of the shaft);
- embedment length;
- relative depth (depth of the top helix divided by its diameter);
- average final installation torque (relative to the final penetration of the pile over a length of three times the diameter of the largest helix);
- total displacement (measured in the test); and
- applied load in the test (target variable for predictions).

In this study, the variable 'number of helices' was not used as it is the same for all observations. The variables Nspt and soil type were also not adopted because preliminary analyses indicated less accurate models. In order to ensure the repeatability of the analyses and enable comparison between the algorithms, a random seed was pre-fixed.

5.1 Training models

The Cubist, RF, and SGB methods were trained using 10-folds 5-repeats cross-validation, allowing the training of 50 models for each combination of hyperparameters, resulting in a total of 2500 trained models at the end of the analysis for Cubist, 300 for RF and 6000 for SGB. The predicted curves are in terms of total displacements.

Figure 1 illustrates the importance of variables from the best-trained models of each analyzed method. The variable importance, ranging from 0 to 100%, indicates the percentage of cases in which each variable explains the target variable. This allows an interpretation of which variables are truly necessary in a Machine Learning model. The results indicate that Cubist has the highest number of variables explaining the target variable compared to RF and SGB. This perception given by Cubist reflects that this algorithm makes better use of the predictor variables in the database.

The variable importance indicates that the 'diameter of the shaft' (d) does not explain the target variable in practically any

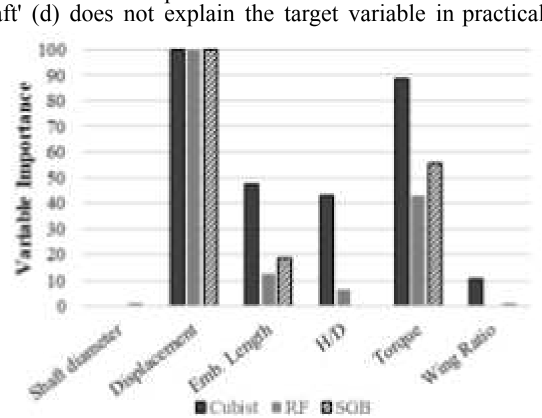

Figure 1 Comparison of the importance of variables for the trained models.

observation, possibly due to its small range of occurrence: 73, 88.9, and 101.6 mm. However, considering that the geometry of the shaft plays a fundamental role in the pile's performance, it was decided to keep this variable in the models.

Figure 2 illustrates the hyperparameters tested by each of the algorithms and the resulting RMSEs for the training phase with the 270 observations. The graphs indicate that the SGB algorithm demonstrated the best performance in training with an RMSE of 19.9 and hyperparameters: n.trees 600, interaction.depth 5, shrinkage 0.1, and n.minobsinnode 1. In second place is Cubist with an RMSE of 20.7 (hyperparameters: 100 committees and 1 neighbor), and in third place is RF with mtry 4 and RMSE 39.7. In terms of R^2, the order remained the same (SGB 0.977, Cubist 0.974, and RF 0.913), but in terms of MAE, Cubist becomes the best in training with a value of 12.5, followed by SGB (14) and RF (27.7).

5.2 Testing trained models

The comparison between the measured and predicted results of the test compartment regarding the tension loads points on the piles is indicated in the Figure 3. The figure show that the Cubist and SGB models exhibit good consistency in predictions across the entire load range of the test database (0 to 800 kN). In contrast, the model trained by Random Forest shows greater dispersion of points (Figure 3b).

During the testing phase, the performance between Cubist and SGB reverses compared to the training phase, and Cubist now exhibits the best performance, with an RMSE of 15.1, followed by SGB and RF, with 20.3 and 51.7, respectively. Figure 4 presents the frequency distribution histograms of the model factor M for the three tested algorithms. This factor is given by the ratio between the applied load on the pile in the field (measured) and the load predicted by the model. Therefore, when M equals one, it means that the load measured in the load test is equivalent to the one predicted.

The histograms of Cubist and SGB in Figure 4 indicate that most predictions produce values of M between 0.97 and 1.02, indicating a condition where the predicted load by the model is very close to the one measured in the load test. However, the dispersion of points observed in Random Forest (Figure 3b) is reflected in the distribution histogram (Figure 4b), where it is observed that the model factor of the test points does not adhere to a normal distribution curve and results in a COV equal to 0.22.

Cubist exhibited the lowest dispersion around the mean, with a coefficient of variation (COV) of only 0.06, followed by SGB and RF, which had COV values of 0.10 and 0.22, respectively. Therefore, it can be inferred that Cubist was the most consistent algorithm in test predictions due to the lower RMSEs and COV observed.

Table 3 summarizes the RMSE, MAE, and R^2 metrics of the best models from the tested algorithms and ranks them in terms of RMSE. Overall, Cubist performed the best, and therefore, it is the chosen model.

5.3 Case study

Conforming to the section 1, five load tests not used in training the machine learning models were reserved for a case study to evaluate the quality of the curves predicted by artificial intelligence and compare it with the method of Perko (2009). Figure 5 illustrates the curves measured in the field, those predicted by AI (both in terms of total and net displacements), and the load capacity calculated by the Perko (2009) method for a net displacement of 10% of the average helices diameters. This criterion is only applicable to normalized curves in terms of net displacement (dashed lines). Figure 5 indicates that the Cubist model performed well in three curves (S5, S9, and S15), where the predicted points adhere closely to the measured curve, and therefore, the load capacities predicted by the AI in these cases are satisfactory. On the other hand, in the two cases where the model performed poorly, S55 and S64, the predicted curves showed points with loads considerably lower than those measured in the field. Table 4 summarizes the RMSE, R^2, and MAE of the predicted curves.

Individually, the three curves in which the model performed well, namely S5, S9, and S15, resulted in the lowest RMSEs (29.9, 20.3, and 19.9 kN, respectively) and were very close to the MAE. This suggests that the predicted values are well adjusted to the measured ones, and the errors are evenly distributed.

On the other hand, the predictions for S55 and S64 resulted in more significant errors with RMSEs of 252.8 and 79.3 kN, respectively, but close to the MAE of the prediction. This indicates that the model exhibits evenly distributed errors and considerably discrepant predicted loads compared to the measurements in these cases.

Analyzing the data from the five Cubist curves together, the model seems to present some considerable errors and discrepant predicted loads from the measurements. This is corroborated by the fact that the RMSE is significantly higher than the MAE. The R^2 value also resulted very low (0.26).

Table 5 summarizes the RMSE and MAE of each predicted load by both Perko (2009) and the Cubist algorithm. The RMSE and MAE are the same in each prediction because they refer to a single

Table 4. Metrics RMSE, R^2, and MAE between predicted and measured curves.

Predicted Curves	*RMSE (kN)*	*R^2*	*MAE (kN)*
Cubist 5 curves	130.1	0.26	84.6
S5-101.6-4H-T3	29.9	0.98	25.4
S9-101.6-4H-T3	20.3	0.99	19.6
S15-101.6-4H-T3	19.9	0.96	18.0
S55-101.6-4H-T6	252.8	0.98	240.0
S64-88.9-4H-T2	79.3	0.90	69.4

et displacement predicted by Perko (2009) and by artificial intelligence through the Cubist

09) - SPT based method			Cubist - Machine Learning Method			
ISE (kN)	*MAE (kN)*	*M*	*Predicted (kN)*	*RMSE (kN)*	*MAE (kN)*	*M*
151.4	151.4	2.27	307.6	36.7	36.7	0.88
70.8	70.8	2.30	147.6	22.4	22.4	0.85
5.9	5.9	0.97	173.9	20.1	20.1	1.12
273.6	273.6	0.69	209.2	387.1	387.1	2.85
140.4	140.4	2.00	155.5	126.0	126.0	1.81

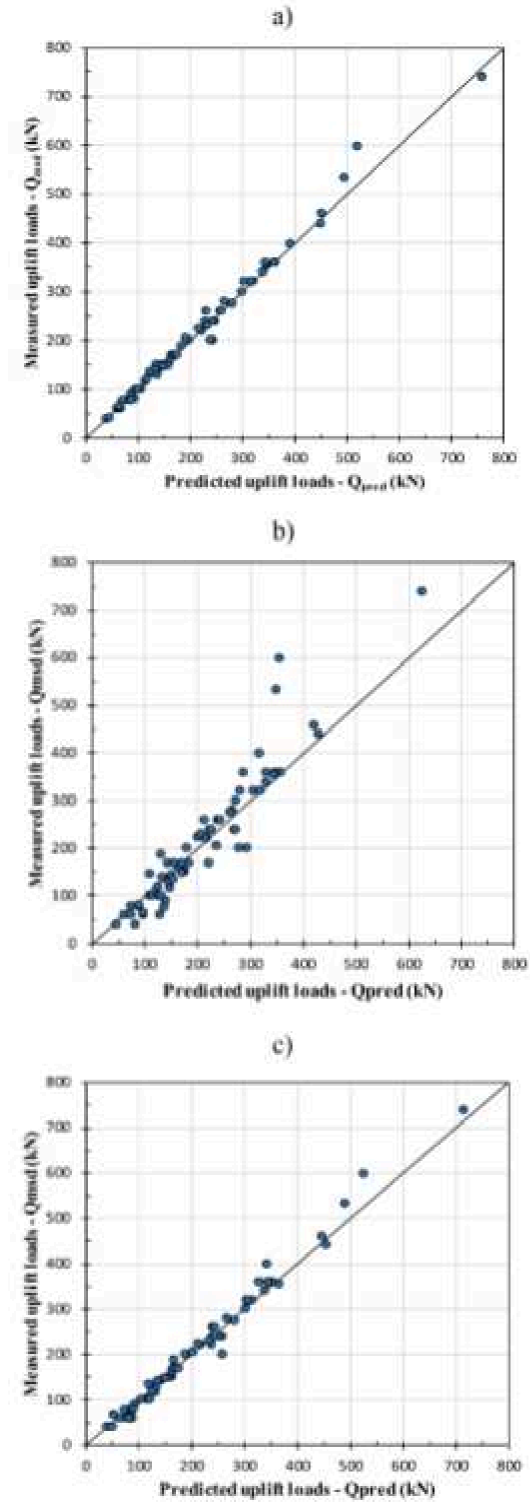

Figure 3 Comparison between measured and predicted tensile loads in tests: (a) Cubist; (b) RF; and (c) SGB.

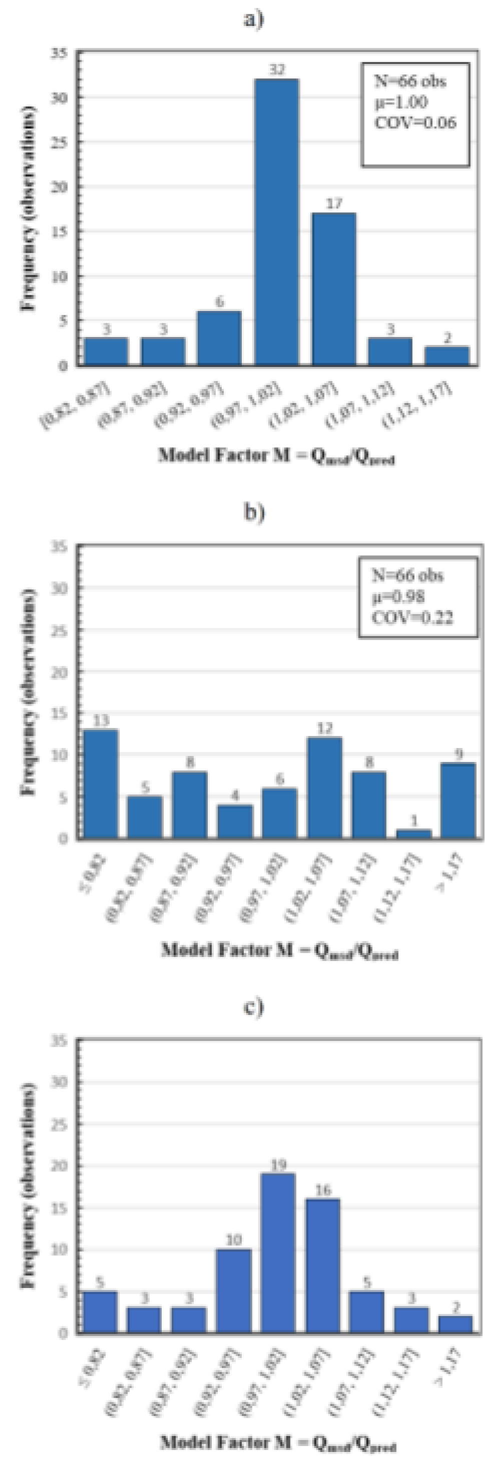

Figure 4 Histograms of frequency distribution for the model factor M of the tensile loads from the models under simplified analysis: (a) Cubist; (b) RF; and (c) SGB.

point of each test and, at the same time, are equivalent in magnitude to the difference between the predicted and measured load.

Perko (2009) method showed good accuracy in only one case out of the five evaluated (test S15) with a Model Factor of 0.97 and an RMSE of only 5.9 kN. In the remaining cases, the calculated loads differed significantly from the measured ones, with an M of 0.69 for test S55 and varying in a range of 2 to 2.37 for tests S5, S9, and S64.

Cubist, on the other hand, was more accurate in predicting the rupture loads. The estimates were satisfactory, with RMSE of 36.7, 22.4, and 20.1 kN for tests S5, S9, and S15, respectively. These results resulted in M's ranging from 0.85 to 1.12. However, the performance in predicting the rupture load of tests S55 and S64 was unsatisfactory, with substantial RMSEs of 387.1 and 126 kN and M equal to 2.85 and 1.81, respectively.

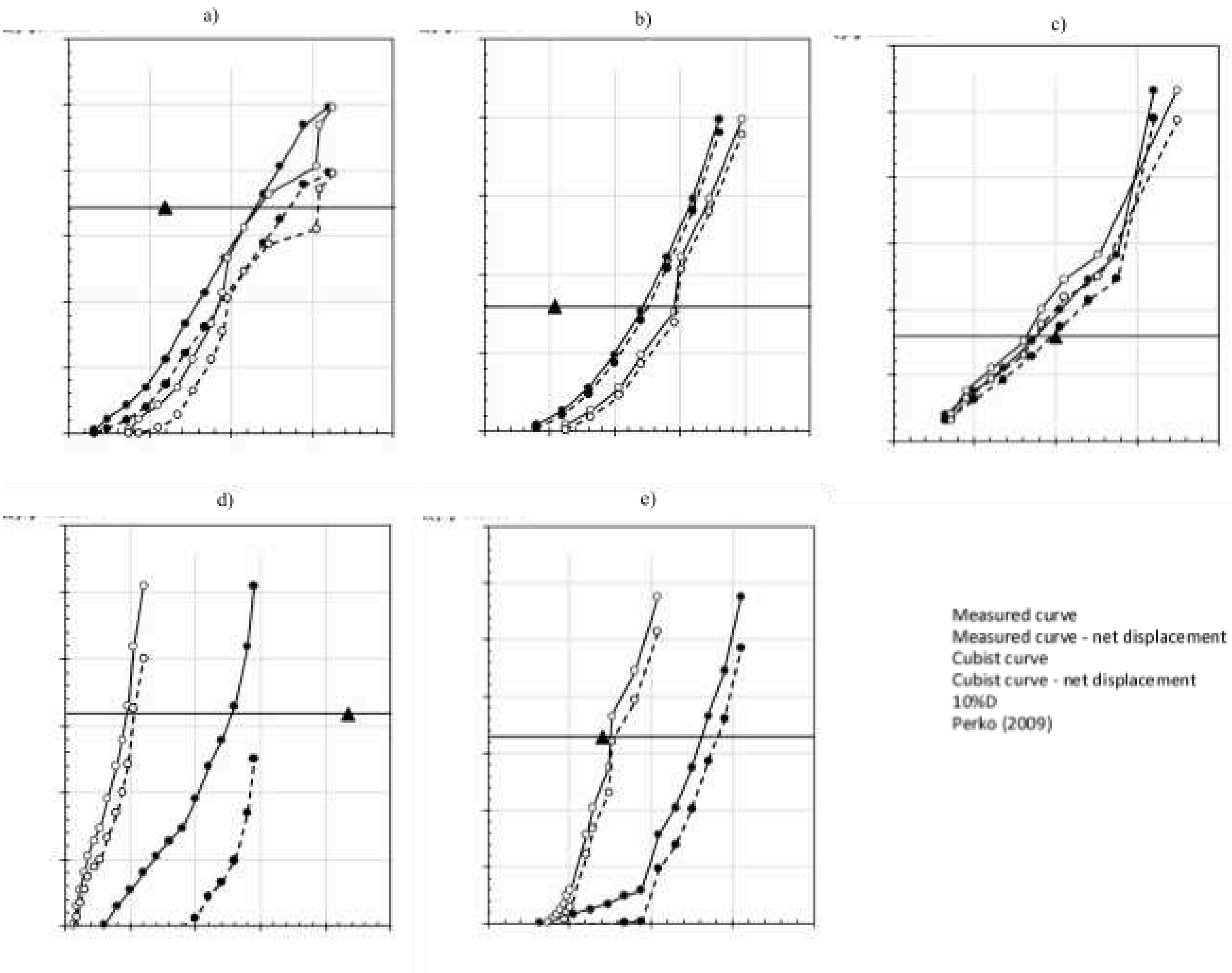

Figure 5 Comparison of ultimate load for 10% of the mean diameter of the helices: measured curves, Cubist-predicted, and load capacity by Perko (2009).

6 ConclusionS

This paper used data from 33 tensile load tests on helical piles to assess the applicability of Artificial Intelligence using machine learning in predicting load-displacement curves. Additionally, five load tests were reserved for evaluation as a case study, where the prediction of pile capacity using a method based on SPT data was compared with the pile uplift capacity values predicted by artificial intelligence. From this study, it was concluded that:

- the algorithms applied to the database proved to be efficient in predicting some load-displacement curves, albeit each with certain limitations. On the other hand, the database used in this study is small (only 336 instances), and the Cubist model was trained with a limited variety of variables combinations;
- even with the implementation of cross-validation, which helps prevent overfitting, the model showed errors in the predictions that were evidenced in the Figure 5d and Figure 5e. This indicates that cross-validation is not sufficient to mitigate the limitation of the database size and the best alternative is to expand the database;
- the results from the testing phase and case studies showed that the models are inaccurate in certain cases, and an error analysis can be conducted in future research. For example, by checking the confidence interval of the predictions and identifying through sensitivity analysis which variables have the greatest impact on the results;
- machine learning prediction results indicate the need for a larger database containing a greater variety of cases. Introducing greater diversity of instances can enhance the trained model's ability to predict unobserved cases, especially in case studies. Currently, the database published by Tsuha et al. (2024) is being expanded by Oliveira (2024) with new data that will allow for the inclusion of a greater diversity of observations and, consequently, improve the predictive capacity of the models trained in this paper;
- new algorithms can be applied to the database, such as Bayesian methods, Support Vector Machine, and Boosting. These methods, among others, have been regularly applied in the geotechnical field according to a study conducted by Phoon and Zhang (2023);
- Perko (2009) method proved to be poorly adherent to the Brazilian cases of helical piles. This indicates that the applicability of this method is limited for Brazilian soils and requires the calibration of the parameters proposed by the author.

7 Acknowledgements

The first author would like to thank CAPES for funding the research. The authors would like to thank Vértice Engenharia and the project PD-07284-0002/2020 of the P&D ANEEL program of the Neoenergia group for the data used in this work.

8 references

Kanai, S. (2007). A seismic retrofitting application by means of multi-helix micropiles. *In Proceedings of the 23rd US–Japan Bridge Engineering Workshop*, Tsukuba, Japan (pp. 5-7).

Li, K. Q., Liu, Y., and Kang, Q. 2022. Estimating the thermal conductivity of soils using six machine learning algorithms. *International Communications in Heat and Mass Transfer*, 136, 106139.

Meyerhof, G. G. 1951. The ultimate bearing capacity of foundations. *Geotechnique*, 2(4), 301-332.

Meyerhof, G. G. (1956). Penetration tests and bearing capacity of cohesionless soils. *Journal of the Soil Mechanics and Foundations Division*, 82(1), 866-1.

Oliveira, C. C. S. (2024). Analysis of pile load tests data to enhance the prediction of multi-helix piles performance based on *in situ* measurements. *Master thesis* (not finished). University of São Paulo, Brazil.

Peres M. S. 2021. Apredizado de máquina – previsão de torque para estacas helicoidais. *Master thesis*, Aeronautics Institute of Technology, Brazil

Perko, H. A. 2009. Helical piles: a practical guide to design and installation. *1st ed. Hoboken*, NJ: John Wiley & Sons, Inc.

Phoon, K. K., & Zhang, W. (2023). Future of machine learning in geotechnics. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, 17(1), 7-22.

Puri, N., Prasad, H. D., and Jain, A. 2018. Prediction of geotechnical parameters using machine learning techniques. *Procedia Computer Science*, 125, 509-517.

Souissi M. 2020. Helical Pile Capacity-to-torque correlation: a more reliable capacity-to-torque factor based on full scale load tests. *DFI Journal–The Journal of the Deep Foundations Institute*, 14(2), 1-11

Terzaghi, K. 1943. Theoretical soil mechanics.

Tsuha, C.H.C., Oliveira, C.C.S., Silva, B.O., dos Santos Filho, J.M.S.M., Schiavon, J.A. and Tang, C. 2024. Development and use of tensile loading test databases for analysis and design of helical piles. *Databases for Data-Centric Geotechnics*

Vesic, A. B. 1963. Bearing capacity of deep foundations in sand. *Highway research record*, (39).

Wang, L., Wu, M., Chen, H., Hao, D., Tian, Y., & Qi, C. (2022). Efficient Machine Learning Models for the Uplift Behavior of Helical Anchors in Dense Sand for Wind Energy Harvesting. *Applied Sciences*, 12(20), 10397

INTERNATIONAL SOCIETY FOR
SOIL MECHANICS AND
GEOTECHNICAL ENGINEERING

This paper was downloaded from the Online Library of the International Society for Soil Mechanics and Geotechnical Engineering (ISSMGE). The library is available here:

https://www.issmge.org/publications/online-library

This is an open-access database that archives thousands of papers published under the Auspices of the ISSMGE and maintained by the Innovation and Development Committee of ISSMGE.

The paper was published in the proceedings of the 17th Pan-American Conference on Soil Mechanics and Geotechnical Engineering (XVII PCSMGE) and was edited by Gonzalo Montalva, Daniel Pollak, Claudio Roman and Luis Valenzuela. The conference was held from November 12th to November 16th 2024 in Chile.