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Random forest regression on pullout resistance of a pile

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ABSTRACT

This research aims to study the pullout resistance of a helical pile using three methods of machine learning techniques, which are: random forest regression, support vector regression, and adaptive neuro-fuzzy inference system, based on experimental results of a helical pile. The performance of these three techniques has been d compared and the results show that random forest algorithm has best performance than neuro-fuzzy inference system and support vector technique. The results show that machine learning considered a good tool in terms of estimating the pullout resistance of helical piles in the soil.

KEYWORDS

helical piles, pull-out resistance, artificial neural network, adaptive neuro-fuzzy inference system, random forest, support vector machine

1. INTRODUCTION

In recent years, significant development and improvement have been observed in engineering fields due to the use of modern computational methods and measurement techniques [1]. One of these fields in which these improvements have been noticed is the field of civil engineering and geotechnical engineering [2, 3]. There are many types of deep foundations; one of these types is helical piles (HPs), as they consist of a central shaft steel column with helix-shaped plates, hence the name helical piles [4]. HPs are used to support building structures, bridges, and other types of infrastructure because they provide bearing capacity and stability for different types of structures and buildings [5]. HPs are also used in cases where traditional deep foundation systems are not practical and feasible, like drilled columns and driven piles for different soil conditions [6] and also used in commercial and residential properties and areas with limited access and space [7]. HPs provide an alternative solution as a foundation that provides good stability and is sufficient to resist horizontal stresses, compression and tension [8]. The helical piles have received great attention from researchers studying their behavior due to their stability and provide good performance in avoiding horizontal pressures, compression and tension. In 2017, G. Spagnoli [8], improved a theoretical model to analyze the bearing capacity and torque of HPs based on cone penetration testing to determine the axial resistance of helical piles and predict the torque required for installation., various methods have been explored [9, 10]. To analyze and understand the behavior of HPs, models of finite elements are widely used for this purpose [11–13]. The researchers discussed different methods and approaches to verify pullout resistance (Pul), as it is one of the important parameters for HPs for both piles and anchors [14–16]. The various soft computing techniques, which represent a set of computational techniques designed to find solutions and deal with incomplete, uncertain, or imprecise data for which it is difficult to find solutions using traditional methods, are vastly used in various engineering fields [17–19]. Fuzzy logic [20], particle swarm optimization [21], neural networks [22], metaheuristic

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techniques [23] and genetic algorithms [24] are some soft computing techniques commonly used in engineering fields. In geotechnical engineering applications, it is widely used, like designing stabilized earth walls [25], assessing landslide and slope stability [26], predicting soil compression coefficient [27], modeling bearing capacity [28] and among others. Within a mathematical framework, these techniques can optimize the relationship between multiple parameters [29], tailored to a specific problem. By taking a cost function, these algorithms perform intricate computations to maximize/minimize this function. Na et al. [30] in 2016, utilized the Harmony Search Algorithm (HSA) to optimally design the material cost of HPs. The HSA was discovered to be an effective approach for this objective, as it resulted in a cost reduction of 27% [30]. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a kind of Artificial Neural Network (ANN) that combines the reasoning capabilities of fuzzy logic and the learning abilities of neural networks to create a hybrid intelligent system. ANFIS is used for modeling complex systems where the relationships between inputs and outputs are not well understood. It works by using a set of input variables and a set of output variables to create a fuzzy inference system. This system is then trained using a combination of supervised and unsupervised learning algorithms to adjust the parameters of the fuzzy logic rules to better match the desired outputs [31]. Helical piles are widely used in civil engineering for foundation construction due to their unique properties, including ease of installation and excellent load-bearing capacity. However, predicting the pullout resistance behavior of helical piles is a complex and challenging problem, as it depends on a variety of factors like soil properties, installation method, and pile geometry. In recent years, machine learning techniques have emerged as a promising tool for analyzing and predicting the behavior of complex systems like helical piles. In this study, three machine learning methods - adaptive neuro fuzzy inference system, random forest regression, and support vector regression – have been applied to experimental results of a helical pile, with the aim of evaluating their performance and identifying the most effective approach for predicting the pullout resistance behavior of helical piles. In this paper, a comparative analysis of three machine learning methods - adaptive neuro fuzzy inference system, random forest regression, and support vector regression - is presented for predicting the pullout resistance behavior of a helical pile. The results show that random forest regression outperformed the other two methods in terms of accuracy and error values. This study provides valuable insights into the potential of machine learning techniques for evaluating the actions of helical piles in soil, and offers practical guidance for engineers and researchers in this field.

2. MATERIALS AND METHODS

The pullout resistance of a helical pile, which is a type of deep foundation, can be affected by various factors. These include the type and characteristics of the soil, the geometry and size of the helix plates, the spacing and orientation of the plates [32], the geometry and size of the pile shaft, the installation torque and method [33], the groundwater level [34] and soil moisture content, the loading conditions and magnitude, the depth of embedment, and environmental factors such as temperature and corrosion [35]. All of these factors can impact the performance of the helical pile in terms of its ability to withstand axial or uplift loads and therefore need to be carefully considered during the design and installation process. In intelligent simulations, the effective factors act as inputs for a target parameter, and the network aims to capture their relationship and identify any patterns. The current study utilizes the dataset provided by Nazir et al. [36] for this purpose [36]. The embedment ratio R_{em} of a helical pile is the depth-to-diameter ratio and is an important design parameter that can affect the performance of the helical pile. The embedment ratio can vary depending on factors like the soil type, the loading conditions, and the required capacity of the pile. A higher embedment ratio generally results in a higher capacity of the pile to resist axial or uplift loads, but may also increase the installation difficulty and cost. The dataset analyzed in this study includes 36 samples that record the P_{ul} of helical piles, as an independent variable, along with the embedment ratio R_{em}, soil density class C_{SD}, and shaft diameter ratio $(R_{SD} = D_b/D_s)$ as input parameters affecting P_{ul} as it is shown in Fig. 1 where D_s is the central shaft diameter and D_b is the helical plate (flange) diameter.

Figures 2–5 display the changes in R_{em}, C_{SD}, R_{SD}, and P_{ul} respectively. The embedment ratio ranges from 0 to 5 with a mean value of 2.5. The soil density class has two recorded

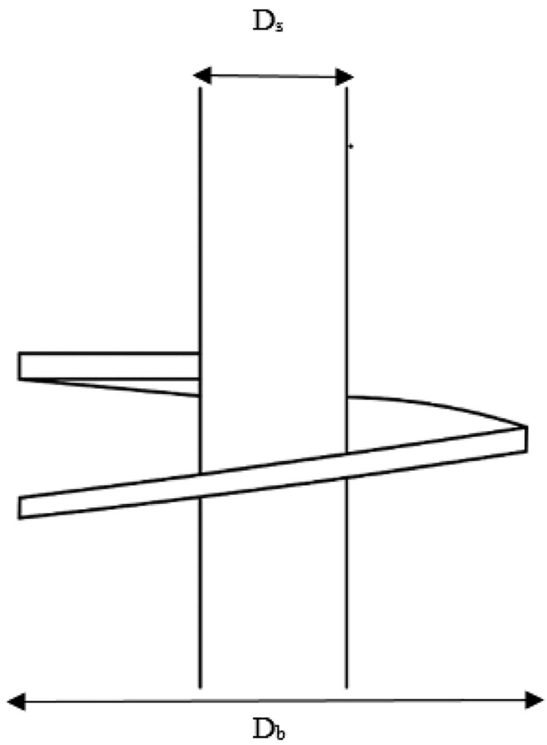

Fig. 1. Shaft diameter ratio in helical pile

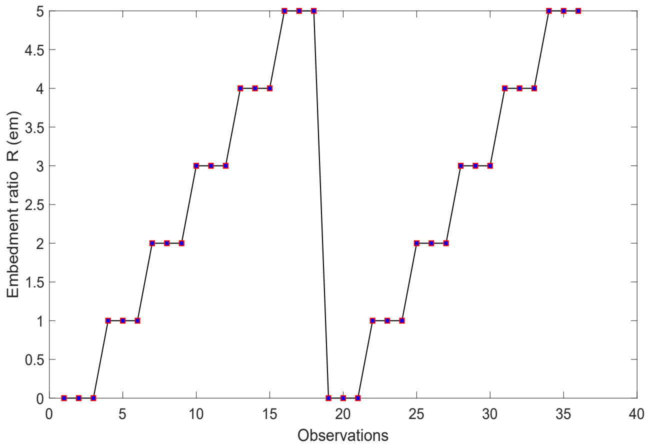

Fig. 2. The embedment ratio

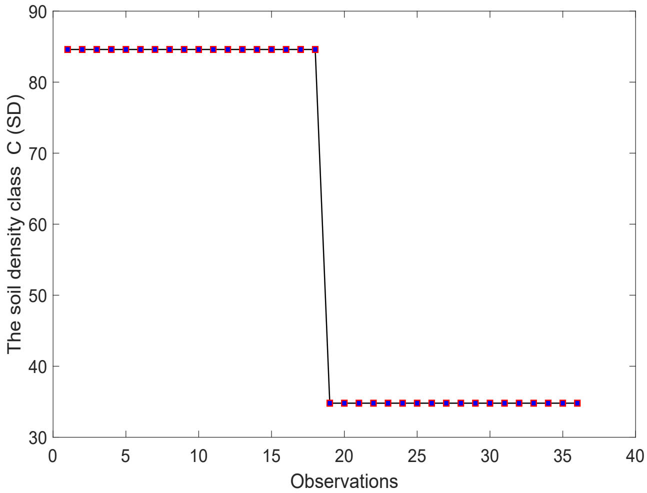

Fig. 3. The soil density class

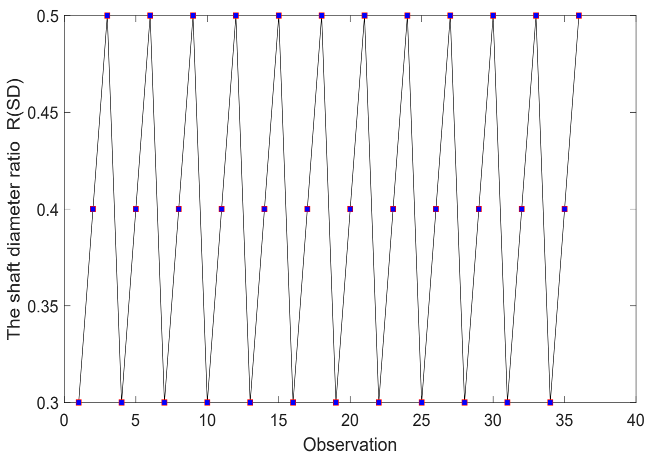

Fig. 4. The shaft diameter ratio

values of 85 and 35 kN m^{-3} that correspond to dense and loose soils, respectively. The dataset consists of an equal number of samples for both dense and loose soil types. The shaft diameter ratio, follows a repeated pattern with the

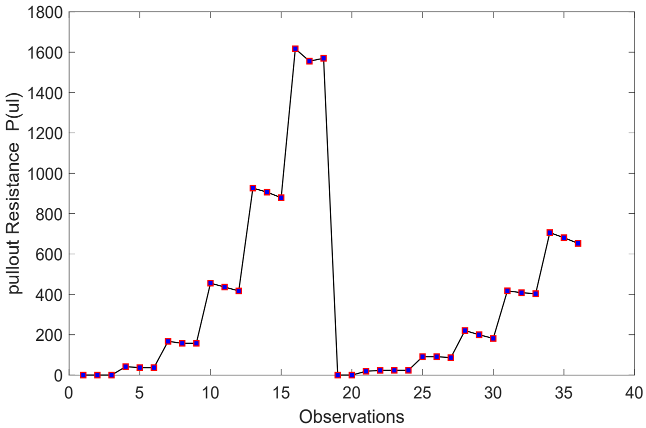

Fig. 5. Pullout resistance

values 0.3, 0.4, and 0.5, resulting in a total of 36 samples in the dataset 6 × 2 × 3. The corresponding P_{ul} values range from 0 to 1622.47 N with an average of 376.8 N. It is observed that the P_{ul} values for dense soils are higher compared to loose soils.

3. METHODOLOGY

Three models were formulated to analyze the performance of the pullout resistance in this work including an adaptive neuro-fuzzy inference system, random forest regression, and support vector machine.

3.1. Adaptive neuro-fuzzy inference system

White [37] introduced the concepts of Generalized Regression Neural Network (GRNN) and Multi-Layer Perceptron Neural Network (MLPNN) as two popular types of ANNs. ANNs are computational models that mimic the functioning of biological neural systems, as described by McCulloch and Pitts [38] and Anderson and McNeill [39]. The key elements of these networks are the neurons, which are interconnected through synapses to process signals, as it is explained by Hu and Hwang [40]. To establish a non-linear correlation between the inputs and targets, the data undergo a series of operations across multiple layers. A GRNN comprises four layers, specifically, the input layer, pattern layer, summation layer, and output layer, as described by Xie et al. [41]. Conversely, an MLPNN has a minimum of three layers, including the input layer, one or more hidden layer(s), and the output layer, as stated by Hornik et al. [42]. In both the GRNN and MLPNN, the number of neurons in the first and last layers corresponds to the dimensions of the inputs and targets, respectively. The number of neurons in the hidden layer of the MLPNN is flexible and usually determined by the user, whereas in the GRNN, the number of neurons in the pattern layer matches the number of instances. In both models, the primary computations are performed in the middle layers, and the output neurons conduct a linear calculation to produce responses. Further details on these models can be found in various literature sources, such as Seyedashraf et al. [43] and Ge et al. [44]. The ANFIS model, introduced by Jang [45], combines the benefits of neural networks and fuzzy logic, as noted by Moayedi et al. [46]. Fuzzy systems involve operations like fuzzification, a fuzzy inference engine, and defuzzification, which are used to transform crisp values into linguistic fuzzy variables for entry into an inference engine. The fuzzy rules are applied to these variables, and the resulting value is subjected to a defuzzification process to convert the response back into crisp values. The ANFIS is similar to ANNs in that it consists of five layers, each of which performs a specific operation, including The ANFIS comprises five layers, with the first layer, called the fuzzification layer, transforming crisp inputs into fuzzy ones. In the implication layer, the ANN's weight functions are calculated, and the obtained weights are normalized in the normalization layer. The fourth layer carries out defuzzification, and the output is produced by the neurons in the output layer, as explained by Alajmi and Almeshal [47].

3.2. Random forest regression

Random Forest Regression (RFR) is widely utilized in machine learning for regression tasks and can be seen as an advancement of the RFR, which is primarily used for classification tasks. In RFR, numerous decision trees are generated, with each tree trained on a randomly chosen subset of the data and features. Afterwards, the algorithm consolidates the predictions from all the trees to produce the final prediction. By decreasing the model's variance, utilizing RFR instead of a single decision tree can enhance the prediction's accuracy. This is achieved by reducing the overfitting of the model, which can be a common issue with decision trees. RFR also has the ability to handle high-dimensional data and non-linear relationships between the features and the output. RFR is implemented in Python using the scikit-learn library. To achieve the intended level of accuracy, the model's hyper-parameters, including the number of trees and the number of features in each tree, can be adjusted. Once the model has undergone training, it is capable of making predictions on new data.

3.3. Support vector regression

Support Vector Regression (SVR) is a machine learning algorithm used for regression tasks. It is based on the Support Vector Machine (SVM) algorithm, which is primarily used for classification tasks. SVR functions by identifying a hyperplane that best suits the data and maximizes the distance between the hyperplane and the nearest data points. This hyperplane is then used to make predictions on new data. One of the advantages of using SVR is that it can handle non-linear relationships between the features and the output by using a kernel function. The kernel function maps the data to a higher-dimensional feature space where it is easier to find a hyperplane that separates the data points. SVR can also handle outliers in the data by controlling the width of the margin around the hyperplane. SVR is implemented in Python using the scikit-learn library. The hyper-parameters of the model, like the type of kernel function and the regularization parameter, can be tuned to achieve the desired level of accuracy. Once the model is trained, it can be used to make predictions on new data. Overall, SVR is a powerful machine learning algorithm that is well-suited for regression tasks, particularly when the data has non-linear relationships between the features and the output. It can also handle outliers in the data and can tune the level of complexity of the model by controlling the width of the margin around the hyperplane.

4. RESULTS AND DISCUSSION

The proposed models were implemented and evaluated using two types of data: training data and testing data. The training data comprised 25 samples, while the testing data contained 11 samples. The data were randomly permuted to enable a random selection, and a 70:30 selection ratio was applied, as stated in the text.

4.1. Indices used to evaluate accuracy

To evaluate the accuracy of both data groups, three widely accepted criteria are employed. The first criterion used to measure the prediction error for J samples is the Root Mean Square Error (RMSE), as it is expressed in the following equation,

$$RMSE = \sqrt{\frac{1}{J}\sum_{i=1}^{J}\left[\left(P_{ul,i_{observation}} - P_{ul,i_{estimation}}\right)\right]^2}. \tag{1}$$

The values of P_{ul} are estimated and expected using $P_{ul,i_{estimation}}$ and $P_{ul,i_{observation}}$, respectively. The second measure used for accuracy assessment is the Mean Absolute Error (MAE) which is calculated on the base of Eq. (2),

$$MAE = \frac{1}{J}\sum_{i=1}^{J}\left|P_{ul,i_{observation}} - P_{ul,i_{estimation}}\right|. \tag{2}$$

4.2. Training and development

The ANFIS with adjustable parameters of its Membership Functions (MFs) is fed by training data and during the training procedure, the system attempts to optimize the tuning of the MFs to capture the relationship between P_{ul} and the independent variables, R_{em}, C_{SD}, and R_{SD}. The ANFIS is optimized over a total of 1000 iterations. The pullout resistance patterns obtained in the laboratory and by predictive models is displayed in Fig. 6. It can be observed from the figure that all models could accurately capture most of the P_{ul} behavior. Nevertheless, the random forest model outperformed the others in predicting the maximum and minimum P_{ul}.

4.3. Results of testing and comparison

During the second phase, the pullout was predicted for new pile conditions, and as with the training phase, the

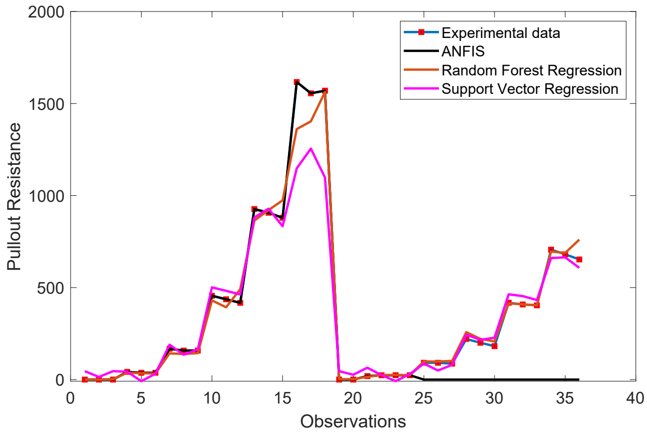

Fig. 6. Predictive models of the pullout resistance behavior

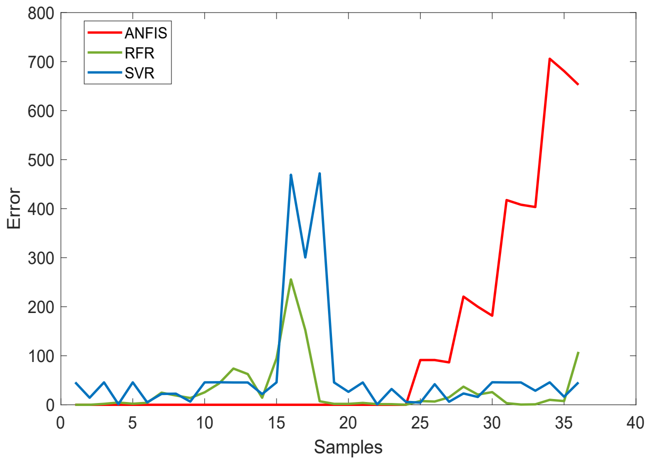

Fig. 7. Performance of the predictive models

performance of each network was evaluated using RMSE, MAE, and PCC by comparing the predicted values to the expected values. Figure 7 displays the difference between the expected and predicted pullout resistance, which is referred to as "Error". The regression chart shows a high aggregation of data points around the ideal line (i.e., $x = 0$), and the graph exhibits a higher frequency of small errors. These results demonstrate the satisfactory performance of the models used.

Based on Fig. 7, it can be concluded that all predicted outputs have a high level of agreement with the laboratory results over a specific domain of the dataset. However, ANFIS has the worst performance while random regression performed better than others.

5. CONCLUSIONS

Three machine learning were utilized to study the behavior of the pullout resistance of a helical pile. Adaptive neuro-fuzzy inference systems, random forest regression, and support vector regression were employed to study and analyze the experimental results of a helical pile. While the adaptive neuro-fuzzy inference system performed well on the training set, it had a deficiency on the test set. The support vector technique has better performance than the adaptive neuro-fuzzy inference system and worse than the random forest algorithm. Overall, random forest machine learning regression outperformed other methods in this study and returns a good prediction state with acceptable error values. Consequently, random forest regression is highly recommended to represent complex data of pile foundation analysis.

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