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RESEARCH

Hybrid FEM-MLP Approach for Evaluating the Ultimate Load Capacity of Bored Piles in Sandy Clay Soil

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Abstract

This study developed a machine learning model based on a multi-layer feedforward neural network to predict the settlement and ultimate load capacity of bored piles using data from three-dimensional finite element simulations. A finite element model was established for sandy clay soil with elastic modulus ranging from 14,000 to 26,500 kN/m², internal friction angle from 28° to 34°, and cohesion from 3 to 6 kN/m². A bored pile with a diameter of 800 mm, a length of 43 m, an elastic modulus of 34.5×10^6 kN/m², and a unit weight of 25 kN/m³ was analyzed under incremental static loading. The simulation results were used to train a neural network with three hidden layers (64–64–32 neurons) and a ReLU activation function. The model achieved high predictive accuracy, with $R^2 = 0.9983$, MAE = 6.60 mm, and RMSE = 11.43 mm, indicating effective representation of the nonlinear load–settlement relationship. The ultimate load capacity was estimated using piecewise linear regression, curvature-based analysis, and the slope ratio method, yielding values between 14,400 and 15,900 kN/m², with deviations of less than 10% compared to field static load test results. The results indicate that the proposed FEM–MLP framework can supplement finite element analyses.

Keywords MLP regressor · Load–Settlement · Ultimate load capacity · Machine learning · Piecewise regression

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1 Introduction

In the design and construction of foundation systems, accurately predicting the settlement and load-bearing capacity of bored piles plays a crucial role in ensuring the safety, stability, and economic efficiency of a structure. Errors in settlement prediction may lead to local instability or cracking of the superstructure, while inaccurate assessment of load capacity can result in unsafe designs or unnecessary material waste (Cao et al. 2024; Liao et al. 2024). Traditionally, these parameters are determined through field static load tests or empirical analyses using formula-based methods; however, these methods have significant limitations (Zhussupbekov and Omarov 2016). Static load testing is costly, time-consuming, and difficult to implement on a large scale. Meanwhile, empirical formulas are typically localized, dependent on specific geological conditions, and incapable of capturing the complex nonlinear behavior of the soil–pile system (Maertens and Huybrechts 2001; Heidarie Golafzani et al. 2020).

In this context, numerical simulation using the finite element method (FEM) has become an important tool for analyzing soil–structure interaction due to its ability to model stress distribution, deformation, and pile soil interaction in detail (Torabi and Rayhani 2014; Numerical models in 2021). However, FEM also has notable drawbacks, including long computation times and the need for high expertise in defining boundary conditions, element meshing, and input material parameters (Monforte et al. 2017; Borst and Vermeer 1984). Alongside the rapid development of artificial intelligence, machine learning (ML) models are emerging as a new approach capable of learning nonlinear relationships between input and output variables without predefined functional assumptions (Pei and Qiu 2024; Zhang et al. 2022a, b). Among these, the multi-layer feedforward neural network (MLP) is particularly well suited for nonlinear regression problems, enabling accurate prediction of settlement and ultimate load capacity based on data from simulations or experiments.

The objective of this study is to integrate simulation results from Plaxis 3D with a machine learning model, MLPRegressor, to develop an efficient surrogate model for real-world static load tests. This approach leverages the advantages of numerical simulation—such as controlled boundary conditions and precise input parameters—together with the power of machine learning in generalizing data and providing rapid predictions. The study aims to establish a robust correlation between applied load and pile settlement, while determining the ultimate load capacity (Pmax) through three independent methods: piecewise linear regression, curvature-based analysis, and the slope ratio method, in order to verify the reliability of the model.

The current research gap lies in the lack of integrated FEM–MLP models capable of accurately predicting settlement and ultimate load capacity under specific geological conditions, particularly for sandy clay soils—a common but highly nonlinear soil type (Nguyen Anh et al. 2025; Jafari 2020; Saltan and Sezgin 2007). Previous studies have often focused solely on FEM simulations or limited experimental datasets, without fully exploiting the potential of machine learning in generalizing numerical data (Zhou et al. 2022).

This paper presents the entire workflow, from pile–soil simulation using Plaxis 3D, construction and training of the MLP model, to the determination of Pmax using three different methods. The model results are compared with field static load test data to evaluate accuracy and practical applicability. Accordingly, the study proposes a new integrated approach combining numerical simulation and machine learning, opening potential pathways for developing automated prediction systems in foundation design and assessment.

2 Materials and Methods

In this study, the foundation soil is modeled as sandy clay, a common soil type in geotechnical engineering conditions in lowland areas. Sandy clay exhibits mechanical characteristics intermediate between sand and clay, possessing relatively good bearing capacity while still being significantly affected by deformation under large loads. To accurately simulate the soil behavior under static compressive loading, the mechanical parameters of the soil are selected within typical ranges obtained from field investigations and standard references.

The basic parameters of the soil layer include: the void ratio (e), ranging from 0.5 to 0.7, reflecting the degree of soil compaction; the unsaturated unit weight (γ_{unsat}) from 18 to 20 kN/m³ and the saturated unit weight (γ_{sat}) from 19.9 to 21.3 kN/m³, representing the moisture state of the ground. The effective cohesion (c′) is selected between 3 and 6 kN/m², while the internal friction angle (φ′) varies from 28°–34°, indicating the shear resistance of the soil. The elastic modulus (E′) is chosen within the range of 14,000–26,500 kN/m² to represent soil stiffness and deformability, and Poisson's ratio (υ′) lies between 0.24 and 0.31 and R_{inter} = 0.9, consistent with the elastic nature of this soil type (Table 1).

All of these parameters are used as input for the three-dimensional finite element model (FEM) in Plaxis 3D. Selecting values within realistic ranges enables the model to represent the natural soil conditions at the site accurately, while also ensuring that the machine learning model can be generalized to similar problems under different geological conditions.

The object analyzed in this study is a reinforced concrete bored pile with a diameter of 800 mm, 43 m, a commonly used dimension in civil and infrastructure projects with medium to large loads. The pile material is assumed to behave linearly elastically, with an elastic modulus of $E = 34.5 \times 10^6$ kN/m², representing the stiffness typical of high-strength concrete. The unit weight of the pile is $\gamma = 25$ kN/m³, corresponding to conventional reinforced concrete, ensuring that the model accurately reflects the self-weight of the structural element. The standard design load of the pile

Table 1 Parameters of sandy clay soil

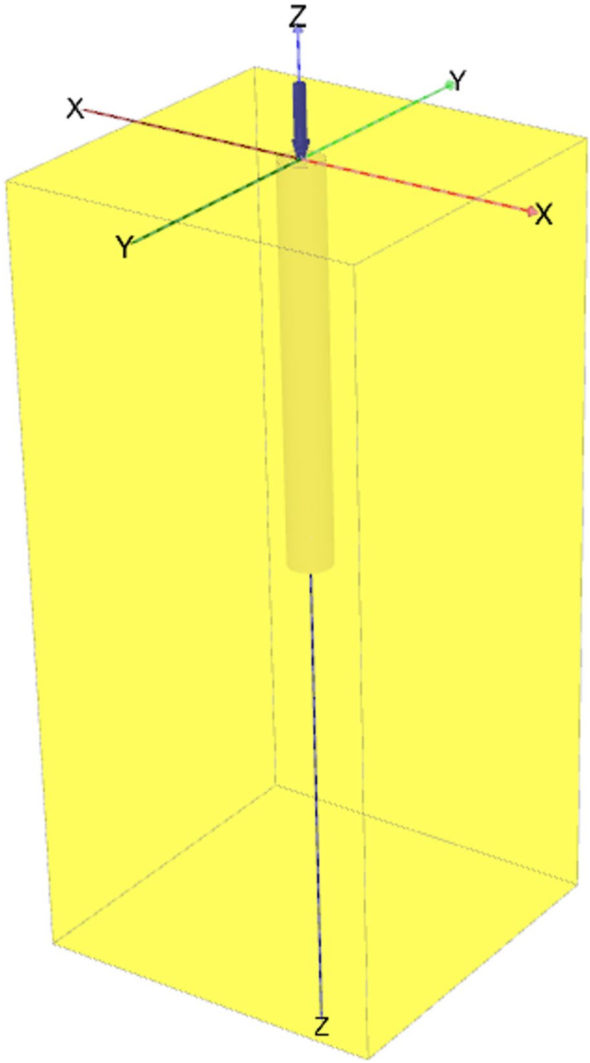
Parameter	Description	Typical range	Unit
e	Void ratio	0.5–0.7	–
γ_{unsat}	Unsaturated unit weight	18–20	kN/m³
γ_{sat}	Saturated unit weight	19.9–21.3	kN/m³
c′	Cohesion	3–6	kN/m²
φ′	Internal friction angle	28–34	degrees (°)
E′	Elastic modulus	14,000–26,500	kN/m²
υ′	Poisson's ratio	0.24–0.31	–

is determined as 5700 kN, which serves as the reference for establishing the load increments in the simulation.

The pile geometry, material properties, and interface conditions between pile and soil are defined in detail within the Plaxis 3D model to accurately represent the load transfer mechanism between the pile and the surrounding soil (Fig. 1). These parameters are also used as input data for the machine learning model during the training stage to maintain consistency between numerical simulation and predictive modeling.

The model is established with boundary conditions reflecting realistic field conditions: lateral boundaries are restricted from horizontal movement, the bottom boundary is fully fixed, and axial compression loads are applied at the pile head. The soil and pile materials are modeled as linear elastic to focus on analyzing the relationship between load and settlement while generating a standardized dataset for training the

Fig. 1 FEM simulation in plaxis 3D



machine learning model. The simulation is divided into 22 incremental load steps, ranging from 1425 kN to 27,000 kN, with a constant increment of 1425 kN. At each load step, the vertical settlement (Uz) at the pile head is recorded, forming a crucial dataset for training the artificial neural network. The choice of 22 continuous load steps allows the model to capture a high-resolution load–settlement curve, enabling analysis of the nonlinear behavior of the pile–soil system under large deformation.

After completing the finite element simulation, the output data are used to train a machine learning model based on an artificial neural network (ANN), specifically a Multi-Layer Perceptron (MLP). The model is built using the Scikit-learn library (Python) through the MLPRegressor tool. The network architecture consists of three hidden layers with 64–64–32 neurons, using the ReLU activation function to optimize nonlinear learning capability. The Adam optimization algorithm is employed to ensure fast and stable convergence. Training is conducted for 1000 epochs, with the option warm_start=True to retain learning states between iterations (Fig. 2).

The input dataset includes 11 features: LOAD, Y_{UNSAT}, Y_{SAT}, e, E', Poisson, c', phi, psi, and Time, in which "LOAD" represents the applied load and "Time" reflects the load application duration (Fig. 3). The data are normalized using StandardScaler to ensure scale consistency. The dataset is randomly divided into 80% for training and 20% for testing to objectively assess model performance.

The objective of the machine learning model is to predict the settlement Uz corresponding to each combination of input conditions, thereby providing a fast and effective surrogate tool for traditional FEM simulations, which require significantly more computation time.

From the load–settlement curve predicted by the machine learning model, three different methods are applied to determine the ultimate load capacity (Pmax) of the bored pile. These methods ensure a multidimensional evaluation, including: Piecewise Linear Regression, the Curvature-based Method, and the Slope Ratio Method.

The piecewise linear regression method divides the load–settlement curve into two linear segments and identifies the intersection point as the boundary between elastic and nonlinear behavior (Table 2) (Chakeri et al. 2014; Zhang and Goh 2013; Dang et al. 2024).

The curvature-based method computes the second derivative of the curve to detect the point of maximum curvature, which reflects the transition in the pile–soil sys-

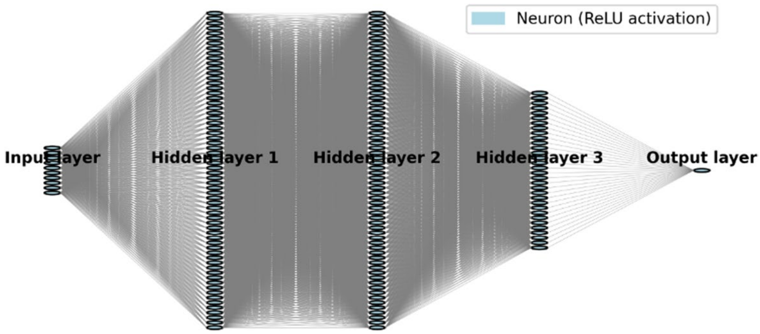


Fig. 2 Architecture of the MLP feedforward neural network (64–64–32)

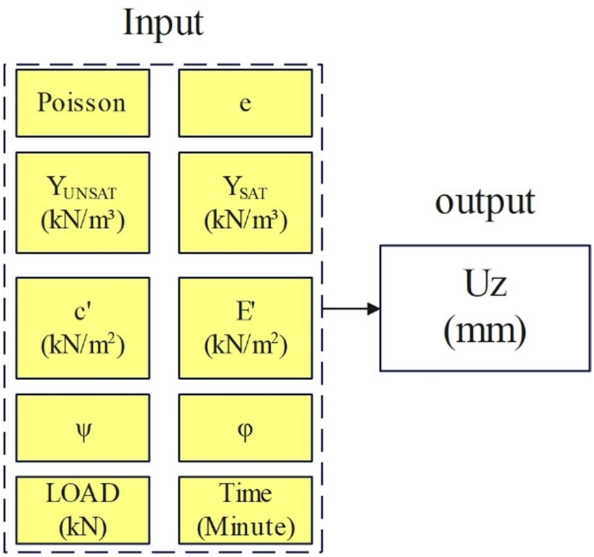


Fig. 3 Input and output variables of the predictive model

Table 2 Piecewise linear regression method for determining ultimate load capacity (Pmax)

Step	Process description	Algorithm
1	Input data preparation	Extract data from MLP model
2	Iteratively divide the dataset at an assumed breakpoint (i).	Split data into two subsets: Region 1: (x_1, y_1=x[: i], y[: i]) Region 2: (x_2, y_2=x[i:], y[i:])
3	Perform linear regression for both regions.	Fit two linear models: (y1=a1x+b1), (y2=a2x+b2).
4	Compute total sum of squared errors (SSE) for each breakpoint.	$SSE_i = \sum (y1-\widehat{y}1)^2 + \sum (y2-\widehat{y}2)^2$
5	Identify the minimum SSE point.	$i^* = argmin\,(SSE_i)$
6	Determine the intersection of the two regression lines.	Solve: $Pmax = \frac{b2-b1}{a1-a2}$

tem from elastic to nonlinear behavior (Yang and Liang 2007; Bhardwaj and Singh 2015). Meanwhile, the slope ratio method identifies the ultimate load based on sudden increases in slope between two consecutive load levels (Georgiadis and Georgiadis 2010; Murff 1993).

These three methods are applied to the same predicted dataset to compare, cross-validate, and determine the representative Pmax value used in the results and discussion. Integrating machine learning with traditional analytical techniques not only enhances reliability but also significantly reduces the time required to determine the ultimate load capacity of bored piles in modern foundation design.

The performance of the machine learning model is evaluated using standard metrics such as the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). These metrics reflect how accurately the model captures the relationship between predicted and actual values. Additionally, the results from the machine learning model are compared with field static load test data to verify reliability and practical applicability.

3 Results

The numerical analysis results from Plaxis 3D simulations allow the evaluation of the behavior of bored piles embedded in sandy clay soil under progressively increasing static loads. The dataset consists of 22 load increments, ranging from 1425 to 27,000 kN/m². The output includes the corresponding vertical settlement (Uz) at the pile head together with the surrounding soil parameters.

Descriptive statistical analysis of the FEM dataset shows that the average settlement Uz is −182.06 mm, with a relatively high standard deviation of 302.25 mm. This indicates an uneven data distribution and a tendency for settlement to increase sharply at higher load levels. The maximum settlement reaches −1777.69 mm (Fig. 4) at the soil configuration presented in Table 3.

Meanwhile, the minimum settlement is only −1.41 mm, highlighting the strong nonlinear relationship between load and settlement.

The applied load has an average value of 13,566.82 kN/m², with a wide range from 1425 to 27,000 kN/m². Soil parameters used in the model include unsaturated unit

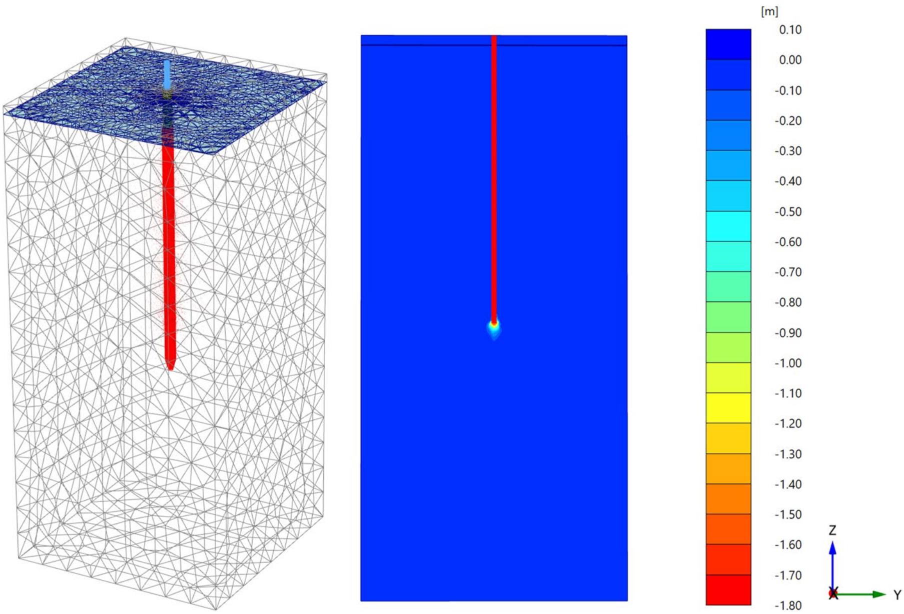


Fig. 4 FEM analysis result at maximum settlement

Table 3 Soil configuration corresponding to maximum Uz

γ_{unsat}	γ_{sat}	e	E’	ν	c’	φ
18.4	20.1	0.71	14,500	0.24	3.1	28

weight (γ_{unsat}) with a mean of 18.98 kN/m³ (range 18.2–19.7 kN/m³) and saturated unit weight (γ_{sat}) with a mean of 20.57 kN/m³. The void ratio (e) has an average of 0.6195 with low variability (standard deviation 0.069), indicating uniform soil conditions within the study area.

The effective elastic modulus (E') ranges from 14,000 to 26,500 kN/m², with an average of 20,175 kN/m², representing moderately dense soil conditions. Poisson's ratio averages 0.2795, suitable for sandy clay soils, with a small variation from 0.24 to 0.31. Effective cohesion (c') averages 4.39 kN/m², while the internal friction angle (φ) averages 31°, indicating moderate shear resistance. The dilation angle (psi) has a mean value of 1.3, increasing gradually with loading time, up to a maximum simulation duration of 1680 s.

From these analyses, it is evident that the soil possesses moderate mechanical properties and is not excessively weak. The FEM model successfully captures the full behavioral response of the soil–pile system under increasing load, providing a reliable dataset for training the machine learning model to predict load–settlement behavior.

After collecting all data from the Plaxis 3D simulations, the MLPRegressor machine learning model was applied to learn the nonlinear relationship between input parameters and settlement output. The model achieved extremely high performance on the test set (Table 4).

Specifically, the coefficient of determination R^2 reached 0.9983, indicating that the model explains 99.83% of the data variance. The mean absolute error (MAE) is only 6.60 mm, while the root mean square error (RMSE) is 11.43 mm, demonstrating high accuracy and robustness in predicting settlement. The learning curve shows that training MSE decreases from ~126,571 to ~61.89, while validation MSE decreases from ~103,191 to ~173.42, indicating good convergence without signs of overfitting (Fig. 5).

Table 4 MLP model performance

Metric	Value
RMSE	11.4291
MAE	6.5961
R^2	0.9983

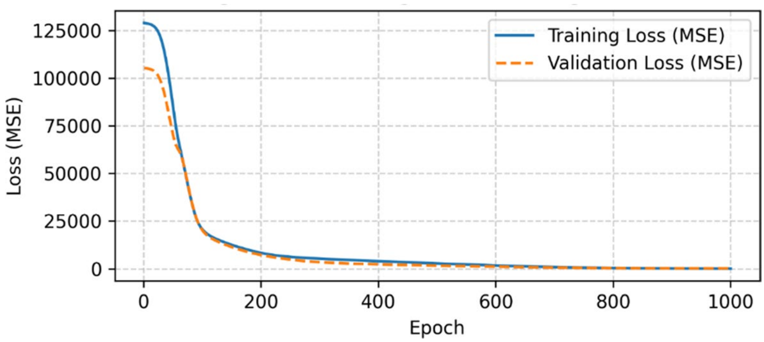


Fig. 5 Learning Curve – MLP

Residual analysis confirms that the MLP model predicts Uz with very high accuracy, with residuals centered around zero and following a normal distribution (Fig. 6).

The permutation-based feature importance analysis indicates that the applied load (LOAD) is the dominant factor governing the settlement of bored piles, as its permutation results in the largest reduction in model performance, with $\Delta R^2 = 1.15$ (Fig. 7). The soil shear strength parameters also exhibit significant influence, with the effective cohesion (c′) and internal friction angle (φ′) causing reductions of $\Delta R^2 = 0.61$ and 0.55, respectively, reflecting the high sensitivity of settlement to the shear resistance of the foundation soil. The Poisson's ratio (ν) plays an important role in the deformation mechanism, as indicated by a performance reduction of $\Delta R^2 = 0.48$. Other variables, including the saturated unit weight, loading duration, and dilation angle, show moderate influence, with ΔR^2 values ranging from approximately 0.20 to 0.26, whereas the void ratio and effective elastic modulus lead to only minor performance reductions of less than 0.05. These results confirm that the MLP model successfully captures the dominant physical factors governing the load–settlement behavior of the pile–soil system.

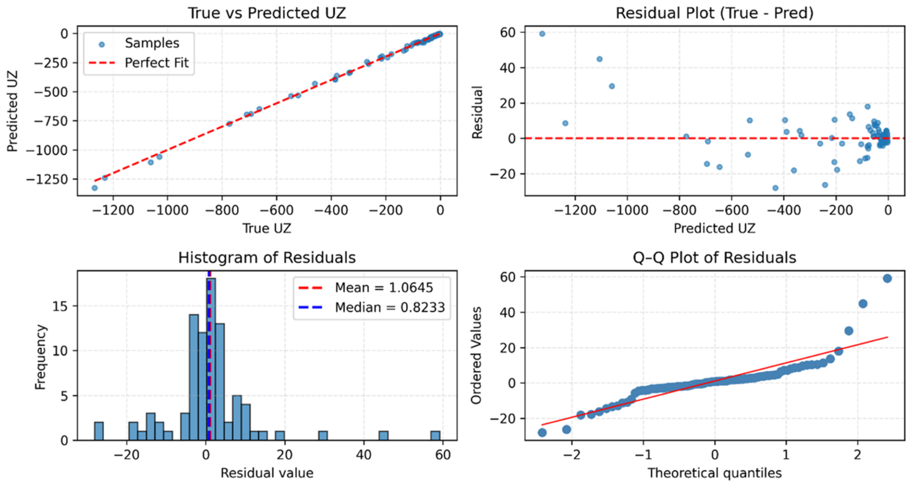
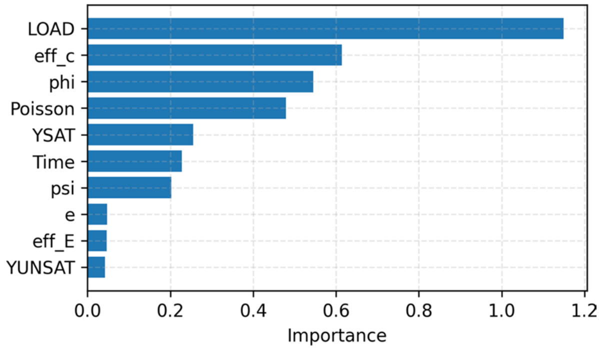


Fig. 6 MLP regressor – UZ prediction

Fig. 7 Feature Importance



Using the trained MLP model, settlement values were predicted for 22 different load levels (Table 5).

The prediction results show a clear nonlinear relationship between load and settlement, reflecting the true behavior of the pile–soil system (Fig. 8).

For small loads such as 1425 kN/m², the settlement is only − 19.89 mm. However, at the highest load level (27,000 kN/m²), settlement increases dramatically to − 1041.20 mm. At intermediate loads such as 15,900 kN/m², settlement reaches − 158.39 mm and increases rapidly afterward, indicating that the system has exceeded its linear working range (Table 6).

These results confirm that the MLP model accurately captures the nonlinear behavior of soil and pile materials under high load conditions.

The piecewise linear regression method yields an intersection point of Pmax = 15,171.66 kN/m², with a corresponding settlement of − 75.33 mm (Fig. 9). The curvature-based method, which identifies the point of maximum second derivative, gives Pmax = 15,900.00 kN/m² with a much larger settlement of − 158.39 mm (Fig. 10), indicating transition to large-deformation behavior. The slope ratio method gives a more conservative estimate of Pmax = 14,400.00 kN/m², with settlement of − 97.16 mm (Fig. 11).

Comparison of the three methods with the field static load test indicates high consistency (Table 7). Specifically, the piecewise linear regression yields 15,171.66 kN/m², the curvature-based method gives 15,900.00 kN/m², and the slope ratio method yields 14,400.00 kN/m². The field test recorded an actual Pmax of 15,725 kN/m². The

Table 5 Input parameters for Uz prediction

γ_{unsat}	γ_{sat}	e	φ	ν	E’	c’
20.2	20.6	0.697	30.8	0.3	25,000	4.3

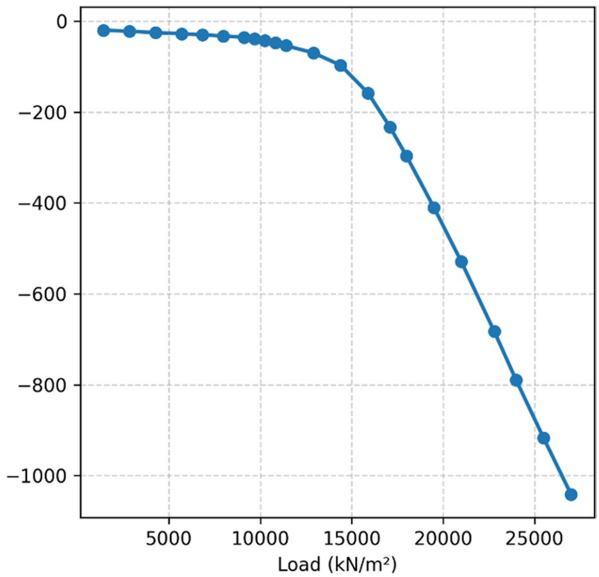


Fig. 8 Predicted load–settlement curve

Table 6 Predicted Uz (MLP)

No.	Load (kN/m²)	Predicted Uz (mm)
0	1425	−19.8856
1	2850	−22.3609
2	4275	−25.1661
3	5700	−27.8155
4	6840	−30.2101
5	7980	−32.6556
6	9120	−35.5396
7	9690	−38.4991
8	10,260	−42.4768
9	10,830	−47.927
10	11,400	−53.9272
11	12,900	−69.7358
12	14,400	−97.1577
13	15,900	−158.387
14	17,100	−233.279
15	18,000	−296.995
16	19,500	−410.034
17	21,000	−529.359
18	22,800	−682.85
19	24,000	−790.111
20	25,500	−917.51
21	27,000	−1041.2

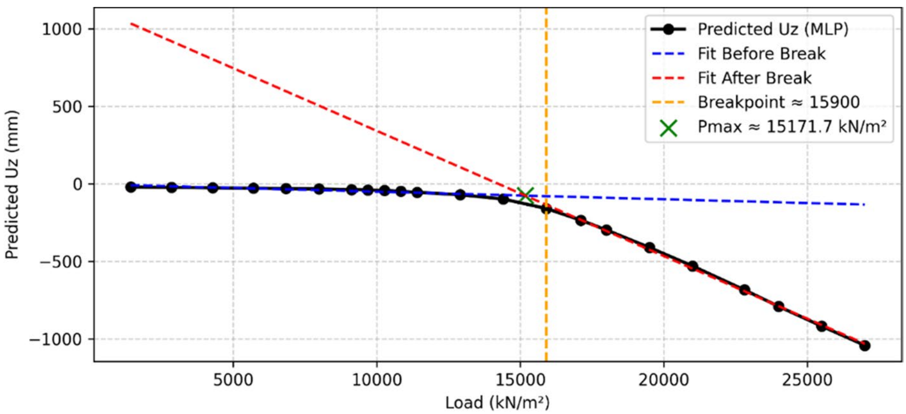


Fig. 9 Piecewise linear regression – ultimate load capacity

deviation between the predicted values and the field result is less than 10%, showing that the machine learning model not only replicates the trend but also approximates real measurements very well.

Among the three methods, the curvature-based method provides the closest estimate to the field value (error ~ 1.1%), demonstrating its sensitivity in detecting the transition from elastic to nonlinear deformation. The piecewise linear regression

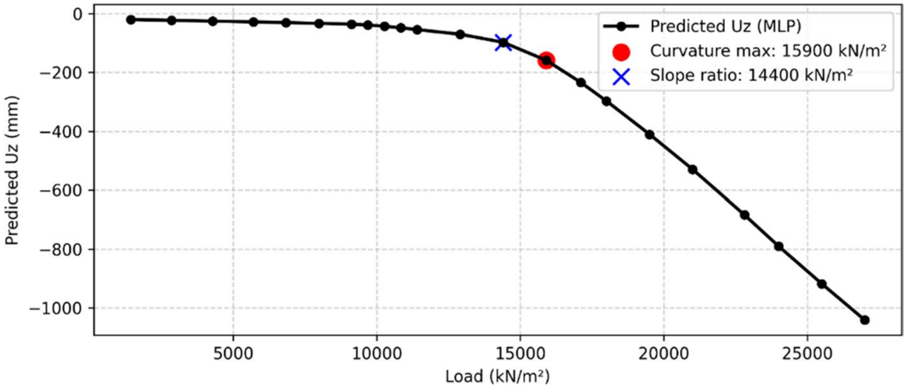


Fig. 10 Curvature-based vs. Slope ratio methods

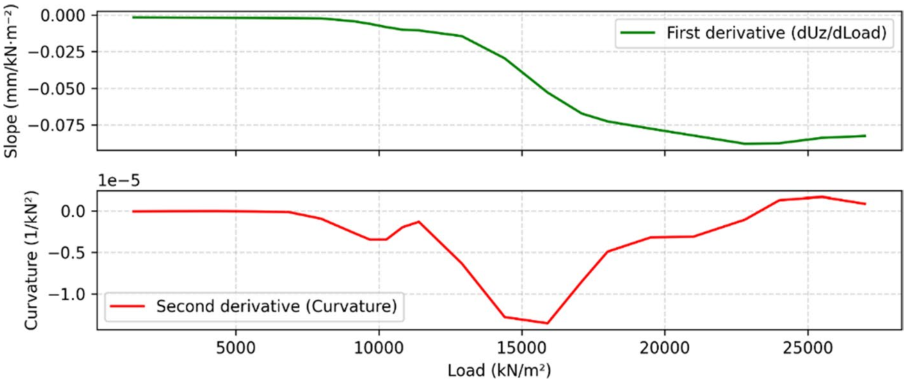


Fig. 11 Derivatives of load–settlement curve

Table 7 Comparison of Pmax among methods

Method	Pmax (kN/m²)
Piecewise Linear Regression	15171.66
Curvature-based	15,900
Slope Ratio	14,400
Field Static Load Test	15,725

method gives a stable and balanced result, while the slope ratio method provides a conservative estimate, making it suitable for safety-oriented foundation design.

The strong alignment between model predictions and field test results confirms the reliability and practical applicability of the MLP model for estimating the ultimate load capacity of bored piles in soft soils.

4 Discussion

The results of this study indicate that the machine learning model based on a multilayer feedforward neural network (MLP) achieves high accuracy in predicting the settlement and ultimate load capacity of bored piles. Comparison with field static load test results shows deviations of less than 10%, with the curvature-based method yielding a Pmax value of 15,900 kN/m², which is very close to the measured value of 15,725 kN/m², corresponding to a difference of approximately 1.1%. This level of agreement confirms the capability of the MLP model to reproduce the load–settlement behavior of the pile–soil system within the studied conditions.

These findings are consistent with trends reported in previous studies, where artificial intelligence models applied to pile capacity prediction typically achieved average errors of 3–8%. The integration of finite element simulation data with machine learning enables the advantages of both approaches to be exploited, allowing accurate reconstruction of the nonlinear response of the pile–soil system. The close agreement among Pmax values obtained from three independent methods, with differences of less than 10%, demonstrates the stability of the input data and the reliability of the load–settlement curves predicted by the MLP model.

Compared with traditional linear regression models, the MLP model shows a clear advantage in representing the nonlinear relationship between load and settlement, as reflected by its high performance metrics ($R^2 = 0.9983$, MAE = 6.60 mm, RMSE = 11.43 mm). However, since the training dataset was mainly generated from finite element simulations with a relatively limited sample size, the potential risk of overfitting should be noted, although the learning curves indicate stable convergence.

Another limitation of the present study is the use of a linear elastic soil model, which does not fully capture the nonlinear behavior of the soil at high load levels. Therefore, the MLP model proposed in this study should be regarded as a surrogate tool to supplement finite element analyses, primarily for interpolation within the investigated parameter range, rather than a complete replacement for conventional finite element methods. Future work should focus on expanding the dataset, adopting nonlinear soil models, and considering more complex geological conditions to enhance the generalization capability and practical applicability of the proposed approach.

5 Conclusion

The results of this study demonstrate that the machine learning model using a multilayer feedforward neural network (MLP), combined with input data obtained from finite element simulations using Plaxis 3D, is capable of accurately predicting the settlement of bored piles under static loading. The model achieves a coefficient of determination of $R^2 = 0.9983$, indicating its ability to almost completely replicate the actual deformation behavior of the pile–soil system. Integrating FEM simulation data enables the machine learning model to learn complex nonlinear relationships among load, soil properties, and displacement, thereby reconstructing the load–settlement curve with high reliability without requiring the extensive numerical computations typical of traditional finite element analysis.

Based on the predicted results, the ultimate load capacity of the bored pile is determined to range from 14,400 to 15,900 kN/m², depending on the evaluation method used. The three methods—piecewise linear regression, curvature-based analysis, and slope ratio—produce closely aligned results with deviations of less than 10% compared to field static load tests. This high level of agreement between the machine learning model and experimental data indicates that the proposed approach can provide strong support for traditional testing and simulation methods in determining the ultimate load capacity of piles, particularly for rapid assessment and preliminary design within the investigated parameter range.

Future research should focus on extending the model to various geological conditions, including weak and heterogeneous soils, and developing automated prediction systems to support foundation design and assessment in practice. Such advancements will contribute to creating a powerful decision-support tool for geotechnical engineers, enabling faster, more accurate, and more efficient foundation design.

Author Contributions Conceptualization: Luan Nhat Vo, Tuan Anh Nguyen ; methodology: Tuan Anh Nguyen, Hoa Van Vu Tran; formal analysis and investigation: Luan Nhat Vo, Tuan Anh Nguyen, Hoa Van Vu Tran; writing-original draft preparation: Luan Nhat Vo, Hoa Van Vu Tran; writing-review, and editing: Tuan Anh Nguyen. All authors read and approved the final manuscript.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Ethics Not applicable.

Consent to Participate Not applicable.

Competing Interests The authors declare no competing interests.

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