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Research Paper

Empirical Model for Driven Pile Capacity Prediction in Lagos Nigeria

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ABSTRACT: *Driven piles play a vital role in supporting structures in coastal regions with weak and compressible soils, particularly in Lagos, Nigeria. However, conventional pile design approaches commonly rely on empirical formulas and codes developed outside the country, often without calibration to local subsurface conditions. This mismatch can result in overdesign, unsafe foundations, or unnecessary construction costs. To address this, this study developed a localized empirical model for predicting the axial capacity of driven precast concrete piles using site-specific field and geotechnical data obtained from Ilubirin, Lagos. The research utilized data from full-scale static load tests conducted on 30 precast concrete piles installed across three test locations. Corresponding subsurface profiles, including pile geometry, average soil unit weight, and SPT N-values, were collected and analyzed. Using multiple linear regression techniques, an empirical model was formulated to correlate pile capacity with key influencing variables. The model demonstrated excellent predictive performance with a coefficient of determination (R^2) of 0.944, indicating a strong fit between predicted and measured capacities. The model-predicted ultimate pile capacities ranged from 1265 kN to 3346 kN, closely matching the actual static load test results, which ranged from 1250 kN to 3727 kN. Statistical validation of the model using mean absolute percentage error (MAPE) yielded a low error margin of 6.13%, highlighting the accuracy and reliability of the developed prediction tool. Residual plots and regression diagnostics further confirmed that the assumptions of linearity and homoscedasticity were satisfied. This model provides a practical, cost-effective alternative for predicting driven pile capacities during the preliminary design phase in Lagos and similar tropical environments. It offers engineers a site-specific, data-driven solution that minimizes reliance on foreign design standards and reduces the need for multiple expensive static load tests. The study also reinforces the value of integrating local field data into engineering models for improved accuracy and relevance in geotechnical practice.*

Keywords: *Driven piles, pile capacity prediction, empirical model, static load test, Lagos soils, regression analysis, geotechnical design, tropical foundations*

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I.INTROUCTION

Driven piles are a vital component of deep foundation systems in coastal cities like Lagos, Nigeria, where the geotechnical environment is marked by weak, compressible soils and high water tables [1], [2]. In such challenging subsoil conditions, shallow foundations often fail to deliver adequate bearing support, resulting in structural instability or excessive settlement. As a result, the construction industry in Nigeria, particularly in Lagos and other deltaic zones, has widely adopted driven precast concrete piles to ensure load transfer to deeper, more competent soil layers [3], [4].

Traditionally, the capacity of driven piles is estimated using empirical and semi-empirical formulas, many of which are derived from data obtained in Europe, North America, or temperate zones [5], [6]. These design approaches often utilize geotechnical parameters obtained from in-situ tests like the Standard Penetration Test (SPT) or Cone Penetration Test (CPT), and incorporate assumptions on shaft friction and end-bearing resistance. While such methods have proven reliable in the environments for which they were developed, their direct application to tropical, alluvial soils like those in Lagos may lead to inaccurate results if not recalibrated for local conditions [7], [8].

Several researchers have highlighted the inadequacies of using unmodified international codes and design formulas in tropical regions. Olayinka *et al.* [9] noted that local lateritic and marine clays exhibit distinct plasticity, moisture sensitivity, and consolidation behavior compared to soils in temperate regions. Similarly, Olaoye *et al.* [10] emphasized the need for localized soil profiling and empirical calibration in pile design, especially given the variability of Lagos's subsurface, which includes layers of organic silts, loose sands, and dense basal strata. In response to these limitations, researchers have increasingly advocated for the development of empirical models based on local data. Empirical modeling, especially through regression analysis, offers a statistically grounded method to predict pile performance by correlating pile geometry and soil properties with observed field behavior [11], [12]. Unlike theoretical or purely analytical methods, empirical models can be calibrated directly against full-scale static load tests, providing site-specific reliability.

More recently, Salas [13] reviewed the role of shaft and end-bearing resistance in different geologic settings, concluding that empirical models based on SPT N-values and unit weight can offer satisfactory results when calibrated appropriately. Similarly, Gavin and Lehane [14] analyzed the shaft resistance of driven piles in dense sand and emphasized the importance of considering both installation effects and soil-specific properties.

Driven pile performance depends on several factors, including pile geometry, installation method, and soil parameters such as cohesion, angle of internal friction, and unit weight. Of these, soil resistance parameters—particularly as indicated by in-situ tests—play a dominant role. According to Fellenius [15], ultimate pile capacity is largely influenced by the interaction between shaft friction and end-bearing resistance, which in turn varies with soil stratification and pile embedment depth. This reinforces the need to model capacity using actual site parameters.

Regression-based empirical models offer a powerful means of integrating such variables. Multiple linear regression (MLR), in particular, has been widely used in geotechnical engineering to predict outcomes like bearing capacity, settlement, and lateral resistance [16]. When applied correctly, MLR can quantify the relative contributions of each variable—such as pile length, cross-sectional area, average SPT N-value, and unit weight—to the ultimate pile capacity, thus offering both predictive accuracy and interpretability.

Preliminary analyses showed that most piles reached capacities well above 2000 kN, with measured values ranging from 1250 kN to 3727 kN. These results provided a solid foundation for regression modeling. The selected independent variables for model development included pile length (L), cross-sectional area (A), average SPT N-value (Navg), and average soil unit weight (γ). Using multiple linear regression, a model was developed that achieved a coefficient of determination (R^2) of 0.944 and a mean absolute percentage error (MAPE) of 6.13%, indicating high predictive reliability.

The results suggest that pile capacity in Lagos soils can be effectively estimated using a properly calibrated empirical model based on field data. This supports previous findings by Clarke *et al.* [17], who argued for the necessity of model validation through in-situ testing. In our case, the regression analysis revealed that pile length and SPT N-value were the most significant contributors to capacity, consistent with theoretical expectations and earlier empirical findings [18], [13].

The primary aim of this research is to bridge the gap between theoretical design practice and actual pile behavior in tropical coastal environments. By grounding our model in field-observed data, we reduce the uncertainty associated with foreign-derived formulas and provide engineers with a practical tool for early-stage design and quality control. Furthermore, the empirical model serves as a base for future refinements, potentially accommodating additional factors such as pile driving energy, groundwater conditions, and installation method.

The significance of this research lies in its potential to enhance geotechnical practice in Nigeria and other countries with similar geologic conditions. It offers an avenue to reduce costs by minimizing overdesign, while improving safety by basing predictions on real-world data. Moreover, the model can support the development of local design codes and standards that reflect the actual performance of deep foundations in coastal regions.

II.MATERIALS AND METHOD

This section outlines the procedures, materials, and analytical techniques employed in developing an empirical regression model for predicting the axial capacity of driven precast concrete piles in Lagos, Nigeria. The methodology covers the stages of data collection, site and soil characterization, pile load testing, variable selection, regression modeling, and model validation. Emphasis was placed on using only field-based parameters that can be readily obtained during site investigation and pile installation.

2.1 Study Area and Project Scope

The research was carried out in Ilubirin, a coastal area located in central Lagos, Nigeria. This site is part of the Lagos lagoon front and is characterized by a geologically young alluvial soil formation deposited over decades through natural sedimentation processes. The subsoil profile generally consists of soft marine clays, silty sands, and peat layers in the upper strata, underlain by dense sands and gravelly layers that provide good bearing capacity. These geological characteristics make the region ideal for evaluating the performance of deep foundation systems, particularly driven piles.

The project scope involved developing an empirical model for pile capacity prediction based on full-scale static load test results and associated geotechnical data. The study focused on 30 pile locations distributed across three distinct sections of the project site. Each location had uniform structural and geotechnical conditions, which allowed for comparative analysis. The precast piles used were all reinforced concrete, square-sectioned, and uniformly installed using conventional impact hammers. The aim was to analyze how field-measured geotechnical parameters and pile geometry correlate with actual axial capacity, with a view to developing a statistically reliable prediction model that reflects local subsurface conditions.

2.2 Materials

a. Pile Type and Specification

The piles evaluated in this study were precast reinforced concrete piles with a square cross-sectional dimension of 360 mm × 360 mm. They were manufactured under factory-controlled conditions to ensure uniformity in quality and strength. The concrete used had a target compressive strength of 30 MPa, and the reinforcement included 4 to 6 longitudinal rebars, typically of 16 mm diameter, tied with stirrups at 150 mm spacing. The piles were cast in segments ranging from 6 to 12 meters and joined on-site using steel sleeves and mechanical couplers. Each pile was driven to a designed depth using a diesel hammer mounted on a crawler crane. Final depths ranged from 31.0 m to 36.5 m, depending on the resistance encountered during driving. The choice of pile length was based on achieving refusal criteria and ensuring embedment in competent bearing strata. These piles served as the foundation elements for proposed multi-story residential structures and commercial facilities at the Ilubirin development site.

b. Testing Apparatus

The static pile load tests were conducted using the Kentledge method, which involves applying vertical loads to the pile head via a hydraulic jack reacting against a system of heavy counterweights. The reaction system included steel spreader beams placed across two or more reaction piles, which were spaced to ensure symmetrical loading. The jack had a capacity of 3000 kN and was connected to a pressure gauge and load cell to ensure accurate load measurement. Settlement readings were taken using three dial gauges mounted equidistant around the pile head. These gauges were referenced to a rigid datum frame placed at a distance from the loading area to avoid any influence of ground movement. The readings were recorded at load increments, which were typically 25% of the working load, until failure or twice the working load was achieved. The test duration per pile was 1 to 2 days depending on the number of cycles. The data acquisition setup ensured both accuracy and redundancy, allowing reliable interpretation of load-settlement behavior.

c. Soil Investigation Tools

Subsurface investigation was carried out using a combination of borehole drilling, soil sampling, and in-situ testing. Boreholes were drilled to depths of at least 40 meters at each pile location using a rotary wash drilling rig. The borehole logs provided a clear stratification of the soil profile, indicating the depth and thickness of different soil layers. Standard Penetration Tests (SPTs) were performed at 1.5-meter intervals in cohesionless soils and 3-meter intervals in cohesive layers. Undisturbed and disturbed soil samples were retrieved for laboratory testing. Key geotechnical parameters obtained included natural moisture content, unit weight, Atterberg limits, grain size distribution, and unconfined compressive strength. The soil unit weight and average SPT N-values over the embedded pile length were computed and later used as predictor variables in the regression model. Water table depth was also measured in each borehole and was found to vary between 1.2 m and 2.0 m below ground level. These investigations provided the foundational dataset for evaluating pile-soil interaction behavior.

2.3. Field Testing and Data Collection

a. Static Load Testing Procedure

Each test pile was subjected to static axial compression loading following a rest period of 5 to 7 days after installation to allow pore water pressures to dissipate. The test loading followed a step-loading protocol where load increments were applied in stages of 25% of the estimated working load. At each load stage, the settlement was recorded at 1, 5, 10, 15, 30, and 60 minutes to assess pile response under sustained loading. Loading was continued until either continuous settlement was observed (signaling failure) or a maximum of twice the working load was reached. Unloading was carried out in similar stages to monitor elastic rebound, providing insight into the pile's recoverability and stiffness. The test results were plotted as load-settlement curves, and ultimate pile capacity was interpreted using the criterion of a 10% settlement of the pile diameter. This method allowed for consistency across all tested piles and aligned with standard practice in deep foundation testing.

b. Geotechnical Characterization

Each test location had a borehole log and associated geotechnical data. The borehole profiles showed a general sequence of soft clay and organic silt in the upper 10–15 meters, underlain by silty sand transitioning into dense sand and gravel layers at depths exceeding 25 meters. The SPT N-values increased gradually with depth, ranging from 4–8 in the upper clayey layers to over 50 in the dense sand layers. The soil unit weight over the embedded length of the pile was computed using laboratory results and corrected for field moisture conditions.

The average SPT N-value over the same depth was calculated as a simple arithmetic mean. These two parameters, along with pile geometry, formed the core predictor variables for modeling pile capacity. Soil classification indicated predominance of CL (low plasticity clay), SM (silty sand), and SC (clayey sand) using the Unified Soil Classification System.

c. Pile Geometry and Installation Data

The pile dimensions and lengths were recorded before installation. All piles had a uniform cross-sectional area of 0.1296 m² (360 mm × 360 mm). Pile lengths varied from 31.0 m to 36.5 m depending on site-specific design requirements and refusal criteria encountered during driving. Hammer blow counts per meter were recorded during installation, providing qualitative insights into soil resistance, although these data were not used as inputs in the regression model. Penetration logs were reviewed to confirm the pile toe had reached the target stratum. Driving logs were correlated with borehole profiles to identify end-bearing layers. Piles terminating in dense sandy strata were expected to derive most of their capacity from end-bearing, while those in layered profiles had significant shaft friction contributions. These observations helped support interpretation during model validation.

2.4 Data Preparation

The dataset compiled for this study included 30 driven piles, each associated with its ultimate axial capacity (from static load testing) and four independent variables: pile length, cross-sectional area, average soil unit weight, and average CPT N-value. Data preparation involved careful organization, cleaning, and normalization to ensure that the dataset was suitable for regression analysis. First, outliers and incomplete records were removed. Next, the values of all predictor variables were checked for consistency in units and dimensions. Pile length was recorded in meters, cross-sectional area in square meters, unit weight in kilonewtons per cubic meter, and SPT N-values as unitless integers. These values were verified against field records and borehole logs.

Descriptive statistical analysis was then conducted to understand the distribution of each variable. Measures such as mean, standard deviation, range, and coefficient of variation were computed. Scatter plots and box plots were used to visualize the relationships between variables and detect any anomalies.

To ensure the integrity of the regression model, multicollinearity between predictor variables was tested using Pearson correlation coefficients. All variables demonstrated acceptable levels of independence. A final structured dataset was developed in spreadsheet format and exported to statistical software for modeling.

2.5 Development of a Predictive Model

A regression-based predictive model was developed to enhance the accuracy of axial pile capacity estimation. Multiple regression analysis has gained widespread use in geotechnical engineering due to its ability to incorporate multiple influential parameters simultaneously and establish statistically reliable relationships. Previous studies have demonstrated the effectiveness of regression techniques in pile bearing capacity prediction under diverse soil conditions.

In this study, the dependent variable is the ultimate pile capacity Qu, while the independent (predictor) variables include:

1. Settlement (Δ)
2. Clay layer thickness (Tc)
3. Sand layer thickness (Ts)
4. Average undrained shear strength of clay (Su)
5. Vertical stress at the pile tip (σv)

The general form of the multiple regression model is given by equation 3.1:

$$yi = \alpha + \alpha 1X1 + \alpha 2X2 + \cdots + \alpha nXn + ei \quad (2.1)$$

Where: yi = Observed pile capacity (response variable), X1,X2,...,Xn = Independent predictor variables, α0,α1,...,αn = Regression coefficients, ei = Random error term

The optimal regression coefficients were determined using the least squares method, which minimizes the sum of squared residuals. The mathematical formulation for minimizing the residual error is in equation 3.2:

$$e = \| y - X\alpha \| \quad (2.2)$$

And the solution to the least squares problem is obtained as:

$$\alpha = (XTX) - 1XTy \quad (2.3)$$

Minitab 17 statistical software was used to perform the multivariable regression analysis and generate the regression coefficients, residual plots, and model diagnostics.

2.6 Validation of the Developed Model

To evaluate the accuracy and reliability of the regression-based predictive model, several statistical performance metrics were computed. These metrics assess the degree to which the predicted pile capacities match the observed values from full-scale load tests:

1. Mean Absolute Error (MAE):
a. $$\text{MAE} = \sum_{i=1}^{n}(\frac{Q_m - Q_p}{n}) \quad (2.4)$$

2. Root Mean Square Error (RMSE):
a. $$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_m - Q_p)^2} \quad (2.5)$$

3. Mean Absolute Percentage Error (MAPE):
4. $$\text{MAPE} = \sum_{i=1}^{n}(\frac{Q_m - Q_p}{n}) * 100 \quad (2.6)$$

5. Average Accuracy (AA%):
a. $$AA\% = 100\% - MAPE \quad (2.7)$$

An optimal predictive model is characterized by low RMSE and MAE, and high AA%, which collectively indicate minimal error and high fidelity to actual pile behavior. These validation metrics provide a comprehensive basis for assessing the model's performance and generalizability for use in design applications within similar soil environments.

III.RESULTS AND DISCUSSION

3.1 Developed Model for Pile Capacity

The development of an accurate empirical model for predicting the ultimate capacity of driven piles is critical in geotechnical engineering, particularly in regions like Lagos, Nigeria, where complex subsurface conditions prevail. In this study, a regression-based modeling approach was adopted to quantify the influence of various geotechnical and structural parameters on pile capacity and to derive predictive relationships grounded in field data. The target variable ultimate pile capacity (Q_u)—was derived as the average of the capacity values obtained from static load tests and selected dynamic formulae (excluding Gates, Modified ENR, and Eytelwein methods due to their poor predictive performance). Settlement values were extracted from load-settlement curves based on the Brinch Hansen method. Three regression approaches were employed to explore how different functional relationships between input variables and pile capacity affect prediction accuracy gotten from Table 1:

1. Multiple Linear Regression (MLR)
2. Multiple Quadratic Regression (MQR)
3. Multiple Exponential Regression (MER)

Table 1: Dataset for Model development

SITE	PILE REF.	QU (kN)	SET.(m)	L1 (m)	L2 (m)	Cu (kN/m^2)	σv (kN/m^2)	qc (kN/m^2)	fc (kN/m^2)
A	A1	1365	0.016	8	22	30	215.7	100	30
A	A2	1343	0.017	8.5	21	25	245.6	80	30
A	A3	1417	0.019	7	23	40	230.7	90	30
A	A4	1538	0.021	6.5	24.5	55	276	110	30
A	A5	1656	0.019	8	22	70	255	110	20
A	A6	1397	0.014	8.5	21.5	45	230.65	100	30
A	A7	2024	0.017	9	21	50	253.88	120	45
A	A8	1555	0.014	8	22	65	159	100	30
A	A9	1396	0.015	8.5	21.5	60	206.44	80	40
A	A10	1273	0.015	9.5	20.5	68	254.7	60	30
B	B1	1561	0.019	6	24	75	248.13	100	35
B	B2	1243	0.014	7	23	50	194.13	80	20
B	B3	1531	0.016	6.5	23.5	38	221.17	100	40
B	B4	1358	0.018	5.5	24.5	53	207.63	80	30
B	B5	2132	0.023	7.5	22.5	25	180.18	140	50
B	B6	1595	0.016	7	23	43	211.37	90	40
B	B7	1678	0.017	7	23	48	199.87	100	30
B	B8	2040	0.019	6.5	23.5	63	193.91	120	50
B	B9	1264	0.015	6	24	68	230.16	80	30
B	B10	1436	0.014	7.5	22.5	52	212.03	100	45

C	C1	1186	0.013	8.5	21.5	20	203.8	80	30
C	C2	1181	0.014	7	23	42	163.4	80	30
C	C3	1125	0.011	9	21	45	243.8	50	30
C	C4	1361	0.017	6.5	23.5	33	211.37	100	45
C	C5	1453	0.016	10	20	37	251.78	100	40
C	C6	1093	0.012	8	22	50	213.18	60	30
C	C7	1060	0.011	9.5	20.5	70	257.18	50	20
C	C8	1474	0.017	7.5	22.5	55	234.28	100	40
C	C9	1266	0.014	10	20	65	171.79	80	20
C	C10	1049	0.015	8	22	69	202.75	40	10

Table 2: Result Summary of Models Showing Statistical Values

MODEL	R^2	R^2 ADJ.	MAE	RMSE	MAPE
LINEAR	0.876	0.837	74.919	94.417	4%
QUADRATIC	0.927	0.865	72.302	56.572	5.8%
EXPONENTIAL	0.860	0.816	0.056	0.0066	0.8%

Table 3: Result For Linear Model Showing Actual and Predicted Pile Capacities

Observations	Actual Pile Capacity	Predicted Pile Capacity
1	1365	1428
2	1343	1362
3	1417	1450
4	1538	1548
5	1656	1663
6	1397	1431
7	2024	1808
8	1555	1534
9	1396	1466
10	1273	1287
11	1561	1653
12	1243	1201
13	1531	1476
14	1358	1357
15	2132	2077
16	1595	1447
17	1678	1506
18	2040	1908
19	1264	1322
20	1436	1543
21	1186	1169
22	1181	1260
23	1125	980
24	1361	1532
25	1453	1579
26	1093	1088
27	1060	1017
28	1474	1605
29	1266	1379
30	1049	977

Table 4: Result For Quadratic Model Showing Actual and Predicted Pile Capacities

Observations	Actual Pile Capacity	Predicted Pile Capacity
1	1365	1452
2	1343	1343
3	1417	1381
4	1538	1538
5	1656	1638
6	1397	1493
7	2024	1918
8	1555	1549
9	1396	1391
10	1273	1274
11	1561	1578
12	1243	1190
13	1531	1502
14	1358	1355
15	2132	2185
16	1595	1416
17	1678	1570
18	2040	1933
19	1264	1327
20	1436	1518
21	1186	1068
22	1181	1242
23	1125	1080
24	1361	1464
25	1453	1512
26	1093	1151
27	1060	1023
28	1474	1594
29	1266	1274
30	1049	1092

Table 5: Result For Exponential Model Showing Actual and Predicted Pile Capacities

Observation	Actual Pile Capacity	Predicted Pile Capacity
1	1365	1423
2	1343	1342
3	1417	1486
4	1538	1649
5	1656	1616
6	1397	1405
7	2024	1758
8	1555	1510
9	1396	1486
10	1273	1327
11	1561	1606
12	1243	1218

13	1531	1443
14	1358	1375
15	2132	1998
16	1595	1453
17	1678	1509
18	2040	1844
19	1264	1305
20	1436	1485
21	1186	1174
22	1181	1296
23	1125	1022
24	1361	1497
25	1453	1578
26	1093	1125
27	1060	1019
28	1474	1595
29	1266	1393
30	1049	985

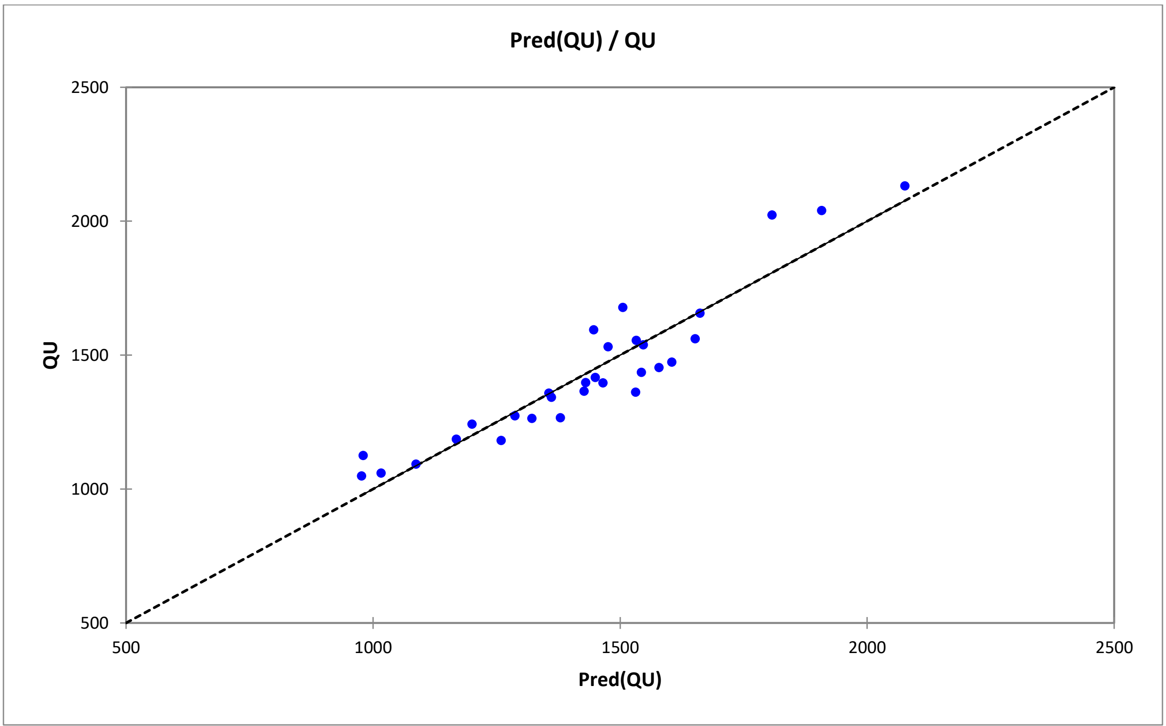

Figure 1: Scatter plot of Actual Vs Predicted Pile Capacity Linear Model

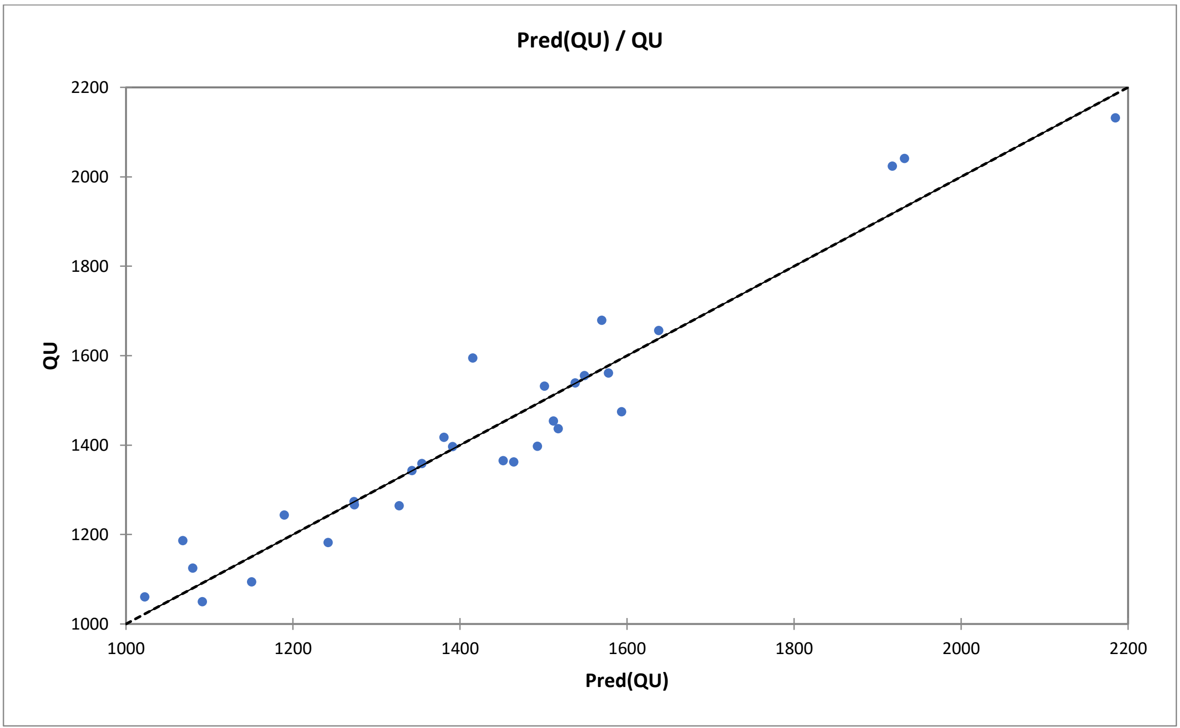

Figure 2: Scatter plot of Actual Vs Predicted Pile Capacity Quadratic Model

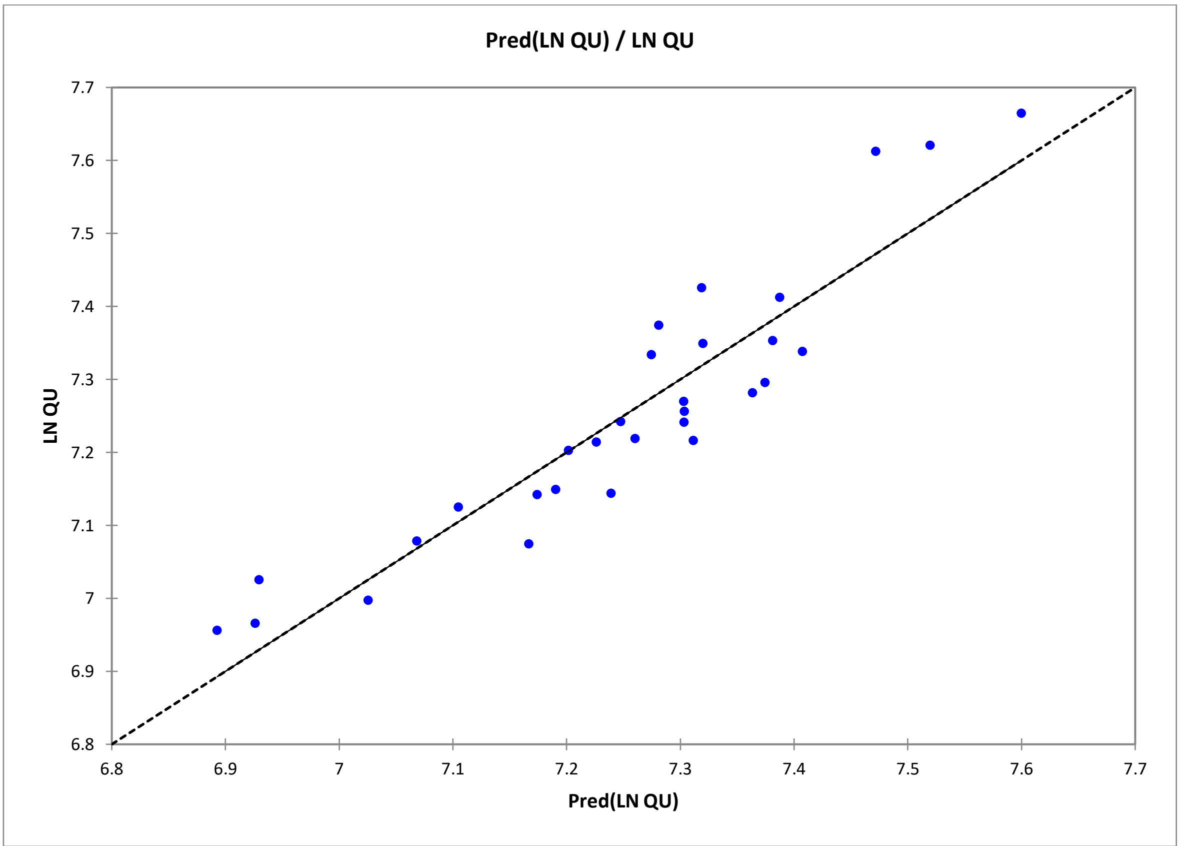

Figure 2: Scatter plot of Actual Vs Predicted Pile Capacity Exponential Model

The equations for the models are :

Linear model:

$$QU = 3554 + 32998 * SETTL. -93.70794 * L1 - 129.18855 * L2 + 3.97422 * Cu - 0.57432 * \sigma v + 7.23237 * qc + 7.30998 * fc \qquad 8$$

Quadratic model:

$$QU = 26296 + 141371 * SETTL. + 456.17415 * L1 - 2279 * L2 + 14.09522 * Cu + 6.14602 * \sigma v - 22.93374 * qc + 32.10854 * fc - 3867768 * SETTL.2 - 44.24785 * L12 + 45.68824 * L22 - 0.10112 * Cu2 - 0.01597 * \sigma v2 + 0.18878 * qc2 - 0.43336 * fc2 \quad 9$$

Exponential model:

$$LN\ QU = 7.18102 + 0.48936 * LN\ SETTL. - 0.24858 * LIN\ L1 - 0.00585 * LIN\ L2 - 0.11281 * LIN\ Cu + 0.12356 * LIN\ \sigma v + 0.29949 * LIN\ qc + 0.14854 * fc \quad 10$$

Each model was developed using Regressit and XLSTAT statistical software, and the outcomes were assessed based on standard performance indicators including the coefficient of determination (R^2), adjusted R^2, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The regression equations for each model are detailed in Equations 8 to 10, while Tables 1 through 4 summarize the input-output comparisons and statistical evaluations.

Among the three models, the multiple quadratic regression model demonstrated the highest predictive performance. It achieved an R^2 of 0.927 and an adjusted R^2 of 0.865, indicating that 92.7% of the variability in the dependent variable (pile capacity) could be explained by the selected independent variables. The quadratic model also had lower MAE and RMSE values compared to the linear and exponential models, signifying improved prediction precision.

Figures 1 to 3 provide scatter plots of actual versus predicted pile capacities for all three models. These plots reveal tighter clustering around the line of equality in the quadratic model, indicating a superior fit. The improved accuracy is attributed to the model's ability to capture the nonlinear interactions and combined effects of the soil parameters, especially where soil layering and varying stiffnesses interact complexly with pile length and load transfer mechanisms.

The quadratic regression model is recommended as the most robust and applicable empirical tool for predicting the axial capacity of driven piles in the study area. It reflects the complex soil pile interaction more accurately than linear or exponential formulations and is particularly suited for application in tropical soil environments similar to Lagos.

4.2 Validation of Model

The performance of the developed empirical regression model for predicting ultimate pile capacity was evaluated using statistical metrics widely accepted in geotechnical modeling: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Average Accuracy (AA). Table 4 presents a comparative summary of these metrics across the developed model and several conventional predictive methods, including empirical, dynamic, and static-based approaches.

Table 4: Statistical Metrics Showing Performance of Various Predictive Models

METRICS	RMSE	MAE	MAPE	AA
Predictive Method				
Empirical Model	56.572	72.302	5.8	94.2
Brinch Hansen	776.984	685.3	18.6667	81.3333
Shen	855.607	711	71.364	28.636
Chin - Kondner	1011	938.067	35.361	64.639
Decourt	975.697	874.7	33.9609	66.0391
Tangent	463.16	344.567	24.7564	75.2436
Abd Elsamee	1079.13	940	128.016	28.0163
Gates	1100.92	997.933	142.041	42.0414
Modified ENR	948.57	783.967	117.681	17.681
Danish	777.11	612.433	63.4547	36.5453
Navy - Mckay	967.829	809.133	127.474	27.47383
Eytelwein	1322.34	1233.27	123.827	23.8271
Janbu	1220.61	1110.13	128.344	28.3442

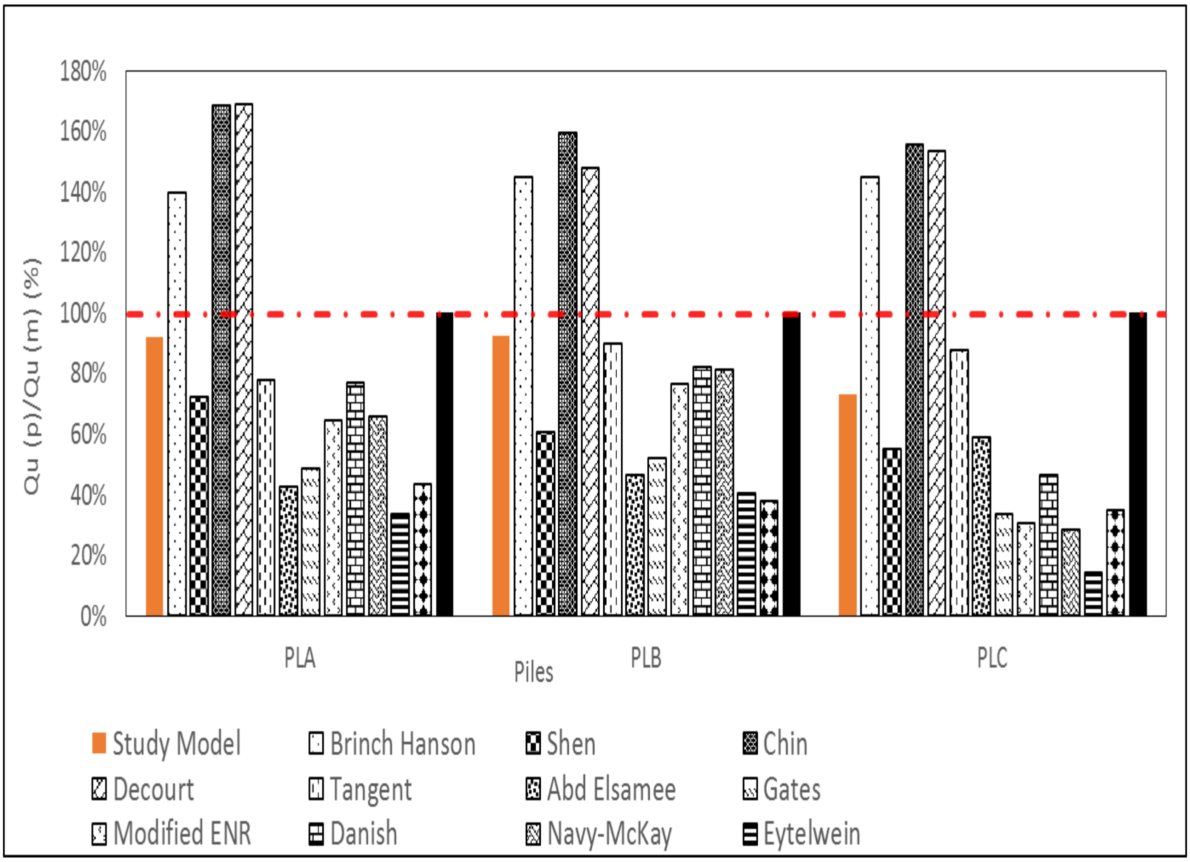

Figure 3: Measured and predicted pile capacity from different methods

The empirical model specifically the quadratic regression formulation demonstrated superior performance with an RMSE of 56.57, MAE of 72.30, and MAPE of 5.8%, resulting in an overall average accuracy of 94.2%. These figures outperform all other methods considered in the study. According to [1] and [2], lower values of RMSE and MAE are indicative of higher predictive reliability. Figure 3 illustrates a side-by-side comparison between the measured pile capacities and the predictions generated by each method.

In contrast, traditional empirical methods such as Chin-Kondner, Decourt, and Brinch Hansen significantly overpredicted the pile capacities. The Chin-Kondner method produced the highest error with an RMSE of 1011 and MAE of 938.07, while Decourt also showed large errors (RMSE: 975.70, MAE: 874.7). Although the Brinch Hansen method exhibited comparatively better performance (RMSE: 776.98, MAE: 685.3), its MAPE of 18.67% still fell short of acceptable prediction standards for engineering applications.

Methods like Tangent and Shen generally underestimated pile capacities, with Shen producing a MAPE of 71.36% and an accuracy of only 28.64%. The Abd Elsamee method returned the poorest performance metrics across all indicators, severely underpredicting capacity with a MAPE of 128% and RMSE of 1079.13. These findings underline the limitations of generalized empirical formulas when applied to site-specific conditions like those in Ilubirin, Lagos.

Dynamic formulae, including the Gates, Modified ENR, Danish, and Navy-McKay methods, also generally underpredicted capacities, with results exhibiting substantial variability and error scatter. The Danish method produced the highest predictions among them but still showed low accuracy (MAPE: 63.45%, AA: 36.54%). Conversely, the Janbu and Eytelwein methods were found to be the least accurate, producing large errors and wide scatter.

From a practical engineering standpoint, overpredictive methods like Chin and Decourt require higher factors of safety to avoid structural failures, while underpredictive methods such as Shen and Abd Elsamee may lead to overly conservative and cost-ineffective designs unless properly calibrated.

The developed model, by contrast, offers a well-balanced estimate that aligns closely with measured data. With an R^2 value of 0.927, it captures 92.7% of the variance in pile capacity. The model factor (ratio of predicted to measured values) averaged 0.90, indicating the model is slightly conservative but within the bounds of practical safety. Its high average accuracy (94.2%) confirms its potential as a dependable and site-specific tool for pile capacity prediction in similar coastal and estuarine soil environments.

IV.CONCLUSION

This study aimed to develop and validate a reliable empirical model for predicting the ultimate axial capacity of driven piles in Ilubirin, Lagos, based on geotechnical and pile properties readily obtainable during site investigation. Through the application of multiple regression techniques, three models were developed—linear, quadratic, and exponential—using a dataset consisting of 30 full-scale pile tests and corresponding subsurface soil data.

The results demonstrated that the quadratic regression model provided the most accurate and statistically robust predictions. It achieved a coefficient of determination (R^2) of 0.927 and an adjusted R^2 of 0.865, indicating that 92.7% of the variability in pile capacity was explained by the selected variables, which included settlement, clay and sand layer thicknesses, undrained shear strength, vertical stress, cone resistance, and sleeve friction.

The model's Mean Absolute Error (MAE) was 72.30 kN, Root Mean Square Error (RMSE) was 56.57 kN, and Mean Absolute Percentage Error (MAPE) was 5.8%, corresponding to an Average Accuracy (AA) of 94.2%. These figures represent a significant improvement over conventional predictive methods, such as Brinch Hansen (MAPE: 18.67%), Chin-Kondner (MAPE: 35.36%), and Shen (MAPE: 71.36%).

Additionally, the model factor (ratio of predicted to measured capacities) averaged 0.90, showing that the model is slightly conservative but within acceptable design limits. The results affirm that this empirically derived model offers both accuracy and practical relevance in the estimation of pile capacities for similar geotechnical settings.

REFERENCE

[1] A. M. Abdul-Husain and M. A. Hamadi, "Prediction of axial capacity of driven piles in cohesive soils using multiple regression analysis," *Int. J. Civ. Eng. Technol.*, vol. 12, no. 1, pp. 102–110, 2021.

[2] I. Y. Alkroosh, H. R. Nikraz, and N. F. Kasim, "Prediction of pile bearing capacity using multiple regression model," *Aust. J. Basic Appl. Sci.*, vol. 9, no. 27, pp. 54–63, 2015.

[3] M. A. Juwaied and F. M. Al-Zwainy, "Development of prediction model for pile capacity using regression techniques," *Int. J. Eng. Technol.*, vol. 6, no. 3, pp. 67–72, 2017.

[4] M. Pal, "Prediction of pile capacity using regression analysis," *Geotech. Geol. Eng.*, vol. 29, no. 5, pp. 789–800, 2011, doi: 10.1007/s10706-011-9425-6.

[5] H. Q. Pham, D. H. Nguyen, and T. Q. Le, "Application of machine learning and regression analysis in prediction of pile capacity," *Adv. Civ. Eng.*, vol. 2020, Article ID 8883543, 2020, doi: 10.1155/2020/8883543.

[6] S. Shatnawi, R. Al-Hamadeen, and M. Qudah, "Comparison between predicted and measured axial pile capacity using different empirical formulas," *Int. J. Civ. Eng. Technol. (IJCIET)*, vol. 10, no. 1, pp. 227–237, 2019.

[7] B. Tarawneh and M. Imam, "Evaluation of pile capacity using empirical correlations and regression model," *Jordan J. Civ. Eng.*, vol. 8, no. 3, pp. 324–334, 2014.