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STATISTICAL CORRECTION OF A DYNAMIC PILE BEARING CAPACITY FORMULA BASED ON PDA DATA

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ABSTRACT

The calculation of pile bearing capacity using a dynamic formula is considered a practical approach for evaluating the capacity of foundation piles. However, its results are often questioned when compared to the CAPWAP analysis outcomes derived from PDA testing. This study aims to assess the accuracy of the dynamic formula, develop a correction model using a statistical approach in the form MLR, and evaluate the effectiveness of the resulting correction model in predicting pile bearing capacity. A total of 84 pile datasets were utilized in this research, comprising various pile dimensions and PDA-derived parameters, including the maximum energy transferred to the pile (EMX), permanent pile settlement (S = DFN), and elastic settlement (C = DMX – DFN). The analysis results indicated that the dynamic formula could be corrected using the MLR approach. The correction model produced multiplier coefficients of 1.09 for parameter S and 0.67 for parameter C, with a coefficient of determination of 0.96 and a MAPE value of 19.21%, which represents the average deviation of the predicted results from the actual values and falls into the accurate category based on Lewis' classification. The model is deemed sufficiently reliable for use as an alternative method in the preliminary evaluation of pile bearing capacity.

Keywords: Pile bearing capacity; dynamic formula; PDA; CAPWAP; MLR

ABSTRAK

Perhitungan daya dukung tiang menggunakan formula dinamik merupakan pendekatan praktis dalam mengevaluasi kapasitas tiang fondasi. Namun, hasil perhitungannya kerap diragukan jika dibandingkan dengan hasil analisis CAPWAP dari uji PDA. Penelitian ini bertujuan untuk mengevaluasi akurasi formula dinamik, mengembangkan model koreksi dengan pendekatan statistik berupa MLR, serta menilai efektivitas model koreksi yang dihasilkan dalam memprediksi daya dukung tiang. Pada penelitian ini digunakan 84 data tiang dengan variasi dimensi tiang dan parameter dari uji PDA yang berupa energi maksimum yang tertransfer ke tiang (EMX), penurunan permanen tiang (S = DFN), dan penurunan elastis tiang (C = DMX – DFN). Hasil analisis menunjukkan bahwa formula dinamik dapat dikoreksi melalui pendekatan MLR. Model koreksi menghasilkan koefisien pengali untuk parameter S sebesar 1,09 dan C sebesar 0,67, serta memiliki koefisien determinasi sebesar 0,96 dan nilai MAPE yang menunjukkan rata-rata deviasi hasil prediksi terhadap aktual sebesar 19,21%, yang termasuk dalam kategori akurat menurut klasifikasi Lewis. Model ini dinilai cukup andal untuk digunakan sebagai pendekatan alternatif dalam tahap evaluasi awal daya dukung tiang.

Kata kunci: Daya dukung tiang; formula dinamik; PDA; CAPWAP; MLR

1. INTRODUCTION

Driven piles are a type of foundation designed to transfer structural loads through weak soil layers to stronger soil or rock strata, typically installed using impact hammers. Foundations are critical structural components that support and distribute the building loads uniformly to the underlying soil. Consequently, meticulous foundation design is essential to withstand potential maximum loads and prevent structural failures with significant implications for project owners, planners, and the public. Furthermore, increasing demand for larger and taller buildings due to population growth heightens the role of foundations in ensuring structural stability and safety (Chiarli & Susilo, 2021; Fernanda & Susilo, 2023; Livia & Suhendra, 2018; Tengdyantono et al., 2018; Veronica et al., 2023).

In foundation design application, bearing capacities derived from static or dynamic methods often fail to reflect actual field conditions. Thus, field validation through load testing is crucial for confirming full capacity mobilization

(Marzuki et al., 2022). The pile driving analyzer (PDA) is a common method for estimating pile capacity. Dynamic formula like engineering news record (ENR) calculates bearing capacity based on impact energy but frequently yield inaccuracies due to unaccounted hammer-pile-soil interactions. Data-driven approaches like Multiple Linear Regression (MLR) offer alternatives for developing correction models for initial estimates. By leveraging PDA data from multiple projects, regression-based correction model can be developed to provide estimates aligned with CAPWAP results. Therefore, this study focuses on developing correction models for dynamic formulas.

This study evaluates the accuracy of the ENR dynamic formula by comparing its results with dynamic test data obtained from the CAWAP PDA, to assess how well the formula represents actual field conditions. Developing a correction model for the dynamic formula using MLR by incorporating input variables such as driving parameters, with the aim of improving the accuracy of pile capacity estimation. Evaluating the effectiveness of the prediction model by comparing its results with the PDA CAPWAP test results and assessing its predictive accuracy using statistical metrics such as R2, MSE, RMSE, MAE, and MAPE.

Pile driving analyzer (PDA)

PDA is a dynamic load testing method widely used in Indonesia to evaluate foundation pile capacity. The procedure involves installing strain transducers and accelerometers near the pile head. Data from these instruments analyze stress waves induced by hammer impact, enabling estimation of ultimate bearing capacity, skin friction distribution, and load-settlement simulation based on wave propagation theory (Rahardjo, 2013). In application, two accelerometers and two strain transducers are installed in opposing pairs at a minimum distance of 1.5 times the diameter piles from the head. This sensor configuration as shown in Figure 1 aims to avoid high-stress zones from hammer impact (Green & Kightley, 2005). The data and parameters recorded in the PDA can be seen in Table 1.

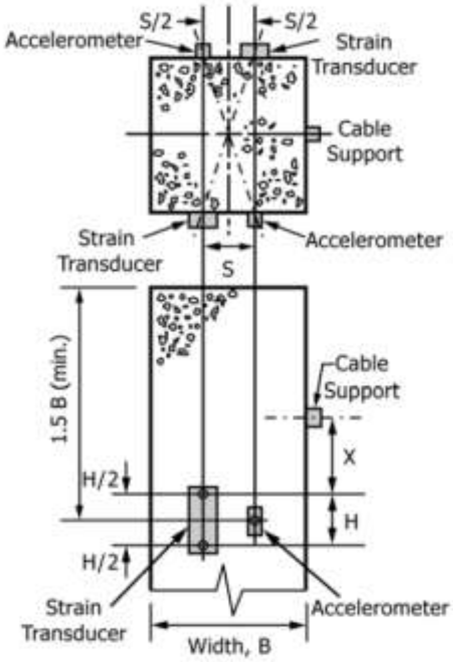

Figure 1. PDA instrument configuration (ASTM D4945, 2012)

Table 1. PDA data and parameters (Rahardjo, 2013)

Code	Description
RMX	Bearing capacity in general condition
RSU	Bearing capacity during unloading caused by pile head rebound prior to the full mobilization of resistance at the tip
EMX	Maximum energy transferred to the pile
CSX	Compressive stress at sensor location
TSX	Tensile stress at sensor location
DFN	Permanent displacement during driving
DMX	Total displacement during driving
BTA	Pile integrity value (100% indicates the pile is in good shape)
ETR	Hammer efficiency

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Case pile wave analysis program (CAPWAP)

CAPWAP is an analytical method used in dynamic pile testing that estimates bearing capacity by combining PDA measurements with one-dimensional wave theory to generate a resistance distribution model along the pile. It enables accurate prediction of end-bearing and skin friction capacities through signal matching or reverse analysis of the foundation's dynamic response to impact loads (Green & Kightley, 2005; Simanjuntak & Suita, 2017).

Engineering news record (ENR) dynamic formula

Pile bearing capacity is achieved when the pile penetrates dense soil or contacts rock strata. However, variable soil profiles often impede reaching design depth. To address this, dynamic formula like ENR were developed to evaluate bearing capacity based on work-energy theory (Das, 2011). The ultimate bearing capacity is expressed as Eq. 1. This formula applies a safety factor of 6 to estimate pile bearing capacity.

$$Q_u = \frac{W_R \, x \, h}{(S + C)} \tag{1}$$

where Q_u: Ultimate pile bearing capacity, W_R: Hammer weight, h: Hammer drop height, S: Final blow penetration (average of last 10 blows), and C: Temporary elastic compression constant.

Relationship between hammer weight, drop height, and maximum energy (EMX)

Driving energy is a critical parameter in dynamic pile bearing capacity analysis. Theoretically, energy transmitted to the pile head equals the product of hammer weight (W) and the drop height (h). However, in reality, energy losses occur due to friction or contact with the cushion on the pile head. Thus, an efficiency coefficient (η) represents the ratio of effective energy to theoretical energy. The effective energy transmitted is expressed as Eq. 2.

$$EMX = \eta \times W \times h \tag{2}$$

In PDA testing, the EMX value is automatically computed by software based on hammer configuration data, inherently accounting for driving efficiency. Therefore, this study directly uses PDA-derived EMX values without explicit consideration of drop height.

Relationship between dynamic parameters and PDA

During pile driving, vertical displacement from hammer impact energy comprises two components: permanent deformation (set) and temporary deformation (elastic). These are recorded in PDA measurement as parameters DFN and DMX. DMX represents the maximum displacement from hammer impact, encompassing both elastic and plastic deformations of the pile and soil. After energy dissipation, the permanent settlement (set) is quantified as DFN. The difference between DMX and DFN reflects elastic rebound shown in Figure 2-3, demonstrating that after reaching peak displacement (DMX), the pile undergoes elastic recovery before stabilizing as DFN (Jarushi et al., 2015; Yazdani et al., 2021). This aligns with the concept of quake-immediate elastic deformation from hammer impact, as shown in Figure 4 as unloading quake (Cosentino et al., 2020; Smith, 1960). This elastic component corresponds to the temporary elastic compression in the ENR dynamic formula. Thus, this study assumed that S is DFN and C is DMX – DFN.

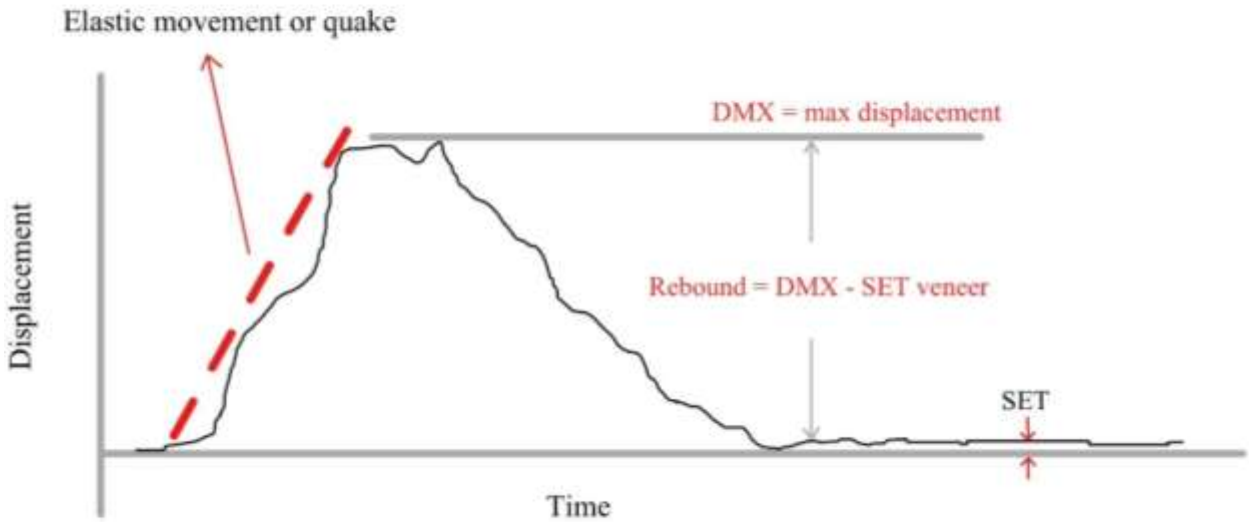

Figure 2. Displacement vs time from PDA (Cosentino et al., 2020, adapted)

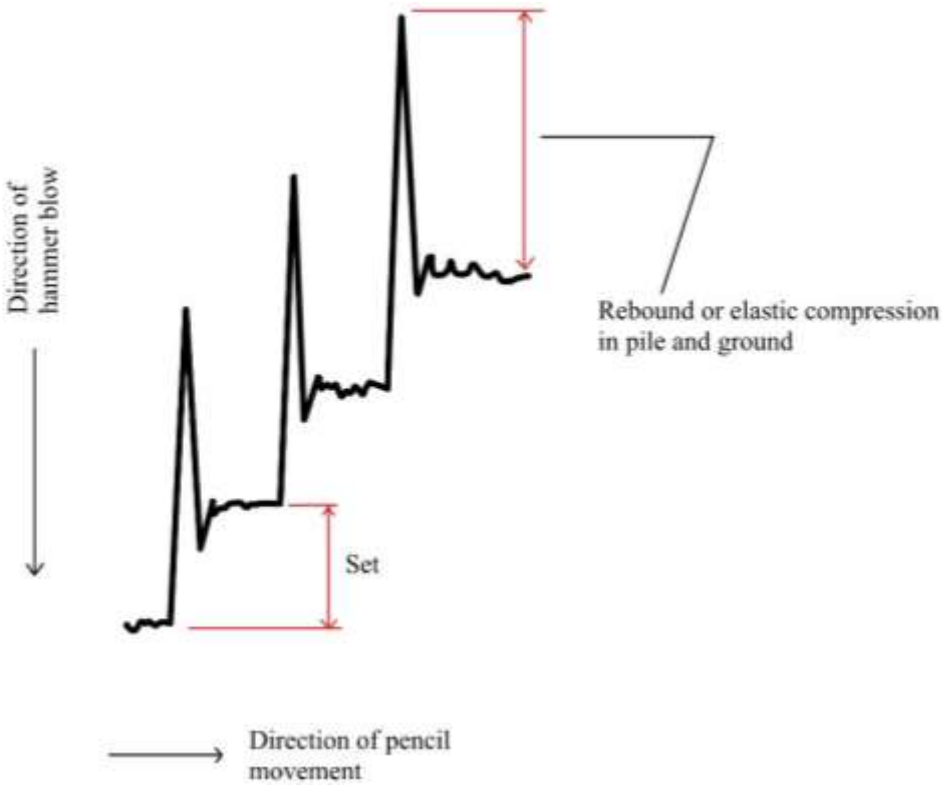

Figure 3. Manual pile displacement record (Cosentino et al., 2020, adapted)

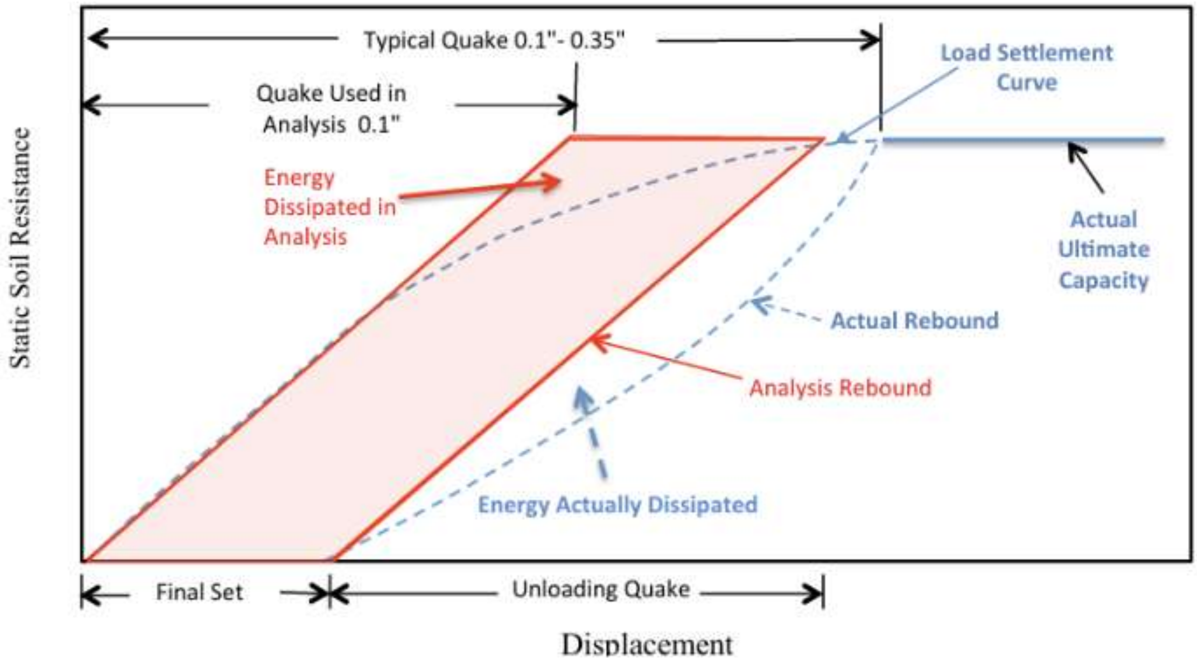

Figure 4. Soil resistance vs penetration per blow (Cosentino et al., 2020)

Machine learning (ML)

ML is a subset of artificial intelligence (AI) that develops systems that learn from data without explicit reprogramming by humans. Valid data are essential for training ML model before deployment to ensure accurate predictions (Cholissodin et al., 2019). One approach in ML is supervised learning, which uses labeled datasets (input-output pairs) to train the model. After training, models predict output based on new input, with accuracy evaluated against actual target (Janiesch et al., 2021).

Multiple linear regression (MLR)

MLR is a statistical method analyzing relationships between a dependent variable and several independent variables. Eq. 3 assumes that one-unit change in one of the independent variables will result in a constant linear change in the dependent variable (Nasteski, 2017).

$$Y = a_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n + \varepsilon \quad (3)$$

where Y: Dependent variable, a_0: Intercept when the independent variable is 0, b_1, b_2, b_n: Regression coefficients, X_1, X_2, X_3: Independent variables, and ε: Residual error (difference between predicted and actual values).

Mean squared error (MSE)

MSE (Eq. 4) measures the average squared difference between the actual and predicted values. Lower MSE indicates better accuracy (Tatachar, 2021).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_1)^2 \quad (4)$$

where n: Number of predictions, Y_i: Actual value, and Y_1: Predicted value.

Root mean squared error (RMSE)

RMSE (Eq. 5) is the square root of the MSE, represents the standard deviation of residuals. RMSE shows how far the actual data is from the regression model prediction (Tatachar, 2021).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_1)^2} \quad (5)$$

Mean absolute error (MAE)

MAE (Eq. 6) computes the average absolute difference between actual and predicted values. The main difference between MAE and MSE is that MAE uses the absolute difference, while MSE uses the squared difference (Tatachar, 2021).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - Y_1| \quad (6)$$

R-squared (R^2)

R^2 (Eq. 7) measured how much of the variation in the dependent variable can be explained by the independent variables in the regression model which indicates the level of goodness of fit, reflects how well the predicted values correspond to the observed data (Tatachar, 2021).

$$R^2 = 1 - \frac{\sum_i (Y_i - Y_1)^2}{\sum_i (Y_i - Y_n)^2} \quad (7)$$

where Y_n: Mean of actual values.

Mean absolute percentage error (MAPE)

MAPE (Eq. 8) is a metric in prediction analysis used to assess the degree of deviation of predicted results from actuals expressed as an average percentage. Lewis (in Ngabidin et al., 2023) states the MAPE value categories in Table 2.

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{Y_i - Y_1}{Y_i}\right|}{n} \times 100\% \quad (8)$$

Table 2. MAPE accuracy criteria

MAPE (%)	Accuracy Level
< 10	Excellent
10 – 20	Good

20 – 50	Fair
> 50	Poor

2. RESEARCH METHODOLOGY

The research stages are as follows:

1. Collect PDA and CAPWAP test data for driven piles from various construction projects.
2. Select data based on parameter completeness: EMX, DFN, and DMX.
3. Transform the basic dynamic formula into a linear regression model.
4. Perform regression analysis using Microsoft Excel Data Analysis ToolPak.
5. Evaluate regression outputs such as regression coefficient, coefficient of determination, and predicted pile capacity with corrected formula.
6. Comparing the model predictions with actual capacities from CAPWAP data.
7. Derive conclusions and recommendations based on research results.

Data description

This study utilized 84 dynamic load test datasets for driven piles (spun and square) from multiple projects with varying lengths and diameters. The ultimate pile bearing capacity data were obtained from PDA and CAPWAP analyses. The dynamic formula used as the basis for predicting pile bearing capacity in Eq. 9.

$$Q_u = \frac{EMX}{(S + C)} \tag{9}$$

where Qu: Ultimate pile bearing capacity (tons), EMX: Maximum energy transferred to the pile (tons·m), S: Permanent settlement (m), and C: Elastic settlement (m).

Model transformation

To enable MLR analysis, the dynamic formula is transformed into Eq. 10.

$$\frac{1}{Q_u} = \beta_1 \left(\frac{S}{EMX}\right) + \beta_2 \left(\frac{C}{EMX}\right) \tag{10}$$

where $\frac{1}{Q_u}$: Dependent variable, $\frac{S}{EMX}$: Independent variable 1, $\frac{C}{EMX}$: Independent variable 2, β_1: Regression coefficient 1, and β_2: Regression coefficient 2.

Data with DFN and DMX values = 0 mm were excluded from the analysis to avoid numerical errors.

3. RESULTS AND DISCUSSION

Regression analysis was performed using Microsoft Excel via data analysis – regression. The regression output is presented in Table 3.

Table 3. Regression statistic results

Regression Statistic	Value
Multiple R	0.98
R Square	0.96
Adjusted R Square	0.95
Standard Error	0.0016
Observations	84

The ANOVA table demonstrating model significance is shown in Table 4.

Table 4. ANOVA results

Source	df	SS	MS	F	Significance F
Regression	2	0.0055	0.0028	1012.7508	4.8909E-58
Residual	82	0.0002	2.7370E-06		
Total	84	0.0058			

Regression coefficients are detailed in Table 5.

Table 5. Regression coefficients

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	0	#N/A	#N/A	#N/A
S/EMX	1.09	0.0761	14.3559	4.3659E-24
C/EMX	0.67	0.0220	30.3994	2.0865E-46

Model error metrics are summarized in Table 6.

Table 6. Model evaluation metrics

Indicator	Value
MSE	1971.94 tons
RMSE	44.41 tons^2
MAE	31.15 tons
MAPE	19.26%

Figure 5 compares predicted bearing capacities against actual CAPWAP results. The y = x line represents perfect prediction accuracy. The distribution of data in the graph shows that the predicted results are close to the actual values, with a deviation < 5% which is still within the tolerance limit.

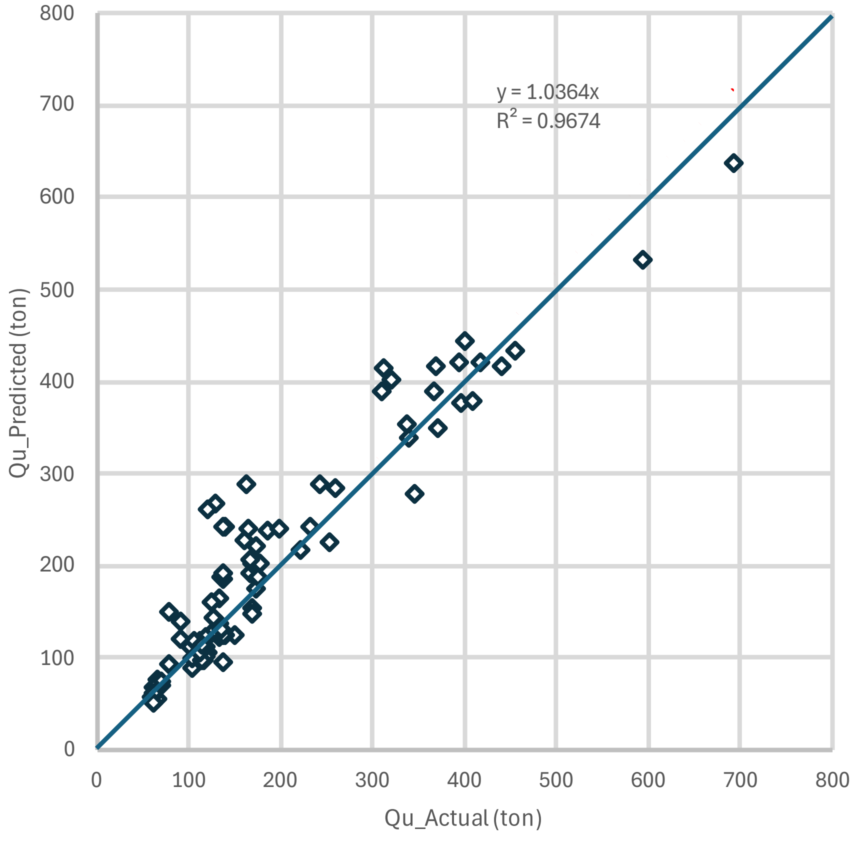

Figure 5. Predicted vs actual bearing capacity

R^2 of 0.96 indicates the model effectively explains variations in bearing capacity. Both parameters S and C contribute significantly to predicted bearing capacity, as evidenced by the p-value < 0.05. With the intercept constrained to zero, the model maintains consistency with the original form of dynamic formula structure. The corrected dynamic formula uses Eq. 11.

$$Q_u = \frac{EMX}{1.09S + 0.67C} \tag{11}$$

where Qu: Ultimate pile bearing capacity (tons), EMX: Maximum energy transferred to the pile (tons·m), S: Permanent settlement (m), and C: Elastic settlement (m).

4. CONCLUSIONS AND RECOMMENDATIONS

Conclusions

1. The original ENR dynamic formula tends to underestimate pile capacity compared to PDA CAPWAP results, indicating the need for calibration. A correction model using MLR was developed, yielding an R^2 value of 0.96, which means the model explains 96% of the variance in ultimate bearing capacity. In addition, the regression coefficients for S and C are 1.09 and 0.67, both are statistically significant (p-value < 0.05) and the corrected model can produce estimates that are closer to the CAPWAP results.
2. The correction results are considered acceptable for civil engineering applications. With a MAPE of 19.21%, the model falls into the "Good" accuracy category according to Lewis' classification. This indicates tolerable error margins for preliminary design evaluation, establishing the model as a viable alternative approach.

Recommendations

1. Future studies should employ larger datasets with diversified soil types, pile dimensions, and calendaring data to enhance the correction model's robustness and prediction accuracy.
2. Additional research should analyze and compare various other dynamic formulas to evaluate estimation results and identify the formula that is most suitable for field conditions.

REFERENCES

ASTM Internasional. (2012). *Standard test method for high-strain dynamic testing of deep foundations* (ASTM D4945-12).

Chiarli, K. T., & Susilo, A. J. (2021). Analisis kekuatan sambungan tiang pancang beton terhadap gaya tarik, lateral, dan momen pada tanah kohesif. *JMTS: Jurnal Mitra Teknik Sipil*, *4*(3), 607-614.

Cholissodin, I., Sutrisno, Soebroto, A. A., Hasanah, U., & Febiola, Y. I. (2019). *AI, machine learning & deep learning (teori & implementasi)*. Fakultas Ilmu Komputer Universitas Brawijaya.

Cosentino, P. J., Bostater Jr., C. R., Franqui, A., Rogulski III, R. J., & Jensen, M. (2020). *Quantifying pile rebound with deflection measuring systems best suited for Florida soils*. Department of Transportation Florida.

Das, B. M. (2011). *Principles of foundation engineering* (7th ed.). Cengage Learning.

Fernanda, N. O., & Susilo, A. J. (2023). Analisis efisiensi tiang ujung pada fondasi tiang bor di proyek Gading Serpong. *JMTS: Jurnal Mitra Teknik Sipil*, *6*(2), 301-308.

Green, T. A. L., & Kightley, M. L. (2005). CAPWAP testing-theory and application. *Proceedings of the 16th International Conference on Soil Mechanics and Geotechnical Engineering*, 2115-2118. https://doi.org/10.3233/978-1-61499-656-9-2115

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*, 685-695. https://doi.org/10.1007/s12525-021-00475-2

Jarushi, F., Cosentino, P., Kalajian, E., & Dekhn, H. (2015). CPT pore water pressure correlations with PDA to identify pile drivability problem. *International Journal of Geological and Environmental Engineering*, *9*(2), 55-61.

Lewis, C. D. (1982). *Industrial and business forecasting methods: a practical guide to exponential smoothing and curve fitting*. Butterworth Scientific.

Livia, & Suhendra, A. (2018). Studi kapasitas tiang bor berdasarkan metode pile driving analyzer (PDA) dan load cell. *JMTS: Jurnal Mitra Teknik Sipil*, *1*(1), 82-91.

Marzuki, A., Norhadi, A., & Eriza, M. (2022). Rasio daya dukung tiang rencana terhadap daya dukung tiang aktual. *Jurnal Gradasi Teknik Sipil*, *6*(1), 1-10.

Ngabidin, Z., Sanwidi, A., & Arini, E. R. (2023). Implementasi metode double exponential smoothing brown untuk meramalkan jumlah penduduk miskin. *EULER : Jurnal Ilmiah Matematika, Sains Dan Teknologi*, *11*(2), 328-338. https://doi.org/10.37905/euler.v11i2.23054

Rahardjo, P. P. (2013). *Manual pondasi tiang* (4th ed.). Universitas Katolik Parahyangan.

Simanjuntak, J. O., & Suita, D. (2017). Analysis of bearing capacity pile foundation with using capwap software for testing pile driving analyzer (PDA) at fasfel development project parlimbungan ketek sikara-kara mandailing natal district (North Sumatera). *Journal of Physics: Conference Series*, *930*. https://doi.org/10.1088/1742-6596/930/1/012010

Smith, E. A. L. (1960). Pile driving analysis by the wave equation. *Journal of the Soil Mechanics and Foundations Division*, *86*(4). https://doi.org/10.1061/JSFEAQ.000028

Tatachar, A. V. (2021). Comparative assessment of regression models based on model evaluation metrics. *International Research Journal of Engineering and Technology (IRJET)*, *8*(9), 853-860.

Tengdyantono, C., Sentosa, G. S., & Kawanda, A. (2018). Analisis daya dukung tiang pancang dengan metode statik, dinamik, dan persamaan gelombang software GRLWEAP. *JMTS: Jurnal Mitra Teknik Sipil*, *1*(2), 171-180.

Veronica, Prihatiningsih, A., & Iskandar, A. (2023). Pemodelan parameter vibration monitoring test berdasarkan hasil iterasi nilai rasio redaman (ξ). *JMTS: Jurnal Mitra Teknik Sipil*, *6*(2), 415-428.

Yazdani, E., Wang, J., & Evans, T. M. (2021). Case study of a driven pile foundation in diatomaceous soil. II: Pile installation, dynamic analysis, and pore pressure generation. *Journal of Rock Mechanics and Geotechnical Engineering*, *13*, 446-456. https://doi.org/10.1016/j.jrmge.2020.10.005