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DATA-DRIVEN PILE OPTIMIZATION UTILIZING COMPUTATIONAL DESIGN

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ABSTRACT

As part of a major design-and-build pharmaceutical project in Denmark, the foundation design for 6 large production and storage facility buildings was required. The foundations for these structures were subject to substantial vertical and lateral loads. Preliminary analyses identified piled foundations as the preferred foundation design concept. Over 200 load combinations were given for each of the principal and auxiliary support resulting in more than 20 000 individual calculations for some buildings. To address this number of load combinations and foundations necessitated, a strategic simplification into peak and lower bound values or leveraging computational optimization and this way calculating all the load cases.

A specialized automation algorithm was developed for individual pile group design assessments, employing structure-specific soil profiles, geometrical restrictions and prescribed point and surface load conditions for each column.

During the construction phase, pile load testing identified that the realizable pile load-bearing capabilities was greater than the predicted values. This prompted an extensive re-evaluation of the pile design for later stages of the project. Outcomes from the re-analyses identified a potential reduction in material use by up to 30%. The collected pile testing data were integrated into a bespoke machine learning model predicated on measured pile capacity values.

The application of this machine learning model across the remaining buildings facilitated an expeditious and efficient reassessment of newly projected load conditions. This innovative approach combined empirical testing with advanced analytical models to enhance the overall efficacy, sustainability and economy of the foundational designs.

Keywords: automation, sustainability, pile capacity, machine learning.

INTRODUCTION

Achieving sustainability in geotechnical structures is challenging due to limitations in suitable materials, typically concrete, steel, and timber. Sustainable designs require geotechnical engineers' involvement from early project stages, as decisions about above-ground layout impact below-ground feasibility. Often, these engineers join later, after critical decisions are made. Optimizing designs to reduce material quantities calls for alternative approaches. To optimize designs and reduce material quantities, alternative approaches are necessary. This paper presents a case study of a large-scale pharmaceutical project in Denmark. It details how comprehensive pile testing and advanced computational algorithms were employed within a fast-track project framework, which estimated material usage reductions up to 30%. By leveraging early pile capacity testing and machine learning models, the project achieved significant sustainability improvements.

CASE STUDY OVERVIEW

At the site in Hillerød, Denmark, a major pharmaceutical construction project of approximately 22,000 square meters is underway as an expansion to an existing drug manufacturing facility. The project comprises two identical buildings, DSM4 and DSM5, along with several additional structures. The initial building being designed and constructed is the DSM4 building, which serves as the basis for developing an automated pile design algorithm capable of processing all load cases for the building.

During DSM4's construction, dynamic pile load testing revealed potential for reducing the number of piles. These insights informed the pile testing program for DSM5, enabling optimization of the pile design. By incorporating analytical methods and early testing data, significant material savings were achieved, demonstrating improved sustainability and efficiency.

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SUSTAINABLE APPROACH TO PILE DESIGN

The approach to sustainable pile design involves integrating empirical testing data with advanced computational models to optimize foundation layouts and minimize material usage. By leveraging results from dynamic pile load tests, it is possible to accurately determine pile capacities and refine design parameters, leading to significant reductions in material consumption and thus enhancing economic efficiency and environmental sustainability.

Automation algorithms play a crucial role in streamlining the evaluation of numerous load cases, resulting in realistic and optimized pile layouts. Computational optimization minimizes reliance on conservative maximum and minimum load combinations, further contributing to sustainable foundation designs.

Machine learning models provide innovative solutions capable of processing detailed pile test data, offering accurate assessments of pile capacities. These models utilize input data such as pile coordinates and calculated capacities, facilitating precise predictions and sustainable decision-making in geotechnical design.

Overall, combining advanced analytical techniques, empirical testing, automation, and machine learning significantly enhances the sustainability, efficiency, and accuracy of pile designs. By prioritizing early involvement of geotechnical expertise and adopting innovative methodologies, more sustainable outcomes can be achieved in geotechnical engineering projects.

PILE TESTING PROGRAMME

The pile testing program was developed to verify higher pile capacities than those predicted by geostatic calculations. Targeting a minimum of 5% of the piles, dynamic pile load tests were chosen to measure both tip resistance and shaft resistance. These tests involve measuring acceleration and strain in a pile during driving, with data analyzed to assess pile capacity using wave analysis.

Test pile locations were strategically selected to ensure comprehensive coverage across the building footprint and accurately represent overall pile performance. Piles were left in the ground post-installation to allow remoulded soil to regenerate before testing. The testing results indicated higher capacities, which informed the optimized pile design for the DSM5 building, thus allowing for significant material reductions.

Figure 1 displays the final pile layout derived from the test results and processed through the automation algorithm where the red-marked piles indicate the test piles. This targeted and systematic approach to pile testing played a crucial role in achieving a sustainable and efficient foundation design by leveraging empirical test data to inform and optimize construction practices.

AUTOMATION IN PILE DESIGN

The automation in pile design evaluated geostatic pile capacity based on soil strength properties and effective stress. Soft soils, identified by unit weights less than 14 kN/m^3, were excluded, and tip resistance in sand was omitted due to unreliable verification through pile driving journals.

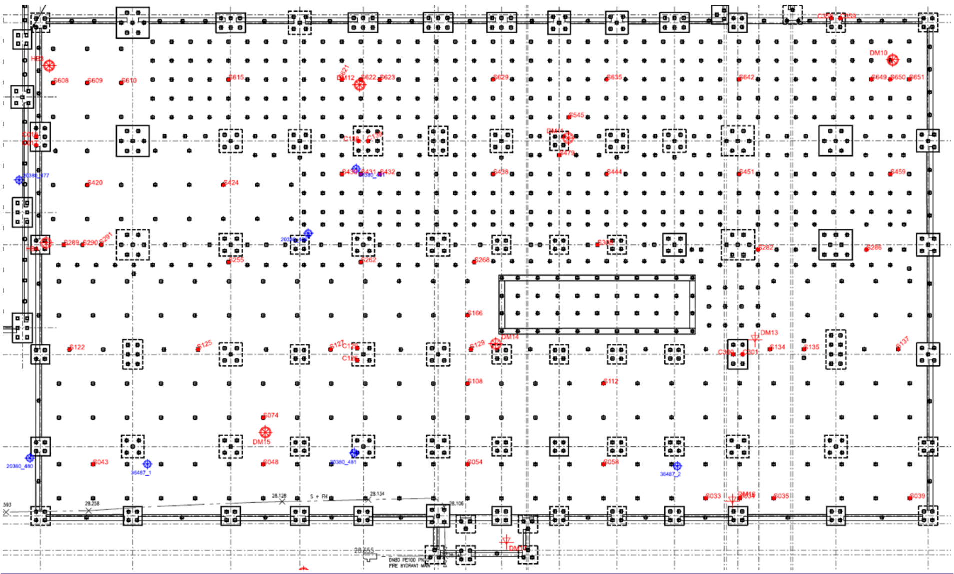

Figure 1 *Pile layout for the DSM5 building - red piles mark the test pileg*

Pile design began with estimating the number and length of piles based on input vertical loads and predefined capacities. The pile cap geometry and positions were determined using a geometry library, ensuring minimal group effects. According to guidelines, piles must be spaced at least three times the pile width apart, and the group's perimeter must exceed the sum of the individual pile perimeters. [M. Tomlinson and T. Woodward (2008)]

Additional load contributions, including vertical loads from moments generated by horizontal forces, self-weight of the pile cap, and surface loads atop the pile cap, were calculated. The moment contribution to vertical load assumed piles acted as pairs with linear elastic distribution under the cap, with those near the edge bearing higher load, as illustrated in Figure 2.

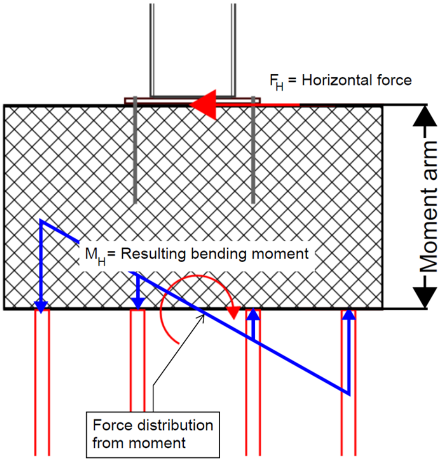

Figure 2 *Vertical force contribution from horizontal loads*

The inertia of the pile group was calculated by:

$$I_\xi = \int_A \eta^2 dA \tag{1}$$

Where η represent the distance to the pile and A represent the area of the pile. As all piles have the same area this value is assumed equal to 1.

This allowed for evaluating the moment contribution by:

$$\Delta p_M = \frac{M \cdot \eta}{I_\xi} \tag{2}$$

Where M represent the bending moment in a given direction.

Surface loads were discretized into fixed interval points across the building footprint. For the load contribution check, all surface load points within 0.5 meters of the pile cap edge were aggregated and added to the total vertical load of the pile cap.

This process was completed across all load cases, storing results for each node and ultimately providing the most conservative pile quantity for each group. Such systematic automation facilitated optimized and sustainable designs by accurately addressing varying load cases.

MACHINE LEARNING MODEL

The machine learning model was developed using the Keras-TensorFlow library [TensorFlow (2023)], comprising two distinct models: one to determine specific pile capacities at defined coordinates, and another to create a depth-based capacity profile for the entire building.

For the coordinate-based model, inputs were pile length, x- and y-coordinates, and design capacity. The model architecture consisted of four layers with 110, 64, 32, and 10 neurons, and a final single-neuron output layer. Training involved iterative predictions compared against validation data, utilizing the Adam optimizer, which combines the benefits of momentum optimization and Root Mean Square Propagation (RMSprop). [GeeksforGeeks (2025)]

The depth-based model, use pile length and design capacity inputs, with three layers of 64, 32, and 10 neurons.

The coordinate-based model provided detailed assessments within pile groups, improving overall geotechnical design accuracy. Results from the depth-based model generated a pile strength profile from field test data. This profile replaced the conventional soil profile in the automation algorithm, enabling the use of higher pile capacities in the pile design.

EVALUATION OF MODEL ACCURACY

The evaluation of the accuracy is by evaluating the decrease in error for each pass in the dataset. The error from training the simple machine learning is seen in Figure 3.

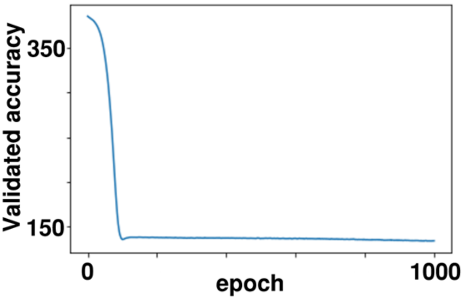

Figure 3 *Accuracy development of simple machine learning model*

After training the model, the final loss is 134kN. This loss is accommodated for when using the values to create the enhanced design profile. The largest loss is at the greater depths and hence the predicted pile strength profile values are reduced with an additional 10% before using them in the pile design algorithm. Additionally, the whole data set for the building is used as input in the model. The model's prediction is compared with the real values, see Figure 4.

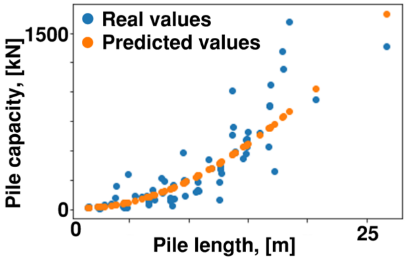

Figure 4 *Predicted pile capacities relative to measured values, for the simple machine learning model*

The advanced model produces a significantly lower loss due to the more precise evaluation of the pile capacities, see Figure 5.

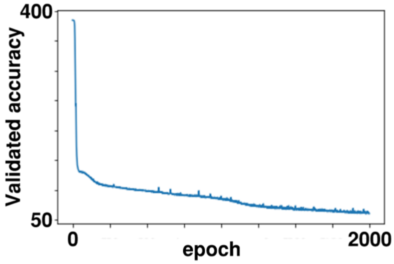

Figure 5 *Accuracy development for coordinate based machine learning model*

The final loss for the coordinate-based model is at 60kN. The accuracy of this model can also be seen in the comparison between the prediction of all values with the real measured design values, see Figure 6.

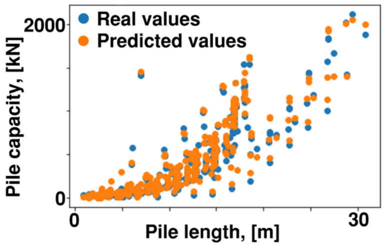

Figure 6 *Predicted pile capacities relative to measured values, for the coordinate-based machine learning model*

It is seen that the predicted values are generally placed close to the real measured values.

APPLICATION OF MACHINE LEARNING MODEL IN PILE DESIGN

The machine learning model leverages extensive data to accurately handle and interpret the large amount of testing data, optimizing pile strength profiles for design. This approach saves materials, money, and time. Larger datasets improve accuracy by offering diverse problem representations and minimizing overfitting. In this project, the model was used to both visualize pile capacities across the building footprint and to integrate testing data, significantly enhancing the pile design process.

SUMMARY, CONCLUSIONS AND PROSPECTS

Combining empirical testing with computational models in the Danish pharmaceutical project improved foundational design, reducing material usage by up to 30%. Dynamic pile load testing and machine learning allowed for accurate reassessment of pile capacities, leading to sustainable and economical designs. The case study underscores the importance of early geotechnical engineer involvement and demonstrates successful innovative techniques.

Future projects can benefit from these methodologies, with further automation and machine learning enhancements, larger datasets, and real-time data integration for adaptive construction practices. Expanding algorithm capabilities to address diverse geotechnical conditions will drive more efficient and sustainable outcomes.

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