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Automated parameter determination: From in-situ measurements to constitutive models

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Abstract: Site characterization relies on both in-situ and laboratory testing. In the early stages of a project, in-situ tests are often performed before launching a full laboratory testing program. At this stage—when soil data is limited—in-situ tests can provide valuable insights for preliminary characterization. To enhance the interpretation of these tests, an automated parameter determination framework has been developed, employing a graph-based approach to derive soil and constitutive model parameters from in-situ measurements. Several studies have been conducted to validate the framework's output in terms of both soil properties and model parameters. The framework is designed to be transparent and adaptable, allowing users to trace the computed values for different parameters and incorporate their experience, knowledge and expertise. In this study, the tool was applied to a well-documented test site in Australia. Additionally, the integration of machine learning models for predicting soil parameters is explored as part of ongoing efforts to incorporate data-driven techniques into the framework.

1 Introduction

In-situ testing offers an alternative approach for determining soil parameters. Compared to laboratory tests, in-situ methods are more economical, faster, capable of assessing larger soil volumes, and cause less disturbance to the in-situ soil conditions. However, parameters cannot be directly obtained from in-situ measurements; their determination depends on interpretation through empirical correlations. These correlations are often limited in applicability, typically developed for specific soil types or conditions—such as a specific overconsolidation ratio (Kulhawy and Mayne 1990). As a result, multiple correlations may exist for the same parameter, introducing (additional) uncertainty in the derived values.

An Automated Parameter Determination (APD) framework has been developed as part of a research project to enable the automated interpretation of in-situ test results. The framework determines parameters using a graph-based approach (Van Berkom et al., 2022). Various publications have addressed different aspects of the tool, ranging from the general structure and implementation of the framework (Marzouk et al., 2024) to the integration of additional in-situ tests (Marzouk et al., 2023). Several studies have focused on validating the tool's output in terms of soil parameters (Marzouk et al., 2024; Marzouk and Tschuchnigg, 2024). An attempt to validate the output with respect to constitutive model parameters was made by Marzouk et al. (2025a), where parameters for the Clay and Sand Model (CASM) (Yu, 1998) were derived and used to numerically simulate a cone penetration test (CPT), with the results compared against the CPT used for interpretation. The automated connection between APD and a finite element (FE) software was demonstrated by Marzouk and Tschuchnigg (2025b), in which a synthetic shallow footing was modelled.

The framework consists of three main workflows, each dedicated to a specific in-situ test method for parameter determination: the cone penetration test (CPT), the dilatometer test (DMT), and shear wave velocity (V_s) measurements. This study explores additionally the integration of data-driven methods as a fourth, complementary approach for parameter estimation. All four approaches—the three conventional workflows and the data-driven method—are applied to a well-instrumented test site in Australia, where the derived soil parameters are compared against reference values interpreted at the site.

2 Automated parameter determination framework

The various components of the framework are described in detail in Marzouk et al. (2024). To avoid redundancy, only the key aspects are outlined in this section; interested readers are referred to Marzouk et al. (2024) for a comprehensive description.

The framework follows a modular architecture that links raw in-situ measurements to finite element (FE) software. In the CPT-based workflow, Module 1 imports raw data and computes some CPT parameters (e.g., normalized cone resistance Q_t). Module 2 performs stratification of the measurements into soil layers. Module 3 evaluates the stress state within each layer, including the overconsolidation ratio (OCR) and the coefficient of earth pressure at rest (K_0). Modules 4 and 5 implement the graph-based approach to derive both soil and constitutive model parameters. The final step involves transferring the output to the FE software.

The graphs are generated using two CSV files: one describing the methods (i.e., correlations) and the other specifying the parameters. The framework is developed in Python, and graph visualization is done using the Graphviz library (Gansner, 2011). The current version of the tool includes a validated database of more than 200 methods, covering both soil and constitutive model parameters.

2.1 Data-driven Site Characterization for Soil Parameter Determination

Within the framework of APD, machine learning can be used as an additional source of information that supports conventional methodologies based on laboratory and in-situ data. Rather than replacing established empirical correlations, ML techniques augment them by data-driven estimations of soil parameters, particularly in contexts characterized by limited availability of correlations. Validation against independent dataset (i.e. Ballina test site) has demonstrated the robustness of ML-based soil parameter predictions.

2.1.1 Databases used for machine learning

Two independent databases were compiled for ML model development. First, the laboratory database consists of paired records of CPT measurements and soil parameters derived from laboratory testing on borehole samples collected in close proximity to the CPT locations. This database contains 622 data pairs for saturated unit weight γ_t and 193 for undrained shear strength s_u. Data sources include publicly accessible datasets from Ballina and NGTS (`geocalcs.com/datamap`), a Dutch dataset (Lengkeek and Breedeveld 2022), as well as confidential datasets from Norwegian and Austrian projects. To ensure an unbiased ML performance assessment, the Ballina dataset was excluded from model training. Second, the in-situ database consists of 46 seismic CPT and 254 seismic CPTu tests, resulting in a total of 21,760 individual records. Data sources include the New Zealand Geotechnical Database (Scott et al., 2015), project data from Premstaller Geotechnik (Oberhollenzer et al., 2021), the Dutch dataset repository (`github.com/snakesonabrain/isc7_datasets`), and site data from Taiwan (`data.mendeley.com/datasets/v7frv3k2d3/1`).

2.1.2 Machine learning algorithm and feature selection

All models developed in this study utilize the XGBoost algorithm (eXtreme Gradient Boosting Decision Tree), which represents an advanced variant of the Gradient Boosting Decision Tree (GBDT) technique. XGBoost improves predictive performance and computational efficiency by incorporating more regularization terms and parallelized tree building.

In supervised ML, a model creates a function between selected input features and the target variable (Deisenroth et al., 2021). The input feature matrix used here comprises depth, cone resistance q_c, sleeve friction f_s, and friction ratio R_f, similar to Felić et al. (2024). Preliminary analyses showed that this feature set is suitable for robust predictions. Due to the use of tree-based models, no feature transformation or normalization (i.e. feature engineering) was required. Separate models were trained for each target variable in this study:γ_t, s_u, V_s.

2.1.3 Training workflow

The model training and evaluation protocol follows standard ML practices, as outlined by Deisenroth et al. (2021). Initially, the data are randomly split into a training set (80 %) and a test set (20 %). The training data are further subdivided to create a validation set for hyperparameter tuning and performance monitoring. The initial training phase is conducted with default hyperparameters. Model performance is assessed on the validation set using the coefficient of determination R^2 as the objective function. To reduce overfitting, ten-fold cross-validation is employed. In addition, early stopping is employed to stop the training process if the validation error does not improve for ten consecutive iterations. Hyperparameter optimization is carried out using the Differential Evolution algorithm implemented via the `pymoo` library, with a population size of 25. The optimization goal is to maximize R^2. The process terminates after 1,000 iterations or when a relative error threshold of 10^{-4} is reached. The best-performing hyperparameter set is then used to retrain the model on the combined training and validation datasets. Final model performance is evaluated on the test dataset. If acceptable performance is achieved, the final model is retrained using the full dataset.

2.1.4 Results of model performance

Figure 1 shows scatter plots comparing predicted and observed values for γ_t, s_u, and V_s of the ML model after hyperparameter optimization. The dashed 45° line indicates perfect agreement. The scatter patterns show good predictive accuracy overall, with R^2 values ranging from 0.58 to 0.83. Some deviations, particularly in V_s predictions in the lower range (0–350 m/s), are observed. These deviations of the ML model is part of ongoing research.

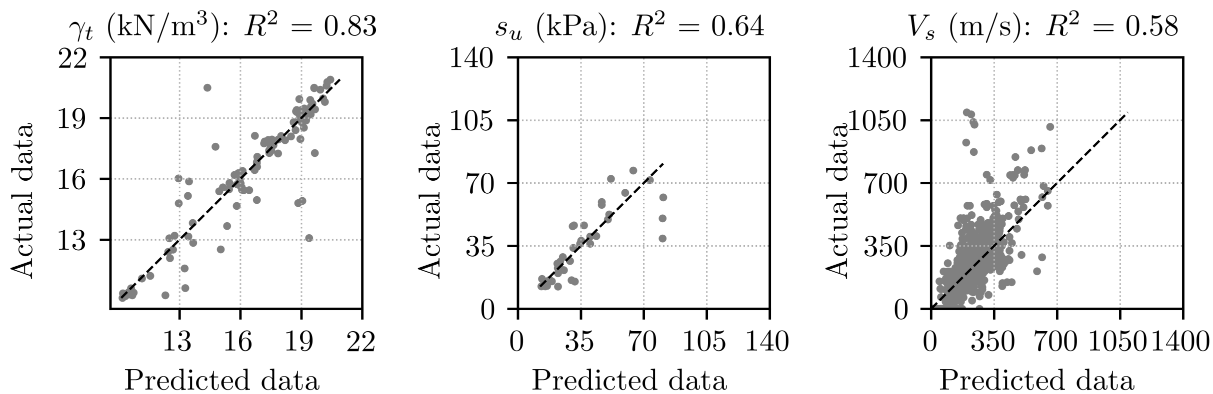

Figure 1: Evaluation of ML model performance after optimization via ten-fold cross-validation and early-stopping criteria.

3 Case study

3.1 Test site

This study focuses on the Ballina Soft Soil National Field Testing Facility (NFTF), located near the town of Ballina in New South Wales, Australia. The facility was established by the ARC Centre of Excellence for Geotechnical Science and Engineering (CGSE). Comprehensive characterization of the site is provided in Pineda et al. (2016) and Kelly et al. (2017). Interpreted values used in this study were obtained from Datamap (Doherty et al., 2018), a web-based platform for managing and accessing geotechnical data.

3.2 Soil parameters

As in Section 2, three parameters are considered in this study: unit weight (γ_t), undrained shear strength (s_u), and small-strain stiffness (G_0). For the determination of γ_t, a total of 13 methods were employed. 4 methods were used in the CPT-based workflow, 5 in the DMT-based workflow, and 4 in the V_s-based workflow. For s_u, 14 methods were utilized—6 from the CPT-based workflow, 5 from the DMT-based workflow, and 3 from the V_s-based workflow. Regarding G_0, 13 methods were applied: 10 from CPT, 2 from DMT, and 1 from V_s measurements. The details of all applied methods are presented in Tables 1 and 3–5 of Marzouk and Tschuchnigg (2025b).

Estimating the unit weight early in module 1 is essential, as it is required for calculating intermediate CPT and DMT parameters that rely on stress-dependent inputs. Consequently, an initial unit weight must be defined at this stage. This value can be specified using either empirical correlations or reference data. In this study, the initial unit weight for both the CPT- and V_s-based workflows was estimated using the method proposed by Mayne et al. (2023), whereas for the DMT-based workflow, it was derived from Marchetti's chart (Marchetti and Crapps, 1981).

3.3 Results

The in-situ tests considered in this study are illustrated in Figure 2. Three piezocone penetration tests (CPTu) (Figures 2(a–c)), one dilatometer test (DMT) (Figure 2(d)), and shear wave velocity (V_s) measurements (Figure 2(e)) were used as input for the APD framework. For improved visualization of the soft Ballina clay layers, Figure 2(a) has been clipped at 3 MPa. Soil parameters were evaluated using the methods described in the previous subsection. Additionally, the three CPTu soundings served as input for the ML models developed to predict the soil parameters (see Section 2).

APD computes soil parameters generally based on layers and supports various stratification approaches. These include built-in stratification algorithms, external sources (e.g., CPT interpretation software), machine learning (ML) models, and manual layering. In this study, manual layering was adopted: the in-situ measurements were averaged every 40 cm to generate thin layers, facilitating a detailed comparison with the reference values.

Figure 3 presents the comparison between ML and the APD-derived parameters—computed using the methods described in the previous subsection and the benchmark values interpreted at the Ballina clay site. The shaded bands in blue, green, red, and grey represent the value ranges obtained from the CPT, DMT, shear wave velocity (V_s) workflows, and ML predictions, respectively. For the blue ranges (representing the output of the CPT-based workflow), the shaded bandwidth reflects not only the variation among different methods but also the variability

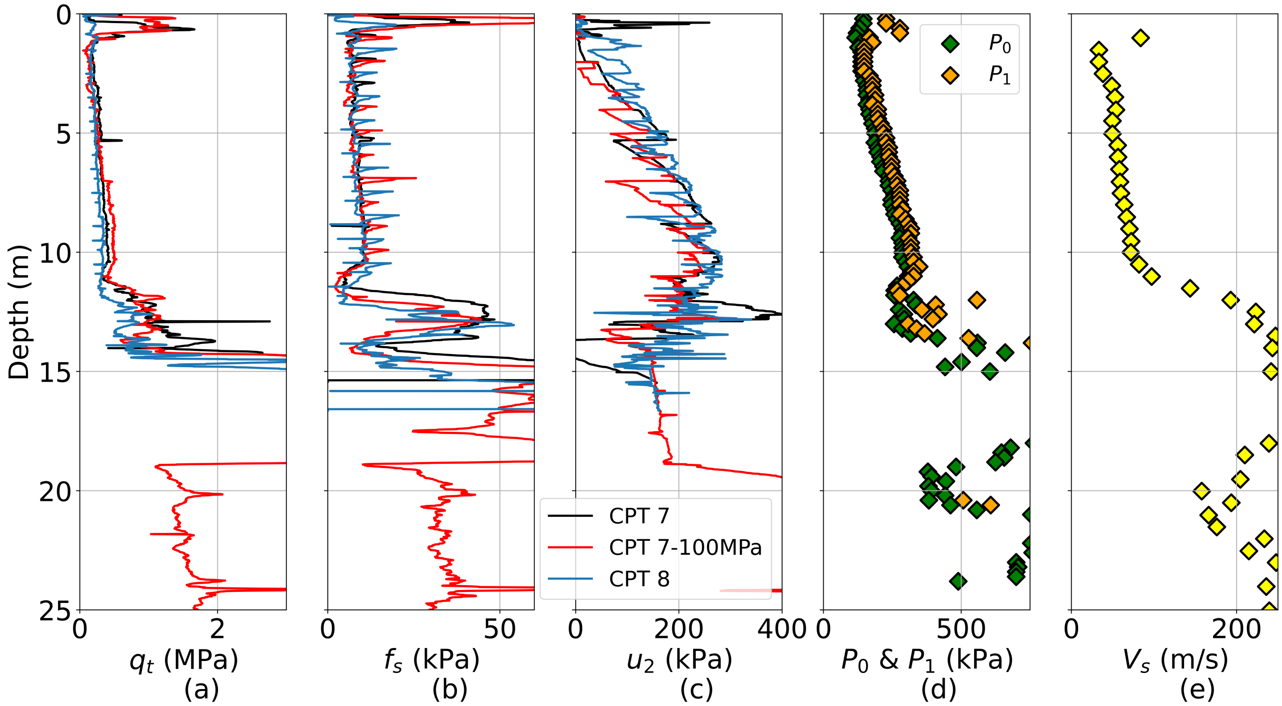

Figure 2: In-situ tests considered in this study, (**a–c**): CPTu results (profiles of q_t, f_s and u_2); (**d**): DMT results (P_0 and P_1); (**e**): V_s.

between the three CPT soundings used as input (see Figure 2). The same applies to the grey ranges (output of the ML model), as the same three soundings were used as input. The solid lines with circular markers denote the corresponding mean values, plotted at the mid-depths of the respective thin layers.

Figure 3a presents the results for the unit weight. The reference values were obtained from two continuous boreholes (Inclo 2 and Mex 9). At the top and bottom of the profile, the average values derived from the CPT, DMT, V_s, and ML workflows tend to underestimate the reference values. Between depths of approximately 2.5 and 10 m, the average values generally provide reasonable agreement with the reference data. However, the ML-based values slightly overestimate the reference unit weights in the depth range of 7 to 10 m.

Figure 3b shows the results for the undrained shear strength (s_u). Reference values are obtained from triaxial compression tests (Inclo 2 and Mex 9) and triaxial extension tests (Mex 9 Ext). The average values from the V_s-based workflow closely match the reference values from the extension tests. Meanwhile, the CPT and DMT-based workflows align reasonably well with the compression test data. The ML-based values tend to overestimate s_u at the top of the profile, but show improved agreement with depth, particularly aligning with the compression test results.

Figure 3c presents the results for G_0. The reference values were derived from the seismic dilatometer test (SDMT 8) conducted at the site, which also provided the shear wave velocity profile used as input for the V_s-based workflow. As a result, the V_s-based workflow aligns

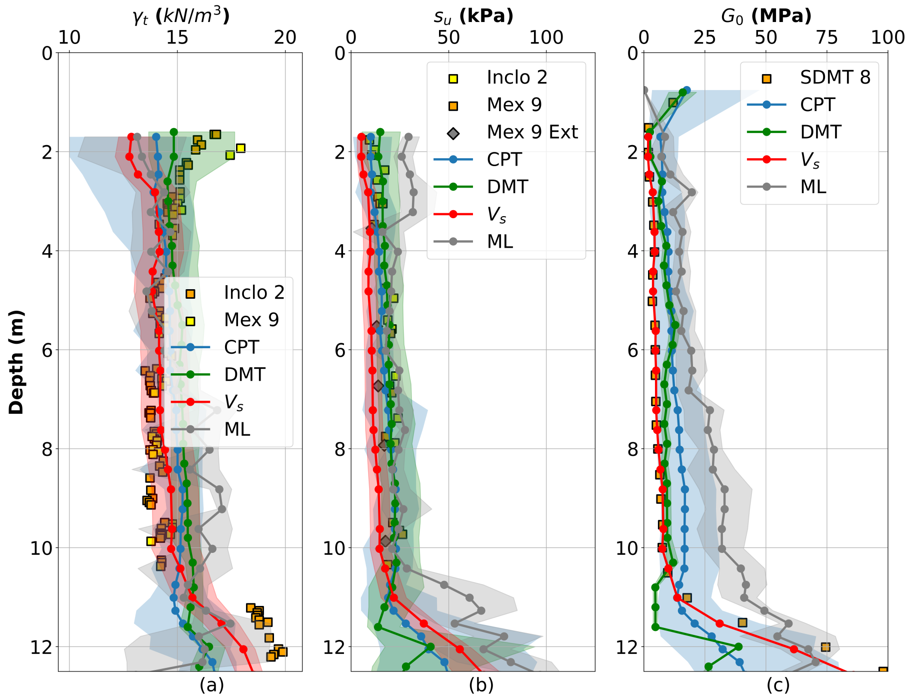

Figure 3: Comparison between APD and interpreted values at Ballina clay test site (the blue, green, red, and grey shaded areas represent the range of values obtained from the CPT, DMT, V_s workflows and ML, respectively): (**a**) unit weight, (**b**) undrained shear strength, (**c**) small-strain stiffness.

of course perfectly with the reference profile. Due to the use of ten different methods, the CPT-based workflow exhibits the largest spread, as reflected by the wide shaded band. The average value of this distribution tends to overestimate the reference values in the upper layers, while underestimating them toward the bottom. A similar trend is observed for the DMT-based workflow. The ML predictions, on the other hand, significantly overestimate the reference values throughout most of the profile, but show improved agreement at the bottom of the layer. A comparable overestimation by the ML approach for clays is also reported in Felić et al. (2025), which might be attributed to the under-representation of clay sites in the training database.

4 Conclusion and Outlook

APD is a parameter determination tool that utilizes a graph-based approach to derive soil and constitutive model parameters from in-situ test data. At the early stages of geotechnical projects—when soil data is limited—the tool supports early site characterization by providing detailed insights. Its purpose is not to replace laboratory testing, but rather to complement it, as laboratory results remain essential for the final design.

In this study, APD was applied using its three core workflows—CPT, DMT, and V_s measurements—at a testing facility in Australia. Additionally, the study explored the potential of incorporating data-driven approaches as an alternative source for parameter estimation. The findings indicate that key soil parameters can be reasonably estimated using all four approaches, although some methods tend to under- or overestimate the reference values which might indicate that both, the validity of implemented correlations and the structure of the database for the ML approach requires some refinement.

Ongoing research aims to enhance the accuracy of the framework through statistical evaluation of the computed values and the inclusion of additional in-situ tests. Furthermore, efforts are underway to improve the machine learning models by expanding the training database to cover a broader range of parameters and soil types.

Data repository

The GitHub repository for the machine learning approach is available here: `https://github.com/harifel/SmartGeotec2025`

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