MACHINE LEARNING-BASED OPTIMIZATION OF LITERATURE MODELS FOR SUBMARINE CABLE INSTALLATION IN SANDY SEABEDS

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1 Introduction

Offshore wind farms are rapidly emerging as a key solution towards green energy production. Offshore infrastructures are connected to onshore substations via submarine cables, which are usually buried in trenches for protection. Submarine cables also serve a strategic role as data traffic infrastructure, highlighting the need for efficient and optimized installation designs. Cable installation techniques vary with geotechnical conditions, with ploughing widely preferred due to its versatility across different soil types. Reliable predictions of the tow force needed to drive the plough is critical for optimal cable installation planning. The literature presents several analytical approaches to estimate this force, based on earth pressure theories. In the case of granular seabed, the tow force comprises a static component and a velocity-dependent (dynamic) component. The static component arises from (i) friction between the plough and the seabed, and (ii) soil resistance (Lauder, 2010). In contrast, the nature of the dynamic component remains debated, but is commonly attributed to shear-induced pore water pressures under partially drained conditions (see e.g. Palmer, 1999). These formulas require a set of semi-empirical factors which have been calibrated from small-scale laboratory tests (Lauder, 2010; Robinson et al., 2017). However, when applied to real-world field projects, their predictive capabilities have shown significant limitations (Marveggio et al, 2025). To overcome these limitations, Machine Learning (ML)-based modeling has recently emerged as a promising alternative for analyzing complex nonlinear processes in various geotechnical engineering fields. This paper explores the possibility of using regression-based algorithms trained on real-world project data to recalibrate existing formulations, popular among practitioners.

2 Available data for data training

Considering the high subsoil variability typical of the offshore environment, and the longitudinal nature of cable ploughing operations, comprehensive investigation campaigns are generally performed to reduce any operational risk. In the current practice, the geotechnical characterization comprises Piezometric Cone Penetration Tests (PCPT), performed approximately every 1 to 2 kilometers. Correlations are available to relate PCPT measurements to estimate different soil properties (e.g. Robertson et al., 1986; Jamiolkowski et al., 2003). Along with PCPTs, soil samples are collected from Vibrocore (VC) tests, usually performed in proximity to the PCPT locations. Laboratory tests on VC samples provide additional information, such as grain size distribution curves, water content, and soil density. Along with the geotechnical survey, an extensive geophysical investigation is also conducted.

In order to assess the performance of tow force prediction models available in the literature, data from three real-world cable ploughing projects have been analyzed (CS1, CS2, CS3). The dataset has been limited to those route segments that are mainly composed of coarse-grained seabed, in line with the goal of this study. The final dataset covers around 100 km and includes as-built data as well as geotechnical data from the investigation campaign. The as-built dataset comprises key installation parameters such as the burial depth, the installation velocity, and the tow force, while the geotechnical survey provides soil properties like the characteristic grain size d_{10} (corresponding to the 10% passing size), the uniformity coefficient C_u, and the average tip resistance q_c. The statistical distributions of these variables are described by means of boxplots in Figure 1 for the three case studies, while the corresponding dispersion and position indices are listed in Table 1. The overall dataset is large enough to support the use of data-driven approaches coupled with analytical models, as those illustrated in the following section, that could operate effectively in practical applications.

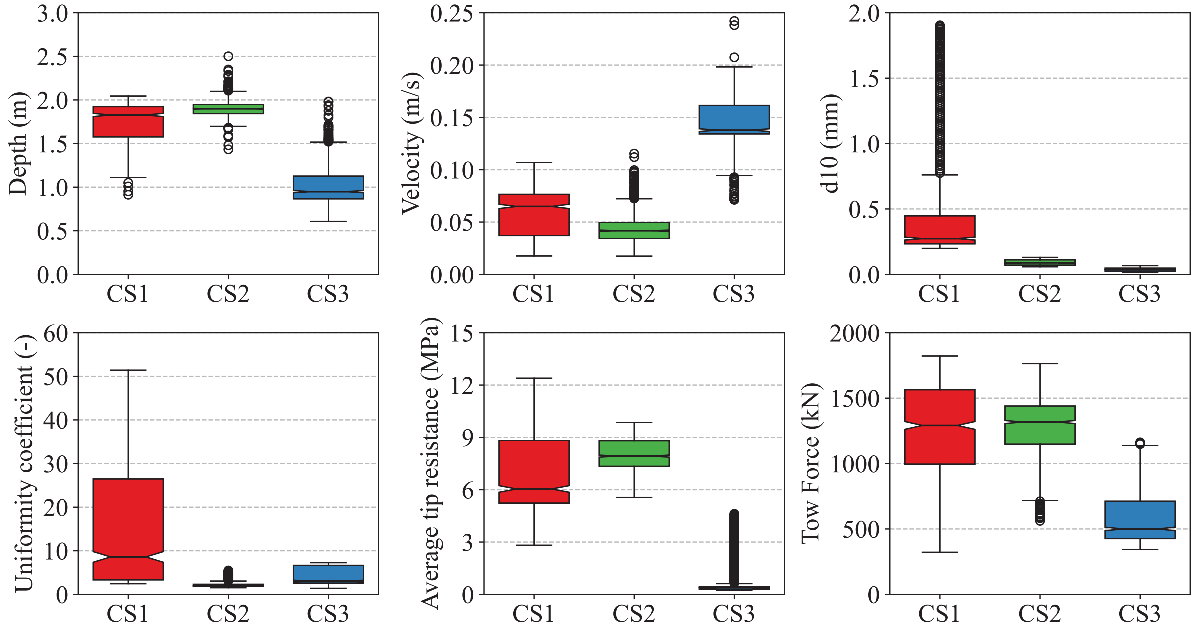

Figure 1. Box and whiskers plots of all the variables employed in the analysis for each case study.

Table 1. Statistical features of the dataset.

Parameter	Min	Max	Range	Mean	Median	Standard deviation
Burial depth (m)	0.61	2.50	1.89	1.58	1.82	0.43
Velocity (m/s)	0.017	0.273	0.256	0.078	0.058	0.048
d_{10}(mm)	0.015	1.904	1.889	0.155	0.083	0.233
C_u(-)	1.383	51.412	50.029	6.078	2.567	9.080
q_c (MPa)	0.230	12.394	12.164	5.390	6.365	3.545
Tow force (kN)	321.7	1822.1	1500.4	1059.4	1113.3	406.6

3 Literature models

The present study explores the possibility of using regression-based machine learning algorithms trained on real-world project data to recalibrate existing analytical methods. To this end, the study considers the approach proposed by Robinson et al. (2021), hereinafter named R model. Robinson et al. (2021) conducted a series of dry and saturated 1/50$^{\text{th}}$ scale model cable plough centrifuge tests at 50g and proposed an improved model building on previous studies by Lauder et al. (2012) and Robinson et al. (2019) on pipeline ploughing. The R model estimates the tow force as follows:

$$F = \left[C_w W' + \frac{3}{2} K_p \gamma' D^2 w + K_{side} \gamma' D A_{side} \tan\delta\right] \times \left(1 + C_{dn\psi} \frac{-\psi V D}{c_v}\right) = F_{st} \times (1 + A \cdot VD), \quad (1)$$

where C_w is a dimensionless friction coefficient (assumed equal to 0.4), W' the submerged plough weight, K_p the passive earth pressure coefficient, γ' the submerged unit weight of the soil, D the depth of burial, w the share width, K_{side} the lateral earth pressure coefficient, A_{side} the embedded area of the share side, δ the soil-to-plough interface friction angle, $C_{dn\psi}$ an empirical coefficient equal to 0.78, V the plough velocity, ψ the state parameter of the soil, c_v the coefficient of one-dimensional consolidation, and A a "dynamic coefficient", which accounts for the soil hydro-mechanical behavior. Robinson et al. (2021) also proposed a series of correlations to infer the model parameters from the results of PCPT tests. A comprehensive overview of the information and the tests required to calibrate the input parameters is provided by Marveggio et al. (2025).

4 Machine Learning-based model

In the case of cable ploughing the use of ML is motivated by the limits of traditional analytical approaches when applied to real-world applications, where soil conditions are much less controlled and parameters identification becomes extremely difficult. This is particularly true for the determination from standard site investigation of c_v and the state parameter ψ. Considering these challenges, this study explores the use of support vector machine (SVM) as a tool to enhance the current prediction capabilities of literature models. As summarized in Table 2, two distinct SVMs were trained and tested on the available dataset, using an 80/20 split and applying a 5-fold cross-validation procedure on the training set. The first algorithm, denoted as the R+SVM model, considers the dynamic coefficient A as target output (label). The inverse of the tip resistance, d_{10}, and C_u, have been selected as input variables and mapped into a higher-dimensional feature space by means of a third-degree polynomial kernel. The second algorithm, called the SVM model, directly performs the regression between the tow force F, and all input variables listed in Table 2, which are mapped into the feature space by means of a Gaussian kernel. The scatter plots in Figure 2 compare the measured tow force with the predictions of the R, R+SVM, and SVM models. As can be clearly visualized, the SVM model outperforms both R and R+SVM approaches across all three case studies. However, the latter provides more reliable predictions with respect to the original R model, especially in CS3, where the seabed consists of fine and loose sands, as illustrated in Figure 1. This is also testified by Figure 4, which shows the root mean squared error (RMSE), normalized with respect to the average measured tow force. While the SVM model consistently achieves an error below 15%, the R+SVM model enhances the predictive capabilities of the R model and it proves effective even when the cable is installed in soil different from those considered in the calibration of the literature model.

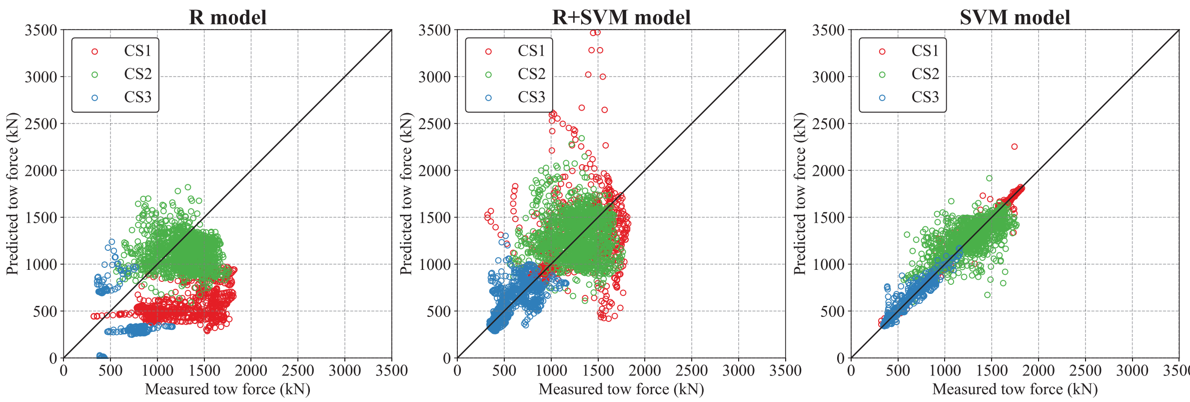

Figure 2. Scatter plots of measured vs. predicted tow forces with the R model (left), R+SVM model (center), and SVM model (right).

Table 2. Summary of the machine-learning algorithms.

Name	Inputs	Label	Feature map	Hyperparameters
R+SVM model	$\left\{\frac{1}{q_c}, d_{10}, C_u\right\}$	A	3rd degree polynomial	$\begin{Bmatrix} C = 10^{-3} \\ \varepsilon = 10^{-2} \\ \gamma = 10^{2} \end{Bmatrix}$
SVM model	$\{D, V, q_c, d_{10}, C_u\}$	F	Gaussian	$\begin{Bmatrix} C = 10 \\ \varepsilon = 10^{-2} \\ \gamma = 10^{2} \end{Bmatrix}$

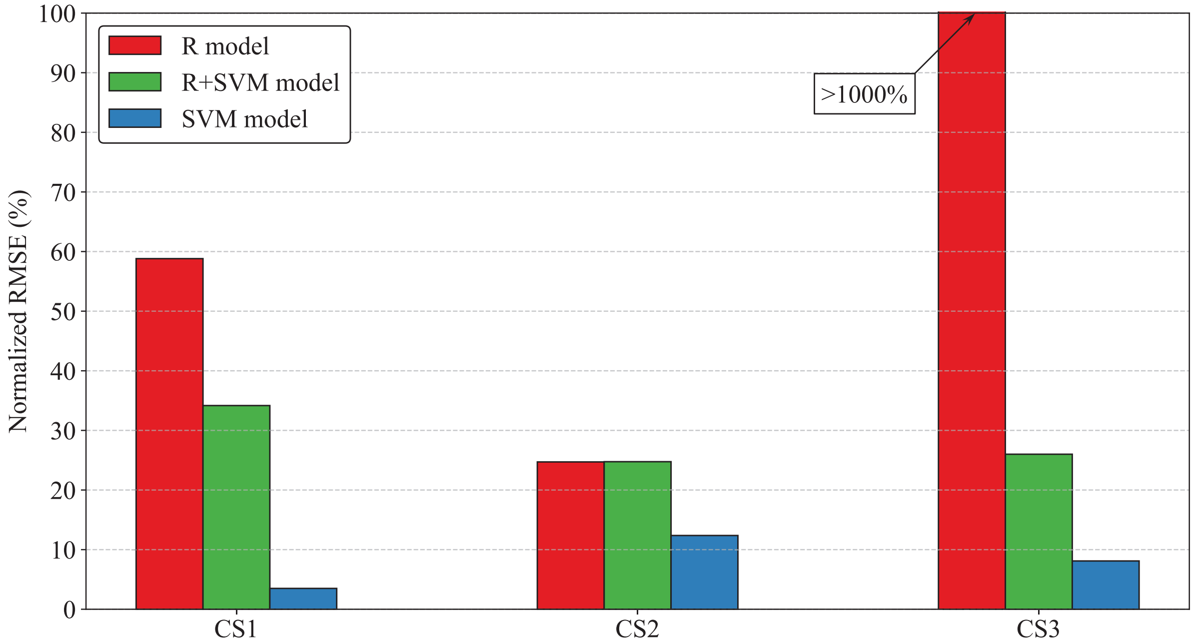

Figure 3. Comparison of the normalized RMSE measured on the predicted tow force with the R, R+SVM, and SVM models.

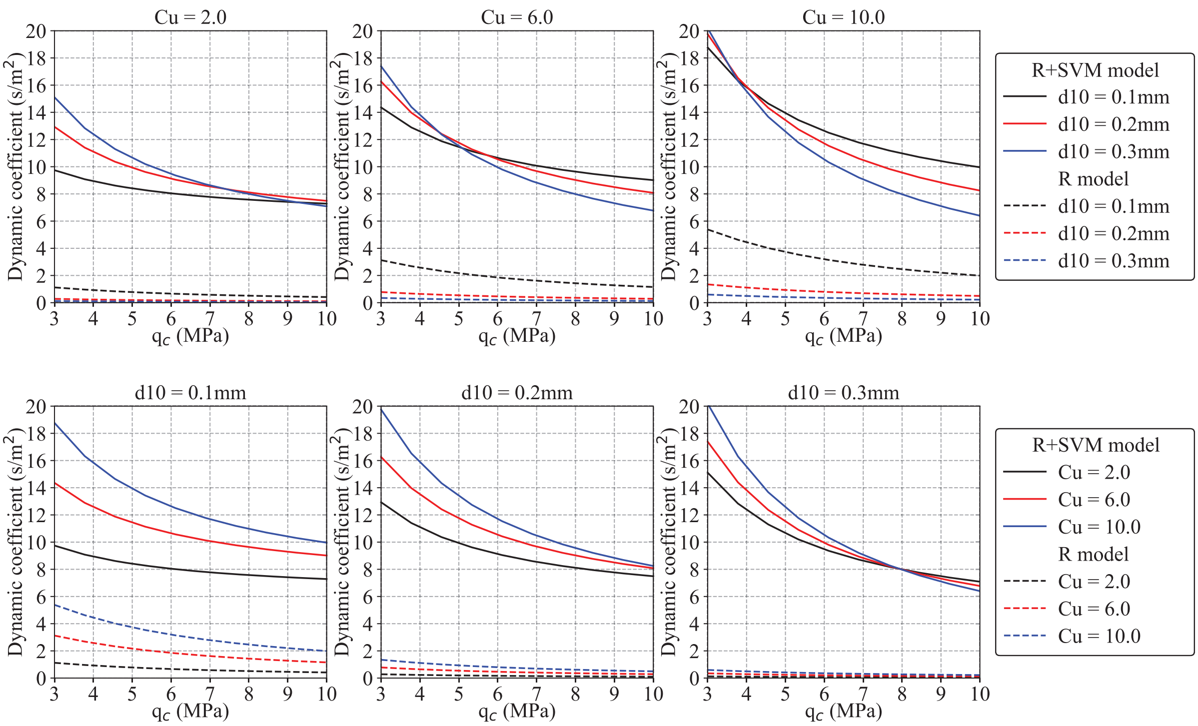

Figure 4. Comparison between the predicted dynamic coefficient A, according to the R and R+SVM model for different combinations of characteristic grain size d_{10} and uniformity coefficient C_u.

Figure 4 compares the dynamic coefficient A according to the original R model with that derived from the data-driven regression. The R+SVM model successfully reproduces the dependence on the uniformity coefficient C_u and tip resistance q_c consistently with the literature, demonstrating its ability to capture the underlying physics of the towing process.

5 Conclusions

This study proposes the use of supervised machine learning techniques to recalibrate established analytical models for cable ploughing tow force prediction, using real-world project data. The approach maintains the analytical structure of widely adopted models, modifying only their empirical coefficients. This ensures compatibility with current engineering practice and enables practical adoption in existing workflows. Field data, particularly post-installation tow force, velocity, and burial depth measurements, are used to recalibrate model parameters via support vector machine (SVM), enhancing prediction accuracy. The interpretability of the original analytical formulation can be preserved by adopting a limited set of input features and a simple feature mapping. This allows for the graphical visualization of the underlying relationship between the rate effect, used as output and selected geotechnical parameters, taken as inputs. This procedure also eliminates the need to infer soil parameters (e.g., hydraulic conductivity or relative density), relying instead on directly measured in-situ PCPT and VC data. As a result, the dependence on uncertain empirical correlations, particularly critical in heterogeneous offshore environments is avoided. At the same time, the use of more complex ML models greatly improves the predictive capabilities at the expense of interpretability with respect to the underlying physical process. Future work will explore other ML models and the extension of the method to different soil types, with the overarching goal of bridging data-driven approaches and established analytical frameworks in offshore geotechnics.

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