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From in-situ tests to probabilistic and sensitivity analysis using FEA and surrogate modelling

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ABSTRACT: This paper demonstrates a comprehensive workflow for probabilistic and sensitivity analysis of settlement of a hypothetical embankment case using realistic CPT data. The stratification reveals layers with different behaviour types, including clays, silt mixtures, sandy mixtures and sands. The dominant layer consists of soft clay which is susceptible to excessive deformation due to the embankment construction. Given the significant variations in the CPT readings, deformation analysis with deterministic parameters is insufficient. Instead, a series of finite element analyses were conducted with different material properties. The soft clay was modeled using the Soft Soil constitutive model, while other layers were modeled using the Hardening Soil Small Strain model in PLAXIS 2D. Model parameters were randomly selected from the parameter sets derived from individual CPT readings of the respective layer. In this way, each reading was considered as an independent measurement instance, with consistent derived parameters. Uniform sampling over depth maintained the actual distribution of the parameters within each layer. Additionally, the unit weight of the embankment was randomly chosen from its probability density function. Latin hypercube sampling was employed to ensure even sampling across the parameter space with a smaller number of samples. The resulting embankment settlements were processed in terms of the probability of exceeding a predefined maximum allowed value. To identify the significant contributing factors to settlement and deformation variation, Sobol' global sensitivity analysis was performed. Uncertain parameters included representative features for each layer and the embankment's unit weight. The Sobol' procedure requires considerably more simulations than required by the probabilistic analysis, which is prohibitive because of the computational demands. Therefore, several surrogate models were trained using machine and deep learning algorithms. To achieve acceptable performance, hyperparameters were tuned automatically over appropriate ranges. The best-scoring model was then employed to estimate the embankment displacements in the sensitivity analysis.

KEYWORDS: CPT, parameters, surrogate model, probabilistic analysis, sensitivity analysis.

1 INTRODUCTION

Geotechnical projects are characterized by substantial uncertainty. This uncertainty is primarily attributable to the intrinsic spatial variability of geomaterial properties, the limited availability of representative data, fluctuations in environmental or loading conditions, and measurement errors in property assessment (ISSMGE-TC304, 2021).

Given the significant impact of such uncertainty on decision-making processes, the reliability of deterministic analyses has been increasingly scrutinized. Consequently, there has been a growing interest in probabilistic approaches within the geotechnical community.

This paper outlines a comprehensive workflow for conducting probabilistic and sensitivity analyses of a geotechnical problem. The specific geotechnical issue addressed involves stress-strain analysis using the finite element method through elastoplastic constitutive models.

Performing a probabilistic analysis on such problems necessitates careful consideration of various inputs, including soil parameters. The workflow illustrates the application of Cone Penetration Test (CPT) data to generate soil parameters for finite element analysis in a probabilistic manner. The outcomes of the probabilistic finite element analysis are subsequently utilized in a global sensitivity analysis.

2 BACKGROUND

2.1 *Probabilistic analysis*

The primary concept of probabilistic analysis involves conducting multiple trials using sets of randomly selected parameters. In the context of probabilistic finite element analysis, there are generally two approaches:

- Random selection and assembly of parameter values in a parameter set, considering their mutual correlation, while the parameter set is assigned to an entire soil layer (e.g. Roubos et al., 2020).
- Random finite element analysis (RFEM) with random selection and assignment of parameter values to individual elements or stress points, considering their spatial correlation and given horizontal / vertical scales of fluctuation (e.g. de Gast et al., 2018).

In this research we have adopted the first approach. In general, such models capture soil response through a set of parameters with complex intercorrelations. Creating trials without considering intercorrelation results in incorrect parameter sets, leading to inaccurate results in finite element analysis. To address this issue, the trials should include a 'consistent' set of parameters. This can be achieved by sampling on the 'core' properties of the soil and calculating model parameters for the sampled core properties, rather than sampling directly on different model parameters, since otherwise inconsistent parameter combinations may occur.

The result of a probabilistic analysis is the probability of an (undesired) 'event' occurring based on the random combinations of uncertain parameters. The 'event' is defined in terms of an objective function or response function f, where $f>0$ represents the (undesired) event and $P(f>0)$ the probability of this event occurring. In this case, the response function f is expressed in terms of results from a finite element analysis.

(Griffiths & Fenton, 2007) provides a comprehensive exploration of probabilistic methods in geotechnical engineering, bridging theoretical foundations with practical applications.

2.2 *Sensitivity analysis*

A probabilistic analysis provides no indication about which parameter, or combination of parameters, has the greatest effect on the variation of the output. Through sensitivity analysis, the most influential parameters can be identified, allowing for more informed decisions, such as targeted site investigations that will yield more precise data.

The method of Sobol'(1990) is a global and model independent sensitivity analysis which determines the contribution of each input (or group of inputs) to the variance of the output. Variance is a statistical measure that represents the degree of spread or dispersion in a set of values. In the context of sensitivity analysis, it quantifies how the output of a model varies due to changes in the input parameters. A higher variance indicates greater variability in the output, suggesting that the input parameters have a significant impact on the model's behaviour.

The outcome of the Sobol' sensitivity analysis is a set of 'sensitivity indices', which include, but are not limited to, the main and total effects for each input.

Consider Y as a function $Y = f(X)$, where $X = (X_1, X_2, \dots, X_d)$ is the parameter set. Sobol' suggested to decompose the function into summands of increasing dimensionality as:

$$Y = f_0 + \sum_{i=1}^{d} f_i(X_i) + \sum_{i=1}^{d}\sum_{i<j}^{d} f_{ij}(X_i, X_j) + \cdots + f_{1,\dots,d}(X_i, X_j, \dots, X_d) \tag{1}$$

Assuming the parameters are mutually orthogonal, the variance of the function can be decomposed as:

$$V(Y) = \sum_{i=1}^{d} V_i + \sum_{i=1}^{d-1}\sum_{j=i+1}^{d} V_{ij} + \cdots + V_{1,\dots,d} \tag{2}$$

Sobol' sensitivity indexes are the ratio of the partial variance to the total variance. More specifically, the first, second and total order sensitivity indexes of the X_i parameter are defined as:

$$S_i = \frac{V_i}{V} \qquad S_{ij} = \frac{V_{ij}}{V} \qquad S_{Ti} = S_i + \sum_{j\neq i} S_{ij} + \cdots \tag{3}$$

The first order sensitivity index, S_i, shows the main contribution of the variation of the X_i parameter to the variation of Y, without considering the interaction of the parameter with others. The second order index, S_{ij}, shows the variation ratio due to the interaction of X_i parameter with any other parameter. Higher order indexes can be defined accordingly for interaction of the parameter with more parameters. The total sensitivity index, S_{Ti}, includes the main effect and the effects of all interactions of the parameter on the variation of Y. The variance terms can be estimated using the Monte Carlo integrals and Sobol' quasi-random sampling. The procedure includes numerous function evaluations (Nossent, et al., 2011).

Sobol' global sensitivity analysis can be used for ranking of the variables, fixing unessential variables and removing high order terms of the decomposed form of a function (Sobol', 2001) .

For non-analytical 'functions' (such as the results of a finite element calculation), the sensitivity analysis relies on a surrogate or proxy model of the 'function', rather than the function itself.

2.3 *Surrogate model*

The calculation of responses for geotechnical engineering problems often requires a software tool, generally based on Finite Element or Limit Equilibrium solutions.

Surrogate modeling has become an effective strategy to reduce the computational cost of probabilistic analyses in complex geotechnical problems. These methods approximate high-fidelity numerical models with simplified representations, enabling efficient response assessment without compromising accuracy. Among various approaches, response surface method, machine learning and deep learning algorithms are commonly employed to construct surrogate models. For instance, Ran, et al., (2023), Siacara, et al.(2024) and Dastpak, et al. (2025) have successfully applied these techniques.

2.4 *CPT-based parameter determination and selection*

Cone Penetration Testing (CPT) is an effective way to obtain good estimates of the sub-soil stratification and corresponding properties. In recent research, a field test-based tool was developed by the authors and co-workers for automated parameter determination (APD) (Marzouk et al., 2024). Moreover, CPT data can also provide insight into the (spatial) variability of soil properties. Since a single CPT consists of multiple readings, it can be used for sampling soil data in an attempt to determine (sets of) probabilistic soil properties. Rather than considering the variation of soil properties over the full depth, it is probably more useful to consider variations within well-defined soil layers. This idea was further explored in a practical application, as described in the next section.

3 WORKFLOW

Figure 1 illustrates the common workflow applicable to any geotechnical system for probabilistic and sensitivity analysis. The workflow comprises five steps: starting with the definition of the problem, followed by the setting of probabilistic parameters. In the third step, numerical simulations are conducted for trials. The results from this step are utilized in the probabilistic analysis step, and subsequently in the sensitivity analysis step.

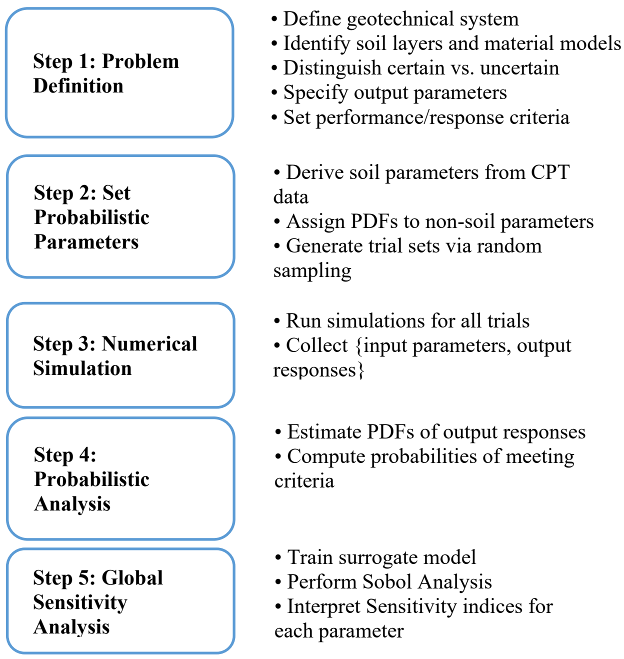

Figure 1. Typical workflow for probabilistic and sensitivity analysis of geotechnical stress-strain problems

4 APPLICATION TO PRELOADING EMBANKMENT

This section explains the various parts of the workflow for a preloading embankment, as a general example. The aim of the probabilistic analysis is to examine the variations in ground surface settlement beneath the center of the embankment (uy0). The probability of exceeding a maximum allowed settlement is computed. In the sensitivity analysis section, the significance of each probabilistic parameter is determined.

4.1 *Problem definition and soil data*

The analysis involves the construction of a preloading embankment, inspired by the situation near the city of Dordrecht, The Netherlands, connecting the N3 provincial road to the A16 motorway. Based on the typical settlement values within the region, the arbitrary maximum allowed settlement of 95 cm is considered for the ground surface beneath the center of the embankment.

The project utilizes data from two nearby CPTs, specifically CPT000000175137 and CPT000000175171 as available from the Dutch online soil database DINOloket.nl. CPT000000175137 starts from reference depth of NAP -0.60m (NAP is the Dutch reference datum) and ends at reference depth of NAP -25.60 m, with measurement intervals of 1 cm. CPT000000175171 is quite similar. Readings of the latter CPT have been merged with data from CPT000000175137 into the corresponding layers to enrich the data set.

The underground geology has been interpreted from CPT000000175137. The stratification algorithm used to identify distinct layers is based on the moving standard deviation of log(q_t/p_a) and log(R_f) (Brinkgreve, et al., 2023), where q_t refers to the corrected total cone resistance, p_a is atmospheric pressure, and R_f is the corrected friction ratio. The stratification algorithm identified 7 distinct layers, as illustrated in Figure 2.

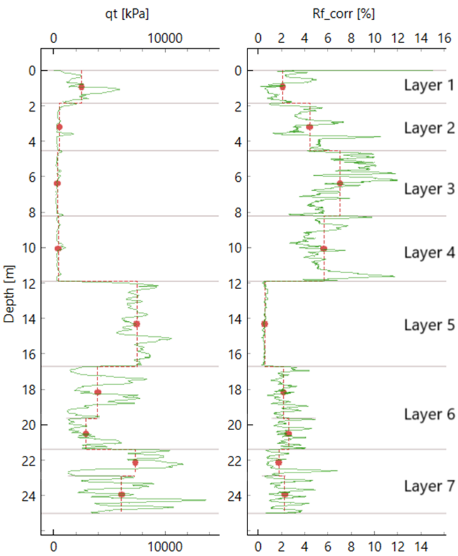

Figure 2. CPT000000175137 with detected soil layers.

The CPT readings for each layer were mapped to the Robertson 2010 soil behaviour classification chart. Layer 1 consists of a mixture of silty clay, clayey silt, and sandy silt soils. Similarly, layer 2–4 exhibited a variety of soil behaviour types, ranging from organic clay to sandy silt. Layers 6 and 7 displayed similar variations. Layers 3 and 4 primarily consisted of organic material and clay to silty clay soils, while layer 5 mainly comprised clean sand to silty sand materials.

While the workflow could be extended to incorporate the spatial variability of the core parameters, this study deliberately excludes such considerations. Accounting for spatial variation requires a 2D/3D model of core parameters and significantly more data, which falls outside the defined scope of this analysis.

4.2 *Probabilistic parameter processing*

In addition to the stratification, CPT measurements were used to determine soil properties and model parameters by means of correlations with the core CPT parameters. In this way, each CPT reading would lead to a complete and consistent set of soil and model parameters. To take a random selection of model parameters for our probabilistic analysis, for each of the relevant soil layers, a random selection from all CPT readings contributing to a particular soil layer was taken and the corresponding consistent parameter sets were used to perform a complete finite element analysis, as explained later.

Detecting outliers in log(qt/pa) and log(Rf) data for each layer is crucial to avoid assigning unlikely parameters. Outliers were identified using robust-z-score and IQR methods, both establishing lower and upper boundaries beyond which data points are considered outliers. Figure 3 displays histograms of log (R_f) and log(q_t/p_a) for layer 2, with outlier boundaries marked. The RZS method resulted in tighter boundaries. To minimize data manipulation, data outside of the IQR method boundaries were dropped from the data set.

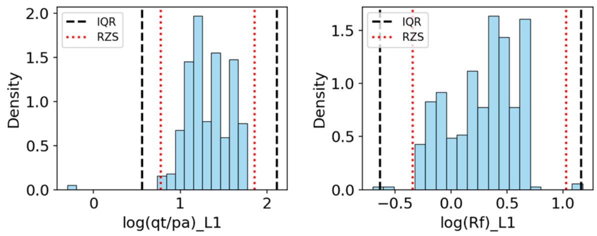

Figure 3. Outliers' boundaries of log(Rf) and log(qt/pa).

Layers 1–5 were considered most 'uncertain' and most relevant in our probabilistic analysis; these layers were assigned randomly selected parameter sets, while deterministic (constant) parameter sets were assigned to Layers 6 and 7.

Besides the distribution of parameters of the top five soil layers, a uniform distribution in the range 15–19 kN/m^3 was assumed for the unit weight of the embankment.

4.3 *Soil parameters from CPT data*

While sampling for several parameters, it is essential to consider correlations between them. For example, it is known that the soil's friction angle and cohesion are adversely correlated. This correlation can be defined with a negative constant factor. For models with multiple parameters and nonlinear correlation, this approach is not practical. Therefore, rather than sampling individual model parameters, samples were randomly selected from the rows of CPT readings contributing to a soil layer. Model parameters (for the most common soil constitutive models) were derived from correlations with the core CPT parameters (q_t/p_a, R_f) and stored in the corresponding row (Figure 4). Hence, the row indexes are the random parameters to be selected, not the individual parameters. In this way, consistent parameter sets from the randomly selected rows for each soil layer were used in the FE calculations.

Index	layer	depth [m]	qc [MPa]	fs [MPa]	Eo_r[Mpa]	E50_r[Mpa]	Eur_r [MPa]	G0 [MPa]	G0_r [MPa]
367	1	1.85	1.32	0.02	1.89	2.72	10.89	19.74	36.89
368	1	1.86	1.34	0.02	1.96	2.79	11.17	19.39	35.91
369	1	1.86	1.57	0.02	1.97	2.76	11.05	20.58	37.54
370	2	1.87	1.37	0.02	1.99	2.82	11.28	19.52	35.92
371	2	1.87	1.80	0.02	23.10	31.43	94.29	23.66	84.86

Figure 4. Rows of CPT-based parameters from correlations.

To ensure that the samples are distributed evenly over the sample space, Latin Hypercube Sampling was used. The histogram comparison between the source data and sampled data shows that this method achieved uniform coverage of parameters.

4.4 *Finite element model*

Although the real situation of the embankment is non-symmetric, a simplified embankment geometry was modelled, considering only one half of the embankment (Figure 5). The mesh is composed of high-order 15-node elements.

The embankment is 3 m high; the (half) base is 10 m wide and the (half) top is 4 m wide. The groundwater level is 1 m below ground surface, assuming a hydrostatic pore pressure distribution. Roller boundaries are applied at the vertical sides while the bottom is fully fixed and the top is free to move.

The layering of Figure 2 was adopted in the geometry. The embankment soil was modeled using the linear elastic perfectly plastic Mohr-Coulomb model; Layers 1, 5, 6 and 7 were modelled using the Hardening Soil small-strain model, while the Layers 2–4 were modelled using the Soft Soil model in PLAXIS. All soil layers were assumed 'drained', to simulate long-term behaviour.

The phasing was as follows: Initially, only a horizontal ground surface was considered to generate gravitational in-situ stresses, after which the embankment was 'activated' and the corresponding soil weight was applied as loading.

A 'master' project was created using deterministic sets of parameter values around the mean for each layer, as listed in Figure 6.

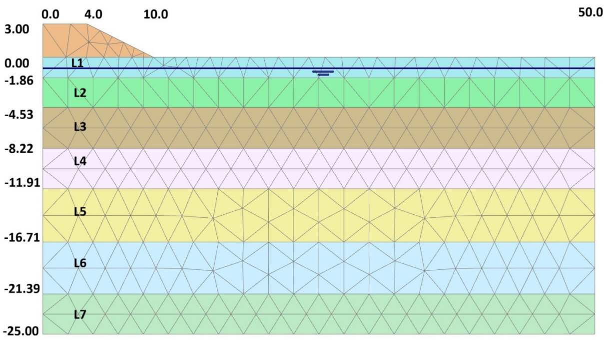

Figure 5. FEM model for probabilistic analysis of embankment.

HSsmall	Unit	L1	L5	L6	L7
γ_{sat}	kN/m³	19	20	18	20
e_0	-	0.5	0.5	0.5	0.5
E_{50}^{ref}	MPa	20	40	15	25
E_{oed}^{ref}	MPa	20	40	12	25
E_{ur}^{ref}	MPa	60	120	45	75
ν_{ur}	-	0.2	0.2	0.2	0.2
m	-	0.5	0.5	0.5	0.5
p^{ref}	MPa	0.1	0.1	0.1	0.1
G_0^{ref}	MPa	75	125	60	90
$\gamma_{0.7}$	-	0.2 E-3	0.1 E-3	0.2 E-3	0.15 E-3
ϕ'	°	31	35	28	32
c	kPa	0	0	0	0
ψ	°	0	0	0	0
K_0^{nc}	-	0.48	0.43	0.53	0.47
R_f	-	0.9	0.9	0.9	0.9

SoftSoil	Unit	L2_L3_L4
γ_{sat}	kN/m³	15
e0	-	2.5
λ^*	-	0.1
κ^*	-	0.02
ν'	-	0.2
ϕ'	°	25
c	kPa	0
ψ	°	0
K_0^{NC}	-	0.57
M	-	1.37

Figure 6. Deterministic sets of model parameters for each layer.

4.5 *Probabilistic analysis*

A Python script was written to automate the finite element calculations. Using PLAXIS' application programming interface (API), the script generated 1500 trials from the 'master' project. For each trial, the script assigned a random unit weight for the embankment and selected random indexes for Layers 1–5. It modified the parameter sets based on the values in the corresponding rows from the CPT-based parameters input file and ran the analysis. Finally, it stored the ground settlement under the embankment's center, uy0 [m], as the output of interest.

Note that the size of the index range of layers is smaller than the number of trials, meaning that the same index number is used multiple times. However, the combination of unit weight and layer index numbers in each trial appeared to be unique.

The distributions of sampled parameters were compared with the distributions of available data to evaluate the sufficiency of the number of trials.

Figure 7 shows a section of trial data sets, listing the sampled unit weight of the embankment and selected index numbers for each layer, referring to the corresponding row in the input file.

Trial	gamma0 [kN/m3]	L1	L2	L3	L4	L5	uy0 [m]
1	15.95	42	594	1384	2160	2946	-0.80
2	18.72	278	625	914	2219	2691	-0.58
3	15.01	168	695	1114	1753	2848	-0.54
4	16.94	318	376	1187	2188	3150	-0.56

Figure 7. A section of trial data sets and corresponding result uy0.

4.6 *Sobol' sensitivity analysis*

It is important to recall that selecting random parameters from a line index number provides several consistent parameters, including $\log(q_t/p_a)$ and $\log(R_f)$ which are considered the core parameters in that line. All model parameters are determined based on these core parameters. Sobol' sensitivity analysis assumes the input parameters are independent and mutually orthogonal. Since the models' parameters are highly correlated, they violate these requirements. Therefore, we developed the sensitivity analysis using the core parameters of layers checking the compliance with Sobol' method requirements.

To check the orthogonality of each pair of parameters, we investigated linear correlation between each pair of candidate parameters. Firstly, the Pearson correlation matrix was calculated. As shown in Figure 8, most probabilistic parameters show insignificant correlations with others, except for $\log(R_f)$ – $\log(q_t/p_a)$ in layers 1 and 2, indicating linear correlations. To inspect the severity of the correlation, the variance inflation factor (VIF) was calculated for $\log(R_f)$ –$\log(q_t/p_a)$ data of all layers. While an orthogonal pair has a VIF of unity, we believe insignificant collinearity can be accepted for geotechnical engineering problems.

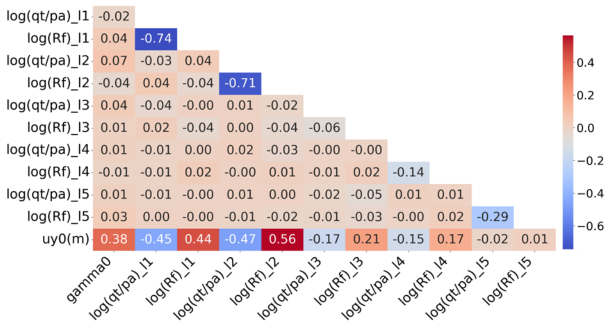

Figure 8. Pearson correlation matrix.

According to Montgomery & Runger (2018) "the larger the VIF, the more severe the collinearity. Some authors suggest that the VIF should not exceed 4 or 5", (Montgomery & Runger, 2018, p. 350). In this case, VIF of all layers was notably less than 4, indicating low collinearity. Although a weak linear correlation does not guarantee independence, visual inspection of pair parameters does not reveal any noticeable non-linear correlation. Therefore, the unit weight of the embankment, and $\log(q_t/p_a)$ and $\log(R_f)$ of layers 1–5 were considered practically independent and uncorrelated and were used here as input variables of the Sobol' sensitivity analysis. Figure 9 shows plots of input variables versus uy0. The trends are significantly scattered, suggesting that the output cannot be strongly correlated with any individual input. Despite the weak relation, the linear correlations of uy0 have a negative correlation with $\log(q_t/p_a)$ in layers 1–2, and a positive correlation with $\log(R_f)$ of these layers. The trends can be explained by looking at Robertson's diagram in which there is generally a weak negative correlation between $\log(q_t/p_a)$ and $\log(R_f)$ considering some variation within a layer from fine-grained (lower right-hand area in Robertson's diagram, i.e. low q_t/p_a and high R_f) to coarse-grained soil (upper left-hand, i.e. high q_t/p_a and low R_f). A similar trend is observed in layers 3 and 4. Layer 5 properties (not shown here) do not show any correlation with output results due to the distance from the applied load.

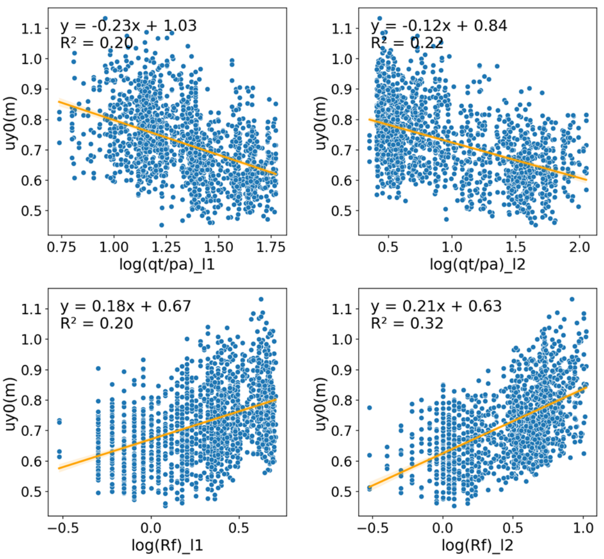

Figure 9. Scatter plots of the output vs input variables of layers.

The input variables of Sobol' sensitivity analysis are defined by a limited number of standard distributions. To represent real data, the best fit among the available options must be determined. The SciPy (Virtanen, et al., 2020) packages were used for this task.

A lognormal distribution fits best for $\log(q_t/p_a)$ of Layer 2 and 4. However the lognormal distribution in the used Python library does not include an upper limit, thus leads to unwanted data on the right tail. Therefore, normal distribution fits, truncated at the lower and upper boundaries, were used for the layer variables. The embankment unit weight was defined using a uniform distribution.

4.7 *Surrogate models to estimate output*

The Sobol' Sensitivity Analysis requires multiple calculations of the output. For this project with 11 input variables (i.e. unit weight and combinations of $\log(q_t/p_a)$ and $\log(R_f)$ of all five layers) and a base sample size of 1024, the output needs to be calculated at least 13312 times. Running complete finite element calculations for this number of trials is impractical. Therefore, various surrogate models using machine learning and deep learning algorithms were developed to estimate the output more efficiently. The models were created using the Python package Scikit Learn (Pedregosa, et al., 2011).

The data set composed for the probabilistic analysis was used. The feature columns included the unit weight of the embankment, and log(qt/pa) and $\log(R_f)$ of layers 1–5. The data set has 1500 rows; 75% was used for training and the rest for testing the model. ElasticNet regression with polynomial features, Support Vector regressor and Random Forest regressor were tested. In all cases wide ranges of hyperparameters were searched using a Bayesian cross validation search technique. In addition, a series of Multi-Layer Perceptron regressor was tested via a grid cross validation search technique. A cross-validation technique evaluates the performance of ML/DL models by dividing the dataset into multiple subsets or "folds." The performance scores of the model are averaged over all folds. The model with the best average performance score across all folds is considered the "best estimator". The coefficient of determination, R^2, was selected as the performance score.

4.8 *Results and discussion – Probabilistic analysis*

The results of the numerical analysis indicate that uy0 varies over a broad range. Figure 10 (left) shows the probability density histogram with the Gaussian estimation for probability density function of the output graphs. According to the cumulative density function, Figure 10 (right), the probability of exceeding the maximum allowed settlement (0.95m) is 4%.

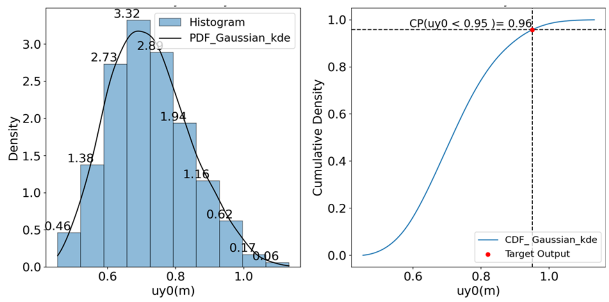

Figure 10. Settlement probability.

4.9 *Results and discussion – Surrogate models*

The best estimator from SVR resulted in scattered estimations compared to the expected values both in the train and test sets. The R^2-score of the estimator was 0.87 and 0.85 for train and test sets, respectively. In contrast, the best estimator from the MLP regressor estimated closer values to the expected values both in the train and test sets. The estimator hit the R^2-score of 0.96 and 0.93 for train and test sets, respectively.

The scores of the best estimator of other algorithms are shown in Table 1. Notably, the Random Forest regressor achieved a higher score on the train set compared to other models. However, it exhibited a significantly lower score on the test set, compared to its score on the train set. This discrepancy indicates an overfitting issue, which should be avoided. The best estimator from MLP was used in the sensitivity analysis.

Table 1. R^2-scores of various models

Model	R^2 train	R^2 test
Support Vector regressor	0.87	0.85
ElasticNet regression	0.91	0.88
Random Forest regressor	0.98	0.85
MLP regressor	0.96	0.93

4.10 *Results and discussion – Sensitivity analysis*

The sensitivity analysis was conducted using varying sample sizes, utilizing the SALib library (Iwanaga, et al., 2022). This library generates $2^{power\_sample}(d+2)$ samples to calculate the total and first-order sensitivity indices, where the $power\_sample$ is a user-defined value and d is the number of parameters. Results were consistent for power sample values above 10. For a power sample value of 12, the sum of all first-order sensitivity indices was 0.945. This value is slightly less than unity, suggesting that the surrogate model is non-additive; however, the variation in output due to higher-order interactions of parameters is minimal. Consequently, calculating the second-order sensitivity indices was deemed unnecessary for this project.

Figure 11 presents the sensitivity indices ST and S1 for all parameters evaluated with a power sample of 12. It is evident that log(R_f)_layer2 is the most significant parameter affecting the variation of uy0(m), since this parameter indicates rather soft soil behaviour, causing most of the settlement. The unit weight of the embankment, gamma0, is identified as the second most important parameter. The parameters of layer 1, log(R_f)_layer1 and log(q_t/p_a)_layer1, exhibit similar levels of significance. Collectively, these four parameters contribute to over 85% of the variation in uy0, while the remaining seven parameters account for approximately 20% of the variation. Based on this comparison, any further measure aimed at reducing the output variation should focus on the four most critical parameters.

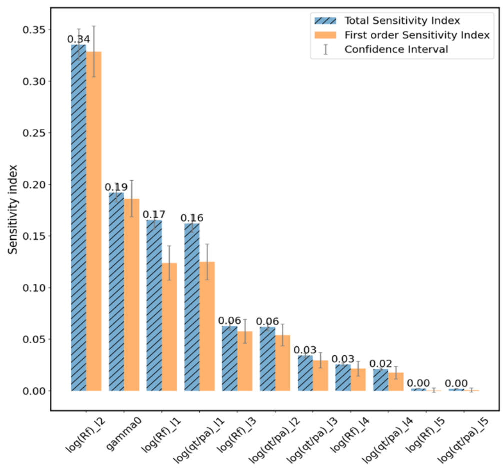

Figure 11. ST and S1 of all parameters (power sample= 12).

5 CONCLUSIONS

Considering the current paradigm shifting from the deterministic to probabilistic analysis among practitioners, this document presented a workflow of conducting probabilistic and sensitivity analyses for deformation problems. The study was performed on a simplified embankment case, while soil layering and properties were derived from CPT data.

The crucial aspect of the workflow is the usage of CPT readings as "core" soil data and the variations therein within each identified soil layer. Consistent sets of soil and model parameters were derived for each CPT reading, from which a random selection was used in each finite element calculation, extracting soil settlement as key analysis result. The input data and results were used to train and test a surrogate model enabling a quick analysis with a larger number of evaluations in a Sobol' sensitivity analysis. Some key conclusions from this study:

- To obtain a consistent set of soil model parameters, sampling should be based on core soil data from which a consistent set of parameters is derived, rather than sampling individual parameters.
- With sampling from CPT readings, as a set, there is no need to assume arbitrary distributions of soil data for probabilistic analysis.
- In the context of finite element calculations, the use of surrogate models is a good way to make sensitivity analyses more feasible.
- A normal distribution, with upper and lower limits, seems to describe the variation of soil properties within a soil layer reasonably well in sensitivity analysis.
- For the application considered here, the MLPRegressor turned out to be the best algorithm for building the surrogate model considering both train and test data sets.
- For the application considered here, sensitivity analysis provided clear insight on the contribution of uncertain parameters on the variation of the output.

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