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Technical Communication

Geotechnical data-driven possibility reliability assessment

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ABSTRACT

Managing scarce, incomplete, or corrupted data is a persistent challenge in geotechnical engineering, often leading to conservative designs. However, the ongoing digitalization has enabled access to large, national-scale databases of indirect geotechnical data containing both qualitative and quantitative information, which can be exploited to support optioneering, site characterization, and design.

Based on a newly proposed concept of possibilistic data-driven reliability, this *Technical Note* outlines a practical, fast, and accessible implementation procedure that does not require specialized expertise. Step-by-step guidance is provided for reliability-based assessment and design of geotechnical problems, ensuring consistency with standard code safety prescriptions.

The procedure demonstrates how to utilize possibility distributions generated from Big Indirect Databases managed by third-party administrators, such as the British Geological Survey, to derive design input values for deterministic evaluations of geotechnical capacity or limit state domains. Engineering judgement is rigorously incorporated through a three-tier 'degree of understanding' framework worked example of an axially-loaded pile in bilayer soil, characterized using cone penetration test data, is also provided.

1. Introduction

Structural Eurocodes (EN 1990:2023, 2024; EN 1997-1:2024, 2024) provide guidance on reliability-based methods to assess structural performance under unusual conditions involving uncertainties during the design process. However, the quantification of uncertainties and their representation, as prescribed by the codes, remain confined to a probabilistic framework. Thus, reliability assessment involves estimating the probability of undesirable events represented by limit states, assuming the applicability of probability theory axioms. Probabilistic models, in turn, require uncertain quantities to correspond to well-defined population sets.

In practice, however, site-specific geotechnical data are often Multivariate, Uncertain and unique, Sparse, InComplete and Corrupted (MUSIC-X coined by Phoon, 2018), making the validity of these assumptions undetermined. Failing to acknowledge the incompleteness of evidence may lead to incorrect choices of probability distributions, potentially resulting in significant biases of the failure probabilities, in a non-conservative manner (Ferson and Ginzburg, 1996; Oberguggenberger and Fellin, 2002).

Incomplete knowledge about parameters can be represented through imprecise probabilities (Dempster, 1967; Shafer, 1976; Dubois and Prade, 1990; Oberguggenberger and Fellin, 2002; Dubois and Prade, 2004; Baudrit and Dubois, 2006; Ferson and Oberkampf, 2009; Beer et al., 2013; Hose, 2022), which consider families of probability distributions, rather than a single distribution, to account for partial knowledge. Various mathematical theories such as fuzzy probabilities (Beer, 2009), probability-boxes (Schöbi and Sudret, 2017), or possibility theory (Dubois and Prade, 2004; Dubois, 2006) have been developed to address such uncertainties.

To reduce the incompleteness of the geotechnical site-specific data, Tombari et al. (2024) recently proposed a data-driven, quantitative, reliability approach by embracing the imprecise probability model defined by the Possibility Theory (Dubois, 2006). This approach has been formulated for being characterized by three features: (i) to be accessible to practitioners through a simple procedure, (ii) to preserve the safety level prescribed by Structural Eurocodes through the probability–possibility consistency, and (iii) to objectively quantify the

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engineering judgement and local experience through the concept of "Degree of Understanding".

This *Technical Note* offers the practical implementation of the proposed reliability approach aiming to encourage the geotechnical engineering community to embrace data-driven approaches and leverage the potential of large and continuously growing indirect datasets.

2. Big indirect database management

A fundamental aspect of the proposed method is that the Big Indirect Database (Phoon et al., 2019) is managed (i.e., partitioning, fuzzyficaton, delivery) by a third-party expert, such as the British Geological Survey (BGS). This arrangement ensures consistency with prescribed safety levels by maintaining target reliability levels, as outlined in Tombari et al. (2024), amid the ongoing expansion of the indirect dataset.

The third party is responsible of defining the classes within the Big Indirect Database while enforcing constraints between lithology and geological unit (stratigraphy). This approach addresses the limitations of relying solely on lithology, which may not adequately capture variations resulting from differences in depositional environments, diagenesis, or subsequent alterations caused by metamorphism or weathering (Hobbs et al., 2002; Northmore et al., 2011; Entwisle et al., 2013). Moreover, the third party will ensure adherence to the requirements and recommendations of the *Q-FAIR* Data Principles (Wilkinson et al., 2016; Harrow et al., 2022), encompassing Quality (fit for purpose), Findable, Accessible, Interoperable and Reusable.

This proposed framework enables practitioners to focus on the direct application of the data for design and reliability assessment by following the step-by-step approach outlined in the subsequent section, without requiring an advanced understanding of Possibility Theory. Moreover, the proposed procedure is applicable to a wide range of geotechnical limit state problems, accommodating both scalar- and function-valued inputs. Nonetheless, readers seeking an in-depth exploration and detailed theoretical background are encouraged to consult (Tombari et al., 2024).

3. General step-by-step procedure

3.1. Step 1 - Obtaining data-driven design values

Step 1 involves deriving data-driven design values. The practitioner identifies characteristic or nominal properties of the engineering problem, determined either statistically (e.g., 5% fractile value) or based on acquired experience or physical conditions (e.g. mean, upper, or lower value), as established in EN 1990:2023 (2024). Relevant attributes, such as lithology and geological unit, as well as geotechnical values such as CPT cone resistance or relative density (for a comprehensive list, refer to Self et al., 2012), are used to query the Big Indirect Database to determine the design distributions of the problem parameters. Each design distribution is obtained by transforming the partitioned dataset into empirical possibility distributions using the λ-Average Cumulative Function (Stefanini and Guerra, 2017), ensuring consistency with the prescribed safety level. The design distribution is then derived using the characteristic value determined by practitioners, for the collocation of two adjacent partitions of the dataset. This procedure is fully automated in codes such as *POSSREL*, available at https://antroxev.github.io/POSSRELAPP, or by implementing the method described in Tombari et al. (2024).

The design values are expressed as possibility distributions, q, using 3-tuples (see e.g., Table 1) for scalar parameters (e.g., angle of internal friction), or arrays of 3-tuples for functional parameters (e.g., CPT cone resistance). Each tuple specifies the lower and upper bounds of the parameter interval, sorted by the α_j- value, which ranges from 0 to 1. The variable, α, does not indicate probability or likelihood but represents the degree of certainty or membership, partially ($\alpha <$ 1) or exclusively ($\alpha = 1$), to the selected soil group. A three-tier system, defined through the "Low", "Typical", and "High" Degree of Understanding (DoU) as explained in *Step 3*, is established to reflect epistemic uncertainty. Fig. 1 shows an example of design distributions obtained by considering subsets of the whole dataset with different numerosity; the increase of the knowledge progressing from Low to Typical and High DoU is reflected as the narrowing of their support's width at $\alpha = 0$.

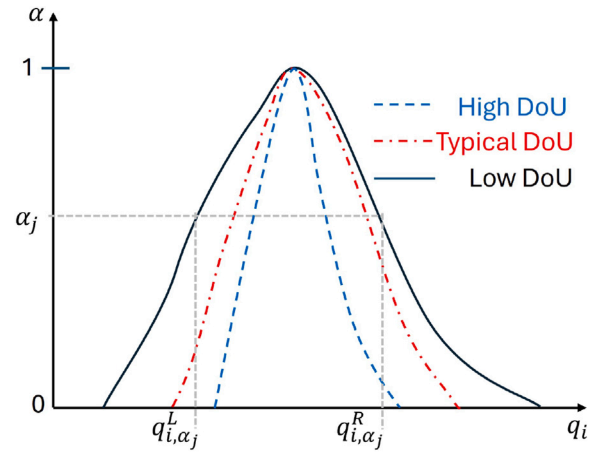

Fig. 1. Example of a design distribution for the ith parameter across the three-tier Degrees of Understanding (*DoU*). The closed interval $[q^L_{i,\alpha_j}, q^R_{i,\alpha_j}]$ represents the possible values of the parameter q_i, for a *Low DoU*, corresponding to the possibility level α_j.

Table 1
Representation of the design distribution of q_i for a given *DoU* in terms of 3-tuple $(\alpha, q^L_{i,\alpha}, q^R_{i,\alpha})$.

α	$q^L_{i,\alpha}$	$q^R_{i,\alpha}$
0	$q^L_{i,0}$	$q^R_{i,0}$
⋮	⋮	⋮
α_j	q^L_{i,α_j}	q^R_{i,α_j}
⋮	⋮	⋮
1	$q^L_{i,1}$	$q^R_{i,1}$

3.2. Step 2 - Determining limit state domain

The distributions of the design parameters obtained in *Step 1* are used to compute the distribution of the performance or limit state function:

$$G(\alpha) = f\left(q_1(\alpha), \dots, q_d(\alpha)\right) \quad (1)$$

where $q_i, i = 1, 2, \dots, d$ are the parameters of the considered problem computed at each α. In the case of structural safety at the Ultimate Limit State (ULS), the conventional performance function is defined as the difference between the resistance of the investigated problem, R, and the applied external load V, as follows:

$$G(\alpha) = R(\alpha) - V. \quad (2)$$

The approach requires finding the minimum and the maximum of the limit state function by sequentially using the intervals of the input parameters from $\alpha = 0$ to $\alpha = 1$. Nevertheless, the analysis is simplified when the relationship between inputs and outputs is monotonic (as is often the case in static capacity problems). For such cases, only the limit values at the lower or upper ends of the resistance parameter interval need to be evaluated for increasing and decreasing relationships, respectively. Therefore, for each α value in the distributions of the design parameters derived from the dataset, $G(\alpha)$, is calculated as a conventional deterministic problem.

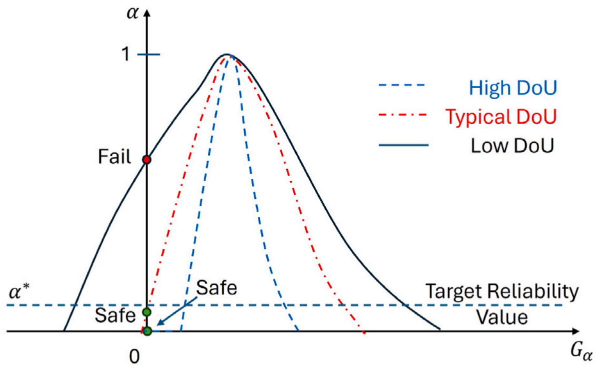

Fig. 2. Possibility reliability assessment on limit state distributions for three *DoU*.

The calculated performance distribution is thus expressed as the 3-tuple of Table 1 where the interval bounds are obtained at each corresponding α of the input parameters. It is worth mentioning that the applied load can be represented as a possibility distribution, $V(\alpha)$, similar to the resistance $R(\alpha)$, or as a scalar value V_d using the load factors from EN 1990:2023 (2024). Alternatively, it can be expressed as a probability distribution. In the latter case, a hybrid approach, as described by Tombari and Stefanini (2019) is required to account for both possibility and probability distributions.

3.3. Step 3 - Possibility reliability assessment

The reliability assessment is based on the achievement of a possibilistic Target Reliability Value (TRV). The TRV is defined as the maximum value, α^*, which divides the safe ($G(\alpha^*) > 0$) from the unsafe ($G(\alpha^*) \leq 0$) domain. The TRV value in Table 2 is derived using the possibility–probability transformation (Tombari et al., 2024) to match the probabilistic safety level prescribed by EN 1990:2023 (2024), ensuring the same reliability outcome for ideally random parameters.

Graphically, the verification procedure checks if $G = 0$ occurs at a value lower or higher than α^*, as illustrated in Fig. 2. Formally, the assessment requires to verify that sign of the value of the state limit distribution computed at α^*, as follows:

$$\begin{aligned}&\text{if } G(\alpha^*)\left(q_1(\alpha^*)\, q_2(\alpha^*), \dots, q_d(\alpha^*)\right) > 0 \Rightarrow \text{Safe}\\&\text{if } G(\alpha^*)\left(q_1(\alpha^*)\, q_2(\alpha^*), \dots, q_d(\alpha^*)\right) \leq 0 \Rightarrow \text{Fail.}\end{aligned} \tag{3}$$

It is worth noting that, computationally, the assessment does not need to be conducted over the entire distribution but only at the interval corresponding to the specific α^*. However, computing the full distribution provides additional insights, such as uncertainty propagation, the skewness of the distribution, and the overall uncertainty proportional to the support width.

The assessment shall be computed at a specific Degree of Understanding (DoU). The DoU provides a robust method for integrating local experience and engineering judgement into the design process, acknowledging that the uncertainty decreases with increased levels of understanding of the site and the prediction model (Fenton et al., 2016). The achievement of a certain DoU, regulated by the proposed recommendations in Table 3, sequentially reduces the uncertainty of the design parameters. Table 3 proposes a classification of the *DoU* based on (i) data availability, (ii) approach used to determine the design value, and (iii) reliability of the calculation method, e.g., determined through the COV of the transformation model (Ching et al., 2017, 2018; Phoon and Kulhawy, 1999), (COV_{trans}).

4. Reliability assessment of an axially loaded single pile

This section demonstrates a practical application of the data-driven possibility reliability assessment on a single pile foundation subjected

Table 2
Proposed recommended values for the target reliability value α^* for ULS.

Reliability class	1-year reference period	50-year reference period
RC1	1.993×10^{-7}	1.708×10^{-5}
RC2	2.602×10^{-6}	1.447×10^{-4}
RC3	2.669×10^{-5}	9.668×10^{-4}

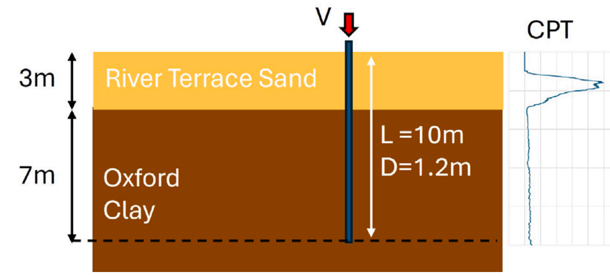

Fig. 3. Axial capacity of single pile on bilayer soil deposit.

to vertical loading. The open-ended pile has a length of L = 10 m, an outer diameter of D = 1.2 m, and a wall thickness of t = 0.015 m. It is driven into a bilayered deposit, where the upper 3 m layer consists of generally dense to very dense silty gravelly sand, classified as River Terrace Deposits, while the lower 7 m layer is composed of generally stiff to very stiff silty, classified as Oxford Clay Formation. A CPT sounding, as shown in Fig. 3, is conducted to characterize the mechanical properties of the soil deposit.

Step 1: According to the geological unit classification of the investigated site, two datasets were selected from the National Geotechnical Properties Database (Self et al., 2012). The first dataset comprises 105 CPT soundings conducted within the Oxford Clay Formation, covering three different members: Stewartby, Peterborough, and Weymouth. The second dataset includes 67 CPT soundings on River Terrace Deposits, forming one of a series of level surfaces in a stream or river valley, made up of sand or sand with gravelly sand and silty sand. CPT soundings that do not cover the full thickness of the relevant soil layer (3 m and 10 m for the upper and lower layers, respectively) were excluded. Fig. 4 shows the corrected cone resistance, q_t, from the selected CPT soundings; a normally distributed aleatory error, with COV of 5%, is also accounted for, by generating 15 random CPT cone resistance functions for each real data curve. This approach allows for the inclusion of random errors such as measurement errors, inherent ground variability and transformation errors; however, caution is advised when data is limited. Fig. 4 also highlights, with a red-coloured curve, the in-situ sounding used for the pile design in the investigated problem.

It is worth noting that additional databases of the same or comparable geological unit can also be incorporated; e.g., national-scale datasets, such as those used in the Netherlands (Gruijters and Derksen, 2018) and New Zealand (NZGD, 2024), or local-scale databases such as provided open-access by the ISSMGE-TC304 committee (ISSMGE TC304, 2021).

Once the geological unit and desired output are selected, the corrected cone resistance, q_t, from the reference CPT sounding is used as the nominal curve to query the database. A limited demonstration version of *POSSREL* software, used to generate the design distribution functions of the input parameters, is available for testing at https://antroxev.github.io/POSSRELAPP. The design distribution of the cone resistance is illustrated in Fig. 5, for the three *DoUs*. At each α, the distribution takes the form of a conventional cone resistance function (i.e., a possibility synthetic CPT); at any depth, z, they are represented by 3-tuples, such those shown in Figs. 6 and 7 for the upper and lower layers, respectively.

Step 2: The axial pile resistance, R, of Eq. (2) is computed through the CPT-based formulation derived by Lehane et al. (2020) and Lehane

Table 3
Proposed definition of three-tier degree of understanding.

DoU	Site-investigation	Design parameters	Calculation model
Low	Limited experience and low number of site-specific data. Mostly, extrapolation from national database or similar sites	Nominal	Simple methods ($COV_{trans} > 0.25$)
Typical	Typical project-specific investigation and sufficient local experience given by past works on similar sites.	Nominal	Established approaches ($0.1 < COV_{trans} \leq 0.25$)
High	Extensive project-specific investigation and local experience given by past works on the same sites.	Characteristic	Established approaches and advanced high-fidelity modelling ($COV_{trans} \leq 0.1$)

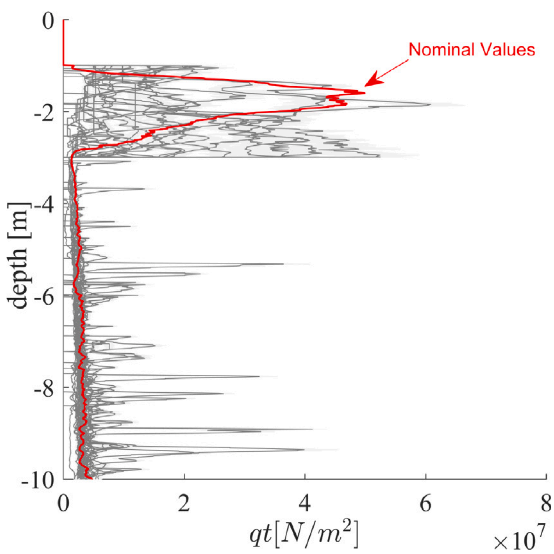

Fig. 4. CPT soundings extracted from the BGS National Geotechnical Properties Database of River Terrace Deposits and Oxford Clay Formation.

Table 4
Possibilistic reliability assessment (α values at $G = 0$ in parentheses).

COV	Low	Typical	High
0	SAFE (0)	SAFE (0)	SAFE (0)
0.05	FAIL (8.632×10^{-3})	SAFE (0)	SAFE (0)

Table 5
Reliability-based design (α values at $G = 0$ in parentheses).

Pile diameter	Low	Typical	High
$D = 1.3$ m	SAFE (0)	SAFE (0)	SAFE (0)
$D = 1.1$ m	FAIL (0.025)	SAFE (0)	SAFE (0)
$D = 0.9$ m	FAIL (0.27974)	FAIL (8.6×10^{-4})	SAFE (0)
$D = 0.8$ m	FAIL (0.61374)	FAIL (0.274)	FAIL (0.025)

et al. (2022), for piles driven in sand and clay, respectively. Notably, this approach has been calibrated by using a unified database, highlighting the growing significance of data-driven methods in geotechnical engineering.

In *Step 2*, the axial pile capacity is determined using the data-driven design possibility distribution of the corrected cone resistance obtained in *Step 1*. Since at each level of α, the distribution is represented by a cone resistance function, $q_t(z)$, a conventional deterministic analysis is carried out. Therefore, the approach requires finding the minimum and the maximum of the desired output by sequentially testing the interval of the input parameters from $\alpha = 0$ to $\alpha = 1$. For monotonic increasing problems, such as the computation of the static axial capacity, the process can be simplified by considering only the lower and upper bounds of each interval (i.e., $q^L_{i,\alpha}$ and $q^R_{i,\alpha}$ of Table 1). At each corresponding α for input parameters, the calculated axial capacity values form a possibility distribution, expressed as a 3-tuple.

Possibility distributions of the pile axial capacity are shown in Fig. 8 for the three *DoU*. As the Degree of Understanding increases, the support (interval at $\alpha = 0$) narrows, reflecting the reduced uncertainty in soil characterization.

Step 3: The reliability assessment is conducted in the final step. In this worked example, the load $V = V_d$ of Eq. (2) is fixed as the design axial capacity computed for the representative CPT sounding of Fig. 3, using the resistance factor approach in combination with the model pile method (prEN 1997-3, 2022). The designed capacity is hence computed equal to 2.75 MN after adopting the partial safety factors as follows:

$$V_d = \frac{R}{\gamma_{Rc} \cdot \gamma_{Rd} \cdot \xi}. \tag{4}$$

where the model factor, γ_{Rd}, is 1.1 for compressive resistance, the resistance factor, γ_{Rc}, is fixed as 1.3, and the correlation factor, ξ, is equal to 1.4 since only one CPT sounding has been used. This choice is made to show the consistency between the probability-based and possibility-based safety levels.

The Target Reliability Value is selected in Table 2 to be consistent with the prescribed level of safety for Reliability Class 2 with 50-year reference period. Results are given in Table 4 which presents an easily interpretable summary of the reliability assessment outcomes. Reliability is ensured for all levels of *DoU* demonstrating the consistency of the proposed approach with the safety standards prescribed by EN 1990:2023 (2024). Nevertheless, when incorporating an additional source of uncertainty, such as aleatory error, the assessment barely fails at *low DoU* levels, while yielding a positive outcome when the level of understanding is higher, as depicted in Fig. 9.

This information is valuable at the planning stage, where the practitioners can decide to improve their "degree of understanding" by employing more advanced calculation models and conducting additional in-situ tests, or choosing to revise the preliminary pile design. Remarkably, the proposed method can also be utilized as a data-driven, reliability-based optimization tool; e.g., the verification with different pile diameters are provided in Table 5 to accommodate every *DoU*.

5. Concluding remarks

This *Technical Note* introduces practitioners to a novel reliability approach designed to align with prescribed safety standards while remaining practical and straightforward to apply. It rigorously integrates engineering judgement and local experience into reliability assessments, effectively addressing both subjective and objective uncertainties in design parameters.

The data-driven approach leverages regional, national, or global indirect databases, enhancing decision-making and supporting the digital transformation of geotechnical engineering.

By shifting the interpretation of the reliability assessment from a frequency-based interpretation (probability of event occurrence) to a possibility-based perspective, the procedure offers a computational advantage, moving from a sampling to discretization problem, and eliminates the need for assumptions about marginal or joint probability

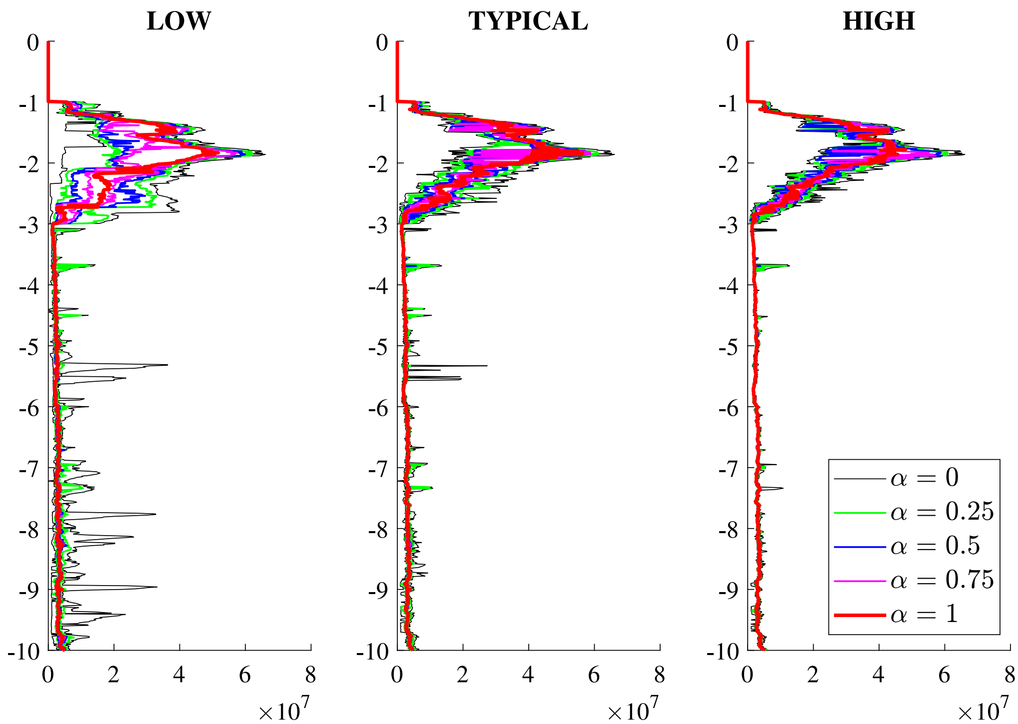

Fig. 5. Data-Driven possibility distributions of the CPT cone resistance for three-tier *DoU*.

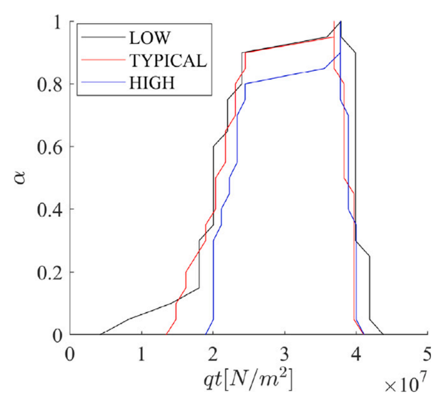

Fig. 6. Possibility distribution of the cone resistance at $2m$ depth (River Terrace layer).

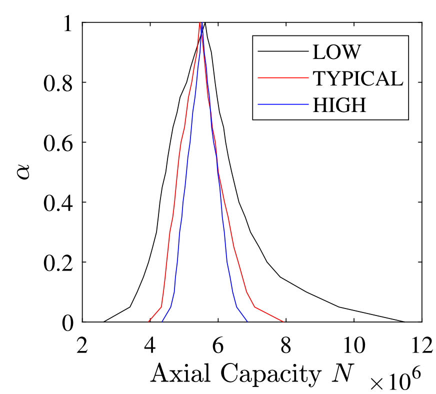

Fig. 8. Possibility distribution of the pile axial capacity, *R*, for three-tier *DoU*.

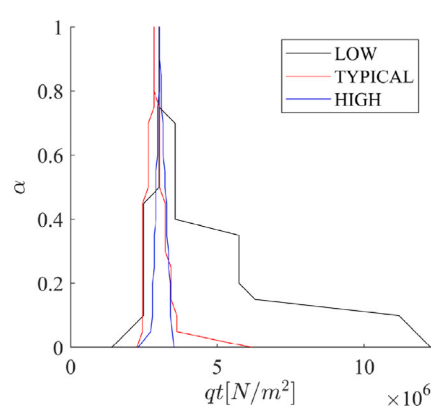

Fig. 7. Possibility distribution of the cone resistance at $6m$ depth (Oxford Clay layer).

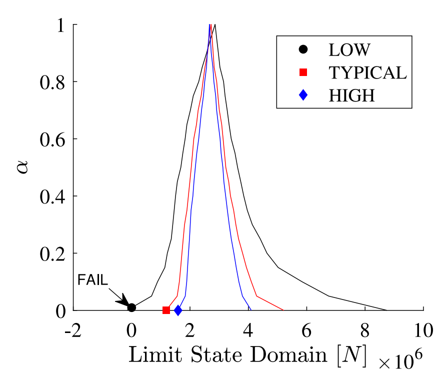

Fig. 9. Reliability assessment for three-tier *DoU*.

distributions, which are rarely constructed in geotechnical engineering because of the notorious lack of site-specific data.

Compared to the frequentist approach, based on counting the number of events that can occur (e.g. failures), the possibility approach defines the degree of belonging to a certain state (e.g., failure condition) transforming the simulation from a sampling to a discretization problem. Moreover, multiple variables can be accounted without requiring the knowledge of their joint distributions, exploiting the interactivity (Fullér and Majlender, 2004; Carlsson et al., 2005) intrinsically embedded by the data of the dataset.

The worked example of the axial load reliability assessment of a single pile demonstrates the procedure's practicality and consistency with Eurocode safety levels.

CRediT authorship contribution statement

Alessandro Tombari: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Luciano Stefanini:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Giovanni Li Destri Nicosia:** Validation, Supervision, Resources, Formal analysis. **Liam M.J. Holland:** Resources, Investigation, Data curation. **Marcus Dobbs:** Resources, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data and tools are provided at https://antroxev.github.io/POSSRELAPP/.

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