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Probabilistic analysis of the thermo-mechanical behavior of energy piles considering correlated non-Gaussian uncertainties

Análisis probabilista del comportamiento termo-mecánico de pilas de energía considerando incertidumbres no gaussianas correlacionadas

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ABSTRACT: During their operation, energy piles experience thermal strains and stresses that must be considered in their geotechnical and structural design. Although several methods have been developed to study the thermo-mechanical behavior of this type of structure, their design process still faces various and significant uncertainties (e.g., thermo-mechanical loads, soil properties, and design model errors). Consequently, some reliability-based design methodologies have been proposed in recent years. Most of these methodologies assume independent Gaussian variables. However, several studies have shown the presence of cross-correlations between soil parameters and that their marginal probability densities differ significantly from Gaussian. Thus, this paper presents a modification of the Monte Carlo Simulation-based method to assess the serviceability performance of energy piles considering correlated non-Gaussian marginal densities. The proposed probabilistic analysis is based on load-transfer curves and uses a copula model to simulate the joint probability distribution of the random variables. To illustrate the proposed framework, the paper studies the reliability of a hypothetical energy pile. The results show that the proposed methodology helps to incorporate a higher degree of realism in the thermo-mechanical behavior of energy piles.

KEYWORDS: energy piles, failure probability, Monte Carlo method, Gaussian copula

1 INTRODUCTION

Energy piles are a closed Ground-Source Heat Pump (GSHP) System in which heat exchange pipes are installed in foundation elements to extract or inject thermal energy from/to the ground for space conditioning. In winter, the system transfers energy from the ground to the building for heating, while in summer, the process is reversed. By using a sustainable energy source (shallow geothermal energy) and due to its high energy efficiency, this technology is an alternative to reduce the environmental impact of the growing energy demand for space conditioning (Brandl 2006). Energy piles are subjected to long-term cyclic temperature changes following the building's thermal loads. Different studies (Bourne-Webb *et al*. 2009; Amatya *et al*. 2012) have shown that these temperature changes can influence the thermo-mechanical behavior of the piles, causing unexpected tensile stresses or excessive settlements. Thus, they should be considered explicitly in the geotechnical and structural design of the foundation elements (Rotta-Loria *et al*. 2020).

Even though energy piles have been in use since the early 1980s, until recently, there were no guidelines or standards for properly accounting the effects of the thermal cycles in their geotechnical and structural design (Bourne-Webb *et al*. 2016). Early projects used subjectively high safety factors (usually twice the one used for conventional piles, but values as high as 13 have been reported) to prevent potential thermally induced damages, leading to overly conservative designs.

In the past 20 years, several methods have been proposed to analyze the thermo-mechanical behavior of energy piles (Bourne-Webb *et al*. 2016). However, their geotechnical design still faces significant challenges due to the uncertainties in soil parameters, the variability of the applied loads (mechanical and thermal), and model errors, among others. To address these issues, recent works (Xiao *et al*. 2016; Luo & Hu 2019; Hu *et al*. 2022) have developed several probabilistic approaches to evaluate the ultimate (ULS) and serviceability limit states (SLS) of individual energy piles.

Although these new approaches represent a breakthrough in developing a more rational approach to addressing uncertainties in the design of energy piles, they generally assume independent Gaussian variables. In general, these hypotheses are not valid. Several studies (Lumb 1970; Griffiths *et al.* 2009; Dithinde *et al.* 2010; Phoon *et al.* 2010; Wu 2015; Huffman *et al.* 2015; López-Acosta *et al*. 2018; Masoudian *et al.* 2019; Bilgin *et al.* 2019; López-Acosta *et al*. 2022; Löfman & Korkiala-Tanttu 2024) have demonstrated that many geotechnical parameters are cross-correlated (e.g., negative correlation between cohesion and friction angle) and that their probability densities differ significantly from Gaussian. Moreover, because of the high variability of soil properties (coefficient of variation, COV, of 20% or above) (Phoon & Kulhawy 1999), they are usually modeled using strictly positive probability distribution (*e.g.*, lognormal or gamma) to avoid sampling negative values (Fenton & Griffiths 2008).

Additionally, these assumptions contradict current building standards. Due to its different characteristics, dead and live loads are considered separately in conventional design standards. Although dead load (L_D) could be modeled using the normal distribution, previous investigations (Ellingwood 1980) have shown that lognormal, gamma, Type-I, and Type-II Gumbel distributions are better choices for the live load (L_D).

Ignoring the above may lead to a biased estimation of the system's probability of failure (Huffman *et al.* 2015). Thus, to perform an accurate reliability analysis, the Joint Probability Density Function (PDF) of the random variables should be considered (Li *et al*. 2012). However, in many cases, only the marginal PDFs and their correlation matrix are available. In this context, copula models (Sklar 1959; Nelsen 2006; Genest & Favre 2009) provide a general, versatile, and practical approach to simulate correlated non-Gaussian uncertainties. This theory has recently been incorporated into several geotechnical reliability analyses (Li *et al.* 2012; Wu 2015; Huffman *et al.* 2015; Masoudian *et al.* 2019; Tang 2020; Löfman & Korkiala-Tanttu 2024).

This paper presents a modification of the Monte Carlo Simulation-based method to assess the serviceability performance of energy piles considering correlated non-Gaussian marginal densities for the design variables. The proposed probabilistic analysis is based on load-transfer curves and uses a copula model to simulate the joint probability distribution of the random variables. The paper studies the reliability of a hypothetical energy pile. The results show that the proposed methodology helps to incorporate a higher degree of realism in the thermo-mechanical behavior of energy piles.

2 DETERMINISTIC ANALYSES OF THE THERMO-MECHANICAL BEHAVIOR OF ENERGY PILES

Under mechanical loads, conventional piles move downwards into the ground, mobilizing positive shaft friction. On the other hand, during cooling, an energy pile contracts. The superstructure and the surrounding soil restrain part of these deformations, inducing tensile stresses. The mobilized shaft friction has the same direction as the mechanical load in the upper part of the pile and opposite it in the lower section. During heating, the pile tends to expand, leading to additional compression stresses with directions opposite to that previously described (Amatya *et al*. 2012). The magnitude and distribution of the additional axial stresses and strains along the pile depend on the type of soil surrounding it and the restraint at the pile ends.

Among the most used analysis methods to study the thermo-mechanical behavior of energy piles are synthetic design charts (Mroueh *et al*. 2018), load-transfer methods (Knellwolf *et al.* 2011), and numerical modeling (Di Donna & Laloui 2015). The load-transfer methods have been particularly successful since it is fast, flexible, and computationally low-demanding. The algorithm subdivides the piles into rigid elements connected by springs (representing the pile stiffness). Independent nonlinear springs are distributed along the pile shaft and at the base to characterize the soil-pile interactions (Knellwolf *et al.* 2011) (Fig. 1).

Several models have been developed to represent the mobilized shaft friction (τ_s) and the base reaction (τ_b) as functions of the element axial displacement ($w_{z,i}$), such as tri-linear, hyperbolic, and point-by-point curves (Luo & Hu 2019). Among these, the tri-linear curves proposed by Frank and Zhao (Frank & Zhao 1982) (FZ model) have widely been used due to their simplicity and the few parameters needed. The FZ model requires four parameters: the first linear branches of the shaft (K_s) and base (K_b) of the load-transfer curve, the ultimate shaft resistance (q_s), and the ultimate base bearing capacity (q_b) (Fig. 1). Both K_s and K_b depend on the pile diameter (D) and the pressuremeter modulus (E_M), obtained from a Pressuremeter Test (PMT). The ultimate bearing capacity parameters (q_s and q_b) can also be determined from a PMT using the limit pressure (p_l) (Burlon *et al.* 2014; Frank 2017). This approach, known as the PMT 2012 model, has the advantage that the load capacity is estimated directly under actual field conditions, avoiding using formulas based on soil strength parameters (*i.e.*, cohesion and friction angle) measured in small undisturbed samples.

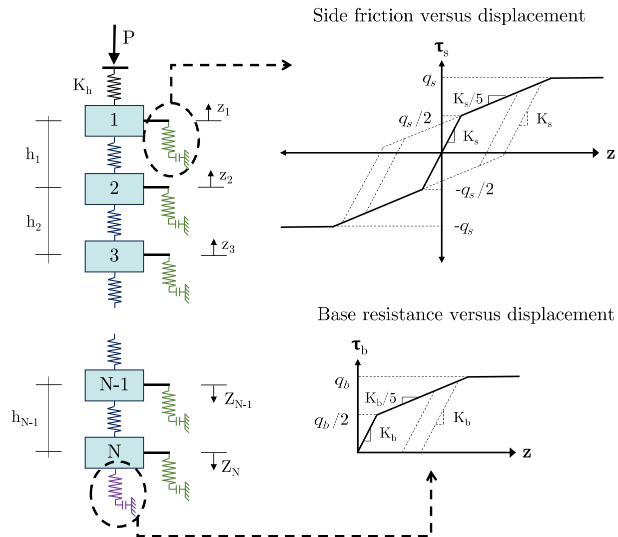

Figure 1. Load transfer method and FZ model (adapted from Knellwolf *et al* 2011).

3 RELIABILITY ANALYSIS OF ENERGY PILES

3.1 *Reliability assessment*

Reliability analysis involves determining the degree to which the capacity of the capacity of an engineering system (C) meets specific requirements (R) (Ang & Tang 1984). Usually, this is performed by calculating the probability of failure (or unsatisfactory performance) $p_f = \mathrm{P}[C < R]$ (*e.g.*, the probability that the induced displacement at the top of a pile is greater than the corresponding allowable displacements). In general, the probability of failure can be expressed as:

$$p_f = \mathrm{P}[g(\boldsymbol{x}) \leq 0] \tag{1}$$

where $\boldsymbol{x}$ is a vector of input random variables required for the system design (*e.g.*, loads, material properties, geometry) and $g(\cdot)$ is a function that determines the behavior or state of the system. Defining the joint PDF of the input random variables as $f_{\boldsymbol{x}}(\boldsymbol{x})$, p_f can be calculated as:

$$p_f = \mathrm{P}[g(\boldsymbol{x}) \leq 0] = \int_{\{g(x)\leq 0\}} f_{\boldsymbol{x}}(\boldsymbol{x}) d\boldsymbol{x} \tag{2}$$

Eq. (2) can be estimated using the Monte Carlo Simulation (MCS) method. In this framework, a large set (size n) of simulation of the random parameters are obtained by sampling from the joint PDFs. Each simulation is evaluated in the limit state function $g(\cdot)$, and the probability of failure is approximated as:

$$p_f = \int_{\{g(x)\leq 0\}} f_{\boldsymbol{x}}(\boldsymbol{x}) d\boldsymbol{x} \approx \frac{1}{n}\sum_{i=1}^{n} I[g(\boldsymbol{x_i})] \tag{3}$$

where $I[\cdot]$ is an indicator function equal to 1 if $g(x_i) \leq 0$. As n increases, the MCS estimator tends to the exact value (Fan *et al* 2014).

3.2 *Limit state design of energy piles*

Recent studies (Xiao *et al*. 2016; Luo & Hu 2019; Hu *et al*. 2022) have evaluated the probability of failure (p_f) for ultimate (ULS) and serviceability limit states (SLS) of energy piles. For ULS, these studies have focused on the geotechnical bearing capacity. The performance function has been defined as a function of the pile ultimate bearing capacity (Q_ult) and the maximum mobilized friction along the pile-soil interface (Q_mob). Two different limit state equations have been proposed in the literature:

$$[g(x)]_\mathrm{ULS} = Q_\mathrm{ult} - Q_\mathrm{mob} \quad (4)$$

$$[g(x)]_\mathrm{ULS} = Q_\mathrm{ult}/Q_\mathrm{mob} \quad (5)$$

For SLS analysis, the studies have evaluated excessive pile settlement $(\mathrm{SLS_{settlement}})$ and concrete cracking $(\mathrm{SLS_{cracking}})$ using the following performance equations:

$$[g(x)]_\mathrm{SLS,settlement} = s_\mathrm{ult} - w_{z,1} \quad (6)$$

$$[g(x)]_\mathrm{SLS,cracking} = f_\mathrm{ult} - \sigma_\mathrm{m} \quad (7)$$

where s_ult is the limiting pile settlement, $w_{z,1}$ is the settlement at the pile head, f_ult is the concrete axial tensile strength and σ_m is the maximum axial tensile stress in the pile.

4 MODELLING CROSS-CORRELATED MULTIVARIATE RANDOM VARIABLES USING COPULAS

A copula $C(\cdot)$ can be interpreted as a function that links (couples) the joint cumulative distribution function $H(\cdot)$ with its marginal cumulative distribution functions (CDF) (Vásquez-Guillén & Auvinet-Guichard 2014). Considering two random variables X_i and X_j with marginal CDFs F_i and F_j, their joint CDF can be written as (Sklar 1959; Nelsen 2006; Genest & Favre 2017):

$$H(x_i, x_j) = C\left(F_i(x_i), F_j(x_j)\middle|\theta\right) = C(u_i, u_j|\theta) \quad (8)$$

where θ is the copula parameter describing the dependence intensity, and $u_i = F_i(x_i)$ and $u_j = F_j(x_j)$. From the above, it follows that $x_i = F_i^{-1}(u_i)$ and $x_j = F_j^{-1}(u_j)$, where F_i^{-1} and F_j^{-1} are the corresponding marginal inverse distribution functions (quantile functions). Thus, the basic idea is to divide the modeling of the joint PDF into simulating the dependence and the marginal distributions separately (Tang *et al* 2020).

Several copula types (*e.g.*, Gaussian, Plackett, Clayton, Frank, Gumbel) have been proposed in the literature to account for specific trends in correlations (*e.g.*, linear or nonlinear correlations, elliptical correlations, and tail-dependent correlations) (Nelsen 2006). Among these, Gaussian copulas are the most frequently used since their parameter (θ) can be determined uniquely based on the correlation matrix between variables, they can account for negative and positive correlations, and their structure can be easily extended to multivariate distributions (Li *et al* 2012).

For the case of a bivariate distribution with random variables X_i and X_j with marginal CDFs F_i and F_j, the Gaussian copula can be expressed as (Nelsen 2006):

$$C(u_i, u_j|\theta) = \Phi_\theta\left(\Phi^{-1}(u_i), \Phi^{-1}(u_j)\right) \quad (9)$$

where $\Phi_\theta(\cdot,\cdot)$ is the joint CDF of a standard bivariate normal distribution with correlation θ, $\Phi^{-1}(\cdot)$ is the inverse CDF of a standard normal, and $u_i = F_i(x_i)$ and $u_j = F_j(x_j)$.

There are several methods to estimate the copula parameter θ. For the present study, the method based on the Kendall correlation coefficient (τ) was used (Li *et al.* 2012):

$$\theta = \sin\left(\frac{\pi\tau}{2}\right) \quad (10)$$

Kendall correlation coefficient (τ) is a measure of dependence between two measured quantities W and Y based on ranks. It is defined as:

$$\tau = \frac{P_n - Q_n}{n_p} \quad (11)$$

where P_n and Q_n are the is the number of concordance pairs, respectively, and n_p is the number of pairs. In this case, two pairs (W_i, Y_i) and (W_j, Y_j) are said to be concordant when $(W_i - W_j)(Y_i - Y_j) > 0$, and discordant when $(W_i - W_j)(Y_i - Y_j) < 0$ (Genest and Favre 2007).

5 CASE STUDY

5.1 *General description*

For the paper, a reliability analysis of the thermo-mechanical behavior of a hypothetical individual energy pile was carried out using the load-transfer method with the FZ model. The probability of failure (p_f) for different temperature changes was estimated using Monte Carlo simulations (MCS) considering only the settlement serviceability limit state (Eq. 7).

The foundation element had a diameter of 0.8 m and a length of 20 m. The pile was subjected to mechanical load (dead and live) and a monotonic temperature change (Δ_T) varying from -20 to 0 °C (Fig. 2). Previous studies (Xiao *et al*. 2016; Luo & Hu 2019) have shown that the SLS design of energy piles is controlled by cooling cycles. Thus, no positive temperature change (heating) was considered. A concrete pile was assumed with Young's modulus (E) of 20 GPa. The pile-structure stiffness was modeled considering a linear spring with 2 GPa/m constant. The PMT 2012 approach was adopted to determine ultimate bearing capacity parameters (q_s and q_b) from PMT limit pressure (p_l).

The uncertainties of the following parameters were evaluated: pressuremeter modulus (E_M), limit pressure (p_l), dead load (L_D), live load (L_L), and concrete coefficient of thermal expansion (α). Mechanical loads were defined using building and bridge design codes criteria (Ellingwood 1980). The soil parameters (E_M and p_l) were determined using a database of 40 PMT published by Narimani *et al*. (2018). An exploratory analysis was performed to obtained to identify possible patterns in the data and estimate the correlation between the parameters. Goodness-of-fit tests were used to fit reasonable marginal probability distributions.

For the load-transfer method, a total of 200 segments were considered (*i.e.*, a thickness of 0.1 m), and 10^5 simulations for each temperature change (-20, -10, and 0 °C) were obtained using a Gaussian copula.

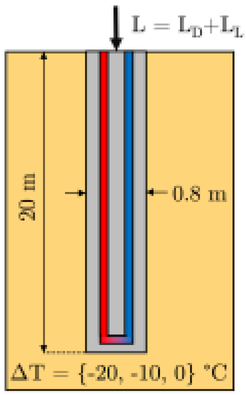

Figure 2. Schematic representation of the study case.

5.2 *Exploratory analysis and goodness-of-fit evaluation*

Table 1 reports the summary statistics of the pressuremeter modulus (E_M) and the limit pressure (p_l) obtained from the 40 PMT. In general, the parameters exhibited high dispersion, with a coefficient of variations of about 45%. Their histogram (Fig. 3 and 4) showed that the soil parameters have asymmetrical distributions with longer right tails. Thus, the lognormal distribution was chosen as a plausible probability density function.

Table 1. Summary statistics of PMT results.

Parameter	Units	n	Min	Max	m	s	COV (%)
Menard modulus	MPa	40	10.6	57.5	23.9	10.9	45.6
Limit pressure	MPa	40	1.1	9.0	3.3	1.5	45.4

Note: n = sample size, Min = minimum, Max = maximum, m = sample mean, s = sample standard deviation, COV = coefficient of variation.

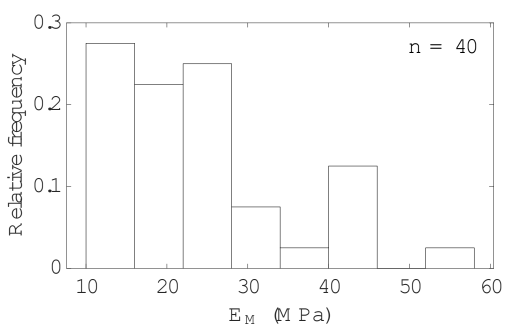

Figure 3. Histogram of Menard modulus (E_M).

The model parameters were estimated according to the Maximum Likelihood Method (Ang & Tang 2007). The goodness-of-fit of the theoretical PDFs was assessed via graphical methods (comparing the theoretical and empirical cumulative distribution functions) and using the Lilliefors-corrected Kolmogorov–Smirnov test (LcKS test) (Lilliefors 1967) at a 5% level of significance. Lilliefors correction was used because the lognormal model parameters were estimated from the sample.

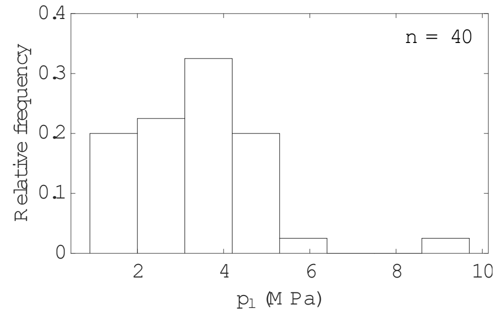

Figure 4. Histogram of limit pressure (p_l).

The LcKS tests did not reject the null hypothesis that the samples derived from a lognormal distribution for any of the soil properties studied (Table 2), suggesting that this provides a reasonable approximation for both parameters. The above was supported by the comparison of the theoretical and the empirical CDFs (Fig. 5 and 6), which did not show any significant deviation.

Table 2. Summary of goodness-of-fit tests.

Parameter	n	Fitted parameter		LcKS Test		
(X_i)		$\mu_{\ln X_i}$	$\sigma_{\ln X_i}$	*Statistic*	*C.V.*	Result
Menard modulus	40	3.08	0.43	0.098	0.140	NR
Limit pressure	40	1.1	0.45	0.084	0.140	NR

Note: n = sample size, $\mu_{\ln X_i}$ = mean of the natural logarithm, $\sigma_{\ln X_i}$ = standard deviation of the natural logarithm, C.V. = critical value, NR = non-rejection of null hypothesis.

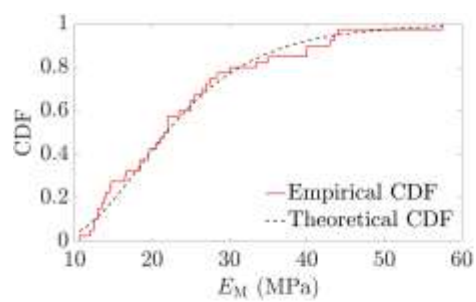

Figure 5. Theoretical vs Empirical Cumulative Density Functions for Menard modulus (E_M).

Based on the 40 measurements, a Kendall correlation coefficient (τ) of 0.701 was obtained. The above suggests that the parameters exhibit a significant positive correlation, and the common assumption of statistical independence may not capture the actual behavior of the soil parameters.

5.3 *Simulations using Gaussian Copula*

The MCS was performed considering the distributions and statistical properties of Table 3. The PDF and the coefficient of variance (COV) of the mechanical loads (dead and live) were specified following the recommendations of Ellingwood (1980). The soil parameters were assigned according to the results of the exploratory analysis in section 5.2. Note that, due to non-linearity in the lognormal transformation, $\mu_{\ln X}$ is not equal to $\ln \mu_X$ (*i.e.*, the mean of the logarithm is not the logarithm of the mean). In this case:

$$\ln \mu_X = \mu_{\ln X} + \frac{\sigma^2_{\ln X}}{2} \tag{12}$$

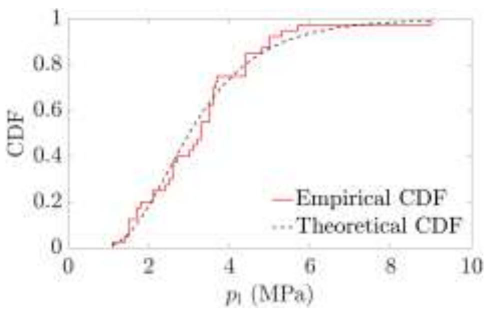

Figure 6. Theoretical vs Empirical Cumulative Density Functions for limit pressure (p_l).

Although in previous studies the coefficient of thermal expansion of concrete (α) was assumed to be constant and equal to 10x10^{-6}/°C, Oesterle *et al.* (2007) point out that its value can vary between 5 to 12x10^{-6}/°C. Considering that this parameter is rarely measured in practice, it was decided to include its uncertainty in the reliability analysis. A four-parameter beta distribution was assigned for its versatility and ability to incorporate the information on minimum and maximum parameter values. The COV was defined using the database published by Effings *et al.* (2012).

Table 3. Statistical properties of random variables.

Parameter	Model distribution	Units	μ	COV (%)	Min	Max
Dead load	Normal	kN	3500	10	-	-
Live load	Gamma	kN	1500	25	-	-
Menard modulus	Lognormal	MPa	23.9	45	-	-
Limit pressure	Lognormal	MPa	3.3	45	-	-
Coefficient of thermal expansion	Beta	x10^{-6}/°C	10	5	12	5

Note: μ = mean, COV = coefficient of variation, Min = minimum, Max = maximum.

The dependency structure between the soil parameters was modeled using a Gaussian copula, while the mechanical loads (live and dead) and the coefficient of thermal expansion were considered independent. The Gaussian copula parameter θ was calculated by Eq. 10 using a Kendall correlation coefficient of 0.7.

The simulations were generated following the algorithm proposed by Li *et al.* (2013). Fig. 7 shows the measured data (40 samples) and the simulations of E_M and p_l (10^5 samples) based on the fitted Gaussian copula (with their respective marginals). The proposed methodology can adequately model the relationship between the soil parameters. For comparison, another 10^5 simulations were generated considering independent variables. The results (Fig. 8) show that, although the marginal PDFs are similar, ignoring the cross-correlation among variables produces unrealistic parameter combinations (*e.g.*, simulations with high E_M and low p_l or vice versa) that could bias the estimation of the probability of failure of the system.

Despite its simplicity, the proposed methodology needs a proper definition of the non-Gaussian marginal PDFs and a reasonably accurate estimation cross-correlation between the soil properties. The previous recommendations require considerably more data than assuming independent Gaussian variables (Fenton and Griffiths, 2008) and may be a limitation for projects with restrained budgets. A suggestion given this limitation is to use case studies or previously published databases to reduce the uncertainty in defining these parameters.

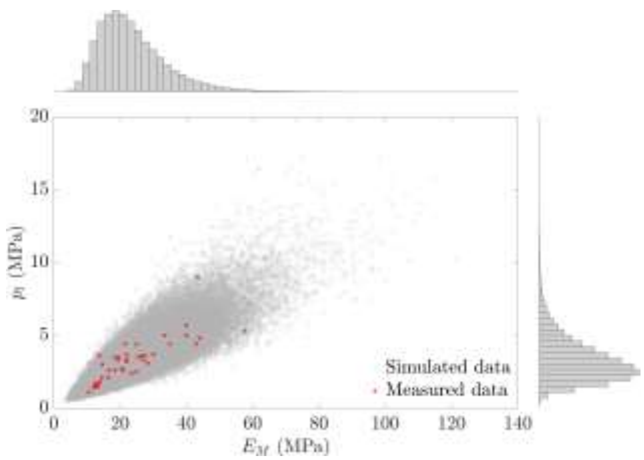

Figure 7. Scatter plot of measured and simulated data considering Gaussian copula.

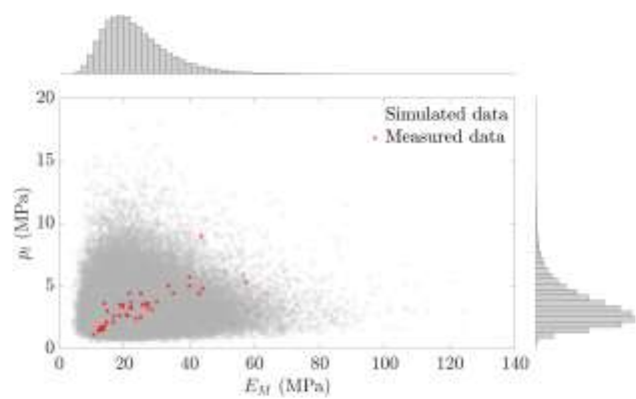

Figure 8. Scatter plot of measured and simulated data considering independent variables.

5.4 *Probabilistic analysis*

For all the Gaussian copula simulations described in section 5.3, load transfer analyses were performed considering different temperature changes (-20, -10, and 0 °C), and the pile head displacement ($w_{z,1}$) was recorded. The resulting histograms indicate that the settlement distribution is asymmetric, with longer right tails in all cases (Fig. 9). The mean settlement for only mechanical load (ΔT = 0 °C) was 5.3 mm with a COV of 45%. As the temperature change was increased, the mean settlement rises to 6.0 and 6.3 mm for -10 and -20 °C, respectively.

Fig. 10 shows the variation of the probability of failure (p_f) estimates with the number of simulations for the three temperature changes (-20, -10 and 0 °C) and a limiting pile settlement (s_{ult}) of 10 mm. In all cases, p_f converges after approximately 60,000 iterations. The estimated probabilities of failure were 0.0765, 0.0689 and 0.0498 for temperature changes of -20, -10 and 0 °C, respectively. This shows the important effect that temperature changes have on the SLS of energy piles.

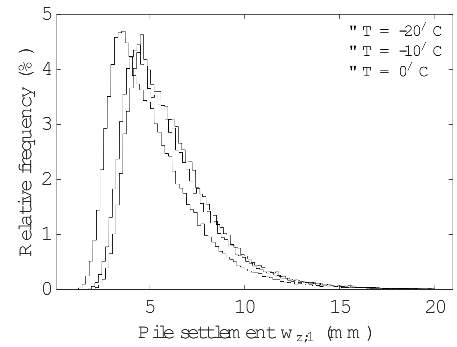

Figure 9. Histogram of computed immediate pile settlement for the different temperature changes.

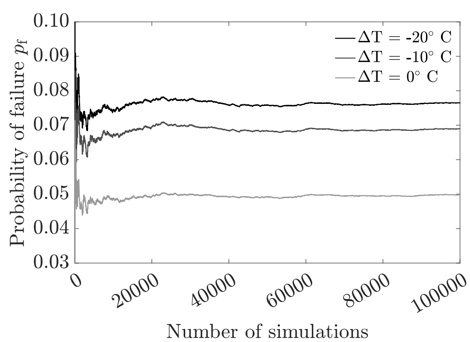

Figure 10. Convergence of the estimates of the probability of failure for a limiting pile settlement of 10 mm.

Fig. 11 shows the probability of failure (p_f) estimated for different limiting settlement. In general, p_f decreases as limiting settlement increases for all the temperature change evaluated. At the same limiting settlement, a higher temperature decrease leads to a higher p_f.

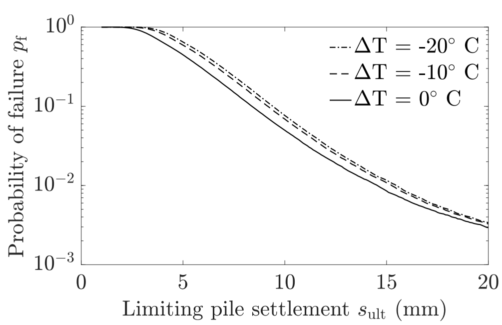

Figure 11. Probability of failure for several limiting pile settlements.

5 CONCLUSIONS

This paper described a methodology to assess the serviceability performance of energy piles considering correlated non-Gaussian uncertainties. The proposed probabilistic analysis used Gaussian copulas to model the joint probability distribution of geotechnical parameters (Menard modulus and limit pressure) with user-specified marginal densities and correlation structures via the Kendall correlation coefficient. From a hypothetical case study, it was shown that the copula theory helps to incorporate a higher degree of realism in the analysis of the thermo-mechanical behavior of energy piles, avoiding possible bias in its probability of failure estimation due to unrealistic combinations of the design parameters.

The proposed probabilistic methodology represents an advance toward a more rational approach to address uncertainties in energy pile analyses, leading to more optimized designs in real-case scenarios. In this regard, further attention should focus on incorporating other sources of uncertainty not previously evaluated in the design process, exploring new methodologies to reduce the calculation times to estimate the probabilities of failure and developing more realistic models to simulate soil properties.

In the present study, the effects of potential degradation of the pile-soil interface parameter due to cyclic thermal loading were neglected. Heating-cooling cycles may lead to cumulative irreversible deformations in the pile head, which may increase the system probability of failure under settlement serviceability limit state. Furthermore, up to now, no study has yet directly addressed the characterization of the thermal loads. The selection of the temperature change is crucial to perform a representative thermo-mechanical analysis of energy piles. The above involves applying analytical or semi-empirical transient heat transfer models that require soil thermal properties and building heating requirements as input parameters.

Despite the Monte Carlo method is a useful technique for reliability analysis, it requires a large number of simulations (10^5 to 10^6) to assess small failure probabilities. This results in long calculation times that hinder its applicability in professional engineering practice. Variance reduction techniques, such as *important sampling*, must be explored to develop more efficient and robust approaches.

Finally, most of the probabilistic methods developed for the analysis of energy piles do not account the spatial variability of soil properties. Using Single Random Variable (SRV) analysis may be conservative. A more realistic approach is to model a soil profile as a random field. The *Copula Theory* could be expanded to simulate random fields with non multi-Gaussian dependence.

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