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Probabilistic three-dimensional soil modeling through dynamic penetrometer

Elaboration d'un modéle de sol probabiliste en 3D à partir de l'essai de pénétration dynamique

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ABSTRACT: In the current state of the knowledge, the elaboration of a geotechnical model which serves as basis for the design, constitutes frequently the crucial point of the geotechnical projects. Nowadays, this elaboration presents a strong subjective character because it rests fundamentally on engineeering expertise. and also it depends both on the quantity and quality of available information. This work focuses on three dimensional soil modelling through a geotechnical campaign based on Panda® penetrometer tests. An overall method involving three main stages is proposed in order to analyze spatially distributed soil resistance statistically. The methodology is applied to a deltaic site in Spain.

RÉSUMÉ: L'élaboration d'un modèle de terrain servant de base à la conception des ouvrages est un point crucial des projets géotechniques. Aujourd'hui, cette élaboration qui repose essentiellement sur l'expertise de l'ingénieur, reste encore fortement subjective et tributaire de la quantité et de la qualité des informations collectées sur site. Le travail présenté ici a pour objectif à construire un modéle de terrain sur la base d'une campagne d'essais réalisée à partir d'essais pénétrométriques de type Panda®. Une méthode globale comportant trois étapes principales est proposée en vue de fournir un modèle probabiliste en trois dimensions du terrain. Cet approche est déployée sur un site deltaique en Espagne.

Keywords: In-situ test; soil modeling; neural networks; conditional simulations; dynamic penetrometer

1 INTRODUCTION

In the current state of the knowledge, the elaboration of a soil geotechnical model which serves as basis for the design, constitutes frequently the crucial point of the geotechnical projects. Nowadays, this elaboration presents a strong subjective character because it rests fundamentally on engineeering expertise and also it depends both on the quantity and quality of available information and on the final goal of the project.

Soils are heterogeneous natural materials whose properties may vary from one location to another and spatial variation constitutes one of the main sources of uncertainty (Auvinet 2002). Thus, the reliability assessment of geotechnical projects needs spatially variable models which involve knowledge of spatial correlation structure of a soil. For this purpose, in situ tests are preferred since they provide vertical profiles to characterize the soil in its natural state of stress.

The analysis of spatial variability needs continuous or quasi-continuous records of soil properties (Vanmarcke 2010). Among in situ tests, the cone penetration test provides for the entire sounding depth nearly continuous test. Thus, it is the most commonly used device to study the nature of soil spatial variability.

Within the framework of the characterization of the shallow soils, the light dynamic penetration test Panda® (Gourvès,1991) presents numerous advantages: a high resolution of measure (about 1 measurement / 5mm), the possibility of collecting a big quantity of data because of its quick implementation and use, and also the possibility of adapting the beating energy which is very convenient for the loose soils. Besides, since its creation this penetrometer benefited from numerous technological and theoretical progress (Benz-Navarrete, 2009) (Escobar, 2015). Due to the portability of the device, it is widely used for all type of site investigation, focusing on shallow soil to 5-6 m depth and for compaction control purposes.

This work focuses on the shallow soil characterization using the lightweight dynamic cone penetrometer Panda®. An overall method is proposed in order to obtain a probabilistic three-dimensional soil model through a geotechnical campaign based on Panda® penetrometer tests. This methodology involves several stages in order to accomplish the main purposes of site investigation.

The application to a deltaic site in Spain of the several techniques as part of the proposed framework is presented here and the main results are discussed.

2 METHOD

The methodology proposed in this work, involves several sequential stages (Figure 1). The first step deals with the automatic identification of statistically homogeneous soil units from dynamic cone resistance measured profile. In order to achieve it, a statistical moving window procedure is proposed. The second step aims to classify the nature of these mechanical homogeneous soil units using artificial neural networks. The third step focuses on modeling the spatial variability of the dynamic cone resistance based on random field theory using conditional simulations.

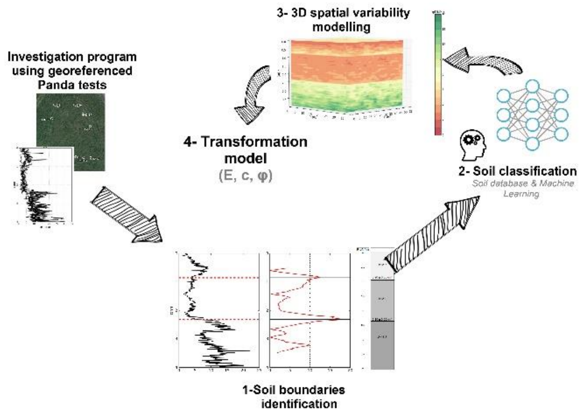

Figure 1: Stages of proposed method

The aim of these 3 stages is to obtain a 3D ground model. Following these stages, how to obtain geotechnical parameters such as compression modulus, cohesion coefficient and internal friction angle by transformation model in the site investigation is not covered by this paper

3 SITE STUDY

The experimental site, serving as support to validate the methodology developed, is situated in the South of Castelló of Empúries (Girona province – Spain) (Figure 2). It is located in an alluvial plain forming a typical Mediterranean deltaic environment. Different investigation campaigns (with CPTU) have been carried out. The stratigraphy is composed of an alternation of mainly sandy layers and layers formed by muddy and clayey deposits, with coarse materials sections.

A campaign of 8 dynamic penetrometer tests, with an average depth of investigation o 5m, has been carried out (Figure 2). The groundwater is located at 2.5m in depth. Two penetrometer tests (P2S3, P2S5) have been carried out near the piezocone tests (CPTU1 and CPTU2) (Figure 2).

Figure 2. Test site location (dot) and implantation of piezocone tests (CPTUi) and Panda tests (P2Si)

Grain size distribution analysis from samples recovered in a continuous borehole established a sequence of fine and granular soils that is characteristic of these deposits (Table 1). We notice the presence of an on-surface sandy soil (s) between 0 and 2 m, then low plastic clays (Ap) between 2 and 6m.

Table 1. Physical characteristics of tested horizons

Depth (m)	**Soil**	**Passing (%)**		**Atterberg limits**	
		75µm	2µm	WL (%)	IP (%)
0.5 – 0.7	Sand	47.3	15.6	-	-
2.6 – 2.8	Clay silts	87.5	33.23	34.9	12.1
4.2 – 4.3	Silt Clay	95.8	55.74	49.4	25.3
5.8 – 5.9	Clay silts	68.2	31.62	25.3	9.7

4 AUTOMATIC IDENTIFICATION OF HOMOGENEOUS SOIL UNITS

The objective of this stage is to develop a numerical procedure to identify homogeneous soil units from Panda profiles. The homogeneity is assessed in terms of soil behaviour since the Panda test provides direct information regarding dynamic mechanical response of soil to cone penetration.

The proposed approach is based on the use of a moving window of a fixed width W_d to determine layer boundary location. The center point of the window defines two sets of data (one above and one below). The two data samples are analyzed for distinctness using the Tratio method (Webster et Wong, 1969) which calculates t-Student's statistics as a sensitive test of the boundary position. For comparing two samples the Tratio is defined as (Eq. 1):

$$Tratio = \sqrt{\frac{n_1 n_2}{n_1 + n_2}} \frac{\mu_1 - \mu_2}{T_w} \qquad (1)$$

With n_1 et n_2 the samples sizes, μ_1 et μ_2 their mean value and T_w the pooled within-class variance defined below (Eq. 2):

$$T_w^{\;2} = \frac{1}{n_1 + n_2 - 1}\left(n_1 \sigma_1^{\;2} + n_2 \sigma_2^{\;2}\right) \qquad (2)$$

Where σ_1^2 et σ_2^2 are the variances of the samples.

The window is moved along the profile in steps equals to the sampling space. We obtain a curve which draws the evolution of the parameter Tratio according to the depth where the local maxima (peaks of the profile) give the optimal soil boundaries. A Tratio threshold of 10 is adopted to identify layer boundaries. It must be noticed that the window size is a parameter fixed by the user which controls the analysis scale. A narrow window corresponds to small scale analysis, thus it allows identifying thin soil layers. However, the smaller is the window, the greater is the sensibility to outliers or to natural fluctuations of soil properties. Wider windows can suppress the identification of spurious layers but may not able to detect boundaries between thin soil layers. In this paper, a 1 m moving window to analyze the logarithm of the dynamic cone resistance q_d profile has been chosen based on the conclusion of the parametric study carried out by (Sastre Jurado, 2018).

Tratio profile calculated from P2s3 test is shown in Figure 3. Black lines indicate the three layer boundaries identified using this approach. We notice a good agreement of the results with the site lithology The analysis highlights a first interface corresponding to the weakening of dynamic resistance q_d from 0.8m in the sand then an interface at 1.5 m indicates the transition between the sandy and the silty materials.

Figure 3 also shows CPTU2 profile with SBT using the normalized chart proposed by (Robertson, 1990), based on normalized cone resistance Q_{tn} and of friction ratio F_r. We can notice a good agreement between these two approaches. In particular, concerning the third interface detected on the Panda® test is located at the same depth as the transition between clayey silt and clays indicated according to the classification proposed by Robertson.

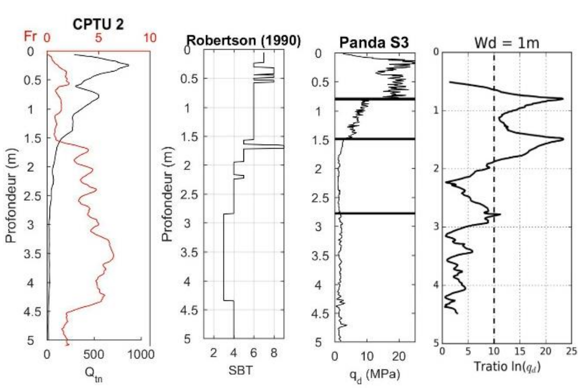

Figure 3. Comparison of stratification from CPTU2 et Panda S3 tests.

The stratification results for the 8 Panda® tests are summarized in Table 2.

Table 2. Layer boundary locations (m)

Panda® tests	Dense sand	Silty sand	Clay-silty clay
P2s1	---	1.9	3.1
P2s2	---	1.8	2.8
P2s3	0.8	1.5	2.7
P2s4	1.0	1.6	---
P2s5	1.1	1.8	---
P2s6	0.8	1.8	---
P2s7	---	1.6	2.7
P2s8	---	1.3	---
Mean	0.9±0.1	1.7±0.1	2.8±0.2

For this site, of deltaic origin and presenting a horizontal homogeneity, this method shows a satisfactory repeatability as for the depth of the interfaces identified from the soil investigation This technique is also low sensitive to the natural ground variability.

5 CLASSIFICATION OF THE SOILS LAYERS USING ARTIFICIAL NEURAL NETWORKS

Techniques based on artificial intelligence can improve the interpretation of the geotechnical tests but to be able to be implemented, these technics require to have access to a large quantity of data. Because of its acquisition resolution and its speed of implementation, the Panda® appears to be a test particularly adapted to the implementation of these approaches. That is why, an approach based on the application of these techniques was implemented to characterize the nature of the investigated soils.

For that purpose, a methodology of automatic classification based on algorithms of Artificial Neurons Networks (ANN) was proposed (Sastre and al. 2016). We try thanks to the ANN, to create an intelligent associative memory between dynamic penetrograms and soils classes defined according to the aimed goals. Figure 4 presents a descriptive scheme of the proposed methodology. Its implementation contains 3 main stages:

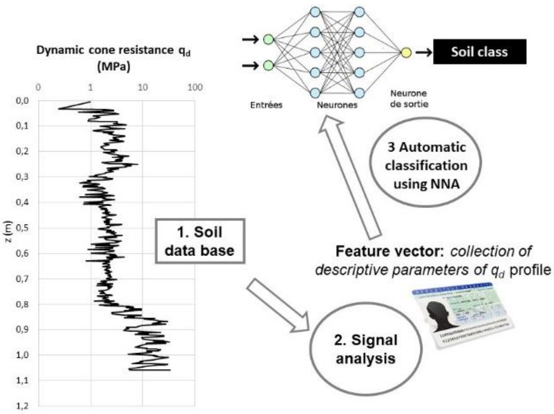

Figure 4. Flowchart of classification methodology using ANN

1. *Data acquisition*: the first stage consists in creating a data bank which will constitute the learning and test base of the model. In our case, this base is constituted by the Panda® tests for which the parameters of identification of the tested soil, measured either in laboratory on real materials or in situ, are known.

2. *Definition of the input data of the model*: we apply various techniques of analysis of the penetrometric signal in order to look for a configuration which will be the penetration test identifier towards the system of classification.

3. *Learning stage*: it consists in the training of the ANN thanks to the database in order to find the soils classes defined beforehand. In our case, we defined four classes of soils (Tab. 3) according to the particles size thresholds of the GTR classification system GTR (NF P 11-300, 1992).

Tableau 3. Target classes for the proposed classification methodology

Target	**Soil type**	**GTR**	**Passing 80µm**	**Passing 2mm**
Class 1	Clays-silts	A1 à A4	>35%	100%
Class 2	Silt and sand mixtures	B5, B6	>12%	100%
Class 3	Sand – gravelly sand	D1, B1 et B2	≤ 12%	> 70%
Class 4	Gravels	D2, B3 et B4	≤ 12%	≤ 70%

The results of the homogenous units dectection algorithm coupled with the classification supplied by the ANN and applied to the tests PdaS3 and S5 are presented in Fig. 5. The results obtained for the rest of the tests are very similar to those presented here. We can notice that the formations situated under the first soil unit are classified by the ANN " as fine soils (class 1) ", what is in good agreement with the results of the particles size analysis carried out on the cored samples (Tab. 1).

In a general way, the developed method gives efficient results but meets some difficulties to classify correctly penetrograms on the sandy materials containing fines particles. Indeed, the first on-surface soil formation, is classified as "gravels (class 4)", which is wrong. This difficulty is probably due to the deficit of representativeness of this class in the learning data base.

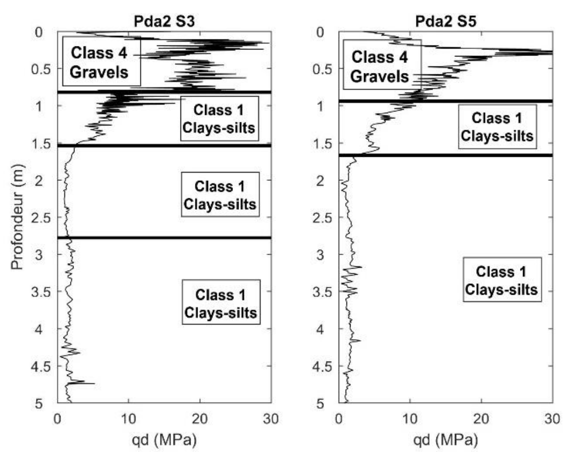

Figure 5. Results of ANN Classification

6 PROBABILISTIC THREE-DIMENSIONAL SOIL MODELING

The last stage aimes at defining a ground model based on the modelling and the simulation of the dynamic cone resisitance profil taking into account the spatial variability. The basis hypothesis rests on the fact that the variable of study (dynamic cone resistance q_d) can be represented by a homogeneous random field (Vanmarcke, 2010).

Spatial variability can be defined thanks to 3 statistical parameters:

1. average value μ;
2. variance σ^2, standard deviation σ or variation coefficient CV;
3. The scale of fluctuation θ.

In a general way the scale of fluctuation can be defined as the distance beyond which the measured parameters do not present correlation. This parameter allows to characterize the spatial structure of the geotechnical parameters. The scale of fluctuation can be estimated by fitting a theoretical model of autocorrelation to the empirical variogram (Vanmarcke, 2010).

The theory of random fields allows to generate simulations or numerical ground models thanks to the statistical inference of the measured data or from the values brought back in the literature.Besides, it is possible to condition a random field to obtain conditional simulations (the experimental data are respected) by means of the kriging, technic of estimation stemming from the geostatistic (Journel et Huijbregts, 1978) :

$$V_{CS}(X) = V_{kd}(X) + [V_{us}(X) - V_{kus}(X)] \qquad (3)$$

The principle is the following one:

i. edition of a simulation of the random field $V_{us}(X)$
ii. kriging at the simulation points by using the observed values$V_{kd}(X)$
iii. kriging at the simulation points by using the values of the not-conditional simulation at teh observed points $V_{kus}(X)$

Besides, to model the value of q_d as a random field, we suppose that the dynamic cone resistance follows a log-normal law. Also, the average of the random field is supposed to be represented by a linear model according to the depth and the decreasing exponential function is held to model the function of autocorrelation.

For the studied experimental site and on the basis of the stratigraphy deducted at the first stage of the proposed method, a ground model with 4 layers was chosen. Due to the site geological environment, the average depth of every layer was obtained by making the assumption of horizontal layers. An orthotropic model was taken on to take into account the anisotropy between the horizontal and vertical directions. The random field is conditioned by the Panda® tests carried out on the site by means of the kriging.

Among all the eight dynamic penetrometric tests realized, six were taken for the estimation of the parameters of the random field on and the two others (P2S3 and P2S8) were used to validate the proposed approach. The value of the scale of horizontal fluctuation is equal to 13 m in the horizontal plan. Random field statistic of ln(q_d), are presented in the table below (Tab. 4) for each of the homogeneous soil unit,.

Tableau 4. Random field parameters of ln(q_d)

Soil unit	**Depth (m)**	**Mean μ**	**Variance σ^2**	**θ_v (m)**
U1	0.0 – 0.9	2.17+0.92z	0.21	0.11
U2	0.9 – 1.7	3.58+1.20z	0.08	0.06
U3	1.7 – 2.8	1.64-0.56z	0.21	0.16
U4	2.8 -5.0	0.50-0.02z	0.10	0.14

θ_v: Vertical scale of fluctuation

In Fig. 6, we present a qualitative comparison between the real dynamic penetrometric tests carried out on the site and both virtual tests modeled at the position of the validation tests P2S3 and P2S8. It can be noticed a good similarity between the real and virtual tests which is due as much the model as the conditioning tests.

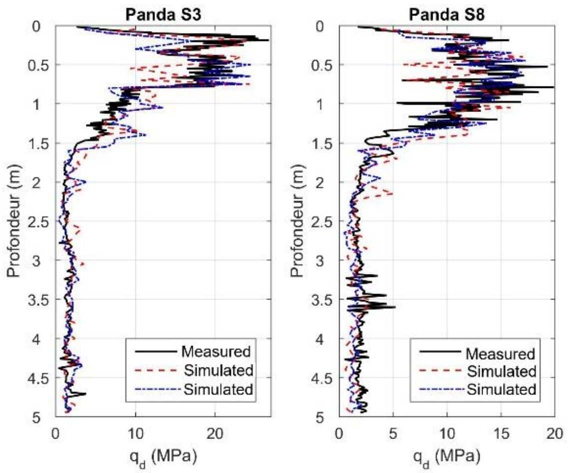

Figure 6. Measured q_d profilesfrom Panda® test and simulated profiles at same location.

Besides and for the studied case, the number of 6 penetrometric tests seems sufficient to propose realistic versions of an unimplemented test. As an example, Figure 7 present the 3D average estimation of the cone dynamic resistance q_d on 500 realized random draws.

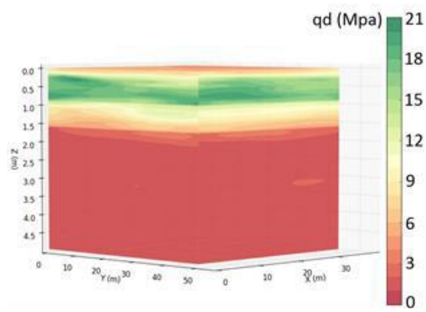

Figure 7. 3D average estimation of the cone dynamic resistance q_d

7 CONCLUSIONS AND PERSPECTIVES

This work concerned the development of a methodology for building a 3D probabilistic geotechnical model of the soil. On the basis of a soil investigation carried out with a dynamic penetration Panda® test, a global method allowing to exploit the on-site measurements and comprising 4 main stages has been carried out. The last stage which will enable to transform the ground model into a geotechnical model by supplying an distributed and probabilistic estimation of the input parameters of design models was not presented in this paper. The proposed methodology has been applied to the tests realized on an experimental site of deltaic origin, to Castelló of Empúries (Girona, Spain).

The first stage of the method consists in automatically detecting the homogeneous soil units from the penetrometric signal by a statistical approach. It turns out to be an objective procedure and allows to rationalize the procedure of soil identification. Within the framework of a geotechnical investigation, this procedure is a complementary way in the soil profiles deducted from the lithologic study made on the basis of the drillings.

Although the dynamic cone resistance is insufficient to identify the complete nature of the crossed soil, we proposed in a second stage, a methodology of automatic classification of the soil homogeneous units detected at the first stage. This methodology is based on the use of the artificial intelligence tools and more precisely on the neurons networks. The results obtained with this methodology showed it is possible to classify the soil units with a satisfactory efficiency. Nevertheless, the possibilities offered by this approach are limited when it is applied to the only dynamic cone resistance value. However, the application of this approach to tests supplying a largest number of parameters (such as CPT or Panda3® (Benz-Navarrete, 2009) (Escobar, 2015)) or on data coming from other techniques carried out at the same location (such as geophysic or geoendoscopy (Breul et Gourvès, 1999)) would allow to advantageously complete the data and to significantly improve the procedure efficiency.

Finally, on the basis of a relatively modest investigation campaign with a dynamic penetrometer, the third stage of the approach provide a 3D probabilistic ground model. This model provides the spatial variability of the dynamic cone resistance by means of a log normal random field within each of the units of the ground model established at the stage 1. The simulations of this field, conditioned by the tests available on the site thanks to the kriging, can be introduced into the probability calculus of the works.

The perspectives of these works are to transform the ground model into a geotechnical model by supplying an distributed and probabilistic estimation of the input parameters of design models and to study the possibilities of incorporating the spatial variability of the mechanical characteristics of the ground determined by this methodology, in methods of reliability calculations.

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