Comparative analysis of different methods for interpreting MWD profiles

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ABSTRACT

To determine a robust geotechnical model from measurements of drilling parameters is one of the great desires of geotechnical investigations. Drilling parameters have the advantage of presenting very granular data (data-points every centimetre) much like the CPT. They allow for the identification of soil samples during the drilling process and can traverse all terrain types, from soft clays to hard rocks. However, interpreting each parameter, like penetration rate or thrust, in isolation can be challenging, as these parameters can vary greatly within each soil layer due to natural heterogeneity, the drill rig's configuration and the noise introduced by the discontinuous interaction between soil and drill bit. Various authors propose using compound parameters such as specific energy, penetration resistance and alteration index alongside cautious filtering allows for a better interpretation, giving physical meaning to the measurements. These compound parameters have been developed from simple correlations, aiming to normalise parameters heavily influenced by drilling conditions or even aiming to evaluate the work or the energy spent in excavating the soil. Beyond that, many authors have devised algorithms to automate or standardize the interpretation of drilling logs by identifying homogenous zones or the probability that a given point belongs to a certain layer. This paper presents a comparison of such methodologies for identifying soil layers based on MWD profiles proposed in the literature. Assessment of the geotechnical structure may be made through different analytic and advanced statistical methods. MWD profiles from worksites throughout France will be used to compare and qualify these methods.

Keywords: geotechnical investigation; in-situ testing; monitoring while drilling; numerical analysis.

1. Introduction

Ground surveying is a necessary part of any construction project. These surveys inform the engineers about the sub-soil's physical properties, structure and any peculiarities that might exist, acquiring valuable data for the design of safe and effective structures (Cardu et al., 2013; Reiffsteck et al., 2018).

There are many different methodologies for ground surveying in situ, and the most common method in France is the pressuremeter test. In this test, an inflatable probe is lowered into a previously dug borehole and filled with pressurized fluids to measure the deformation of the material that surrounds it. Hydraulic drilling machines are used to create the borehole for this test and the machine's parameters are often recorded, in a process called Monitoring While Drilling (MWD), as they can also provide valuable data about the soil (Girard, 1985; Kreziak and Pioline, 2005).

This type of surveying is considered a destructive method, as soil samples can't be recovered for later laboratory testing. The only result of it are the logs of the various machine parameters as a function of depth of the drill bit. The classic parameters are applied rotation speed and thrust and measured advance rate, rotation torque and drilling fluid pressure. Other values can also be recorded, such as reflected percussive energy, drilling fluid inflow and outflow or even electrical conductivity and radioactivity (Duchamps, 1988; Lossy, 1990; Gambin, 1997; Nuyens et al., 2005; Reiffsteck et al., 2018).

All these parameters are considered to have a qualitative significance, with correlations between their behaviors and the characteristics of the soil drilled or the way the machine was operated. The transition between two different soil layers is generally marked by variations in one or multiple drilling parameters (Reiffsteck et al., 2018).

To facilitate the interpretation of MWD logs and limit the driller's influence over the results, multiple authors propose the use of combined parameters achieved through mathematical relations between the measured parameters. These parameters are designed to be nearly independent of operating conditions and make the transition between layers more evident (Reiffsteck et al., 2018).

2. Interpretation methodologies

De Paoli et al. (1988) identified two different manner of interpreting MWD logs. The first and simplest one consists of qualitative comparisons between logs with the aid of data from previous surveying campaigns and surveys in the area. The authors explain that this can be done in regions of well-known geology.

Another way of interpreting MWD logs treats them as measurements with physical significance. The basic assumption is that the drill bit reproduces in a reduced scale the same mechanisms that govern soil behavior in large scale excavations such as the construction of foundations (de Paoli et al., 1988). An algorithm can then be used to identify possible layers and lithological formations.

2.1. Signal filtering and regularization

But before using any interpretation method, Bourget and Rat (1995) reinforce the need for treating the raw data in order to achieve better results. This treatment consists of two processes: eliminating aberrant values and filtering noise.

The first process consists of eliminating measurements that don't represent the terrain's reality, such as the readings done while the machine stops drilling, and another rod is added to the drill string and any readings from faulty sensors. Bourget and Rat (1995) estimate that the lowering and subsequent rise in pressure in the hydraulic circuits leads to false readings, and at the same time the percolation of the drilling fluid during the stoppage alters some of the soil below the drill bit. The authors recommend using the longest rods available for the drill rig and replacing any aberrant readings by copying those just before to erase the sudden spikes.

The second step, filtering noise, is needed because the logs can be considered as the resultant of a random function with an average value of 0 superimposed over a deterministic function (Amokrane, 1988). The random component is produced when the drill bit breaks the soil's particles and momentarily loses contact with them. This is more evident when drilling through coarser soils as they tend to have larger voids (Bourget and Rat, 1995).

Bourget and Rat (1995) consider that this component carries no valuable information about the soil's properties and also makes it more difficult for changes in the other component to be noticed. Thus, it needs to be eliminated or reduced. Schunnesson (1998) considers noise to be the largest obstacle to reliably determining lithology from MWD logs. Bourget and Rat (1995) recommend using a Fourier Transform while Kreziak and Pioline (2005) and other authors use a moving average or moving median filter to eliminate it.

2.2. Algorithms

The aim of the interpretation algorithms is to identify the soil layers.

2.2.1. Amokrane's algorithm

Amokrane (1988) explains that, when drilling through a homogenous soil layer while keeping entry parameters constant (thrust and rotation speed), the logs for the parameters that depend on the soil's response (advance rate, rotation torque, fluid pressure) should be constant as well. Consequently, a significant change in those logs would indicate that the drill bit has encountered a new layer.

From this, Amokrane (1988) created an algorithm that aims to determine these homogenous zones in a drilling log and their frontiers. For this, it is necessary to choose an acceptable statistical risk by fixing the maximal acceptable variability inside a layer and the acceptable resolution by determining the minimal number of readings evaluated.

The algorithm then separates the log into blocks with the same number of parameter measurements. The values in each block are considered as independent samples of a population that follows a gaussian distribution. The blocks are then compared to determine statistically if they are samples taken from the same population, meaning they are part of the same soil layer, or if they are statistically different, in which case the limit between two lithological layers has been found.

For this comparison, Amokrane (1988) chose the Aspin-Welch test as it is designed for comparing populations through their averages and variances. In the test, sets *a* and *b* composed of n_1 and n_2 samples respectively, with averages m_1 and m_2 and variances s_1 and s_2 represent populations *A* and *B*, whose averages M_1 and M_2 and variances σ_1 and σ_2 are unknown.

Then, the square of the standard deviation between both sets and the value *T* are determined through Eq. (1) and Eq. (2).

$$sd^2 = \frac{s_1^2}{n_1} + \frac{s_2^2}{n_2} \tag{1}$$

$$T = \frac{m_1 - m_2}{sd} \tag{2}$$

T is then compared against a value from Student's t-test, a test that determines how likely it is that two populations have the same average and variance when only samples of each population are known. The results from this test are tabulated in function of the degrees of liberty ν and the statistical risk *r* chosen. The degrees of liberty are considered to be the closest integer to the inverse of:

$$\frac{1}{\upsilon} = \frac{1}{n_1-1}\left[\frac{s_1^2/n_1}{sd^2}\right] + \frac{1}{n_2-1}\left[\frac{s_2^2/n_2}{sd^2}\right] \tag{3}$$

Finally, the values *T* from the two sample sets and $T(\upsilon, r)$ from the t-test are compared:

- If $|T| \leq T(\upsilon, r)$ the two sets are statistically similar
- If $|T| > T(\upsilon, r)$ the two sets are statistically dissimilar

Using this, Amokrane (1988) describes an algorithm in which a drilling log is initially divided into multiples sets with the same number of parameter readings. The first set is compared to the second set through the t-test and if they're determined to be similar, both sets are merged, and the new merged-set is then compared to the third one. If the t-test returns negative, the first set is considered to be a homogenous zone and the process restarts with the second and third sets. This will continue until the algorithm reaches the last set of measurements.

2.2.2. Moussouteguy's algorithm

The algorithm presented by Moussouteguy (2002) aims to establish a plausible lithology from both MWD logs and a rough estimation that can be defined by the rig's operator or based on previous knowledge of the area's geology. The final results are series of probabilities as a function of depth, one for each soil layer in the preliminary model, where each value represents how likely it is for that point to belong to that layer.

The preliminary lithology is also interpreted as probabilities by the algorithm, and these probabilities are established according to the data given as a starting point. For each layer, its maximal depth z_i is required. In between each of these points, the corresponding layer is assigned a very high probability (the author recommends 95%) with a zone of uncertainty (z_{inc}) around the transition point where this probability decreases linearly and that of the next layer increases in tandem. The probabilities are defined by Eq. (4) to (8).

When $z \leq z_1 - \frac{z_{inc}}{2}$:

$$p(form_1) = p_{sur} = 95\% \tag{4}$$

When $z_1 - \frac{z_{inc}}{2} < z < z_1 + \frac{z_{inc}}{2}$:

$$p(form_1) = a * z + b_1 \tag{5}$$

$$a = \frac{1-(NF*p_{sur})}{z_{inc}(NF-1)} \tag{6}$$

$$b_1 = p_{sur} - a\left(z_1 - \frac{z_{inc}}{2}\right) \tag{7}$$

When $z \geq z_1 + \frac{z_{inc}}{2}$:

$$p(form_1) = \frac{1-p_{sur}}{NF-1} \tag{8}$$

Where *NF* is the number of geological formations or layers. The resulting probability functions are represented in Fig. 1 below.

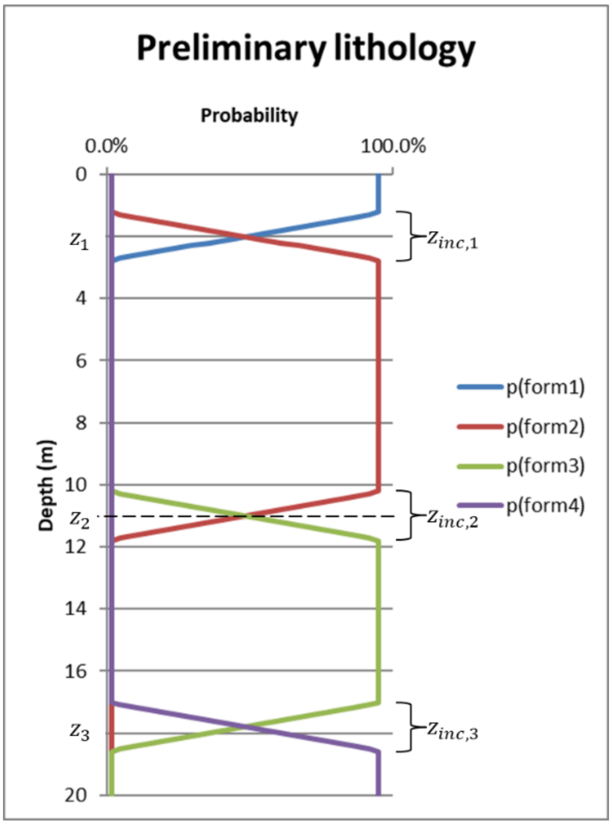

Figure 1. Log of probabilities from the preliminary lithology

The next step examines the MWD log for the parameter chosen, creating distribution functions for the entire log and for each layer separately. From these functions, the probabilities that a point in the log will have a value smaller than or equal to a given number are determined. These probability functions are then interpolated, dividing the probability axis in 50 segments of equal size. The interpolated functions are then used to calculate probability densities $p(D/form_i)$ for each layer of the preliminary lithology.

The probability density is then multiplied by the probabilities corresponding to the preliminary lithology. To avoid values higher than one, each value is then normalized by dividing it by the sum of probabilities for that depth.

$$p(form_i/D) = p(D/form_i) * p(form_i) \tag{9}$$

$$p(form_i/D)_{normalized} = \frac{p(form_i/D)}{\sum_{i=1}^{NF}(p(form_i/D))} \tag{10}$$

This algorithm is an iterative process, and the variation of $p(form_i/D)_{normalized}$ from one iteration to another is the convergence criterion monitored. To begin a new iteration, the preliminary lithology is replaced by the results from the previous iteration and all subsequent calculations follow the same step-by-step. The convergence criterium ϵ_k for the kth iteration is calculated by Eq. (11), where NF is the number of soil layers and N is the number of datapoints in the original MWD log. Moussouteguy (2002) estimates that a satisfactory result has been achieved when $\epsilon_k \leq 2 * 10^{-2}$.

$$\epsilon_k = \frac{\sum_{j=1}^{N}\sum_{i=1}^{NF}\frac{1}{NF}\left|p_j(form_i/D)_k - p_j(form_i/D)_{k-1}\right|}{N} \tag{11}$$

It can be said that this methodology refines the field report given by the driller. If their report is accurate, the final results will show zones where the probability for a given layer approaches 100%, with sudden transitions into another layer at depths similar to those indicated in the preliminary lithology. The algorithm presented in Moussouteguy (2002) was devised for a maximum of 4 different layers, but here it has been adapted to work with any quantity.

2.2.3. Entropy

Bourget and Rat (1995) present a simpler alternative method, analyzing the signal's entropy. This parameter is defined in Eq. (12).

$$H(X,z) = \int_{z_0}^{z}\left|\frac{dX(u)}{du}\right| du \tag{12}$$

Where z_0 is the reference depth at the start of the drilling process (can be 0 or the surface's elevation). After being filtered, a log can be quickly analyzed by this method to highlight zones of constant variation. The authors explain that if the soil is homogenous, the readings taken will regularly increase in value as depth increases resulting in a linear entropy graph, and a change in lithology will appear in the graph as a change in slope. However, highly heterogeneous soils will also lead to changes in slope, or even sudden jumps in the graph and the authors recognize that there are no clearly defined criteria for differentiating changes due to heterogeneity and those that indicate a transition into a new lithological layer.

3. Comparison and analysis

To evaluate each of these methodologies, a synthetic signal with very little noise was used at first for calibration. Afterwards, some MWD drillings executed in France (more specifically in the Pays Basque region) in 2023 by the engineering company Fondasol.

The drilling parameter chosen to represent each of these drillings was the Alteration Index I_A, a compound parameter easily calculated by Eq. (13) where P_E is the effective thrust on the drill bit and V_A is the advance rate, $P_{E,max}$ and $V_{A,max}$ are the maximal values achieved by each parameter, and both k_0 and k_1 are proportionality constants. This parameter varies between 0 and 2, with 2 signaling stronger soils. For these analyses, both constants were considered to be equal to 1.

$$I_A = 1 + k_0 \left(\frac{P_E}{P_{e,max}} - k_1 \frac{V_A}{V_{A,max}} \right) \tag{13}$$

But before using Eq. (13), the original recordings were filtered with a moving median filter as suggested by Kreziak and Pioline (2005) and Reiffsteck et al. (2018). In this method, a window moves down the log calculating for position n the median of all values from position $n - k$ through $n + k$. If this median value differs from the measurement at that point by more than 5%, the sensor reading is replaced by the calculated median. This simple method can quickly eliminate any aberrant values and reduce signal noise. For these analyses, the constant k was chosen to be 10.

3.1. Synthetic signal

The synthetic signal tested reached a depth of 5,3m with values every centimeter for a total of 530 “measurements”. It was divided into distinct zones in which the value for each depth was given by a constant added to a random value between 0 and 2 to simulate noise. This random value was determined via software and had a distribution function equal to a gaussian curve. For the first test, the signal was divided into 2 zones with an abrupt transition at 2,5m, shown in Fig. 2.

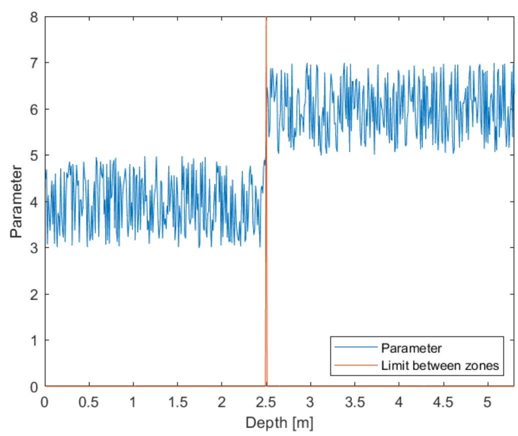

Figure 2. Synthetic 2-zone signal and the zones found by Amokrane's algorithm for synthetic signal 1

Amokrane’s algorithm was able to find this transition point correctly. Using the same signal, Moussouteguy’s algorithm was tested at first with the correct transition depth given as preliminary lithology. The method converged after 2 iterations, resulting in Fig. 3, where the probabilities for each layer at a given depth are shown stacked. The test was then repeated by informing a wrong depth as preliminary lithology and similar results were found each time with the transition point at the correct depth, though one or two extra iterations were necessary then.

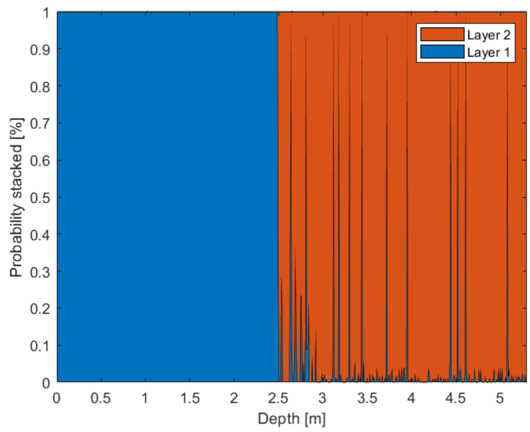

Figure 3. Probabilities calculated by Moussouteguy's algorithm for synthetic signal 1

A second synthetic signal was then tested, this time with 3 distinct zones. Once again, Amokrane’s algorithm found the transition points correctly, Fig. 4, and Moussouteguy’s algorithm converged after 3 iterations, Fig. 5, with clear transition points at the correct depths.

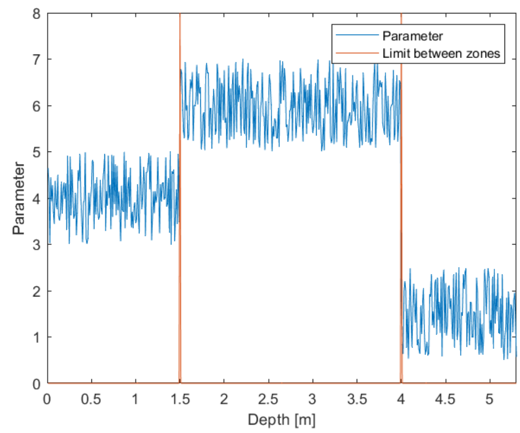

Figure 4. Synthetic 3-zone signal and the zones found by Amokrane's algorithm for synthetic signal 2

The entropy method couldn’t be tested with these synthetic signals as the noise present in those followed a normal distribution and was, by consequence, almost constant. This means that the entropy of both signals formed one single straight line. The entropy method was evaluated in the following tests.

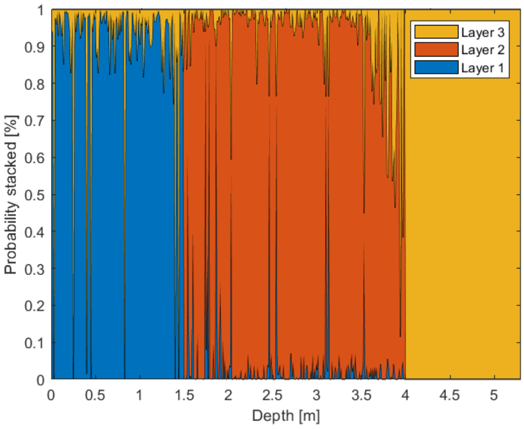

Figure 5. Probabilities calculated by Moussouteguy's algorithm for synthetic signal 2

3.2. Real MWD profiles

The first MWD log examined was came from a project in Bayonne, a city in the French region of Pays Basque, close to the Spanish border. According to the driller's report, the local lithology consisted of 5 layers: a layer of landfill from a previous construction, clayey silt, clayey sand, another layer of clayey silt and finally marl with the changes in lithology estimated to occur at the depths of 1.1, 8.1, 18.7 and 25.5 meters.

Amokrane's algorithm divides the drilling's alteration index into 19 zones that it considers homogenous, as shown in Fig. 6. Calibrating the code to reduce its sensitivity to signal variations doesn't reduce the number of zones in the final result. Even though the algorithm overshot the number of soil layers found in situ, some of the limits it determines are at the same depth or a few centimeters apart from the depths estimated by the driller. This indicated that while the t-test is too sensitive to random fluctuations and tends to divide the drilling log into too many layers, the methodology is capable of finding the actual transitions between layers with good accuracy.

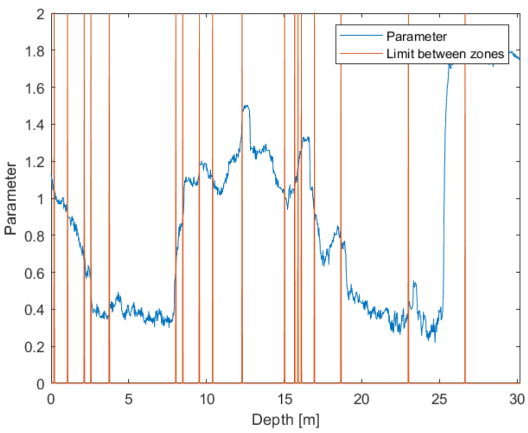

Figure 6. Alteration index and subdivisions determined by Amokrane's algorithm for survey 1

Giving the same signal to Moussouteguy's algorithm and using the drillers report as the preliminary lithology needed for the method, convergence is reached after 2 iterations. As seen in Fig. 7, there are some areas of uncertainty and some artifacts like the ones seen when testing the synthetic signal, but the final graph can still be very easily interpreted. The first depths at which the probability for each layer approach 1 very closely match those informed by the driller.

Table 1 shows the depths in meters estimated in situ, the limits between homogenous zones estimated by Amokrane's algorithm that are closer to the estimations, and the transitions in probability determined by Moussouteguy's algorithm.

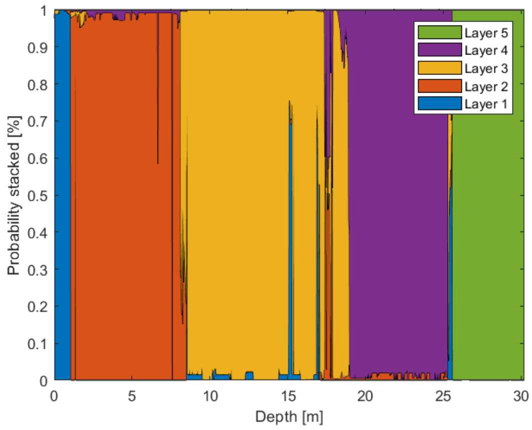

Figure 7. Figure 7. Probabilities calculated for each point in the drilling log of belong to a given soil layer for survey 1

Table 1. Depth of each layer as determined in situ and by the two tested methods

Layer	Driller's report	Amokrane's algorithm	Moussouteguy's algorithm
1	1.10	1.05	1.09
2	8.10	8.03	8.21
3	18.70	18.66	18.92
4	25.50	26.65	25.60
5	30.20	30.20	30.20

Another survey was then examined. The area surveyed was in Hendaye, a small town in the Spanish border, still in the Pays Basque region. After reaching the depth of 9.7m, the driller reported a thin, 0.7m, layer of clay covering a rock formation. Amokrane's method divides the log of alteration index into 10 zones considered homogenous, presented in Fig. 8. As with the previous example, the limit between two of these zones very closely matches with the depth estimated in situ for the change in lithology.

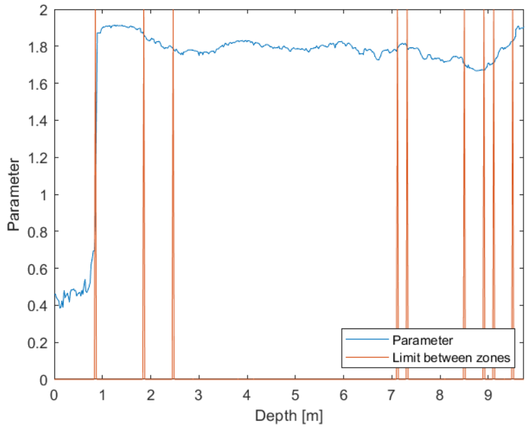

Figure 8. Alteration index and subdivisions determined by Amokrane's algorithm for survey 2

For the same signal, Moussouteguy's algorithm converges after 3 iterations, with the result presented in Fig. 9. Although the two different layers have very distinct intervals with no overlap, as was the case in survey 2, the algorithm attributes to the lowest values of layer 2 a high probability of belonging to layer 1.

This tendency was also observed in the tests with synthetic signals, where the lowest values of a layer with higher average are given high probabilities of representing a preceding layer of lower average values. This may create uncertainties if the algorithm runs for too much iteration, creating multiple points where the probability shifts back and forth between two layers and reducing legibility as seen in Fig. 10.

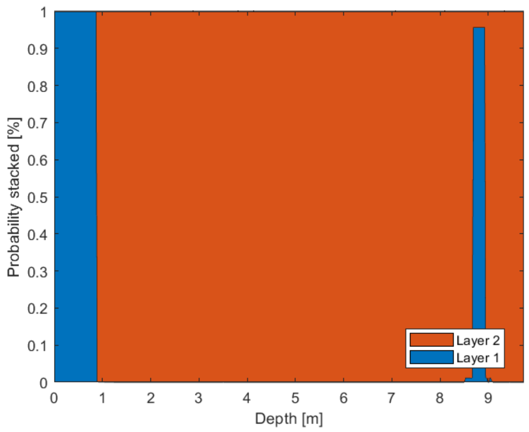

Figure 9. Probabilities calculated for each point in the drilling log of belong to a given soil layer for survey 2

For the signal used in Fig. 10, the driller's report indicates the existence of a layer of fill up to 0.5 meters, clay between 0.5 and 1.7 meters clearly discernible in Fig. 10 then followed by a layer of decomposed rock between 1.7 and 8.2 meters and fissured rock below that. Layers 3 and 4 occupy very similar intervals, see Fig. 11, which confuses the algorithm and leads to the sections in layer 3 where layer 4 receives a high probability. There is also a section of lower alteration index, visible in Fig. 11, that is interpreted as being part of layer 1, even though those values are higher than those found in the actual layer 1.

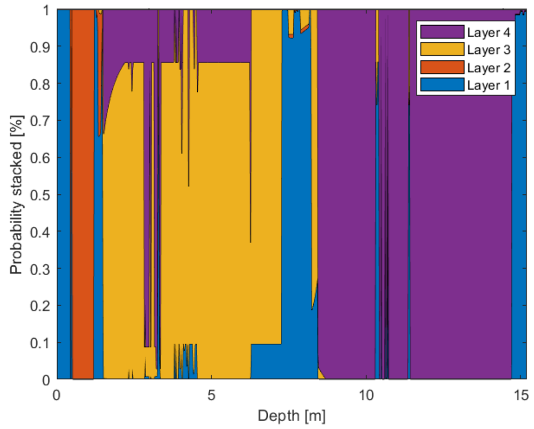

Figure 10. Probabilities calculated for each point in the drilling log of belong to a given soil layer for survey 3

The combination of these two factors can make it difficult to interpret the results given by the method and cause uncertainty about the depth at which one given layer transitions into the next.

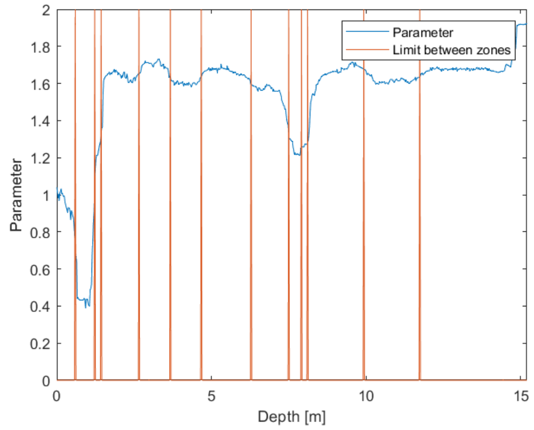

Figure 11. Alteration index and subdivisions determined by Amokrane's algorithm for survey 3

As Bourget and Rat (1995) don't specify which parameter's log would be best suited to be analyzed by their entropy method, all base parameters were investigated for the 3 surveys previously presented. In all three cases, the entropy of the advance rate showed the best fit to the reported lithology and downward thrust correlated well for survey 1 while effective thrust did the same for survey 2. Their graphs are shown in Figs. 12, 13 and 14 normalized so that their maximal values are equal to 1.0 and alongside the site's lithology.

But even in these cases, the changes in slope don't always line up exactly with the depth indicated in the report. At other points, the entropy curves change in slope in the middle of a given layer, as shown by Fig. 13 at the depth of 6m, which could be misinterpreted as the transition into a new layer if the lithology determined *in situ* wasn't known. Some transitions aren't very noticeable as well, i.e. between layers 3 and 4 in Fig.12.

A more robust methodology must be defined around this concept of entropy to eliminate these uncertainties. Which parameter to investigate through this method also merits further investigation, as only a few parameters correlated well in the cases examined. Perhaps a compound parameter would be better suited for it, or the joint analysis of multiple curves.

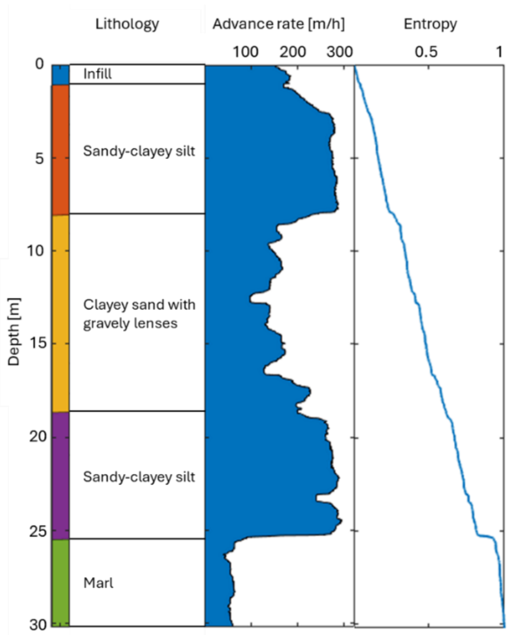

Figure 12. Reported lithology, advance rate and normalized entropy of survey 1

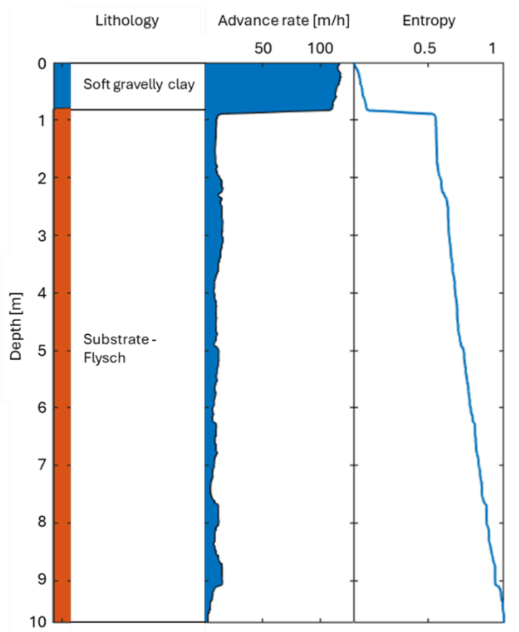

Figure 13. Reported lithology, advance rate and normalized entropy of survey 2

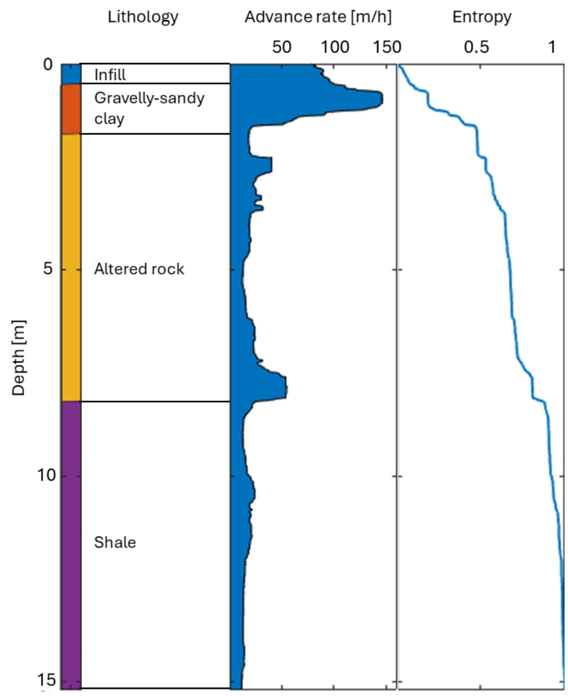

Figure 14. Reported lithology, advance rate and normalized entropy of survey 3

4. Conclusions

Three interpretation methods for MWD logs were evaluated in this paper via comparison with the lithologies estimated *in situ* by the driller. The results correlated well, but improvements are necessary. The first method, presented in Amokrane (1988), needs to be less sensitive to random fluctuations in order to subdivide the examined log into only a few layers.

Moussouteguy's algorithm needs to be amended to remove uncertainties when two soil layers have similar averages and around the lowest values found in each layer. These issues stem from the use of multiple distribution functions to calculate probabilities.

If these issues are fixed, perhaps both methods could be used in conjunction, with Amokrane's algorithm providing the preliminary lithology required by Moussouteguy's.

The analysis of the signal's entropy showed good correlations with the reported lithologies in all three surveys, but only when the drill bit transitioned from softer into stronger soils. The choice in signal used for this also needs to be better examined, as many drilling parameters had little to no correlation with lithology. As it is presented in Bourget and Rat (1995), the method is not sufficiently defined to allow for its automation.

Future work in this subject will continue to use real drilling logs to validate and improve these methodologies. Possible correlations between drilling parameters and soil properties will also be evaluated.

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