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The estimation of shear wave velocity, Vs, from seismic piezocone penetration tests (sCPTu) in tailings storage facilities (TSFs) in northern Mexico and the development of local correlations based on soil behavior.

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ABSTRACT: This study focuses on reviewing conventional empirical correlations used to determine shear wave velocity (V_s) from cone penetration test (CPTu) parameters, but instead of applying them to natural soils, they are modified for Mexican tailings storage facilities (TSFs). To this end, a database of 897 data points obtained from the study of nine TSFs using the seismic piezocone (sCPTu) was constructed, covering various tailings types as a function of solids content, which depends on the deposition method, including conventional slurry (unthickened, thickened or cycloned) and filtered, and minerals (gold, silver, copper, iron, lead, zinc, molybdenum). With correlations adapted to different deposition methods, it is possible to increase the correlation coefficient to values of $0.6<\rho^2<0.9$ and eliminate the underestimation of V_s presented by conventional correlations, particularly at shallow depths. Given that the value of V_s is multifactorial, an artificial neural network system (ANN) is proposed to consider all the parameters of the CPTu and those that characterize the TSFs (q_T, f_s, u_2, σ'_v, z/H, I_c, tailings and mineral type). The ANN system provides a superior approximation ($0.83 <\rho^2< 0.9$) in comparison to modified correlations, whilst maintaining equivalent generalization. Moreover, it attains enhanced convergence with the V_s trend in relation to depth. Finally, a sensitivity analysis performed on the ANN indicates that the parameters that have the greatest influence on the determination of V_s are q_T, σ'_v, and f_s.

KEYWORDS: Tailings deposits, shear wave velocity, sCPTu, empirical correlations, artificial neural network.

1 INTRODUCTION

TSFs are man-made structures that serve the purpose of storing mining waste. Due to their nature, tailings deposits are formed with very young soils, which in some cases are still in the process of consolidation. These soils exhibit high heterogeneity, low shear strength, high deformability, are partially saturated and sometimes contain aggressive chemicals.

The geotechnical characterization of these deposits is complicated by the difficulty of obtaining unaltered samples. Consequently, in addition to conventional tests such as standard penetration (SPT), field tests such as seismic piezocone with pore pressure measurement (sCPTu_Δu), field vane (VST), seismic dilatometer (sDMT), pressuremeter (PMT) and geophysical tests (seismic refraction, MASW, SPAC, downhole, etc.) are frequently employed.

A key aspect of the geotechnical exploration on TSFs is the determination of compressional (V_p) and shear (V_s) wave velocities. The purpose is to assess their dynamic behaviour and saturation conditions, as well as to estimate other geotechnical parameters, with the aim of performing stability analyses and risk assessments on TSFs or monitoring the evolution of rigidity over time.

Regarding the determination of V_s, there are two categories of method: direct methods, which include geophysical geoseismic methods (*e.g.* down hole, MASW, etc.), and indirect methods based on empirical correlations with field tests, such as the number of blows to standard penetration (N_{SPT}) and the tip and friction resistances of the piezocone (q_T and f_s). The correlations currently in use have been proposed mainly for natural soil deposits; consequently, when applied to tailings deposits, they tend to produce generally low velocities, mainly at shallow depths, with very large estimation errors.

This article reviews the empirical correlation equations used to determine the V_s value in natural soil deposits based on CPTu parameters for application to Mexican TSFs. An alternative method based on ANN is also proposed to consider additional CPTu parameters and TSF characteristics.

2 BACKGROUND

A variety of empirical correlations for determining shear wave velocity have been developed in recent decades. Table 1 shows those most commonly used.

As can be seen, these correlations generally consider tip resistance tip resistance, q_c or q_T, behaviour index I_c, effective stress σ'_v and shaft resistance f_s, and that, with the exception of Equation 6, they were developed on natural deposits. However, the direct application of these correlations to tailings materials is not well-defined.

Tailings deposits are inherently different from natural soils: they are very young (still undergoing consolidation), highly heterogeneous (with frequent intercalation of hard and soft lenses) and partially saturated (sometimes exhibiting negative dynamic pressures, u_2, or possible suction effects) and contain chemicals that are uncommon in natural soils, so, consequently, empirical correlations frequently underestimate shear wave velocity in these materials.

These factors introduce significant uncertainty when transferring empirical relationships from natural soils to tailings, emphasizing that predictive accuracy is strongly dependent on the representativeness of the original measurement dataset, as will be demonstrated in subsequent sections.

Table 1. Main criteria for determining shear wave velocity from piezocone measurements.

Criterion	Remarks	Equation, V_s(m/s)
Bandi *et al* (1989)	Developed for sandy soils and gravel in Italy. The tip resistance q_c (MPa) and the effective vertical stress σ'$_v$ (MPa) are used.	$V_s^B = 277\, q_c^{0.13} \sigma_v'^{0.27}$ (1)
Mayne & Rix (1995)	Used for unaltered and fissured clays. The correlation factor obtained was ρ^2=0.736.	$V_s^{M_R} = 1.75 q_T{}^{0.627}$ (2)
Hegazy & Mayne (1995)	Used for all types of soil, where q_c and f_s are in MPa	$V_s^{H_{M2}} = (10.1 \log q_c - 11.4)^{1.67} \left(\frac{f_s/q_c}{100}\right)^{0.3}$ (3)
Hegazy & Mayne (2006)	Database of 73 sites. q_c and f_s in kPa; q_{c1N}(kPa): normalized tip resistance according to σ'$_v$, and I_c is the behaviour index according to Robertson & Fear (1998).	$V_s^{H_{M1a}} = 11.711\, q_c^{0.3409}$ (4a) $V_s^{H_{M1b}} = 78.311\, f_s^{0.2375}$ (4b) $V_s^{H_{M1c}} = 11.711 q_{c1N} \left(\frac{\sigma_v'}{100}\right)^{0.25} * e^{1.786 I_c}$ (4c)
Robertson (2009)	Database of 100 sCPT at 22 sites in California. Soils were uncemented coarse-grained, exhibiting drained behaviour during penetration.	$V_s^R = \left(10^{0.55 I_c + 1.68} \left(\frac{q_T - \sigma_v'}{p_a}\right)\right)^{0.5}$ (5)
Morales *et al* (2024)	Modification of Eq 1 for use in tailings deposits in Chile.	$V_s^{B\_Op} = 337\, q_c^{0.12} \sigma_v'^{0.24}$ (6)

3 DATABASE

To evaluate the applicability of the above correlations, or to propose new ones for TSFs in northern Mexico, a database consisting of 897 sCPTu measurements was compiled. These measurements correspond to 45 sCPTu soundings conducted across nine tailings dams. The database includes TSFs constructed using downstream, upstream, and dry-stack methods, and the characteristics of the tailings and their mineral types are summarized in Table 2.

Table 2. Tailings deposit characteristics and number of analyzed cases.

Tailings type	Mineral	Site	Number of sCPTu	Cases
Thickened slurry	Silver, Copper, Lead and Zinc	1	4	85
	Copper, Molybdenum and Zinc	2	13	275
	Copper, Lead and Zinc	1	9	173
Slurry or unthickened	Gold, Silver and Copper	1	3	23
	Iron	1	7	125
	Silver. Copper and Zinc	1	4	85
Cycloned slurry	Silver, Copper, Lead and Zinc	1	2	69
Filtered	Gold and Silver	1	3	62
	Total	9	45	897

It is important to note that the shear wave velocity was obtained at one-meter depth intervals, meaning that each measured value represents the average behavior of all materials present within that meter. Since piezocone measurement are nearly continuous, multiple values of q_T, f_s, u_2 and I_c can occur within the depth corresponding to a single V_s measurement.

The value assigned to each one-metre interval corresponds to the 30th percentile of the parameters measured by piezocone ($q_{T,30}$, $f_{s,30}$, $u_{2,30}$ and $I_{c,30}$). This approach is widely adopted in tailings stability analyses, as it provides a conservative estimate that reflects the weaker or softer portions of the profile, which are typically the most critical for assessing general behavior.

Prior to developing the empirical correlations, homogeneity and consistency of the dataset were carefully evaluated to identify representative trends. Given the inherent variability of field measurements, it is essential to preprocess the data in a systematic manner to ensure reliability.

To achieve an acceptable correlation coefficient (*i.e.*, ρ^2>0.5) for each defined data family, a structured preprocessing workflow was adopted, consisting of the following steps:

1. *Review of experimental data:* All measurements were examined to detect potential noise, inconsistencies, or anomalies. This quality control step ensures that spurious, erroneous, or unrealistic readings are detected.
2. *Outlier identification and removal:* Removal of outliers using objective and justified criteria. Each removal was justified to maintain the statistical integrity of the dataset. This step is particularly important in tailings data, where extreme values may reflect localized heterogeneities—such as coarse lenses, cemented layers, or abrupt changes in saturation—rather than representing the general behavior of the material. Distinguishing between true anomalies and genuine site-specific variability is essential to ensure that the derived relationships reflect the representative geotechnical conditions of the tailings deposits.
3. *Comparison before and after cleaning:* The dataset was compared before and after the preprocessing steps to assess the effects of data cleaning and to validate that key trends were preserved. Empirical criteria were applied to ensure that the processed dataset remained representative of the site conditions, capturing the variability.

By recognizing noise, heterogeneity, and extreme values, the methodology ensures that the resulting empirical relationships are both statistically and physically meaningful, facilitating reliable predictions of shear wave velocity and other geotechnical properties.

Figure 1 shows a matrix graph of all the data collected on tailings dams in northern Mexico. The main diagonal shows the histograms for each parameter measured using the sCPTu: V_s, $q_{T,30}$, $f_{s,30}$, $u_{2,30}$, σ'$_v$, z/H and $I_{c,30}$ (in the calculation of effective vertical stress, the contribution of suction was not considered, a factor that is recognized as potentially influencing the estimated correlations). The "Tailings" category refers to the type of tailings:1) Slurry or unthickened, 2) Thickened slurry, 3) Cycloned slurry, and 4) Filtered. The "Mine" category describes the mineral composition of the deposit. 1: gold and silver; 2: gold, silver, and copper; 3: silver, lead and zinc; 4: silver, copper, lead and zinc; 5: copper, lead and zinc; 6: copper, molybdenum and zinc; and 7: iron). The remaining elements of the matrix graph illustrate the relationships between the parameters. The first column, or top row, shows the relationships between V_s and all the other parameters. The variables with the strongest relationships are q_T (ρ^2 = 0.75) and f_s (ρ^2 = 0.71), while the other parameters show greater dispersion. This dispersion suggests that the relationship between shear wave velocity and piezocone parameters is multifactorial. Part of this dispersion is also due to variation in the piezocone parameters along the 1 m interval where V_s is measured, as well as to potential measurement errors or inaccuracies when the piezocone passes through alternating hard and soft lenses.

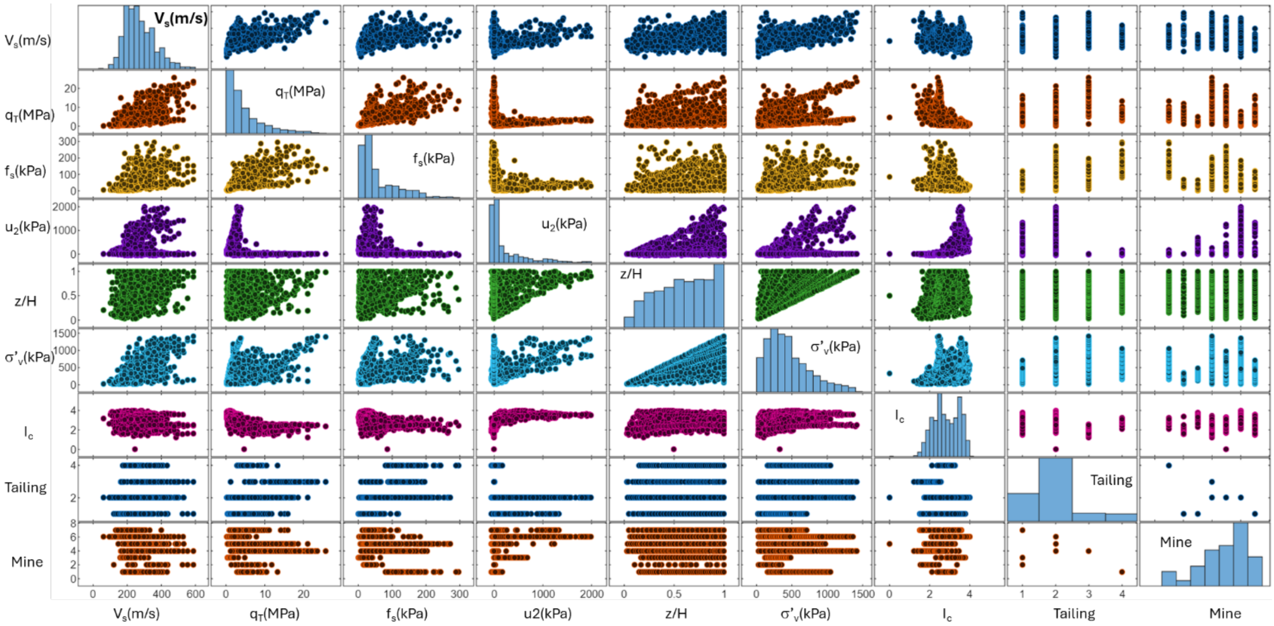

Figure 1. Database consisting of piezocone parameters: V_s, $q_{T,30}$, $f_{s,30}$, $u_{2,30}$, σ'_v, z/H, $I_{c,30}$, Tailings and Mine.

4 DETERMINING SHEAR WAVE VELOCITY USING CORRELATIONS.

All piezocone parameters were correlated with V_s for the above-described database, and correlation expressions were obtained for each site.

Figure 2 shows the q_T–V_s relationship for the entire database, including the corresponding equations and correlation coefficients for each tailings deposit. Among the parameters, q_T exhibited the least dispersion. Strong correlation coefficients ($0.87<\rho^2<0.94$) were obtained for each site (9 TSFs). However, when a single equation was applied to the entire database, the correlation coefficient decreased to a moderate level (ρ^2=0.75), reflecting increased variability across sites.

To obtain more general correlation equations, the sites were grouped according to tailings type and mineral composition, resulting in five general correlations as function of q_T, presented in Equations 7a to 7e and shown in Figure 3 to Figure 5. A summary of these correlations is provided below.

Empirical q_T–V_s correlation	Tailings type	Eq.
$V_s = 214.67\, q_T^{\ 0.40}$	Thickened Slurry: Cooper, molybdenum and zinc.	(7a)
$V_s = 239.02\, q_T^{\ 0.18}$	Thickened Slurry: Zinc, lead and cooper.	(7b)
$V_s = 189.11\, q_T^{\ 0.18}$	Unthickened Slurry: Iron.	(7c)
$V_s = 176.80\, q_T^{\ 0.34}$	Unthickened and Cycloned Slurry: Silver, copper and zinc.	(7d)
$V_s = 149.78\, q_T^{\ 0.39}$	Filtered: Gold and silver.	(7e)

As shown, this approach produces higher correlation coefficients ($0.6<\rho^2<0.9$), which are similar to those obtained when each site is assigned an equation (see Figure 2). The correlation follows the general form:

$$V_s = \alpha\, q_T^{\ \beta} \tag{8}$$

Where q_T is expressed in MPa and V_s in m/s. For TSFs in Mexico, the coefficients α (scale factor) and β (exponent which define the curve shape) are within the following ranges: $150<\alpha<240$ and $0.18<\beta<0.40$.

Figure 6, for example, compares the proposed expressions with two of the previously mentioned criteria (Equation 5: Robertson, 2009; and, depending on the value of I_c used, Equations 1: Baldi et al., 1989, for sands; and 2: Mayne & Rix, 1995, for clays).

It can be observed that equations 1, 2 and 5 produce very low values in the q_T<4MPa (V_s<200m/s) range and abrupt variations in the estimated value of V_s; while the proposed equations (7a to 7e) recognize the observed trend.

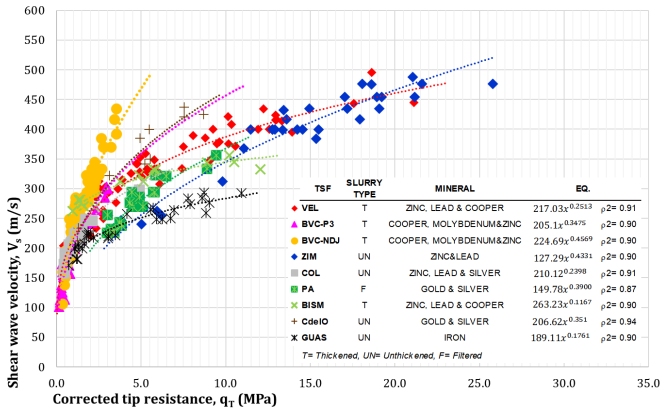

Figure 2. Relationship between q_T-V_s and correlation coefficients obtained for each tailings deposit.

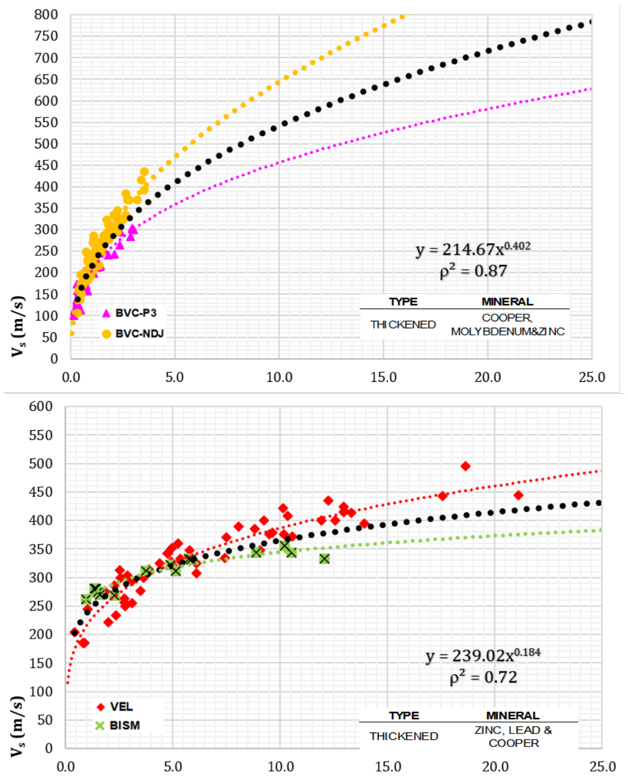

Figure 3. Part.1. Proposed general correlation equations for conventional tailings (thickened).

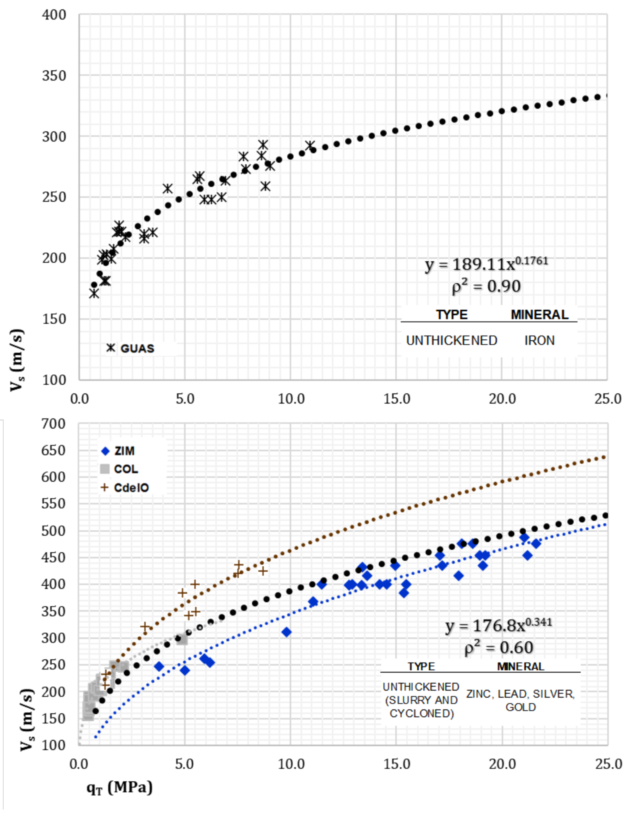

Figure 4. Part.2. Proposed general correlation equations for conventional tailings (unthickened and cycloned slurry).

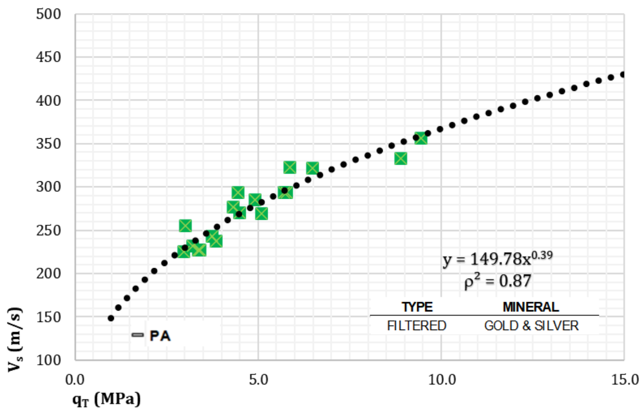

Figure 5. Part.3. Proposed general correlation equation for filtered tailings.

5 DETERMINING SHEAR WAVE VELOCITY USING ARTIFICIAL NEURAL NETWORKS

To evaluate V_s, considering all the variables measured by the piezocone ($q_{T,30}$, $f_{s,30}$ & $u_{2,30}$) and additional variables (σ'_v, z/H, $I_{c,30}$, Tailings & Mine) is proposed a system consisting of backpropagation artificial neural networks (ANN). The ANN is constructed using the database shown in Fig 1, with 803 cases used for training and 94 cases for evaluating the network.

The input layer consists of eight neurons, corresponding to the number of available parameters, while the output layer consists of single neuron from which the V_s value is obtained. Different network architectures were tested to determine the one that produced the minimum error in V_s estimation. The optimal architecture was a three-layer ANN with Gaussian transfer functions. The first layer is the input layer with eight neurons, next is followed by a hidden layer with 20 neurons and finally a third output layer with a single neuron (see Figure 7, ANN-8:20:1).

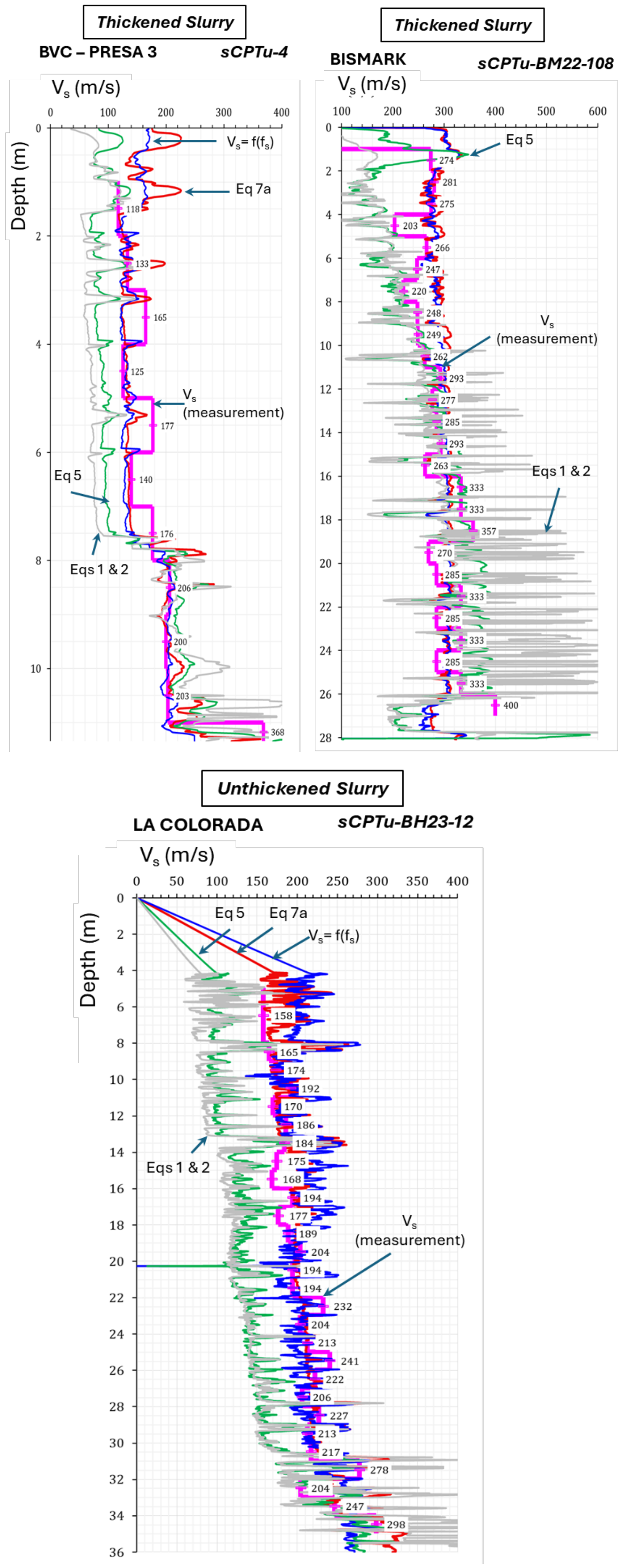

Figure 6. A comparison of the correlations proposed (Equations 7a to 7e) with those generated for natural soils (Equations 1, 2 and 5), in the case of Mexican tailings deposits of the Thickened Slurry and Slurry types.

During ANN training, learning was monitored to ensure that the system did not memorize; in other words, the error obtained for both the training and test datasets was comparable ($RMS_{training}$=6.4% and RMS_{test}=5.9%)

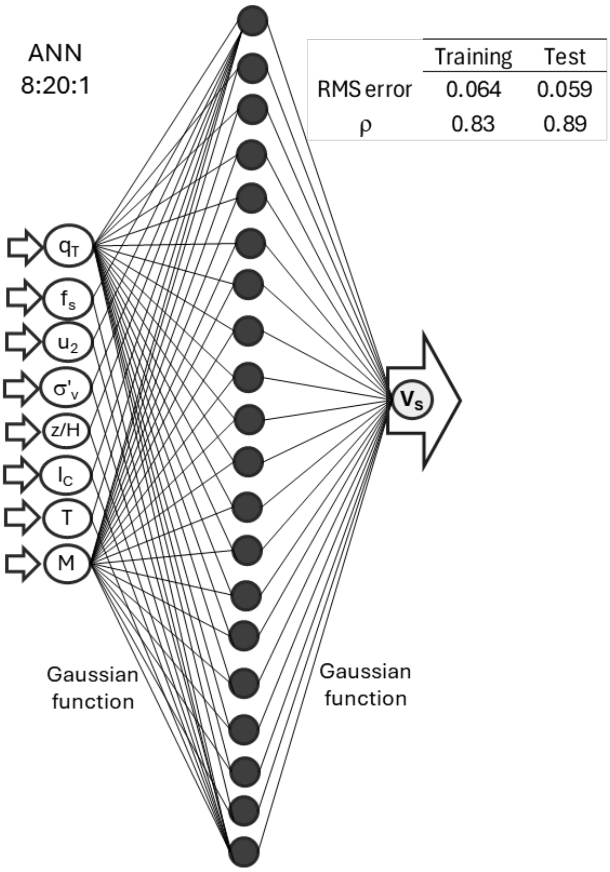

Figure 7. ANN for determining V_s.

The trained ANN outputs each input parameter's percentage contribution to estimating V_s (Fig 8). The primary parameter is q_T, which is consistent with previous findings. Subsequently, σ'_v and f_s contributions, followed by the other parameters, with the z/H ratio exhibiting the lowest contribution. Interestingly, the first three parameters (q_T, σ'_v, and f_s) account for 60.2% of the V_s determination. However, it is not advisable to ignore the remaining parameters, as together they impact the response by 39.8%.

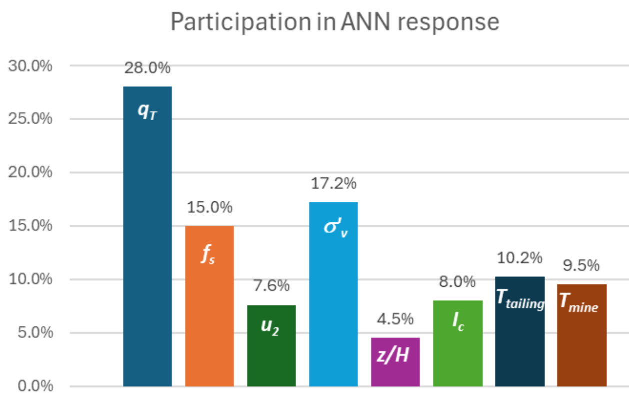

Figure 8. Percentage contribution of input parameters to the ANN response.

<u>Differences between modified correlations and ANN results</u>

The following table illustrates the correlation coefficients obtained in each approximation. The application of either 9 equations to group the data by site (9 TSFs, Fig 2) or five equations to group the data by type of deposition method and mineral composition (7a to 7e) has been demonstrated to result in a significant increase in the correlation coefficient. Using the ANN system also improves the correlation, raising values from ρ^2=0.75 to 0.83 < ρ^2 < 0.89, which are similar values to those obtained when grouping the data by site. However, with 5 or 9 correlation equations, generality is lost in approximation. With ANN, this is not the case, which is an outstanding feature of these systems: they capture the general trend of the problem. In addition, the ANN exhibits superior convergence with the measured V_s trend with respect to depth, as shown below.

	Approach	Correlation index
Empirical correlation	General	ρ^2=0.75
	Grouped by site, 9 equations. (Fig 2)	0.87<ρ^2<0.937
	Grouped by deposit type and mineral composition, 5 equations. (Fig 3 to 5)	0.6<ρ^2<0.9
ANN	General, 1 system	0.83<ρ^2<0.89

Figure 9 compares the results of the empirical correlations with those obtained using the ANN for different Mexican tailings deposits. The ANN response was consistent and adequate for the several types of deposits; in fact, it produced the best results in all three cases. Equations 7a, 7c and 7e (modified correlations) also produced good results, whereas equation 6 (Morales *et al*, 2024), developed for Chilean TSFs, overestimated V_s (as expected, given that Mexican tailings deposits are generally partially saturated). As mentioned above, equation 5 (Robertson, 2009) responded adequately but underestimated V_s for low values of q_T.

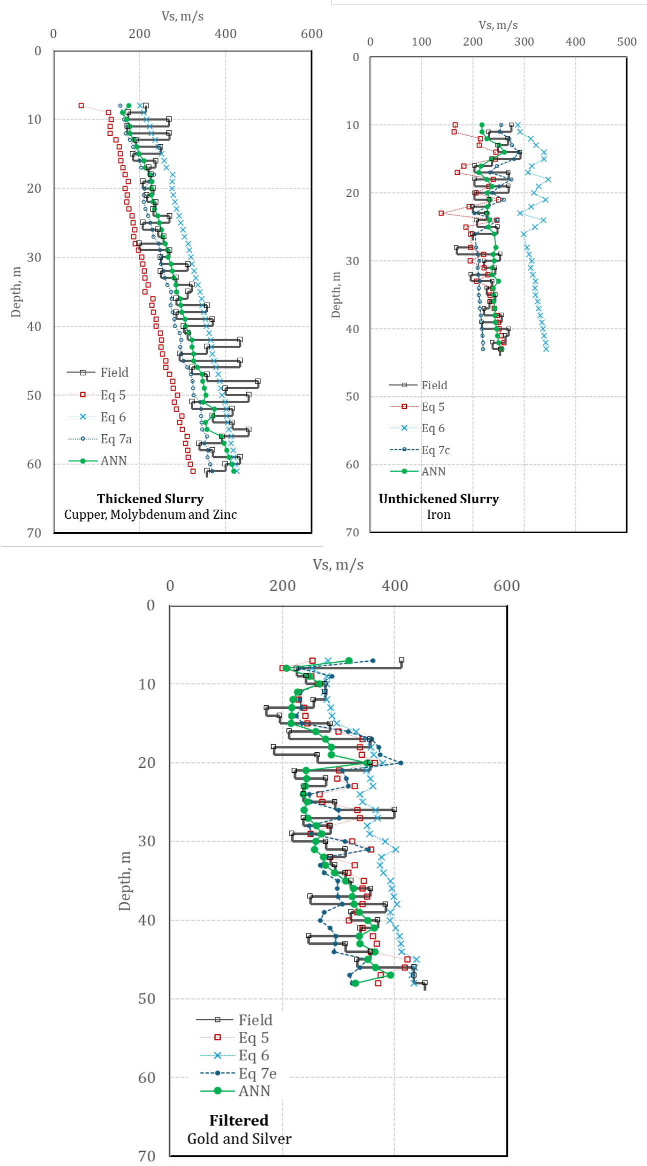

Figure 9. A comparison of the responses of equations 5, 6 and 7 with those of the ANN, in three different tailings deposits.

6 VARIATION OF NORMALISED WAVE VELOCITY WITH DEPTH.

An important point to note that, in all the Mexican tailings deposits studied, the variation in measured shear velocity with respect to effective vertical stress (V_s/σ'_v) exhibits a clear trend with depth. Figure 10 illustrates this variation for the entire database. For depths less than 10 m, the V_s/σ'_v varies between 1 and 8, showing a high degree of dispersion. Subsequently, the variation is less and ranging between 0.3 and 1, and the dispersion decreases significantly. Figure 10 also shows a correlation for estimating V_s as a function of the parameters σ'_v and z (depth), $V_s/\sigma'_v=8.27\ z^{0.838}$, which can be useful for obtaining an initial value of shear wave velocity.

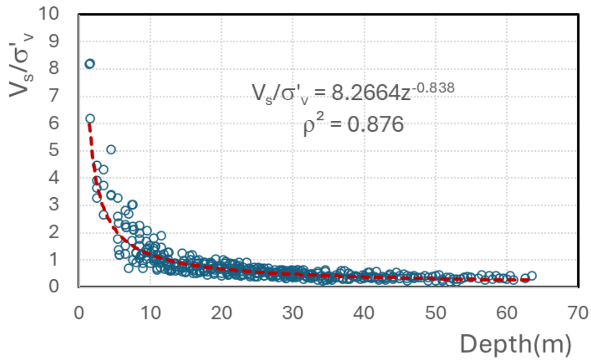

Figure 10. Variation of V_s/σ'_v *versus* Depth for the Mexican tailings deposit database.

7 CONCLUSIONS AND RECOMMENDATIONS

This article modifies the correlation proposed by Mayne and Rix (1995) to determine V_s in Mexican TSFs, using a database consisting of 897 sCPTu measurements. This correlation is based on the q_T parameter and also considers the deposition method and the type of ore extracted from mine. The result is a correlation in the form of equation 8 (eqs 7a to 7e), where the scale and shape factors (α and β, respectively) vary within the intervals $150<\alpha<240$ and $0.18<\beta<0.4$. Using this strategy, the correlation coefficient increases from $\rho^2=0.75$ (original correlations, table 1) to $0.6<\rho^2<0.9$. The best modified correlation is found for an unthickened deposit containing iron minerals ($\rho^2=0.9$), and the lowest correlation is found for an unthickened deposit (slurry and cycloned), containing zinc, lead, silver and gold minerals ($\rho^2=0.6$). The following intervals have been identified as the limits of these correlations: $100\text{m/s} \leq V_s \leq 500$ m/s and $0.5\text{MPa} \leq q_T \leq 25\text{MPa}$.

In light of the multifactorial nature of the V_s determination process, as evidenced by the database depicted in Figure 1, an alternative strategy is hereby proposed. This strategy is predicated on the utilization of an ANN, wherein the input variables are: $q_{T,30}$, $f_{s,30}$, $u_{2,30}$, σ'_v, z/H, $I_{c,30}$, Tailings & Mine. The ANN has been trained with the database, thereby increasing the approximation of V_s to values of $0.83<\rho^2<0.89$. This is achieved without compromising the network's capacity for generalization. Furthermore, the ANN demonstrates superior convergence with the measured V_s trend with respect to depth. Analysis of the designed ANN reveals that the most important parameters for determining V_s are q_T, σ'_v, and f_s (Figure 8), given that they contribute 60.2% of the value of V_s. However, it is important to note that the other parameters (which contribute 39.8% of the total) should not be disregarded.

Figure 10 shows a trend in V_s measured between the effective vertical stress (V_s/σ'_v) with depth, for all cases studied: for depths shallower than 10m, normalized velocity varies widely, from 1 to 10. Beyond 10m, both the variation and dispersion decrease significantly, stabilizing a value near 0.3.

The presence of significant heterogeneity in tailings deposits, attributable to the intercalation of hard and soft lenses, gives rise to pronounced variations in parameters such as q_T, f_s and u_2, and to a lesser extent V_s. To improve correlations, it is recommended that V_s measurements should be taken at smaller intervals than those used in this study (1 m).

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