Tailings Characterization: Exploring Laser Granulometry with Machine Learning

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ABSTRACT

The conventional particle size test has been a widely used method in the characterization of soils and tailings. Such information is particularly useful in the evaluation of materials deposited in tailing stacks or compacted landfills, which must follow reference particle size ranges. However, the method has limitations, the main one being the execution time, which usually lasts around three days. On the other hand, laser testing appears as a viable alternative. This innovative method obtains the grain size curve of the soil through the light dispersion pattern and lasts a few minutes, a significant improvement over the conventional method. Furthermore, this method can cover particle size ranges of up to 0.1 micrometers, while the conventional method is limited to 1 micrometer. Despite the benefits of using this equipment, the laser grain size test does not yet have specific standardization for use in the field of soil mechanics. In this context, this work proposes the use of machine learning techniques to demonstrate the existence of compatibility between both methods. To this end, tests were carried out using both methodologies on different samples of iron ore tailings and an algorithm was developed to predict the material classification. The evaluation of the results made it possible to verify the consistency and precision of the results between the two methods, reinforcing the reliability and viability of the laser test as an efficient alternative to the traditional method.

Keywords: Laser granulometry; machine learning; tailings characterization.

1. Introduction

The stacking of filtered tailings presents an alternative to the use of dams for tailings disposal in mining, aiming to reduce the risk of catastrophes. However, challenges are associated with stacking due to the complexity of these structures, as the properties of the tailings and the storage processes vary for each mine (Cruz 2023).

Alves (2020) suggests that the most relevant physical properties within the characterization of tailings include granulometric distribution, presence of clays, specific mass, rheology, plasticity, consolidation, and hydraulic conductivity. The granulometry of the tailings influences the behavior of stacking structures and dams, as the grain size impacts their stability. Fine particles can increase the permeability of the material, while larger particles can compromise structural integrity (Pinheiro et al., 2018).

The granulometric distribution curve is a fundamental physical property of the soil and is presented as the percentage of the total dry weight of the soil occupied by a certain granulometric fraction. This property is commonly used for soil classification and for estimating some hydraulic properties (Campbell & Shiozawa, 1994).

To determine the particle size distribution curve of the material in the conventional way, the NBR 7181 standard (ABNT 2016) is used. It is possible to determine the sand fraction by sieving and the silt and clay fractions through the sieve-hydrometer method (SHM), using a glass cylinder, densimeter, and deflocculant.

According to the preparation standard for compaction and characterization tests, NBR 6457 (ABNT 2024), to carry out this test on material with particles smaller than 5 mm, it is necessary to use 1 kg of sample. Furthermore, the granulometry test by sieving and sedimentation, according to NBR 7181 (ABNT 2016), lasts approximately 3 days. The stages include drying the sample in an oven until a constant mass is achieved, sieving the coarse material, and dispersing the material in deflocculant for 12 hours.

Following this, a sedimentation stage is carried out using a symmetric bulb densimeter and graduated rod. The fine material is also sieved after being dried in an oven. In addition to the long time to obtain the particle size distribution curve, the sedimentation stage also gives unreliable results for particles of 0.001 mm due to the effect of Brownian motion on the sedimentation rate (Stefano et al., 2010).

The potential use of laser diffraction method (LDM) was identified due to its ability to reduce both the time and the amount of material required for analysis. Pinheiro (2018) highlights several advantages of granulometric analysis by laser diffraction. These include a short analysis period, high repeatability, the use of a smaller sample (as shown on Figure 1), and the ability to determine fine particles up to 0.1 μm. This method is simple and quick, thus facilitating its use and potential for wider application.

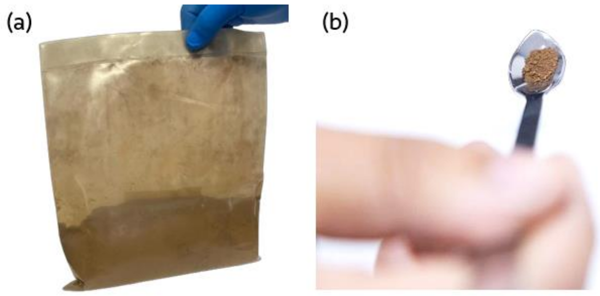

Figure 1. Sample required for the execution of (a) SHM test and (b) LDM test

The methodology of this test is based on the principle that particles have a certain size. Therefore, when dissolved in a standardized medium and subjected to incident light, they absorb and diffract part of the light at a certain angle, which is inversely proportional to the particle size. The model (Anton Paar – PSA 1190) of equipment used (Figure 2) has a measuring range of 0.1 to 2500 µm, with a measurement principle of laser diffraction, repeatability less than 1%, and a measurement time less than 1 minute. The complete process, considering the preparation of the sample and the equipment, lasts about 15 minutes.

Figure 2. LDM equipment

Considering that the SHM is an accepted and standardized method, and that the LDM provides reliable, quick, and highly repeatable information, a relevant question is whether there is a correlation between the fine size fractions obtained by both methods.

2. Particle Shape Parameters

- D_{10}, D_{30}, D_{60}: Terms used in soil mechanics to represent the particle size distribution of a soil sample. The D_{10}, D_{30}, and D_{60} values represent the particle sizes at which 10%, 30%, and 60% of the soil particles are finer, respectively.
- Coefficient of Curvature (C_C): Measure of the curvature of a soil particle size distribution curve. It is a dimensionless value, usually between 1 and 5, calculated using Eq.1.

$$C_C = \frac{(D_{30})^2}{(D_{10} \times D_{60})} \quad (1)$$

- Coefficient of Uniformity (C_U): Defined as the ratio of the D_{60} to the D_{10}. A larger C_U indicates a wide range of particle sizes (non-uniform soil).

3. Method

The study conducted consisted of creating supervised machine learning models for the prediction of particle shape parameters from LDM - traditionally obtained by SHM.

3.1. Tailing

For the execution of the tests, filtered iron ore tailings were used, originating from the Iron Quadrangle in Minas Gerais, Brazil.

The collection of this material took place on various dates over a span of three months, all from the same plant. This approach was adopted to ensure the representativeness and variability of the tailings used in the experiments, thereby enhancing the robustness of the results.

3.2. Tests

Approximately 180 granulometry tests were conducted using both SHM and LDM. According to Papini (2003), it is essential to ensure material dispersion so that fragile aggregates and agglomerates are not considered as single particles. This enhances the stability of the analyses and improves reproducibility.

For the SHM tests, chemical dispersion was used, with sodium hexametaphosphate at a concentration of 45.7 g of salt per 1000 ml of distilled water. Additionally, the solution was buffered with sodium carbonate until it reached a pH between 8 and 9, as recommended by the reference standard NBR 7181 (ABNT 2016).

For the LDM tests, a physical dispersion method can be employed, using the ultrasound present in the equipment. As Pinheiro (2018) points out, despite the procedures for its use in soils not being standardized, physical dispersion with the aid of ultrasound proves efficient in some cases. Tests were conducted with an amplitude of 50 w. Furthermore, tests were also carried out without ultrasound.

From the results of the tests performed, it is possible to observe the particle size distribution of the material. Figure 3 presents a graph with the variation of percentages by fraction – defined in accordance with NBR 6502 (ABNT 2022).

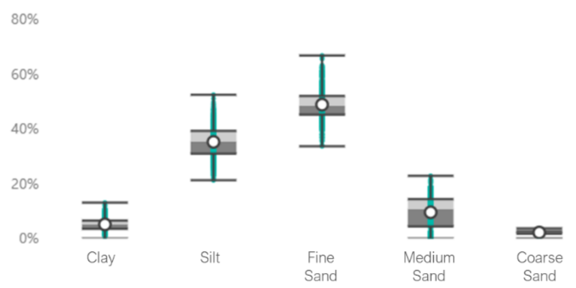

Figure 3. Box plots illustrating the distribution of values for Clay, Silt, Fine Sand, Medium Sand, and Coarse Sand from the conducted tests

The Silt and Fine Sand fractions concentrate the largest quantities in the granulometric distribution of the samples, followed by Medium Sand.

3.3. Machine Learning

The results derived from both laser and conventional granulometry tests were paired and archived in a database. This dataset was then utilized as a training set for the machine learning algorithm. The training process involved the algorithm learning to establish a correlation between the laser and conventional granulometry tests. This correlation served as the foundation for the algorithm's capability to predict material classification parameters, using only the data derived from the laser granulometry test. This methodological approach ensures a robust and reliable prediction model for material classification.

3.3.1. Algorithm

The aforementioned database was initially utilized for training the prediction model for D_{10}, with the objective of pinpointing the most effective algorithm for the task. At this juncture, three algorithms were put to the test: Decision Tree, K-Nearest Neighbor, and Voting Regressor. The performance of these algorithms was assessed based on the maximum error and mean absolute error, with the Decision Tree algorithm emerging as the most efficient, as evidenced in Table 1.

Table 1. Evaluation of machine learning methods

	Mean Absolute Error	Maximum Error
Decision Tree	0.000993	0.004128
KNN	0.001415	0.005592
Voting Regressor	0.001216	0.012657

3.3.2. Prediction

The algorithm was meticulously designed to predict the results of D_{10}, D_{30}, D_{60}, C_C, C_U, as well as the percentages of Clay, Silt, Fine Sand, Medium Sand, and Coarse Sand. To prevent overfitting of the model, it was configured such that the minimum number of samples in the leaves was set to 5. This methodological approach ensures a robust and reliable prediction model for material classification.

3.3.3. Evaluation

The evaluation of the results was conducted through the calculation of the Mean Absolute Error (Eq. 2), the Maximum Error, and the Mean Absolute Percentage Error (Eq.3).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - p_i| \tag{2}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - p_i}{p_i}\right| \tag{3}$$

Furthermore, the results were assessed by creating scatter plots with the actual and predicted values. In this type of plot, exemplified in Figure 4, the closer the values are to the highlighted diagonal, the higher the model's accuracy.

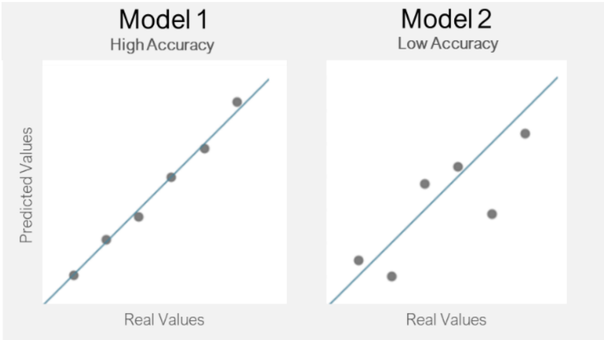

Figure 4. High and low accuracies examples shown on scatter plots

4. Results and Discussion

The results obtained by the prediction with the Decision Tree model are presented in Table 2, where for each parameter, the Mean Absolute Error, the Maximum Error, and the Mean Absolute Percentage Error are listed.

Table 2. Evaluation of machine learning methods

	Mean Absolute Error	Maximum Error	Mean Absolute Percentage Error
D_{10}	0.000986	0.006474	14.1%
D_{30}	0.001576	0.006659	3.1%
D_{60}	0.001908	0.009200	1.8%
C_C	0.532	3.646	15.7%
C_U	3.74	38.07	16.5%
Clay (%)	0.007068	0.023129	12.7%
Silt (%)	0.012507	0.047097	3.4%
Fine Sand (%)	0.013075	0.060339	1.9%
Medium Sand (%)	0.007995	0.036249	4.0%
Coarse Sand (%)	0.002666	0.009177	14.5%

4.1. D10, D30 and D60

Among the prediction results of D_{10}, D_{30}, and D_{60}, the first presents the highest percentage error, as shown in Table 2. However, Figure 5 displays an acceptable distribution of the predicted values, with few outliers and a uniform shape.

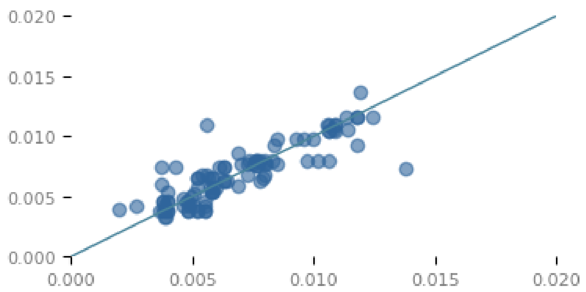

Figure 5. Prediction accuracy for D_{10}

This occurs because, for D_{10}, due to the characteristics of the tested material, the values are much lower than those obtained for the other parameters, but with greater variability.

Regarding D_{30} and D_{60}, presented in Figure 6 and in Figure 7, respectively, greater accuracy is observed in the results.

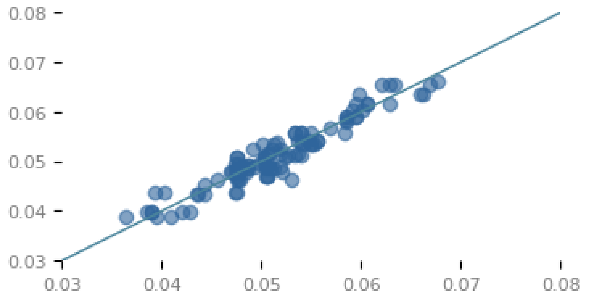

Figure 6. Prediction accuracy for D_{30}

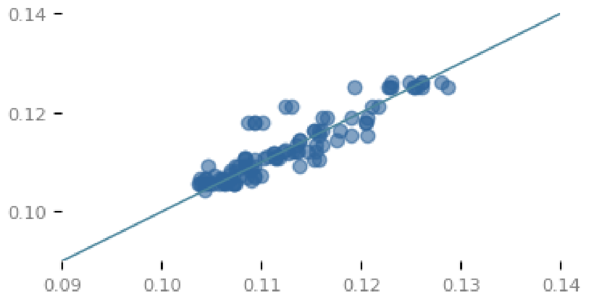

Figure 7. Prediction accuracy for D_{60}

4.2. C_C and C_U

The prediction of the C_C (Figure 8) and the C_U (Figure 9) exhibited larger errors, along with less uniformity in the graphs and a higher number of visible outliers.

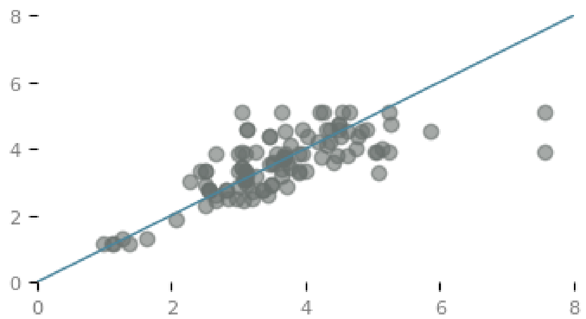

Figure 8. Prediction accuracy for C_C

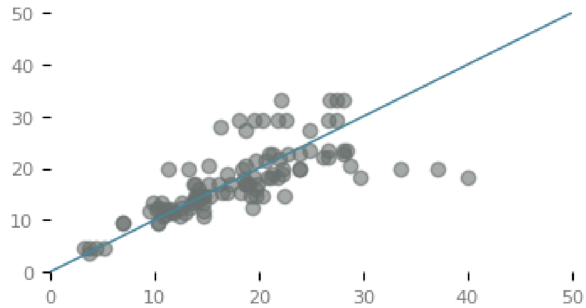

Figure 9. Prediction accuracy for C_U

4.3. Clay, Silt and Sand

The forecast of the Clay percentage value, despite indicating a higher error (as indicated in Table 2), presents satisfactory values.

Similar to the findings in the D_{10} values, the Clay percentage values in the granulometric distribution are smaller. Therefore, even with a lower maximum error and less than the maximum error of other fractions, the error relative to the clay percentage value stands out.

However, the shape of the graph presents homogeneity and proximity of the values to the highlighted diagonal, without presenting a large number of outliers, as in the case of C_U.

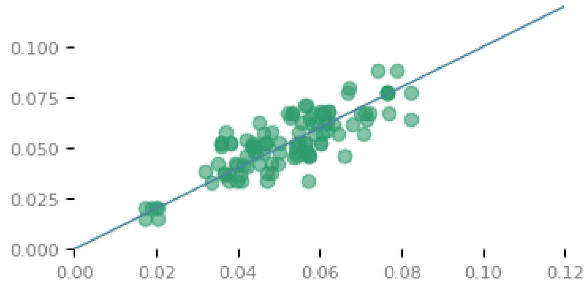

Figure 10. Prediction accuracy for percentage of Clay

For the prediction of the percentages of Silt (Figure 11), Fine Sand (Figure 12), and Medium Sand (Figure 13), which correspond to the largest granulometric fractions in the tested material, satisfactory results were obtained, with a mean absolute percentage error up to 4%.

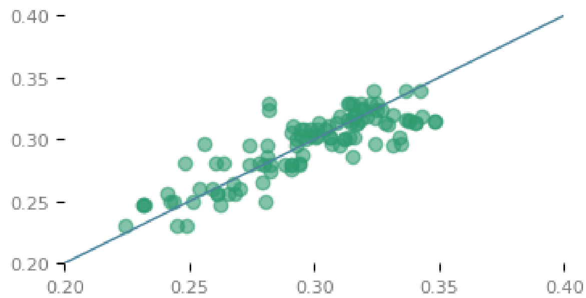

Figure 11. Prediction accuracy for percentage of Silt

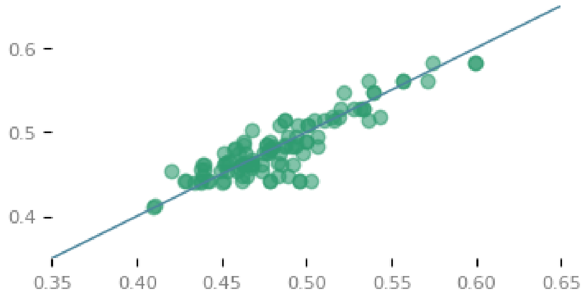

Figure 12. Prediction accuracy for percentage of Fine Sand

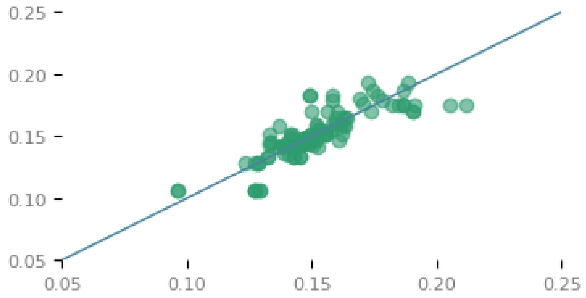

Figure 13. Prediction accuracy for percentage of Medium Sand

For coarse sand (Figure 14), among the predicted values, on average the mean absolute percentage error was 14.5% of the predicted value. However, when analyzing the maximum error of the coarse sand range in the granulometric distribution, the maximum error was 0.9% - a fact that occurs due to the low representation of coarse sand in the tested material.

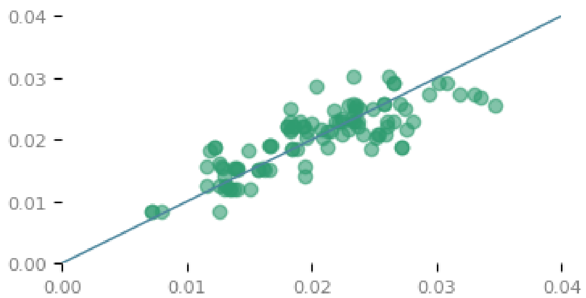

Figure 14. Prediction accuracy for percentage of Coarse Sand

5. Conclusion

This study has successfully demonstrated the potential of laser granulometry as a viable and efficient alternative to the conventional method for characterizing iron ore tailings. By employing machine learning techniques, a significant correlation was established between the outcomes derived from both methods. This correlation facilitated the prediction of material classification parameters using data exclusively from the laser granulometry test.

The Decision Tree algorithm, in particular, exhibited remarkable consistency and precision, especially in predicting D_{30} and D_{60} parameters, which showcased superior accuracy. While certain parameters such as D_{10}, clay percentage, and coarse sand percentage exhibited higher MAPE values, the distribution of predicted values was deemed satisfactory, characterized by minimal outliers and a uniform shape.

It was observed that the prediction errors were notably larger for the C_U and the C_C. This could be attributed to the fine-grained nature of the material tested. Given these findings, it is suggested that further tests be conducted on a variety of materials, including those with different granular compositions.

In conclusion, this study represents a step towards exploring the potential of laser granulometry in characterizing iron ore tailings. It offers an alternative approach that may be more efficient and expedient than conventional methods.

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