Development of a Model to Predict Average Moisture of Bauxite Shipments from Moisture of the Stockpile, Residence Time and Rainfall

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Abstract

The moisture content of bauxite is one of the main characteristics of the ore that needs constant monitoring and control, due to operational, commercial and financial impacts throughout the production chain. It is important especially in cases where ore transportation takes place in by vessels, since there are intensive material handling considerations and high costs involved in this stage of production. The Amazon Rainforest biome, where the operation of bauxite mining in the north of Brazil is located, is characterized by its high temperature and intense rainfall, directly influencing the moisture content of the ore shipped, due to storage in stockpiles, which exposes the material to the climatic conditions. The objective of this paper is to demonstrate the existence of the relationship between the average moisture of bauxite shipments, the moisture content of the stockpile, the residence time and the rainfall during the pre-shipment storage period, through a model using these variables that could predict the average moisture of bauxite shipments. In this study, different methods of data analysis were used, among them the Machine Learning, a method of data analysis that automates the construction of analytical models, providing advanced statistical analyzes from different regression methods. The following machine learning methods were directly tested: Random Forest Regression, Support Vector Regression, Gradient Boosting Regression, and Polynomial Regression, to find out the best model for the prediction of the average moisture content. For the database used for the analysis considers the period from April 2016 to March 2018 as a reference. It was possible to figure out the best parameters for each method of predicting the average moisture content of bauxite shipments, resulting in a variation between methods of at most 10 %. The Random forest regression produced the greatest results with a correlation of 0.7141 between the variables.

Keywords: Bauxite Moisture Content, Average Moisture Content; Machine Learning Regression Analysis.

1.   Introduction

1.1.   Amazon Bauxite Moisture Content

The bauxite deposits from the north of Brazil are located in the Amazon Rainforest with a considerable high moisture content, that may increase during the washing stage, the process step needed for the enrichment of the product, is required in order to reduce the grade(s) of reactive silica and enriching the available alumina content.

Ore shipping to refineries, when done by shipment or railroad, can be impacted by the moisture of the material since the costs in material handling is related to the quantity of mass moved. So, moving ore with high moisture content can result in greater production costs [4]. In addition, the

moisture content can also create operational difficulties and delays, making civil maintenance services needed for the continuity of production [5].

Also, the refinery processes the ore by the Bayer Process - in which bauxite is treated with a hot solution of sodium hydroxide, and the high moisture content can dilute the solution, resulting in a greater consumption of sodium hydroxide, one of the main costs of refinement [4].

Alcoa's Juruti Mine is located in the north region of Brazil which is subject to high rainfall, a dry season ranging from July to December and a rainy season from January to June) [9]. It is possible to observe the effect of the climate on the moisture content of the shipped ore, having an average variation of 1 % in the moisture content of ore shipped between seasons.

The last stage in the bauxite production at the Juruti Mine is the stockpiling of the material for homogenization and drainage before the material is shipped to the refineries. The process of storing the ore in stockpiles allows the drainage of excess moisture, and it must be stored for a determined time. For iron ore the indicated period is from days to weeks, while for coal it can last from 6 – 8 weeks [8]. During the stockpiling stage, the ore is exposed to the climatic conditions of the environment, the moisture content being affected by rainfall during the time of residence.

Considering all the exposed variables and the importance of moisture content control and monitoring, the present work aimed to demonstrate the relationship between residence time of the stockpiles, the rainfall in the pre-shipment storage period, and formation moisture content with the shipped moisture content.

1.2.   Multivariate Regression Analysis

The exposed problem presents 3 independent variables for the prediction of the shipped moisture content model, the stockpile formation moisture content, rainfall and time of residence; making it necessary to use multivariate analysis techniques to study the interrelationship of variables [7].

Multivariate statistics started to be cited in the early twentieth century, but it was only with the advancement of technology that it became possible to conduct studies quickly and clearly [7]. Learning the parameters of a prediction function and testing it on the same data would just repeat the labels of the samples that it has just seen but would fail to predict new unseen data. Machine learning algorithms allow us to learn the trend of the database and to generalize it as accurately as possible, thus improving the quality of the model developed [1].

Figure 1 shows the relationship between the accuracy of the model with its complexity and the point at which the model reaches the best fit of reality. The line corresponding to Training are the results obtained with the data that allows the generation of the model, and the line corresponding to generalization are the results obtained when generalizing the results of the model for the resultant simulation in the training [1].

5. References

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