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Article

Machine Learning Methods for the Prediction of the Inclusion Content of Clean Steel Fabricated by Electric Arc Furnace and Rolling

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Abstract: Machine Learning classification models have been trained and validated from a dataset (73 features and 13,616 instances) including experimental information of a clean cold forming steel fabricated by electric arc furnace and hot rolling. A classification model was developed to identify inclusion contents above the median. The following algorithms were implemented: Logistic Regression, K-Nearest Neighbors, Decision Tree, Random Forests, AdaBoost, Gradient Boosting, Support Vector Classifier and Artificial Neural Networks. Random Forest displayed the best results overall and was selected for the subsequent analyses. The Permutation Importance method was used to identify the variables that influence the inclusion cleanliness and the impact of these variables was determined by means of Partial Dependence Plots. The influence of the final diameter of the coil has been interpreted considering the changes induced by the process of hot rolling in the distribution of inclusions. Several variables related to the secondary metallurgy and tundish operations have been identified and interpreted in metallurgical terms. In addition, the inspection area during the microscopic examination of the samples also appears to influence the inclusion content. Recommendations have been established for the sampling process and for the manufacturing conditions to optimize the inclusionary cleanliness of the steel.

Keywords: inclusion content; machine learning; classification; random forest

1. Introduction

The steelmaking industry imposes tight controls on steel cleanliness because non-metallic inclusions (NMIs) negatively influence both the manufacture and the application of steel products. NMIs of different nature (mostly oxides, sulfides and nitrides) are always present in steel, but their amount and size greatly varies. They come from the combination between the low solubility metallic elements present in the liquid steel with elements such as oxygen, sulfur or nitrogen. The type, size, shape and quantity of NMIs depend on the steel grade and the details of the steelmaking and casting processes. NMIs are classified as "endogenous" or "exogenous". The former occurs within the liquid steel, precipitating out during cooling and solidification (for example, during deoxidation, because of the intentional addition of calcium to combine with sulfur). Exogenous inclusions are, in turn, entrapments of materials from refractory interfaces, slag or other materials in contact with the melt. Endogenous inclusions are typically more uniformly distributed than exogenous

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