NITROGEN CONTROL IN SECONDARY REFINING USING ARTIFICIAL INTELLIGENCE

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Abstract
The production of Special Bar Quality (SBQ) steels for high-responsibility mechanical applications demands strict chemical composition control, particularly regarding nitrogen content. In steelmaking routes that include vacuum degassing (VD), nitrogen behavior is governed by simultaneous and opposing absorption and removal mechanisms, conditioned by bath chemistry, pressure, and injected gas volume, forming a nonlinear system that limits the effectiveness of deterministic models. This work describes the development and industrial implementation of a machine learning model at Gerdau Charqueadas, designed to suggest the adequate gas injection volume during the vacuum degassing stage to meet both degassing requirements and the nitrogen target range. The model operates in two sequential stages: clustering of heats based on chemical and operational process characteristics, followed by gradient boosting regression applied to each group. Results obtained between 2024 and 2025 show a 15.8% reduction in heats with nitrogen outside internal specification across the full range of steel grades produced. For the individual families SAE 41xx, 51xx, and 86xx, assertiveness gains ranged from 25% to 33%. In the subset of steels requiring Al/N stoichiometric ratio compliance, the most operationally constrained scenario due to the need for simultaneous adjustment of the absolute nitrogen content and its ratio with aluminum, the reduction reached 8.36%. The model presented a coefficient of determination R^2 of 0.92 and a mean absolute error of 106.65 Normal Liters under real-target conditions. These results validate the proposed architecture as a robust and industrially applicable approach for nitrogen control in SBQ steel production.
Keywords: nitrogen control; vacuum degassing; machine learning; XGBoost; SBQ steels; Al/N ratio.

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1 INTRODUCTION

The global steel industry faces growing pressures for quality, operational efficiency, and cost competitiveness — demands that become especially critical in the production of Special Bar Quality (SBQ) steels, intended for high-responsibility mechanical applications such as axles, gears, and fastening elements, where the strictness of technical specifications leaves minimal margin for deviations in chemical composition [4]. Among the controlled elements, nitrogen stands out for the inherent difficulty of its control: in production routes that include vacuum degassing of the VD type, absorption and removal phenomena occur simultaneously, governed by the partial pressure of the gas, the chemical composition of the steel, and the volume of injected gas [3][11]. The presence of surface-active elements such as oxygen and sulfur adds further complexity by blocking interfacial reaction sites and conditioning the kinetics of nitrogen transfer [7][11], creating a system of coupled and conflicting variables that imposes limitations on traditional deterministic modeling.

In this context, machine learning-based models emerge as an effective alternative, capable of empirically capturing non-linear interactions from production history without the need to explicitly formulate each physicochemical mechanism involved [1][8]. Based on this approach, Gerdau Charqueadas, in partnership with EVCOM, developed and implemented an artificial intelligence model aimed at suggesting the appropriate gas injection volume during the vacuum degassing step, simultaneously addressing hydrogen content limits and the specified nitrogen range. The model was deployed in a production environment between 2024 and 2025, and its results are described in the present work, with emphasis on reducing the percentage of heats with nitrogen outside the internal meltshop specification.

2 MATERIALS AND METHODS

2.1 Production Route and the Criticality of Nitrogen Control

At Gerdau Charqueadas, Special Bar Quality (SBQ) steels are produced through an electric steelmaking route comprising an Electric Arc Furnace (EAF), a Ladle Furnace (LF), a vacuum degasser of the VD type (Vacuum Degasser), and Continuous Casting (CC).

To monitor the evolution of chemical composition and, consequently, nitrogen content, samples are collected at five critical points throughout the production process. The first sample is collected after the refining step in the EAF; the second is taken at the beginning of the Ladle Furnace and establishes the entry condition for secondary refining. The third is collected at the end of the Ladle Furnace and serves as the basis for the decision on the gas injection volume during the vacuum degassing step. The fourth sample is collected after the vacuum degassing step. Finally, the fifth sample is obtained at the midpoint of continuous casting and constitutes the final chemical composition proof sample.

2.2 Sources and Factors of Nitrogen Variation in the Process

Nitrogen in liquid steel is governed by a superposition of thermodynamic and kinetic mechanisms that act in opposing directions throughout the production route. At a given temperature, the solubility of a diatomic gas is a function of the square root of its partial pressure, and the thermodynamic equilibrium reaction at the gas-metal interface for nitrogen is expressed by:

$$\frac{1}{2}\mathrm{N2(g)} = \mathrm{N}$$

The solubility of nitrogen in liquid steel is dependent on temperature and strongly influenced by the chemical composition of the steel. Elements such as oxygen and sulfur exert a blocking effect on the interfacial reaction sites at the gas-metal interface, inhibiting both the absorption and desorption of nitrogen [11]. Throughout the melting, refining, and casting stages, the steel is exposed to various sources of nitrogen, among which the rinsing flow rate, slag composition, nitrogen pick-up at the beginning of casting, exposure time to the electric arc, and the nitrogen content present in the ferroalloys added stand out — the latter being of particular importance in the production of SBQ steels, which receive significantly larger addition volumes than other steel grades, proportionally increasing nitrogen absorption from the alloys [3].

2.3 Operational Conflict in the VD: Nitrogen, Hydrogen, and Temperature

Vacuum degassing imposes a conflict among three simultaneously constrained variables: nitrogen content, hydrogen content, and steel temperature at the end of treatment. The vast majority of SBQ steels have a maximum hydrogen limit of 2 ppm, a requirement necessary to prevent defects such as hydrogen flakes and internal porosity [6], which demands gas injection in sufficient volume to promote bath agitation and favor the nucleation and growth of H_2 bubbles [14]. However, this same agitation mechanism promotes nitrogen removal: increasing gas volume enhances denitrification, while reducing it to preserve nitrogen content compromises hydrogen removal [11].

Added to this is the thermal impact: bubbling increases heat losses through radiation and convection at the metal-vacuum interface, reducing the final temperature available for subsequent flotation steps and the target casting temperature [2].

2.4 The Additional Complexity of the Al/N Ratio

In steels intended for case hardening, such as gears and axles subjected to long thermal cycles at high temperatures, nitrogen control goes beyond simply adjusting the chemical composition range — it is necessary to achieve the stoichiometric Al/N ratio in order to favor the precipitation of fine aluminum nitrides (AlN), which act as grain boundary pinning agents during reheating, inhibiting excessive austenitic grain growth and preserving the mechanical properties of the component [4]. The apparently simplest solution is to increase the aluminum content to ensure the desired ratio; however, high Al levels promote the formation of alumina and spinel inclusions, compromising steel cleanliness [12]. The correct approach is the opposite: controlling nitrogen with sufficient precision so that the Al/N ratio is achieved with the lowest possible free aluminum content, eliminating the conflict between grain size control and inclusion cleanliness. This requirement substantially increases process complexity, transforming nitrogen control into an optimization problem with coupled constraints and reinforcing the need for a model capable of robustly capturing this interdependency [8].

2.5 The Need for Artificial Intelligence

The set of interdependent variables described throughout this section — nitrogen sources in ferroalloys and in the ladle furnace, variable VD vacuum efficiency conditioned by chemical composition levels, the coupled conflict between hydrogen removal and nitrogen control, the requirement to achieve the Al/N ratio under inclusion cleanliness restrictions, post-vacuum rinsing, and nitrogen pick-up during casting — constitutes a high-dimensionality multivariable optimization problem with coupled constraints, non-linear behavior, and limited intervention windows. Traditional analytical models, although valid for understanding individual mechanisms, require simplifications that compromise their accuracy under real industrial plant conditions with heat-to-heat variability. Artificial intelligence, specifically machine learning algorithms such as XGBoost, is capable of empirically capturing these non-linear interactions from production history, generating consistent operational suggestions without the need to explicitly formulate each mechanism, making it the most suitable approach for this level of process complexity [1].

2.6 Data Collection

The data used for the development of the predictive model were collected from automation software that enables complete plant information management, covering the period between 2022 and 2024. The information was structured to be directly linked to each heat, organized to enable temporal and relational analysis of physicochemical factors. The monitored variables included temperatures at the LF, VD, and CC outputs, as well as complementary parameters such as carbon content, heat position in the casting sequence, slag type, ladle preheating time, and billet cross-section.

2.7 Developed Model

The artificial intelligence model developed in this study has as its primary objective suggesting nitrogen and argon gas additions during the vacuum degassing step, so that the final product strictly meets technical specifications. It operates through a sequential two-stage process combining clustering and regression analysis. Initially, the system focuses on suggesting the total VD gas volume during vacuum degassing for heats with a minimum nitrogen range. The second phase of the model is based on the gas volume determined in the first phase, which is used as the primary input to provide the nitrogen gas volume suggestion.
The methodology applied in each phase is divided into two main steps: Clustering and Regression Modeling. In the clustering stage, heats are segmented based on similar chemical and process characteristics using a clustering algorithm to identify common patterns. In the LF step, heats are grouped using a decision tree algorithm. For both steps, highly relevant variables were selected, such as: predicted vacuum time, heat position in the casting sequence, steel family, and

whether or not the heat has an aluminum-to-nitrogen ratio requirement to be met — cases that may require nitrogen and argon addition in the VD to promote adequate degassing while meeting the chemical specifications for both the ratio and nitrogen content. This classification reduces data variability, enabling more robust and accurate modeling.
In the modeling step, gradient boosting regression machine learning models are applied to each group defined in the clustering stage.

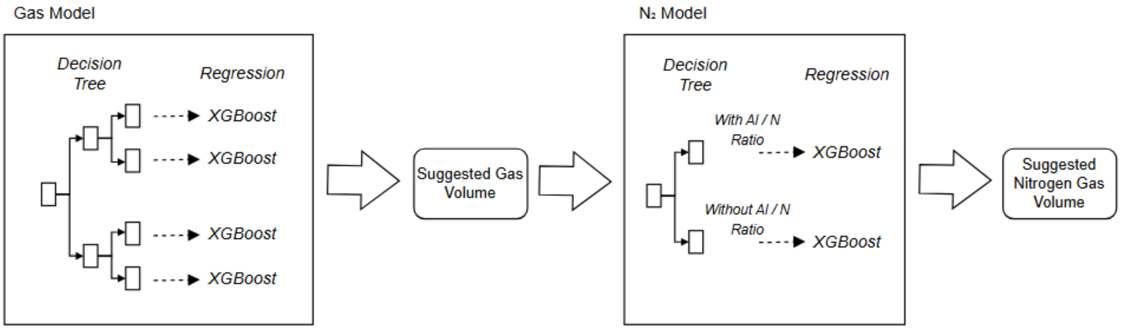

Figure 1. Block Diagram of the two-stage operation of the Nitrogen model

3 RESULTS AND DISCUSSION

3.1 Analysis and Correlations

Process and operational variables exert direct and indirect influence on the nitrogen content at the end of vacuum treatment [2], as illustrated by the Pearson correlation analysis with the final chemical composition proof sample presented in Figure 2.

The variables with the greatest impact in absolute terms were the nitrogen chemical specification range limits and the carbon content of the steel. The negative correlation with carbon reflects an interaction of simultaneously thermodynamic and kinetic nature: carbon directly reduces the solubility of nitrogen in the liquid bath [3] and, by consuming dissolved oxygen, diminishes the blocking effect that oxygen exerts on interfacial reaction sites [3][7], with the thermodynamic effect being dominant, as observed in these correlations [13]. The argon volume during low vacuum presents a negative correlation, evidencing that greater agitation favors denitrification [11][3]. In addition to continuous variables, categorical variables such as slag type and indicators built from previous heats also integrate the model, expanding its capacity to capture relevant operational patterns.

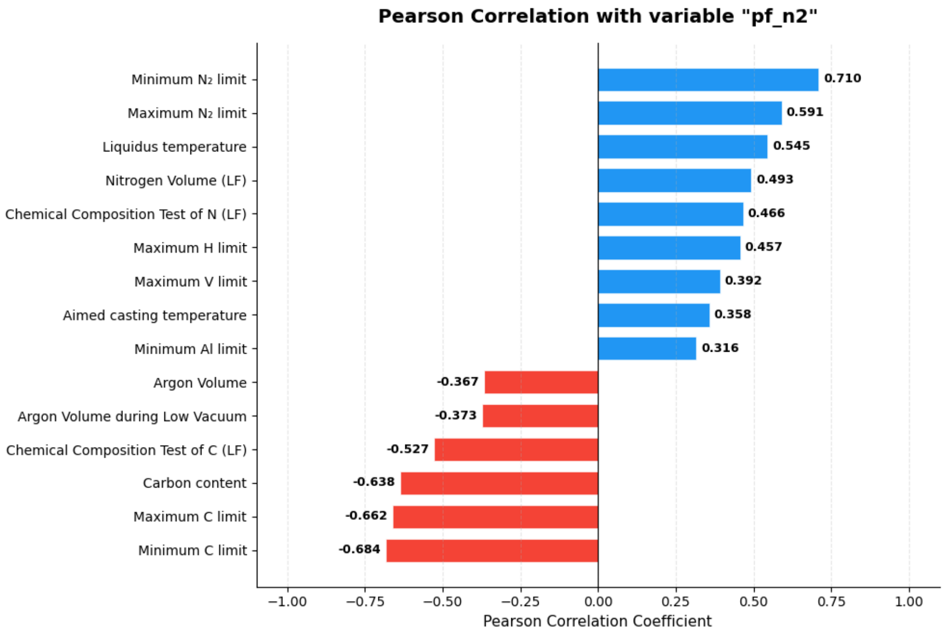

Figure 2. Pearson correlations of process variables with the variable "pf_n2", corresponding to the final nitrogen chemical composition proof sample**.**

3.2 Model Assertiveness

The model presented a coefficient of determination R^2 of 0.92 and a mean absolute error (MAE) of 106.65 Normal Liters, obtained in the scenario where the chemical composition variable is fed with the actual value measured during the heat, as shown in Figure 4. Considering that heats involve considerably high injection volumes, this mean deviation represents a small fraction of the total volume consumed, attesting to the viability of the prediction for use in production [1].

As discussed in section 2.1, the chemical composition of the bath exerts direct influence on the steel's capacity to incorporate nitrogen [3][11]. Chromium, manganese, and molybdenum increase nitrogen solubility, while nickel, carbon, and silicon produce the opposite effect. This compositional dependency makes model transfer between steel families a critical validation point, since a model calibrated for chromium-molybdenum steels may, in principle, respond differently when applied to simple chromium or nickel-chromium-molybdenum steels, as the nitrogen absorption and retention mechanisms operate in different regimes across these families.

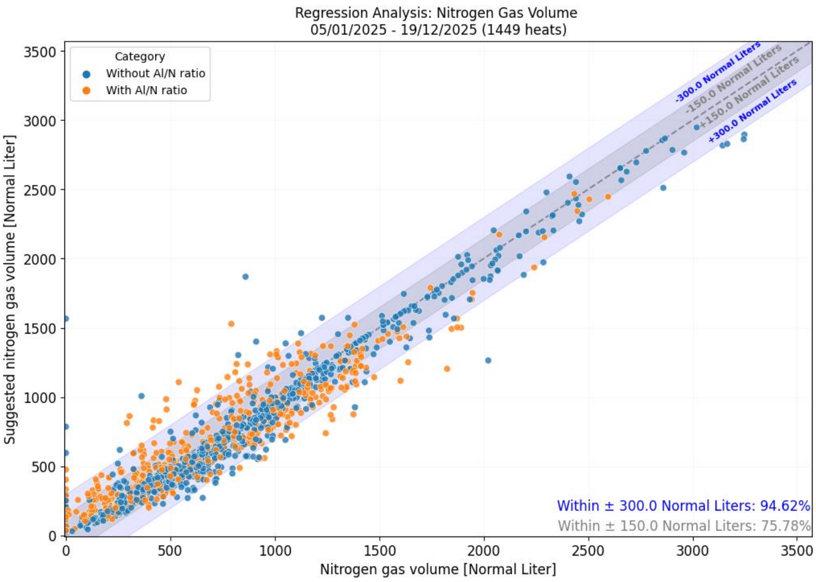

Figure 3. Model assertiveness considering real target.

To evaluate this behavior, the model was applied to three representative grades, each belonging to a distinct SAE steel family and selected for being among the main improvement opportunities identified in operation:

a) Grade A — 41xx family, chromium-molybdenum steels;

b) Grade B — 51xx family, chromium steels;

c) Grade C — 86xx family, nickel-chromium-molybdenum steels.

Grade	Assertiveness Improvement
A	26%
B	33%
C	25%

Table 1: Nitrogen assertiveness improvement from 2024 to 2025.

The results, presented in Table 1, show assertiveness gains between 25% and 33% from 2024 to 2025 across the three evaluated grades. The narrow range of these values indicates that the model does not exhibit relevant sensitivity to compositional differences among the tested families. This behavior was expected, given that the clustering approach described in section 2.5 segments heats precisely based on chemical and operational characteristics, allowing the regression submodels to operate on internally more homogeneous datasets. The result validates the robustness of the adopted architecture across the range of grades that make up the plant's SBQ steel production.

3.3 Annual Performance Comparison

Figure 4 presents the evolution of the total index of heats with nitrogen outside the meltshop's internal working specification between 2024 and 2025, expressed in normalized form. The year 2024 was adopted as the reference base (index 100%), allowing the variation observed in 2025 to directly reflect the magnitude of the improvement obtained with the model's implementation, regardless of the absolute production volumes of each period.

Panel (a) shows the result across the complete universe of produced grades, with a 15.8% reduction in the index of out-of-specification heats from one year to the next. This gain demonstrates that the advances verified in individual families, discussed in section 3.2, also translate into consistent improvement in the aggregated view of the process. Panel (b), in turn, presents the model's performance specifically on the subset of steels with Al/N stoichiometric ratio requirements — a group that, as discussed in section 2.3, imposes an additional compositional coupling constraint and therefore represents the most operationally challenging scenario. In this subset, the model delivered an 8.36% reduction in the index of out-of-specification heats, a result of particular relevance when one considers simultaneously controlling the absolute nitrogen content and its ratio with aluminum significantly reduces the available operational margin during the process.

The model performs more expressively across the general universe, where variability is greater and the space for improvement is proportionally wider, while simultaneously demonstrating robustness in the Al/N subset, where constraints are more severe and any improvement directly reflects on the quality of products intended for case hardening applications.

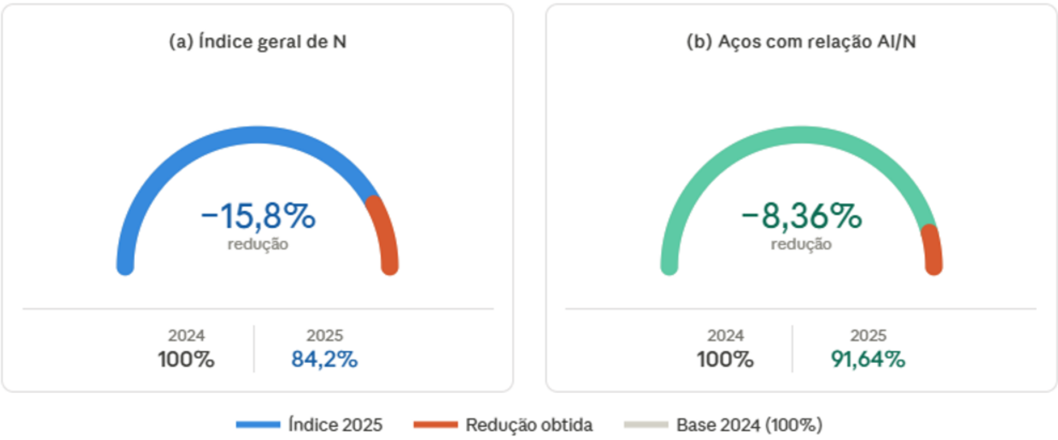

Figure 4 – Comparative normalized index of heats with nitrogen outside specification between 2024 and 2025: (a) result across the complete universe of produced grades; (b) subset of steels with Al/N stoichiometric ratio requirements. The year 2024 is adopted as the reference base (index = 100%).

4 CONCLUSIONS

The implementation of the artificial intelligence model for gas volume suggestion during the vacuum degassing step at Gerdau Charqueadas resulted in significant gains in nitrogen control for SBQ steels. The results demonstrate that the machine learning approach is capable of capturing non-linear interactions among process variables without the need to explicitly model each thermodynamic and kinetic mechanism involved, making it particularly suitable for a high-dimensionality, heat-to-heat variability problem such as the one addressed here.

The results obtained between 2024 and 2025 evidence the solution's effectiveness across different dimensions. Across the complete universe of produced grades, the index of heats with nitrogen outside specification was reduced by 15.8%. In the individually evaluated steel families, belonging to the 41xx, 51xx, and 86xx groups, assertiveness gains ranged between 25% and 33%, with a narrow spread among groups, confirming that the model responds consistently regardless of chemical composition differences among the tested families. In the subset of steels with Al/N stoichiometric ratio requirements, the group of greatest operational difficulty due to the simultaneous adjustment of absolute nitrogen content and its ratio with aluminum, the reduction reached 8.36%. Although numerically smaller than the overall result, this gain is of metallurgical relevance, since any improvement in this group directly translates into quality gains for products intended for case hardening applications, where tolerance to compositional deviations is minimal.

The two-stage architecture adopted, with clustering by process characteristics followed by gradient boosting regression, proved adequate for handling this complexity without requiring simplifications that would compromise accuracy under real plant conditions. Continuous monitoring of deviations and the expansion of the input variable set represent the natural path for model evolution, with concrete prospects for further quality gains in the production of special steels.

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