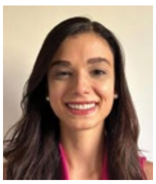
Predictive Modeling of Iron Runner Wear in Blast Furnaces: A Machine Learning Approach



The refractory wear of the runner in blast furnaces impacts process efficiency, operational continuity and maintenance planning. Traditional monitoring methods rely on periodic inspections, limiting predictive accuracy. This study presents a machine learning–based approach using a Random Forest Regressor to predict refractory wear heat by heat, enabling proactive maintenance and process optimization. The model was trained on data from the last eight campaigns, incorporating hot metal and slag composition, thermal conditions, and production metrics. Predictions were made for eight critical points of the runner (four per side), with individually optimized hyperparameters. An advanced data expansion strategy, combining probabilistic modeling and scenario simulation, enhanced prediction granularity. Validated through Mean Absolute Percentage Error, the model demonstrated high accuracy over traditional interpolation methods. Industrial implementation resulted in optimized maintenance scheduling, fewer unplanned stoppages and improved efficiency.

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Introduction

The blast furnace is responsible for the production of pig iron and slag, where iron ore is reduced in contact with countercurrent reducing gas, using coke or charcoal as fuel. Inside the hearth of the blast furnace, the produced pig iron and slag segregate due to density differences and accumulate in a limited space within the equipment, making it essential to have a regular drainage process for the proper functioning of the blast furnace through the taphole.[1] This drainage system releases a jet of liquid metal into the runners, which act as conveyors for the pig iron and slag to follow subsequent processes.

The progressive wear of the runner represents one of the main operational challenges, as it can compromise process efficiency and cause unexpected stoppages,[2] leading to a loss of pig iron productivity. Traditionally, the evaluation of refractory wear occurs only at specific moments within each campaign, such as during the initial inspection, scheduled stoppages and the end of the campaign. The number of scheduled stoppages varies according to the length of the campaign cycle of the runner, which may occur only once in campaigns lasting an average of 30 days. This reduced number of measurements makes it difficult to predict wear heat by heat, leading to imprecise maintenance planning and, consequently, unscheduled blast furnace stoppages.[3]

The stoppage process requires the support of multidisciplinary teams, including the operational, refractory technical and maintenance teams. This process occurs in a highly aggressive environment due to the high temperatures of the runner, requiring agility in its execution. Additionally, there is the possibility of pollutant emissions during the process. Due to the environmental and safety issues involved in the stoppage process, it is essential to develop predictive models capable of estimating wear heat by heat, ensuring greater reliability and operational efficiency. Accurate predictions allow for better-scheduled maintenance, avoiding excessive stoppages and optimizing the lifespan of the refractory lining.[4]

In recent years, machine learning techniques have been applied to predict various aspects of blast furnace performance, such as pig iron composition, thermal efficiency and slag formation.[5] However, few studies address the direct prediction of refractory wear at specific points of the pig iron runner.[6] This work proposes an innovative approach that combines time series reconstruction methods with a Random Forest-based model to predict wear throughout the campaign. The presented methodology allows for heat-by-heat estimation, providing more robust support for maintenance and operational decisions.

The following sections detail the methodology used, the processed data and the obtained results, demonstrating how this solution can contribute to reducing operational stoppages and increasing productive efficiency in the blast furnace, using an online platform for real-time refractory wear monitoring in runners utilizing artificial intelligence techniques.

Methodology

The proposed approach for predictive modeling of wear in the iron runner follows a structured sequence of steps, as illustrated in Fig. 1. This pipeline encompasses data collection and preparation, temporal data expansion, and predictive model development and evaluation.

Data Collection and Preprocessing

The data used in this study were extracted from previous pig iron production campaigns, covering a comprehensive set of measurements related to refractory wear at different points of the runner. Additionally, operational variables that play a critical role in refractory material deterioration were collected, including:

- Chemical composition of pig iron and slag — determines the aggressiveness of the reaction with the refractory.
- Thermal conditions of the process — temperatures from the pig iron that influence the wear rate and refractory temperatures collected via an Internet of Things system.
- Historical data from previous campaigns — contain measurements from scheduled inspections, allowing for comparative analysis.
- Environmental and operational variables — such as continuous operation time, thermal cycles and time between maintenance.

Data preprocessing included:

- Cleaning and handling of missing data, ensuring the temporal consistency of historical series.
- Normalization and standardization to avoid distortions caused by different scales among variables.
- Identification and treatment of outliers, using statistical and machine learning-based methods to avoid undue influences on the model.
- Creation of new features, exploring derived relationships between temperature, chemical composition and wear, enhancing the model's predictive capacity.

Data Expansion

Predicting wear heat by heat faces a significant challenge: the low availability of measurements throughout the campaign. Under normal operating conditions, inspections occur only at specific moments, such as at the beginning of the campaign, during a scheduled pause and at the end of the cycle. This reduced number of direct measurements makes it unfeasible to train conventional machine learning models, which generally depend on a larger volume of data to achieve good generalizations.

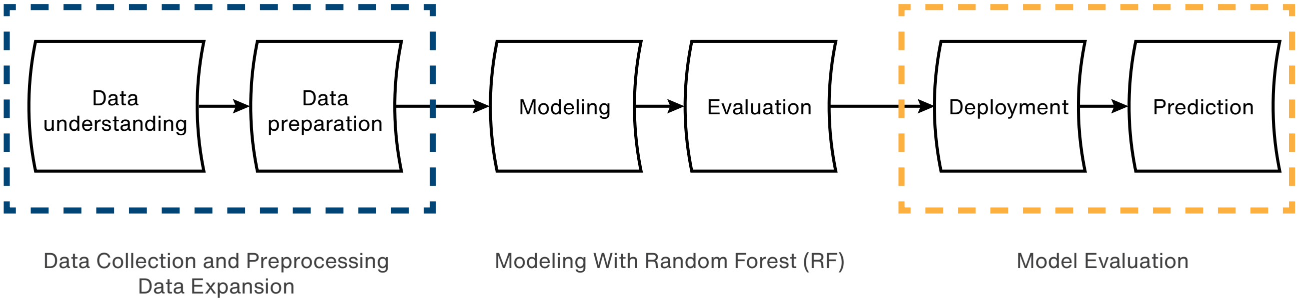
To overcome this limitation, a proprietary approach was developed to expand the temporal granularity of the data without compromising prediction quality. This methodology is based on a dynamic method of time series reconstruction, ensuring that the physical relationship between refractory wear and operational variables is preserved.

The data expansion strategy was implemented through several pillars, with two main ones being:

- Probabilistic wear modeling:

Figure 1

CRISP-DM – Predictive Method workflow.



  - Using stochastic process-based approaches to represent uncertainties in wear estimates.
  - Implementation of Bayesian methods and smoothing techniques to adjust predictions to historical data without distorting trends.
- Operational scenario simulation:
  - Incorporation of dynamic operational variations, such as changes in the chemical composition of pig iron and refractory temperature.
  - Application of statistical reinforcement methods, where wear patterns from previous campaigns are adjusted to generate plausible scenarios of evolution throughout the current campaign.

This transformation enabled the model to predict wear heat by heat more robustly, even in scenarios where the availability of direct data is limited. As a result, the modeling reliability was significantly enhanced, allowing for better anticipation of wear patterns and more precise support for operational and maintenance decisions.

Modeling With Random Forest (RF)

With the enriched data set, Random Forest Regressor was implemented to estimate wear heat by heat at key points of the runner. The Random Forest was chosen for its ability to handle:

- Complex nonlinear relationships between variables.
- High dimensionality, ensuring stability even in scenarios with multiple correlated variables.
- Noise in the data, preserving predictive capacity even with imprecise or incomplete measurements.

The modeling was structured to predict refractory wear at eight points of a runner and will be discussed in more detail in the following sections.

Variables Used in the Model

The input features were selected based on correlation and importance analyses in the operational context, covering three major groups:

- Operational variables.
- Wear history.
- Derived and statistical variables.

The combination of these factors allows the model to not only predict future wear but also to understand the underlying factors influencing runner deterioration.

This methodology was applied and rigorously validated in the field at a steel plant in Brazil, demonstrating its effectiveness in a real industrial environment.

Development

Predicting refractory wear in blast furnaces requires a predictive approach that considers the complexity of the process and the dynamics of operational factors. In this study, a machine learning model was used, specifically a Random Forest Regressor, to estimate degradation heat by heat and provide support for maintenance planning and operation optimization. Other types of machine learning (ML) models were tested, but the previously mentioned ML model performed the best.

The methodology was structured into four main stages:

- Preparation and refinement of data to ensure a reliable modeling base.
- Construction and training of the predictive model considering operational and historical variables.
- Incremental heat-by-heat prediction, adjusting estimates as new observations become available.
- Evaluation of variable importance, ensuring model interpretability and reliability.

Data Preparation and Refinement

The data used in this study were extracted from previous campaigns, from July 2023 to January 2025, and underwent a rigorous treatment and transformation process, ensuring that the model operated with consistent and representative information of the operational reality.

The main stages of data refinement included:

- Filtering and treating missing values, ensuring the continuity and quality of historical data.
- Normalization and standardization of variables, avoiding distortions caused by different scales.
- Creation of derived variables, combining operational factors to capture relevant patterns in refractory wear.
- Dimensionality reduction, selecting only the most relevant variables to optimize model performance.

This set of transformations enabled more efficient modeling, ensuring that only the most relevant information was used in wear prediction.

Construction and Training of the Predictive Model

The model training was structured to ensure accurate predictions aligned with the wear evolution throughout the campaign. For this, historical data from the last eight campaigns were used, allowing the model to learn refractory degradation patterns before making predictions for the current campaign. The prediction was specifically made for eight positions, four on the right and four on left sides of the iron runner. This segmentation enabled the creation of specialized models for different regions of the runner, capturing variations in wear behavior at each monitored point.

Model Training Configuration

The training followed these guidelines:

- Data division: The model was trained using data from the previous eight campaigns and validated with the most recent data available before the current campaign.

- Independent training per position: To ensure maximum accuracy, a specific model was created for each position of the runner, totaling eight distinct models.
- Individual hyperparameter tuning: Each model had its hyperparameters optimized separately, ensuring that the predictions were adjusted to the specific characteristics of each refractory region.

The main hyperparameters adjusted included:

- Number of trees ($n_{estimators}$): Defined to balance bias and variance, ensuring stable predictions without overfitting.
- Depth ($\max_{depth}$): Controlling the level of tree division to capture patterns without excessive complexity.
- Minimum samples per split ($\min_{split}$): Adjusted to avoid excessive splits and preserve model robustness.
- Minimum samples per leaf ($\min_{leaf}$): Defined to regularize predictions and avoid oscillations caused by small data sets.
- Random seed (random_{state}): Used to ensure reproducibility of results.

Incremental Heat-by-Heat Prediction

The heat-by-heat wear prediction was structured based on an iterative cycle in which the model continuously receives new data and adjusts its predictions as the campaign progresses. The adopted strategy followed these steps:

- Initial training with historical data: The model is adjusted using previous campaigns as a reference.
- Incorporation of new runs: As the campaign progresses, new measurements are added to the training set.
- Generation of incremental predictions: Refining predictive values and allowing real-time wear pattern detection.

This approach enabled continuous model adaptation to the operation dynamics, providing more accurate predictions aligned with the campaign's real conditions.

Variable Importance Evaluation

To ensure model interpretability and reliability, a variable importance analysis was performed, identifying the most relevant operational factors for wear prediction.

The main results indicated that:

- Production had a significant influence on wear, showing a high correlation pattern.
- The temperature of the pig iron had the greatest influence on wear, highlighting its direct relationship with refractory degradation.
- The chemical composition of the slag showed a significant impact, being essential to understand the chemical aggressiveness on the refractory material.
- Derived variables based on operational factors proved relevant, helping to capture nontrivial patterns in degradation over time.

The following sections present quantitative results, demonstrating the effectiveness of this methodology in optimizing industrial performance and reducing operational costs.

Model Evaluation

The model's effectiveness was validated through a comprehensive set of interpretative and quantitative metrics, ensuring that wear predictions presented high accuracy and stability throughout the campaign.

Mean Absolute Percentage Error (MAPE)

MAPE measures the accuracy of predictions by comparing the values estimated by the model with the actual values. It expresses the average error in percentage terms, facilitating interpretation and comparison between different data sets.

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

(Eq. 1)

where

n = the total number of samples,

y_i = the actual value of the ith observation and

p_i = the value predicted by the model for the ith observation.

Table 1

Hyperparameters Used for Prediction Model for One of the Runner's Positions

Hyperparameters	Final value
$n_{estimators}$	300
$\max_{depth}$	12
$\min_{split}$	10
$\min_{leaf}$	5
random_{state}	42

Industrial Application

The machine learning technique explained in this section was implemented in a blast furnace with four runners with an annual production potential of 1,680,000 tons. Eight positions in the runner were selected, where the region with the highest refractory wear, called the turbulence zone, is located. Of these eight positions, four are located on the right side and four on the left side of the runner.

Results and Discussion

The developed modeling for refractory monitoring in runners generated an online platform where it is possible to monitor wear on a heat-by-heat basis, in real time, during a campaign. Fig. 2 shows the visual result of on-line monitoring for one campaign studied.

According to Fig. 2, the thickness reduction over the observed period for eight points can be seen, indicating the real-time campaign potential for stoppage planning. Additionally, the platform has an alarm system to notify when the lowest value point reaches the safety limit (300 mm).

Additionally, it is possible to see a runner in plant view through the platform, as shown in Fig. 3. This graphic shows the latest measurement generated by the model in real time.

Following this, Fig. 4 presents the MAPE values obtained by the predictive model over campaigns C1 to C4, considering the predictions for eight positions, divided between the right and left sides of the runner. For example, nomenclatures such as P1-L and P1-R would, respectively, represent the first position on the left and right sides of the runner. It is also worth noting the color scheme of the table used to facilitate result interpretation, where green indicates lower error, yellow indicates moderate error and orange indicates points of higher model inaccuracy.

The analysis of the results confirms an already expected and widely recognized pattern in the dynamics of runner wear in the blast furnace. The positions closest to the taphole show greater instability, while the more distant positions follow progressively more predictable behavior. This phenomenon is directly related to the nature of the pig iron flow, which, when initially inserted into the runner, generates an environment of intense thermal and mechanical variability. As the pig iron travels through the structure, these oscillations tend to dissipate, resulting in more regular wear in the more distant meters. The following is a MAPE analysis of the predicted campaigns.

Campaign C1

In campaign C1, the model showed quite stable performance, with relatively low error values in almost all positions. However, an isolated deviation is observed in position 4 on the right side (10.75%), an atypical point within a campaign that, overall, proved predictable.

This result can be interpreted as an indication that, even in stable campaigns, certain positions may exhibit anomalous behaviors, either due to

Figure 2

Online platform.

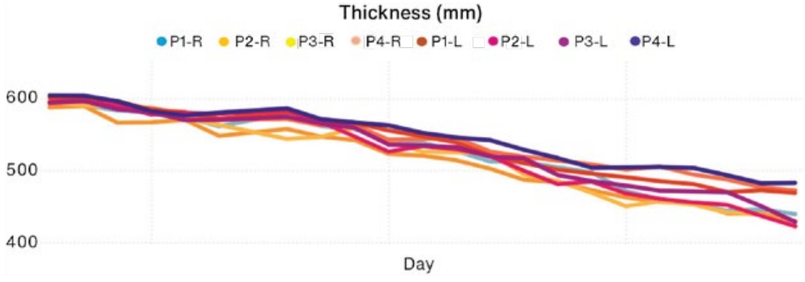


Figure 3

The final runner measurement.

Figure 4

Mean absolute percentage error of the predictive model for different campaigns and positions.

Model Position	ML Model C1	C2	C3	C4
P1-R	3,79%	6,70%	0,69%	4,57%
P1-L	1,76%	8,65%	4,45%	6,75%
P2-R	9,51%	8,89%	1,26%	14,35%
P2-L	2,43%	3,10%	2,44%	10,07%
P3-R	4,39%	17,16%	3,18%	12,92%
P3-L	7,14%	3,40%	0,33%	0,14%
P4-R	10,75%	5,18%	3,09%	10,08%
P4-L	9,06%	8,90%	0,64%	4,04%

small variations in the pig iron flow or asymmetries in the runner's thermal process. The fact that this peak occurs in a position further from the taphole also suggests that wear does not occur homogeneously and that occasional events can compromise stability even in regions considered more predictable.

Campaign C2

Campaign C2 represents the greatest challenge for model predictability, with a significant error peak in position 3 on the right side (17.16%) — the highest error recorded in all campaigns. This phenomenon reinforces the hypothesis that the positions closest to the runner taphole are inherently more unstable, as they concentrate the greatest thermal and mechanical variations of the process.

The large error discrepancy suggests that campaign C2 may have been characterized by a more dynamic operational environment, making wear behavior significantly more erratic. This behavior can be attributed to:

- Greater interaction between the pig iron and the runner walls in the first positions, intensifying wear and making prediction more complex.
- Fluctuations in the pig iron flow regime, which may have caused abrupt changes in the structure's thermal distribution.
- Asymmetries on the right side of the runner, indicating that thermal dissipation and wear do not occur uniformly between the two sides.

The magnitude of the error in C2 reaffirms that the behavior of the positions closest to the taphole does not follow a regular pattern, making this region a point of greater uncertainty for any predictive approach.

Campaign C3

Campaign C3 stands out as the period of greatest model predictability, with error values ranging from 0.33% to 4.45%. This stability reinforces the damping effect of thermal and mechanical variability as one moves away from the runner taphole.

This behavior can be explained by two main factors:

- The more distant positions tend to suffer less direct impact from pig iron flow oscillations, resulting in more uniform wear throughout the campaign.
- Thermal dissipation along the runner gradually reduces abrupt temperature differences, making the environment more predictable for a predictive model.

The results of C3 demonstrate that the greater the distance from the runner taphole, the more stable the wear behavior becomes, allowing the model to capture patterns with greater precision.

Campaign C4

Campaign C4 again shows an increase in errors, particularly in position 2 on the right side (14.35%) and position 3 on the right side (12.92%). This pattern suggests a cyclical behavior of instability, where wear oscillations do not remain fixed in a single position but can propagate along the structure in subsequent campaigns.

Compared with campaign C2, it can be seen that the zone of greatest error shifted from position 6 to 5, indicating that thermal and mechanical instability can migrate along the runner as new wear layers form due to the presence of residual materials from previous campaigns. This observation suggests that, although the positions near the taphole are always the most unstable, the exact location of the greatest unpredictability can vary between campaigns.

The observed error patterns throughout the campaigns are not random but directly reflect the physical dynamics of wear on the runner. The analysis confirms that:

- Proximity to the runner taphole is a determining factor for prediction instability due to the intense thermal and mechanical variations that occur in this region.
- The more distant meters exhibit progressively more stable behavior, as the pig iron reaches a more homogeneous flow regime and thermal dissipation smooths out process fluctuations.
- The migration of the zone of greatest error between campaigns suggests that wear does not occur in a fixed manner but rather with dynamic behavior over time.

Therefore, the variation in model errors should not be interpreted solely as a reflection of the predictive approach's limitations but rather as an intrinsic phenomenon of the physical process under study. The regularity of error patterns reinforces that the runner structure responds predictably to certain stimuli and that the challenges for prediction are less a matter of modeling and more a reflection of the inherent complexity of the blast furnace's operational environment.

Conclusion

The developed model demonstrated the feasibility of a robust and scalable approach for predicting wear in the pig iron runner in blast furnaces.

The combination of Random Forest with advanced feature engineering techniques allowed for capturing wear patterns with high precision, providing essential predictive support for industrial operation optimization.

This approach ensures that predictions are accurate, reliable and applicable to industrial environments to:

- Anticipate or postpone maintenance needs based on wear predictions.
- Optimize the lifespan of the runner, avoiding unexpected operational failures.
- Reduce costs with unscheduled stoppages.

Therefore, it is concluded that the online platform for refractory monitoring in runner has proven to be an effective and field-validated tool. The implementation of this technology allows for quick and efficient decision-making, optimizing maintenance and ensuring greater process reliability.

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Did You Know?

Texas A&M System Opens STEM Education and Research Center at RELLIS

The Texas A&M University System celebrated the opening of the STEM Education and Research Center at Texas A&M-RELLIS in March. The new collaborative facility allows students, researchers and industry partners to work side by side to advance applied research and prepare the next generation of Texas' STEM workforce.

The 53,000-square-foot center serves as a systemwide hub for hands-on learning, innovation, interdisciplinary collaboration and industry engagement, strengthening connections between higher education, research and emerging technology sectors critical to Texas' future.

"Students are at the center of everything we do, and this facility is designed to give them opportunities they simply cannot get in a traditional classroom," said Chancellor Glenn Hegar. "By working alongside researchers and industry partners, students gain real-world experience, develop practical skills and graduate better prepared to lead and serve. This center reflects our commitment to putting students first while helping meet the workforce needs of Texas."

The center features advanced makerspaces and collaborative environments that support student design projects, applied research and interdisciplinary innovation across fields ranging from engineering and advanced energy to digital technologies and virtual reality.

Students from the RELLIS Academic Alliance will utilize the facility alongside System research initiatives and industry partners.