Predictive Prioritization of Railway Bearings Using Acoustic Similarity of NOISY(RS1) Alarms from Wayside Monitoring Systems

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ABSTRACT

The operational reliability of heavy haul railways, such as the Carajás Railway (EFC), depends on early detection of failures in critical components like bearings. This study proposes a predictive prioritization approach based on acoustic similarity analysis of NOISY(RS1) alarms from the RailBAM® wayside monitoring system. Traditionally discarded due to suspected interference, these alarms have shown statistical overlap with confirmed failures. By applying multivariate similarity analysis using Mahalanobis distance and acoustic parameters—ERS DB, ERS Neighbors DB, and ΔERS DB—the methodology identifies patterns indicative of real defects. A new rule was developed to reclassify NOISY(RS1) alarms based on statistical thresholds and repetition criteria, enhancing failure detection accuracy. Experimental validation revealed previously unprioritized bearings with physical damage, demonstrating the rule's potential to complement existing predictive matrices. The approach improves maintenance planning, reduces undetected failures, and supports the integration of data-driven strategies in Prognostics and Health Management (PHM) for railway assets.

1. INTRODUCTION

The operational reliability of railway systems heavily depends on the ability to detect failures in critical components, such as bearings, at an early stage. This challenge is even more pronounced in heavy haul railways, like the Carajás Railway (EFC), which operates long-haul, high-tonnage trains and demands elevated levels of performance, safety, and asset availability.

In this context, sensor-based predictive maintenance has become an essential strategy. EFC is equipped with a robust infrastructure of wayside systems—non-intrusive monitoring equipment installed along the track that continuously assess critical parameters of wheels, bearings, brakes, and other components. Among these systems, RailBAM stands out for its acoustic detection capabilities, identifying bearing anomalies through the analysis of sound signatures generated during wagon passage.

The management and analysis of data from these systems are centralized at the Asset Monitoring Center (CMA), a unit responsible for consolidating information, applying prioritization models, and issuing maintenance recommendations based on technical, statistical, and regulatory criteria. The adopted guidelines follow the principles of ISO 17359, which establishes a systematic approach for condition monitoring and machine diagnostics, focusing on the identification of potential failures and the definition of corrective actions (ISO, 2018).

Additionally, EFC's maintenance strategy is aligned with the concepts of Prognostics and Health Management (PHM), which integrate continuous monitoring, diagnostics, and prognostics to estimate the Remaining Useful Life (RUL) of components. This approach enables failure anticipation based on degradation trends, optimizing resource allocation and reducing operational risks. According to Hu, Liu, and Zhang (2021), PHM combines operational data and analytical models to predict the future state of assets and support risk-based maintenance decisions. Kumar et al. (2024) highlights that RUL estimation in rotating machinery can be achieved through physical, data-driven, or hybrid models, with promising applications in industrial and railway systems.

In 2024, 18 bearing failure events were recorded, all in wagons equipped with 6 ½ x12 bearings. By June 2025, 12 additional events were identified—91.7% in wagons with 6 ½ x12 bearings and 8.3% in wagons with 7x12 bearings—indicating an upward annual trend.

During the same period, CMA issued 1,096 maintenance recommendations, of which 10.1% (111) were classified as emergency cases. Among these, 89.2% were due to grease leakage, 9.0% to early-stage Hot Box Warning, and 1.8% to acoustic anomalies. Notably, 91.5% of emergency cases were associated with wagons using 6 ½ x12 bearings, reinforcing the concentration of failures in this equipment type.

Internal analyses revealed that some of these failures were not predicted by the current prioritization matrix, which relies solely on available alarms. NOISY(RS1) alarms and their variants, often dismissed due to suspected interference, have shown notable correlation with unexpected bearing failures.

This study proposes a new prioritization approach based on statistical analysis of acoustic similarity, focusing on NOISY(RS1) alarms and their variants. The methodology aims to complement the existing matrix by improving the predictive detection of real bearing failures, even when masked by noise or ambiguous classifications. The proposal is grounded in acoustic parameters extracted from the RailBAM system, such as ERS DB, ERS Neighbors DB, and ΔERS DB, and seeks to establish objective criteria for alarm reclassification based on statistical patterns observed in confirmed failures.

To achieve this, the study employs multivariate similarity analysis using Mahalanobis distance as the classification metric. This approach accounts for correlations between acoustic variables and enables the identification of bearing clusters with behavior similar to real failures, even when individual values are not extreme. According to Ribeiro Junior et al. (2023), combining Mahalanobis distance with Gaussian mixture models allows for highly accurate fault pattern identification in dynamic components, proving especially effective in early detection of defects in bearings and rotating systems.

2. TECHNICAL FOUNDATIONS OF THE RAILBAM SYSTEM AND ACOUSTIC BEARING ANALYSIS

RailBAM is a wayside acoustic monitoring system for railway bearings that classifies each bearing and wheel passage using a standardized structure composed of prefixes, types, severity levels, and descriptors, as described by Uygun & Terzi (2023) and Tarawneh et al. (2021):

- Prefixes (indicate noise/interference): NOISY, FBS, Shrk, Clpd;
- Types: RS (Running Surface), LF (Looseness/Fretting), WHLFLT (Wheel Flat);
- Severity Levels: 1 (severe), 2 (moderate), 3 (minor), 4 (no fault);
- Descriptors (suffixes): _p (cup), _n (cone), _r (rollers), _m (multiple), _e (extended).

Bearing surfaces include the cup, cone, and rollers. Acoustic signatures may result from defects such as spalling, brinelling, water corrosion, electrical corrosion, and chemical corrosion. The specific nature of a defect can be inferred from the roller pass frequency, which varies according to the component's geometry. When a fault is clearly identifiable, a descriptor is added to the severity classification (e.g., RS1_p indicates a severe fault on the cup surface).

Approximate rollers pass frequencies and corresponding descriptors for different types of running surface (RS) defects are presented in Table 1.

Fault Description	Frequency (Hz)	Description
Cone	12,5 - 14	_n
Cup	10 - 11,5	_p
Rollers	3,5 - 4,8	_r
Multiples	Any combination of the above	_m
Extended	Any of the above with additional indication of extended fault	_e

Table 1. Roller pass frequency for different clear faults.

In the current workflow, maintenance requests are guided by criteria defined in the predictive severity matrix (Table 2). This matrix establishes intervention priorities (C0, C1, and C2) based on fault type, severity level, and repetition (consistency), considering a rolling 30-day evaluation window.

Alarms	C0	C1	C2	Obs.:
Clear level 1	≥1 & Exp. Mov Average Consistency≥0,7	≥1		Repetitions of alarms
Clear level 2		>1	=1	Repetitions of alarms
Clear level 3		>1	=1	Repetitions of alarms
>"." e consistency		>2	=2	Repetitions of alarms
Potencial 1 & 0,1≤exp. Moving consistency<0,4		≥6	≥5	Count in the last 12 passes
FBS(RS1			≥40%	≥4 alarms in the last 12 passes (6 ½ x12 bearings)

Table 2. Predictive Severity Matrix for RailBAM Alarms.

Consistency is a feature available in the supervisory system designed to identify persistent noise patterns in the acoustic signals of railway bearings over time. The tool analyzes the historical acoustic measurements to determine whether the recorded spectra remain similar across different time points, even under varying load and speed conditions.

Clear alarms of levels 1, 2, or 3 with descriptors, even when accompanied by a prefix, are treated as standard clear alarms without prefix, following the classification and actions defined in the current predictive severity matrix.

The presence of a descriptor indicates that the RailBAM algorithm successfully identified the physical nature of the anomaly in the bearing component. While prefixes suggest noise or interference, they do not eliminate the possibility of a real fault. Treating these alarms equivalently helps prevent the underestimation of events with genuine potential to evolve into severe failures.

3. METHODOLOGY

The methodology consists of a descriptive statistical analysis and a similarity-based comparison between two groups:

- Group A: Bearings with Clear Level 1 alarms, due to their high accuracy in identifying actual faults.
- Group B: Bearings with NOISY(RS1) alarms and their variants (_p, _n, _r, _e, _m).

The following acoustic parameters extracted from the RailBAM system were analyzed:

- ERS DB: A characteristic value in decibels (dB) derived from the processed acoustic signal, normalized by speed, which may indicate an advanced or extended defect on the bearing surface;
- ERS Neighbors DB: Acoustic energy of neighboring bearings.
- ΔERS DB: The difference between the ERS value of the bearing and that of its neighbors.

The use of ΔERS DB helps minimize the influence of systemic noise or extreme operational conditions by focusing on localized deviations. ERS DB is more sensitive to advanced surface defects than RMS values. An increase in ERS DB, regardless of neighboring ERS values, is more likely to result from an actual bearing defect rather than external factors. Elevated ERS DB values, combined with repeated NOISY(RS1) alarms and their variants, suggest the presence of advanced or extended defects on the bearing surface.

The analysis was conducted using rolling 30-day windows to identify statistical behavior similarities between the two groups. The methodology aimed to detect statistical intersections between bearings flagged with NOISY(RS1) alarms and those with confirmed faults (Clear Level 1), to establish a new prioritization rule based on acoustic similarity.

4. RESULTS

Based on the statistical analysis of data extracted from the RailBAM system, it was observed that bearings with confirmed Clear Level 1 failures share common value ranges across the three analyzed acoustic parameters. These intervals served as the foundation for formulating the new prioritization rule.

4.1. SIMILARITY ANALYSIS BETWEEN ACOUSTIC ALARMS

Figures 1, 2, and 3 below illustrate the overlap in statistical values between bearings flagged with NOISY(RS1) alarms and those with Clear Level 1 alarms, highlighting the intersection region that motivated the development of the new rule. The report considered a sample window covering data from May 27 to June 9, 2025, which corresponds to the period when the acoustic parameters used in this study became available in the supervisory system. The analysis focused exclusively on data from 6 ½ x12 bearings. Table 1 presents the descriptive statistics for bearings that exhibited Clear, NOISY(RS1), and variant alarms, as well as those with other attribute types.

Variable	N	μ	σ	Min	Q1	Med	Q3	Max
Noisy ErsDB	1068	74,79	5,77	63	70	75	79	95
Noisy Ers Nghbrs DB	1068	72,97	6,54	61	66	74	78	92
Noisy Delta Ers DB	1068	1,817	2,48	-6	0	1	3	14
Clear ErsDB	225	66,65	3,51	58	64	67	69	76
Clear Ers Nghbrs DB	225	62,69	2,34	57,7	61	63	64	72
Clear Delta Ers DB	225	3,97	2,66	-1	2	4	6	15

Table 3. Descriptive Statistics.

Figure 1 shows the distribution of ERS DB for bearings that triggered Clear and NOISY(RS1) alarms

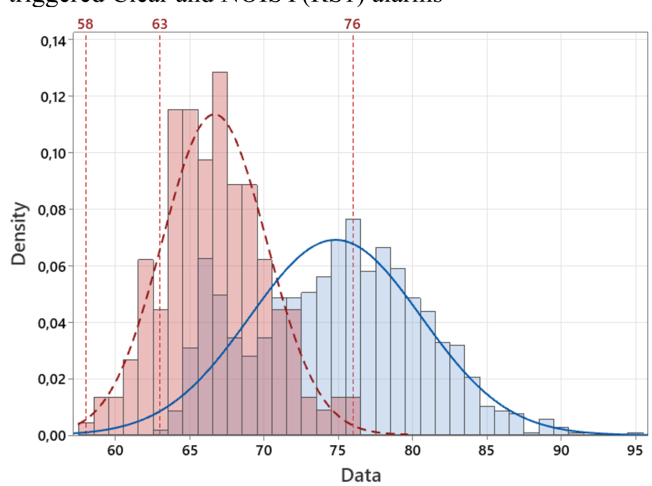

Figure 1. Distribution ERS DB.

Figure 2 shows the distribution of ERS Neighbors DB for bearings that triggered Clear and NOISY(RS1) alarms.

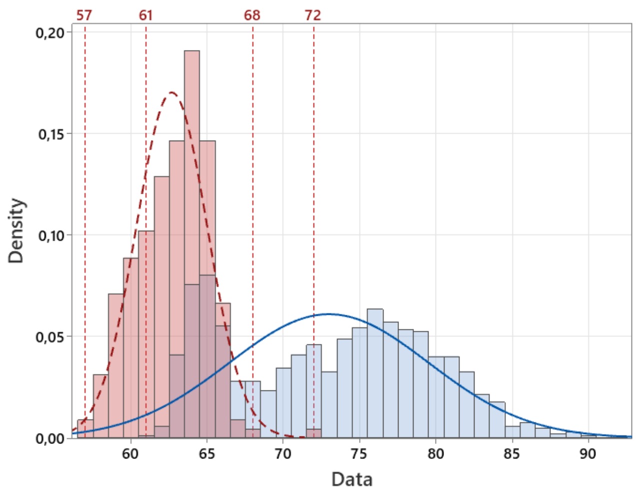

Figure 2. Distribution ERS *Neighbors* DB.

Figure 3 shows the distribution of ΔERS DB for bearings that triggered Clear and NOISY(RS1) alarms.

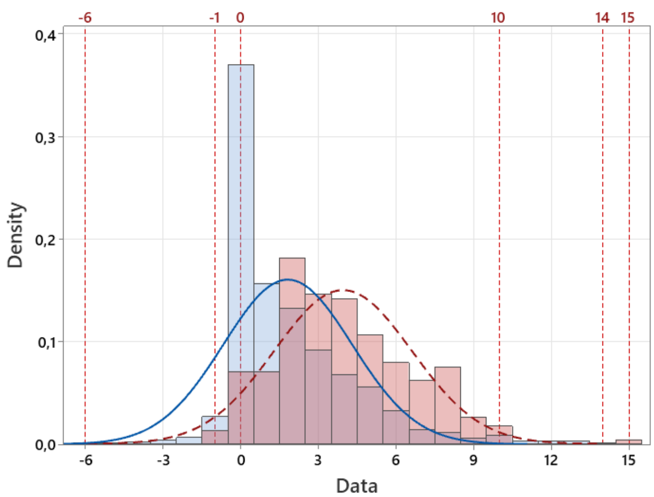

Figure 3. Distribution ΔERS DB.

Centroid Discriminant Analysis is a statistical method used to classify observations into known groups based on predictor variables, assuming that each group can be represented by its centroid (the mean vector of the variables). The analysis is based on the premise that each class—in this case, NOISY(RS1) and Clear—has a mean vector for the variables of interest. Each new observation is then assigned to the group whose centroid is closest, typically using either Euclidean distance or Mahalanobis distance.

The Mahalanobis distance between an observation vector x and the group mean μ is given by:

$$D_M(x) = \sqrt{(x - \mu)^T S^{-1} (x - \mu)} \qquad (1)$$

where:

- x is the vector of acoustic variables (ERS DB, ERS Neighbors DB);
- μ is the mean vector of the reference group (Clear Level 1);
- S^{-1} is the inverse covariance matrix of the variables.

In the analysis conducted using MINITAB 2022, ERS DB and ERS Neighbors were used as predictor variables. Since ΔERS is a linear combination of these two variables, it does not add a new informational dimension to the Mahalanobis analysis. Therefore, it was applied only as an additional filter after the main analysis was completed. The quadratic method was also used for class response, which does not assume equal covariances, and cross-validation was performed. The scatter plot with 95% confidence ellipses for each group is shown in Figure 4.

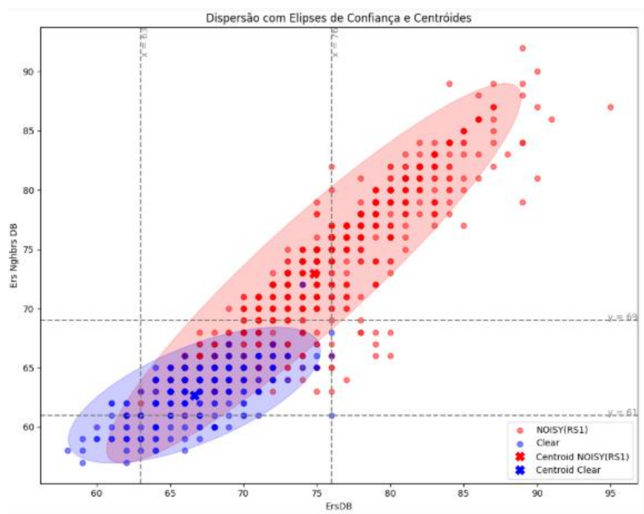

Figure 4. Scatter plot with 95% confidence ellipses.

Each point represents an observation based on the variables ERS DB and ERS Neighbors. The ellipses indicate the region where 95% of the observations for each group are expected to fall, assuming a normal distribution. This visualization helps to distinguish the separation between groups and the internal dispersion within each class.

The analysis identified 288 indications that were initially classified as NOISY(RS1) but were reallocated to the Clear group. Additionally, three indications originally classified as Clear were reassigned to the NOISY(RS1) group. As a result, 98.7% of the Clear group indications and 73% of the NOISY(RS1) indications remained in their original groups, as shown in Table 4.

Table 4. Summary of Classifications with Cross-Validation

Prediction	True Class: Clear	True Class: NOISY(RS1)
Clear	222	288
NOISY(RS1)	3	780
Total N	225	1068
Correct N	222	780
Proportion	0,987	0,730

The centroid of each group is, the mean of each variable within the respective group—is presented in Table 5.

Table 5. Group Centroids.

Class	Centroid ERS DB	Centroid ERS Neighbors DB
Clear	66.66	62.69
NOISY(RS1)	74.79	72.97

A statistical analysis was performed on the 288 NOISY(RS1) indications that exhibited Clear-like characteristics in the ERS DB, ERS Neighbors DB, and ΔERS parameters, as shown in Table 6.

Variable	N	μ	σ	Min	Q1	Med	Q3	Max
Noisy ErsDB	288	68,17	3,31	63	66	67	70	80
Noisy Ers Nghbrs DB	288	64,63	1,19	61	4	65	65	68
Noisy Delta Ers DB	288	3,54	2,90	0	1	3	5	14

Table 6. Descriptive Statistics of 288 NOISY(RS1) indications that exhibited Clear-like characteristics.

Due to the complexity of operational deployment, univariate thresholds were selected as the metric for limit definition, rather than adopting a multivariate criterion based on similarity ellipses.

Based on data analysis using descriptive statistics and individual value plots, it was possible to define acoustic ranges observed in bearings associated with Clear Level 1 alarms. The newly established rule considers bearings with NOISY(RS1) alarms (and its variants) as potentially faulty when they simultaneously meet the following criteria within a 30-day observation window:

- ERS DB between 63 and 76 dB;
- ERS Neighbors DB between 61 and 68 dB;
- ΔERS DB between 0 and 11 dB;
- Repetition: ≥3 occurrences of NOISY(RS1) alarms or variants.

The requirement of ≥3 repetitions within 30 days for NOISY(RS1) alarms is a key criterion because it:

- Reduces false positives (isolated noise events);
- Reinforces evidence of persistent real faults;
- Increases the reliability of fault signaling.

Criticality levels were defined based on the number of observed repetitions, according to the following criteria:

- Criticality 1 (C1): 4 or more occurrences, with a maintenance deadline of 30 days;
- Criticality 2 (C2): exactly 3 occurrences, with a maintenance deadline of 60 days.

Initially, Criticality 0 will not be considered in the application of this rule; therefore, the process will initially be guided by weekly demand planning

Experimental application of the rule led to the identification of two bearings that, although not prioritized by the current predictive matrix, exhibited real faults during physical inspections. Although repairable, these failures demonstrate the potential of the new approach to detect risk conditions that might otherwise be overlooked.

The first inspected bearing was from Wagon 1, axle 1, right side. As shown in Figure 6, the workshop inspection revealed:

- Presence of noise;
- Adapter marks with uneven seating;
- Resistance to rotation;
- Two bolts with excessive torque compared to the reference of 570 N·m ±4% (710 N·m and 705 N·m);
- Rollers with signs of overheating;
- Cup with contact marks from rollers.

Figure 6. Wagon 1, bearing 1, right side, with nonconformity marks on rollers and cup.

The second inspected bearing was from Wagon 2, axle 3, right side. As shown in Figure 7, the workshop inspection revealed the following issues:

- Presence of noise;
- Signs of grease leakage;
- Resistance to rotation;
- Two bolts with torque values outside the reference of 570 N·m ±4% (400 N·m, 560 N·m, and 700 N·m);
- Rollers with signs of overheating;
- Seal ring with groove;
- Backing ring with impact marks and excessive punching.

Figure 7. Wagon 2, bearing 3, right side, with nonconformity marks on rollers and signs of grease leakage.

By analyzing the ERS DB and ΔERS DB values, a noticeable drop is observed after the wheelset replacement, as expected. This behavior is illustrated in Figure 8 and 9 for bearing 1.

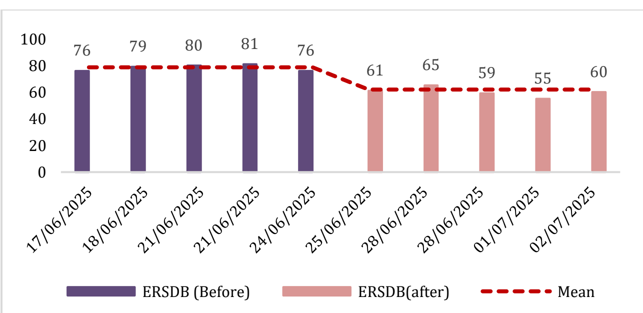

Figure 8. Reduction in ERS DB values for bearing 1,

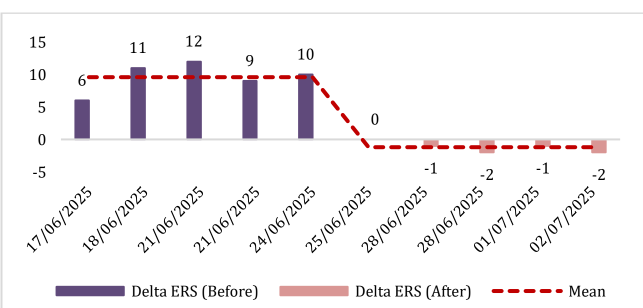

Figure 9. Reduction in ΔERS DB values for bearing 1.

For the data from bearing 3, wagon 2, right side, a similar drop in ERS DB and ΔERS DB values was observed after the wheelset replacement, as shown in Figure 10 and 11.

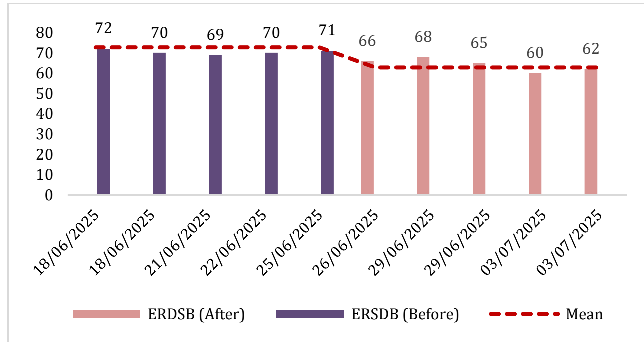

Figure 10. Reduction in ERS DB values for bearing 3, Wagon 2, right side, after replacement of the wheelset with a damaged bearing.

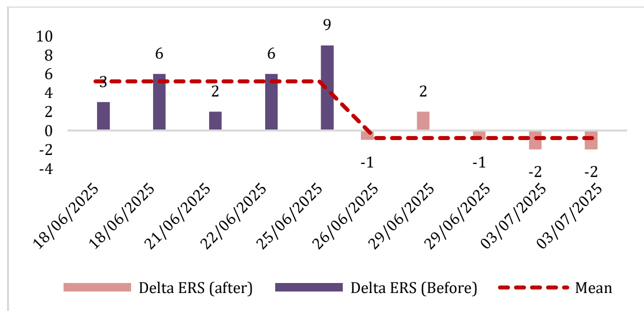

Figure 11. Reduction in ΔERS DB values for bearing 3.

This experimental correlation validated the potential of the new business rule to identify real bearing failures that were either hidden or not captured by the current prioritization model.

On August 12, 2025, a survey was conducted using the proposed rule within the supervisory system. As a result, 19 bearings were identified that had not previously been mapped for maintenance and were subsequently included through predictive indication. For the initial samples (12 bearings), the accuracy exceeded 80%, with 10 confirmed faulty bearings.

The study indicated that 27% of the bearings identified by the new criterion exhibit acoustic characteristics corresponding to clear level 1 alarms yet show potential to avoid being scrapped. Based on a projection using 2025 data, this could represent significant cost avoidance.

5. DISCUSSION

The implementation of the proposed rule represents a significant advancement in predictive prioritization accuracy, enabling earlier identification of bearings with real faults before they progress to more critical stages. This approach not only complements the existing prioritization matrix but also expands its coverage by incorporating cases that might otherwise go unnoticed. By substantially reducing the occurrence of undetected failures, especially those masked by wheel anomalies or ambiguous classifications, the methodology directly contributes to improved operational reliability.

Moreover, the proposed rule is grounded in a solid scientific foundation, supported by statistical principles that enhance its robustness within the context of predictive railway maintenance. It effectively addresses key gaps in the current matrix, particularly in situations where bearings with critical acoustic behavior are not flagged for investigation due to their classification as NOISY. By employing a statistically driven approach, the rule reduces subjectivity in analysis and strengthens the system's ability to detect real faults early, even when obscured by noise or interference.

The methodology also presents potential for further development through the integration of supervised machine learning models, where physically confirmed failures can serve as labels and acoustic parameters extracted over time windows as predictors. To ensure the rule's continued effectiveness, it is essential that it be periodically re-evaluated in light of new samples and emerging patterns. Additionally, seamless integration with existing systems and rules must be maintained to avoid operational conflicts. Finally, it is important to recognize that the rule's applicability may vary depending on wagon type, axle configuration, or operational conditions, requiring caution in its generalization.

6. CONCLUSION

This analysis demonstrated that NOISY(RS1) alarms and their variants, when evaluated based on multiple occurrences and specific statistical ranges, show potential for indicating early-stage real failures.

The new prioritization rule, based on descriptive statistics, represents a methodological and technical advancement, enabling a more precise, agile, and data-driven approach to support predictive maintenance of railway bearings.

The results obtained indicate the feasibility of incorporating this rule as a complementary prioritization tool, enhancing operational safety and the efficiency of predictive maintenance. Further testing and expansion of the data set are recommended to strengthen the robustness of the approach.

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BIOGRAPHIE

Leandro Rocha Lopes was born in São Luís, Maranhão, Brazil, on January 24, 1984. He holds a B.Sc. in Electrical Engineering and an M.Sc. in Automation and Control from the Federal University of Maranhão (UFMA), where he conducted research on reinforcement learning and adaptive dynamic programming for MIMO systems. He also completed a postgraduate specialization in Railway Engineering through Vale's technical development program.

With over 14 years of experience in railway maintenance, his professional focus lies in the application of predictive analytics and reliability engineering to support asset integrity and operational performance. From 2011 to 2019, he worked in the reliability division of automation systems at the Carajás Railway (EFC), contributing to the development of diagnostic strategies and reliability metrics for field instrumentation. Currently, he serves as an engineer at the Asset Monitoring Center (CMA) of EFC, where he leads initiatives involving the estimation of remaining useful life (RUL) of components, the formulation of predictive business rules, and the deployment of intelligent instrumentation-based solutions. His work integrates statistical modeling, acoustic signal analysis, and condition-based maintenance frameworks. He has participated in applied research projects in partnership with UFMA/CEMAR and served as an engineering evaluator at international science fairs. His technical qualifications include certifications in Reliability Engineering, Asset Management, and Data Analysis. His research interests encompass predictive maintenance, statistical fault detection, and intelligent monitoring systems for railway applications.