

Article

Diagnostic Analytics Powered by IoT and Machine Learning for the Fault Evaluation of a Heavy-Industry Gearbox

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Abstract

Predictive maintenance based on vibration monitoring can significantly improve gearbox reliability in heavy-industry environments. Although it is well established in vibration engineering that operating regimes influence vibration levels, the contribution of this work lies in providing an integrated, data-driven diagnostic linkage between continuously acquired IoT vibration indicators and key process/operational variables to identify and quantify the dominant drivers of vibration escalation. This study deployed wireless IoT sensors for continuous acquisition of RMS vibration and lubrication temperature in gearboxes operating in cement and mining plants and applied multivariate machine learning models to detect anomalies and identify root causes. We compared boosted multilayer feedforward neural networks, boosted trees, and k-nearest neighbors using RMS vibration and process variables including mill feed, lubrication pressures, and temperature. The boosted neural network delivered superior validation performance and isolated low or near-zero mill feed during operation as the primary driver of elevated RMS vibration, with lubrication instability acting as a secondary interacting factor. This shifts the diagnosis from a generic “high vibration during transients” statement to actionable operational mitigations—minimum feed set-points, controlled ramping logic, and lubrication pressure governance—supported by multivariate evidence. Our results motivate further validation with k-fold and out-of-time tests.

Keywords: predictive maintenance; vibration monitoring; industrial IoT; boosted neural networks; boosted trees; k nearest neighbors



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1. Introduction

The reliability of industrial gearboxes [1] is pivotal to maintaining the operational efficiency of heavy-industry production plants. These gearboxes endure significant mechanical stress, resulting in increased vibration levels [2], mechanical wear [3], and eventually failures [4].

While recent advancements have enhanced the operational precision of gears, the escalating demand has led to the emergence of minor issues such as gear misalignment, excessive backlash, and tooth cracks. These defects generate vibrations that can propagate failures to supporting components, including bearings and shafts. Vibration refers to the dynamic response of a machine’s mechanical components to internal or external excitations. According to international standards such as ISO 10816-3 [5], excessive vibration levels

measured on non-rotating parts are a key indicator of deteriorating mechanical condition in industrial machinery.

Vibration signal analysis is a highly effective method for detecting and diagnosing faults in gears [6–10]. Continuous monitoring of gearbox vibration signals is essential for identifying deterioration due to fault propagation, enabling the appropriate scheduling of preventive maintenance tasks and resulting in significant cost savings [11]. The main factors influencing the dynamic behavior of gears in transmission systems include excessive load, manufacturing tolerances, and installation errors. Although traditional vibration analysis techniques [12] are effective for diagnosing certain mechanical faults, they often struggle to detect complex failure patterns that are strongly influenced by operational conditions and system-level interactions [13].

Predictive maintenance relies on data-driven approaches to anticipate equipment failures before they occur, allowing maintenance actions to be planned at optimal times. By using Internet of Things (IoT) technologies [14] to collect real-time data from embedded sensors and applying machine learning (ML) techniques to identify patterns and anomalies [15–17], industrial operators can significantly reduce downtime, extend asset lifetime, and lower maintenance costs. Shankar et al. [18] demonstrated that vibration measurements in industrial environments can be effectively performed using low-cost commercial sensors integrated with IoT development platforms such as Arduino and Raspberry Pi.

Recent advances in machine learning have enabled more accurate and proactive maintenance strategies, allowing anomalies to be detected before they escalate into catastrophic failures [19–21]. In particular, unsupervised and self-supervised learning approaches have shown strong performance under variable operating conditions, as demonstrated by Dai et al. [22] for bearing anomaly detection using multisensor data. Praveenkumar et al. [23] applied Support Vector Machine (SVM) algorithms to vibration measurements for gearbox fault diagnosis. Neural networks have also been widely adopted, with Wang et al. [24] demonstrating their effectiveness for gearbox failure identification. Furthermore, explainable artificial intelligence techniques are increasingly being applied to improve interpretability in machine fault diagnosis [25].

In addition to vibration data, acoustic signals have been employed for condition monitoring; Abraham et al. [26] combined acoustic analysis with the J48 decision tree algorithm for gearbox fault classification. Regression-based approaches have also been explored, with Lv and Hu [27] applying multiple linear regression techniques for gearbox health assessment, and Hadi and Al-Haddad [28] proposing interpretable gradient-boosting models for vibration-based gear fault diagnosis.

This paper presents an approach that combines IoT-based vibration monitoring [29] with machine learning models for gearbox anomaly analysis. The study was conducted in two heavy-industry plants where gearboxes exhibited persistently high vibration levels, leading to unplanned downtime and increased maintenance costs. The main contributions of this work include the practical deployment of a wireless IoT-based vibration and temperature monitoring architecture on industrial gearboxes, a comparative evaluation of multiple machine learning model families with the selection of a validated champion diagnostic model, and a multivariate root-cause failure analysis linking startup vibration excursions to mill feed regimes and lubrication stability.

2. Methodology

2.1. Experimental Setup

The experimental setup corresponds to an industrial finishing mill gearbox operating in a heavy-industry environment. This study was conducted using data collected from two

similar installations, referred to as Plant 1 and Plant 2, each equipped with an IoT-supported condition monitoring system integrated with process telemetry from the finishing mill.

The monitored gearbox is a multi-stage reduction gearbox driving the finishing mill, operating under variable load and throughput conditions. To enable diagnostic analysis, vibration and process data were continuously acquired and synchronized, allowing the relationship between mechanical response and operating conditions to be analyzed under real industrial regimes.

2.1.1. Vibration Measurement Configuration

Six vibration measurement points were instrumented on the gearbox housing, distributed symmetrically on both sides of the casing, as illustrated in Figure 1. Due to the large axial shaft float/endplay (in the order of >1 inch) exhibited in the gearbox design, the operating loads of interest for this case were predominantly radial under these conditions, and axial vibration velocity (in/s) was not considered a primary indicator for the type of vibration escalation observed.

Wireless Sensors Software Asset/Components Hierarchy

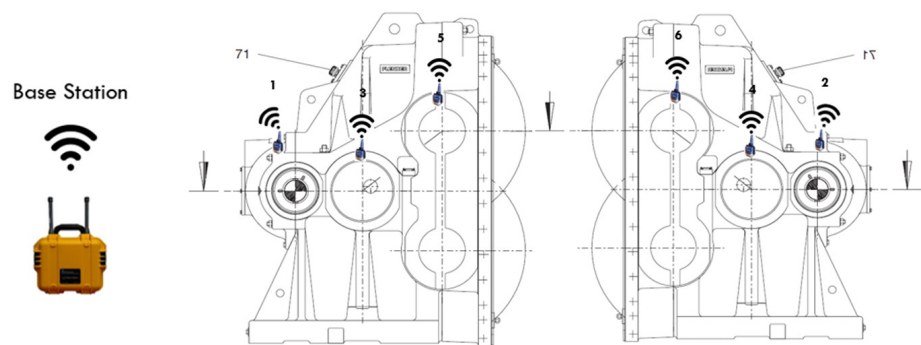
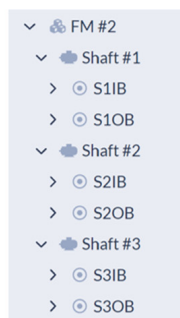


Figure 1. Gearbox IoT Architecture (IoT vibration temperature sensors deployment).

Because of this, sensors were installed in orthogonal directions (X and Y axes) to capture radial vibration responses associated with Shaft 1 bearing locations. This configuration enables the observation of directional vibration behavior and supports shaft-specific diagnostic modeling.

The machine learning models use an overall (global) RMS vibration indicator reported at 1 s resolution. This RMS value is computed from the underlying accelerometer signal over a defined time window and represents a time-domain summary metric (not a spectrum), while the spectra (FFT plots) are generated from the raw accelerometer waveform (high-rate stream), which is then transformed into the frequency domain to obtain the spectral content and identify the relevant frequency components.

The selected measurement locations and orientations were chosen to maximize sensitivity to gearbox dynamic behavior while ensuring robustness for long-term industrial monitoring.

2.1.2. Process and Operating Variables

In addition to vibration data, key finishing mill process variables were acquired from the plant automation system and synchronized with the vibration measurements. These variables represent the operational context of the gearbox and are critical for distinguishing load-driven effects from mechanical anomalies. The monitored process variables include mill feed rate, motor power, lubrication oil temperature, and lubrication system pressures at both the feed and discharge ends. A regime classification flag (stopped, startup, and

steady-state) was derived from process signals and incorporated into the dataset to support condition-dependent diagnostic modeling.

2.1.3. Data Synchronization and Dataset Construction

All vibration and process variables were time-aligned and aggregated to a common 1 s resolution. Continuous monitoring was performed over approximately six months per plant, resulting in a final dataset of approximately 2×10^6 synchronized samples per plant. As a result, the historian contained a very large number of timestamped records for each plant. The final modeling dataset was produced through a structured cleaning and selection workflow, which was a significant data-engineering challenge in this heavy-industry cement application.

The data preparation steps were guided by subject-matter expertise from professionals experienced in heavy-industry rotating machinery, specifically gearboxes, and included the following:

- Outlier and invalid-signal handling: removal of records associated with clearly non-physical readings and/or inadequate sensor signals (e.g., dropouts, spurious spikes, or corrupted measurements).
- Operating-regime filtering: Exclusion of startup and shutdown transient periods, which were not within the scope of this study. Only stable/steady-state operation was retained for modeling.
- Time-based equalization/consolidation: within steady-state operation, measurements were consolidated to provide a consistent representation of comparable time intervals and to reduce redundancy from highly correlated records.

This dataset forms the basis for machine learning-based diagnostic analytics focused on characterizing the vibration response associated with a previously detected gearbox anomaly.

2.1.4. Experimental Setup Summary

Table 1 exhibits the summary of the experimental setup.

Table 1. Summary of the experimental setup.

Category	Description
Industrial System	Finishing mill gearbox in a heavy-industry application
Plants	Two installations (Plant 1 and Plant 2)
Monitoring Approach	IoT-supported continuous condition monitoring
Vibration Measurement Points	6 locations on gearbox housing
Sensor Orientation	Radial directions (X and Y axes)
Monitored Shaft	Shaft 1 bearing locations
Vibration Metrics	RMS vibration velocity (in/s RMS)
Sampling and Aggregation	Continuous acquisition, aggregated to 1 s RMS
Process Variables	Mill feed rate (T/h), motor power (kW), lubrication oil temperature (°C), lubrication feed-end pressure (bar), and lubrication discharge-end pressure (bar)
Operating Regimes	Stopped, startup, and steady-state
Monitoring Duration	~6 months per plant
Dataset Size	~ 2×10^6 synchronized samples per plant
Diagnostic Focus	Machine learning-based diagnosis of a previously detected gearbox anomaly

2.2. IoT-Based Vibration Monitoring System

A wireless IoT-based system was deployed on the gearbox to continuously monitor vibration and temperature. The system architecture is shown in Figure 1 and consists of the following:

- **Wireless Vibration Sensors:** high-rate piezoelectric accelerometers SD-VSN-3 (see specifications in Appendix A) with 100 mV/g sensitivity and an effective frequency bandwidth of approximately 5 kHz were installed on the bearing housings associated with the three high-speed shafts by using magnetic bases to capture real-time vibration data.
- **Data Acquisition and Transmission:** sensors report overall RMS vibration derived from the accelerometer signal, together with lubrication temperature, and transmit data to a central cloud-based platform for further analysis.
- **Software Asset Hierarchy:** includes features for trend visualization, spectral analysis, and failure frequency tracking.

Wireless vibration and temperature sensors were installed on gearbox housings in two plants, referred to as Plant 1 and Plant 2. Sensors recorded the RMS vibration and the lubrication oil temperature. For reproducibility, the following dataset assumptions were used: continuous monitoring over six months per plant; effective vibration sampling at 10 Hz with RMS aggregation per 1 s window; and timestamp synchronization with process telemetry including feed rate, motor power, lubrication pressures, and lubrication temperature. The final modeling dataset comprised approximately 2×10^6 synchronized instants per plant after cleaning and aggregation to 1 s resolution.

Preprocessing steps:

- Lowpass filtering to remove high-frequency sensor noise.
- RMS computation per 1 s window to align vibration and process signals.
- Z-score normalization of continuous features.
- Outlier handling by winsorization at the 1st and 99th percentiles and removal of unsynchronized records.
- Feature enrichment with time lags and derivatives (lags of 1–60 s) to capture transient behavior.

Model inputs and targets:

- **Inputs:** vibration RMS X and Y axes (in/s RMS), oil temperature °C, lubrication discharge pressure bar, lubrication feed-end pressure bar, mill feed T/h, motor power kW, and regime flag (stopped, startup, and steady).

Targets: axis-specific RMS vibration series for Shaft 1 (S1OBX and S1OBY), modeled separately.

2.3. Severity Criteria

The vibration data was processed to determine severity levels based on industry standards and proprietary criteria developed for large-scale heavy-industry machinery, see Figure 2. The thresholds for risk classification were established as follows:

- **Warning:** >0.15 IPS RMS
- **Alert:** >0.20 IPS RMS
- **Alarm:** >0.30 IPS RMS

ISO 10816-3 standards [5] were referenced but supplemented with in-house criteria tailored for high-power cement industry gearboxes.

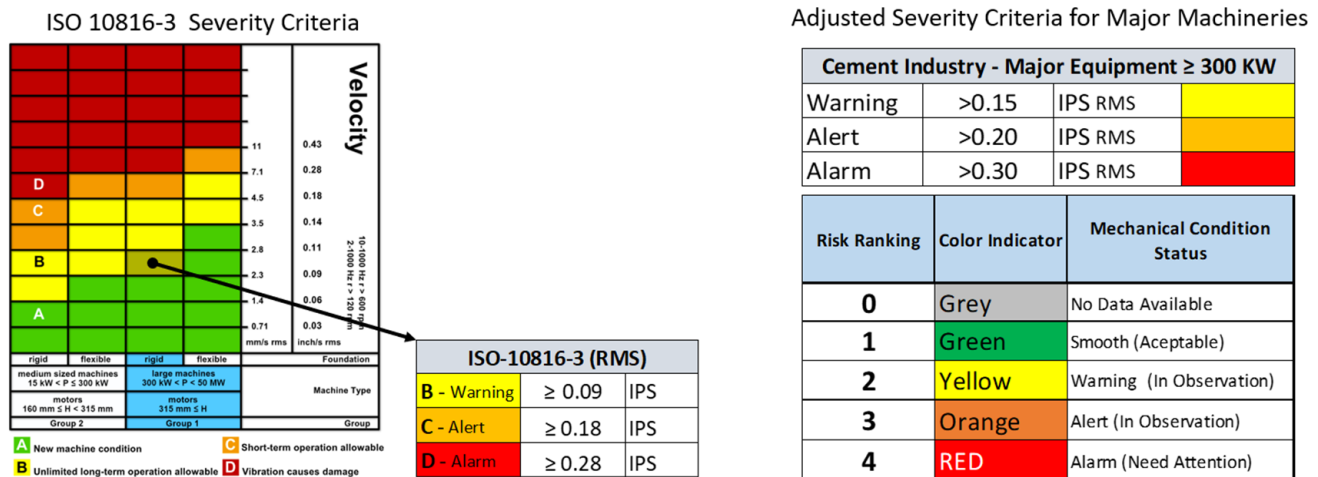


Figure 2. Vibration severity criteria for major gearboxes.

2.4. Modeling Approach and Selection

A data cleaning and filtering process was applied prior to modeling. Specifically, we restricted the modeling dataset to steady-state operating conditions, excluding startups and shutdowns, to avoid mixing transient dynamics with steady behavior.

All modeling was performed using JMP Pro 17 (SAS Institute), a commercial analytics and machine learning platform which provides built-in implementations of supervised learning methods (including boosted neural networks, boosted trees, and k-nearest neighbors) and integrated workflows for model training, validation, and comparison. A random holdback split of approximately 67% training and 33% validation was employed for initial selection. Selection prioritized a higher R^2 on validation and a lower RMSE on validation. Recommended additional validations before deployment include k-fold cross-validation and out-of-time validation.

Candidate models and key parameters:

- Boosted multilayer feedforward neural network boosted (MFNN): activation tanh; final architecture with three hidden layers with 64, 32, and 16 neurons; L2 regularization $\lambda = 1 \times 10^{-4}$; early stopping on validation loss; boosting with learning rate of 0.05; and inputs normalized.
- Boosted trees (BT): maximum depth, 4; n estimators, 100; learning rate, 0.1; and standard subsample and regularization from the Model Screening defaults.
- K-nearest neighbors (kNN): k swept 1 to 10; Euclidean distance on normalized features; and k selected by validation performance.

Robustness recommendations prior to production scoring run k-fold with $k = 5$ or 10, out-of-time validation, and stability checks, including bootstrap permutation importance and residual diagnostics.

2.4.1. Boosted Multilayer Feedforward Neural Network (MFNN)

A boosted multilayer feedforward neural network (MFNN) is an advanced neural network architecture that combines the structure of a multilayer feedforward network with the boosting technique to improve performance. This means that it uses multiple layers of neurons with connections that only move forward (no cycles) and combines multiple weaker models to create a single, more accurate, and robust final model.

It is often used for complex tasks like pattern recognition, where it can improve accuracy and robustness compared to a standard MFNN.

Thus, the architecture can be divided into the following layers, as it is shown in Figure 3:

1. **Input Layer:** it is the starting layer of the network that has a weight associated with the signals.
2. **Hidden Layer:** this layer lies after the input layer and contains multiple neurons that perform all computations and pass the result to the output unit.
3. **Output Layer:** it is a layer that contains output units or neurons and receives processed data from the hidden layer; if there are further hidden layers connected to it, then it passes the weighted unit to the connected hidden layer for further processing to obtain the desired result.

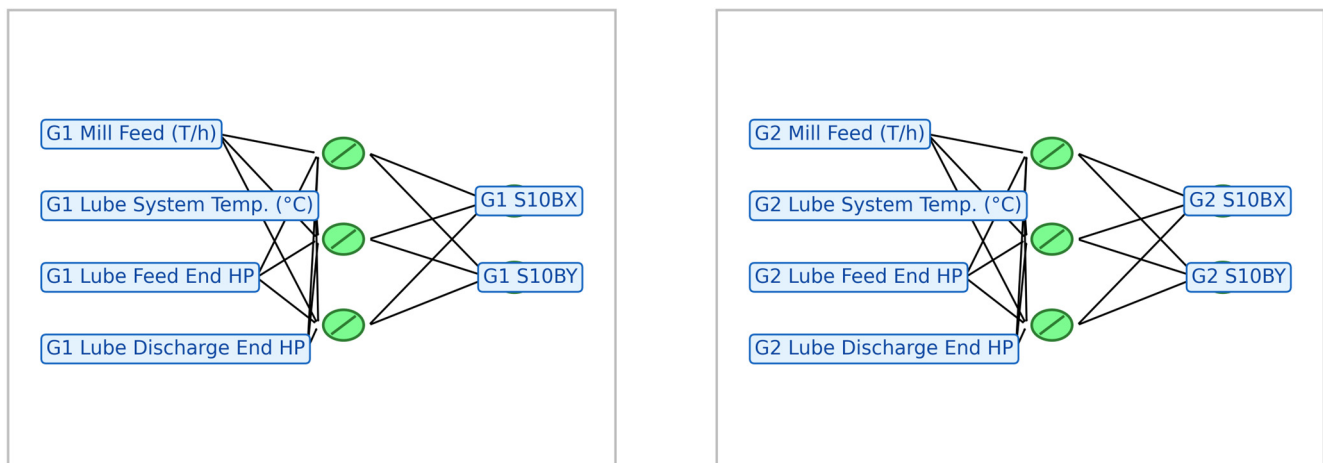


Figure 3. Architecture of the MFNN.

The MFNN was implemented in JMP Pro 17 via Model Screening. The activation function chosen was a hyperbolic tangent ($\tanh$) network with boosting, see Equation (1). The data were split by random holdback (~67/33). Across targets, validation R^2 was in the high range of 0.98–0.99, having the lowest RMSE among all candidates.

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (1)$$

This model captures interactions among process variables and vibration response and tracks regime changes (e.g., operating transients) better than purely linear approaches.

Advantages: strong nonlinear modeling capacity; best validation metrics among the candidates in this study.

Limitations: lower interpretability than trees or linear models; requires routine checks for overfitting and stability (recommended k-fold cross-validation and out-of-time validation).

2.4.2. Boosted Trees (BTs)

Boosted trees (BTs) are developed based on the decision tree (DT) model and derived from the Ensemble Learning Boosting algorithm. BT represents a flexible, non-parametric statistical learning technique that ranks among the most potent ML models for predictive analyses, making it a widely adopted method in ML applications. Its distinctive framework enhances the stability, precision, and computational efficiency of the predictions, rendering it the preferred choice for diverse applications demanding optimal accuracy and robustness. Boosting deals with errors created by previous decision trees. In boosting, new trees are formed by considering the errors of trees in previous rounds. Therefore, new trees are created one after another. Each tree is dependent on the previous tree. This type of learning is called sequential learning, where parallel computing is not ideal to perform (see Figure 4).

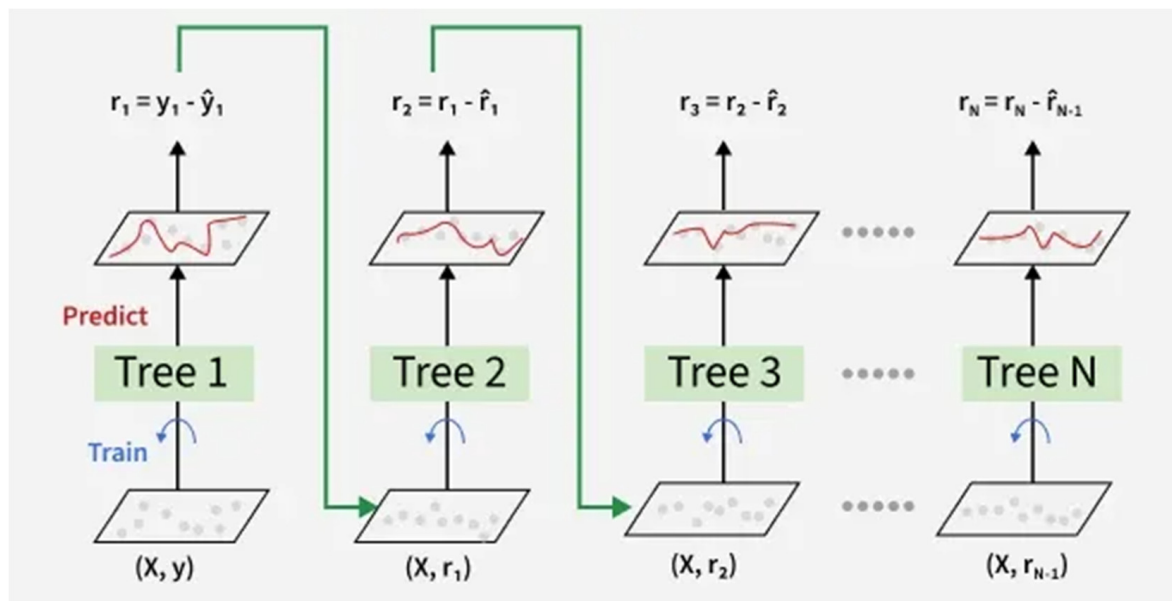


Figure 4. Boosted trees sequential learning process.

The prediction from one DT is given by Equation (2):

$$\hat{y}(x) = \sum_{m=1}^M c_m 1\{x \in R_m\} \quad (2)$$

where

- R_m is the region of the feature space corresponding to the m-th leaf;
- c_m is the average (or median) of the target values in leaf m during training;
- $1\{x \in R_m\}$ is an indicator function that equals 1 if the input x falls into region R_m and 0 otherwise.

Once all trees are trained, predictions are made by summing the contributions of all the trees. The final prediction is given by Equation (3)

$$y_{pred} = y_1 + \eta \cdot r_1 + \eta \cdot r_2 + \dots + \eta \cdot r_n \quad (3)$$

where $r_1, r_2, \dots, r_n$ are the errors predicted by each tree and η is the learning rate.

BTs were implemented in JMP Pro 17. Their parameters and properties used were as follows:

- Tree options: the number of levels (tree depth) is 4.
- Boost options: the number of models is 100, the learning rate is 0.1, and the alpha is 0.95.

In the runs documented here, boosted trees reported training fit but lacked holdback validation rows in several targets, which prevents a fair generalization comparison.

The observed performance in training R^2 can appear high in some contexts, but without validation evaluation, the generalization error is unknown, and apparent accuracy may be inflated.

Advantages: intuitive, fast to train, and helpful for variable influence and rule-like insight.

Limitations: Sensitive to configuration and data partitioning; without explicit validation, the overfitting risk is elevated. Did not surpass the boosted neural model on validated comparisons in this study.

2.4.3. K-Nearest Neighbors

KNN is a non-parametric, supervised learning classifier method that makes classifications or predictions about the grouping of an individual data point.

Unlike neural networks, it does not involve parameter learning during the training period or phase. Instead, it relies on the distance matrix to classify the new examples as it is shown in Figure 5 where new sample is classified within Class 2 based on its distance to the other data.

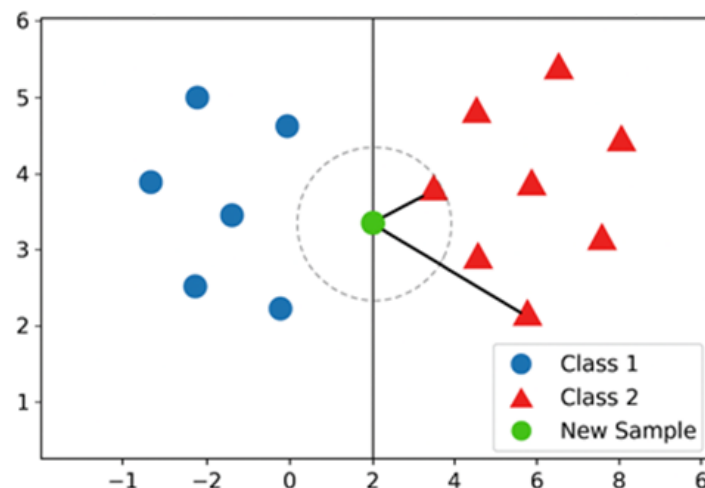


Figure 5. Example of how KNN classifies a new sample.

The K-NN algorithm calculates the distance between a new data point and all the examples in the training set. The matrices of common distances include the following two types of distances:

- **Euclidean distance:** This is the most commonly used distance measure, and it is limited to real-valued vectors. Using Equation (4), it measures a straight line between the query point and the other point being measured.

$$d(x, y) = \sqrt{\sum_{i=1}^n (y_i - x_i)^2} \quad (4)$$

- **Manhattan distance:** this is also another popular distance metric, which measures the absolute value between two points, as it can be seen in Equation (5).

$$d(x, y) = \left(\sum_{i=1}^m |x_i - y_i| \right) \quad (5)$$

kNN was implemented in JMP Pro 17 with a sweep over k (e.g., 1–10). In these runs, kNN primarily reported training metrics; holdback validation was not available for all targets, limiting generalization assessment.

The observed performance was a competitive training fit in some targets, but without consistent validation.

Advantages: simple baseline, low modeling assumptions, and can capture local structure.

Limitations: sensitive to feature scaling, noise, and irrelevant variables; computationally heavier at prediction time; and requires careful validation to avoid optimistic training results.

3. Results and Discussion

3.1. Vibration Trends and Failure Patterns

Figure 6 illustrates the vibration trends during the monitoring of Gearbox #1. The blue trace depicts the overall vibration trend (in/s) for Shaft #1 along one axis (X or Y). Notably, this axis occasionally spikes into the red alarm zone, surpassing the yellow alert threshold. Meanwhile, the red trace—representing the other axis on Shaft #1—generally remains within the yellow alert band, although it also shows intermittent peaks. A key observation is that vibration levels often rise significantly right after the mill stops and again during startup, emphasizing how transient conditions can provoke higher mechanical stress.

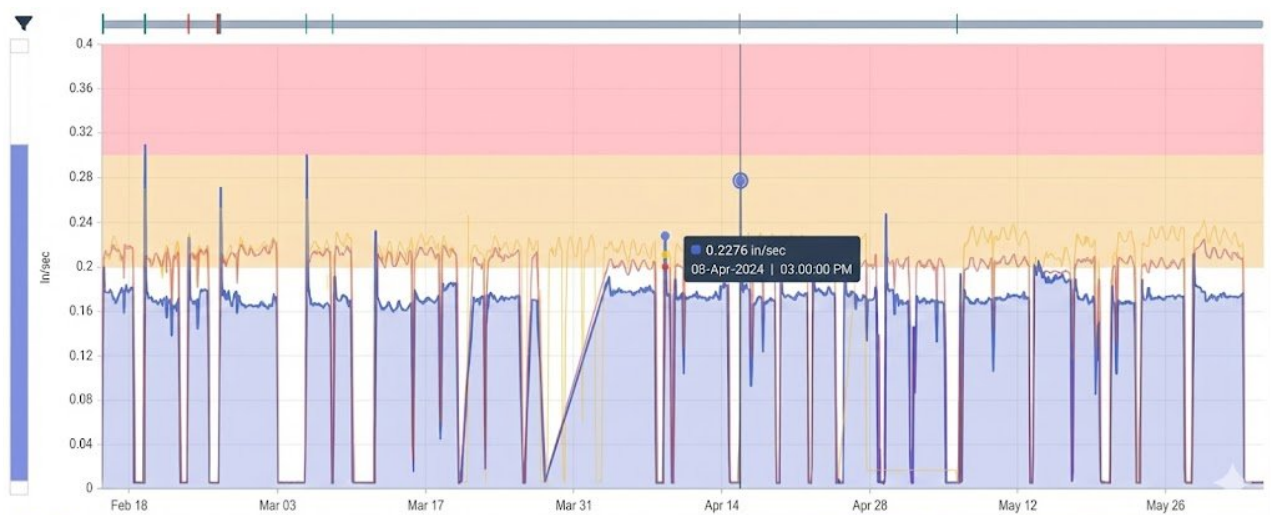


Figure 6. Mechanical vibration trends in Gearbox #1.

The vibration analysis showed that anomalies predominantly occurred during mill startup phases. Significant increases in vibration levels (>0.36 in/s IPS) were observed during these periods. The ML model identified clear correlations between these vibration peaks and process variables such as mill loading, lubrication system pressure, and operational startup procedures.

The vibration spectrum for Shaft #1 in Gearbox #1 is shown in Figure 7, with frequency (Hz) on the horizontal axis and amplitude (in/s) on the vertical axis. A dominant peak appears around 458 Hz at 0.33 in/s, indicating a principal vibration frequency. Several in-depth analyses, performed by Category 3 and 4 vibration specialists, noted irregularities in the vibration patterns. The apparent randomness prompted an expanded investigation into potential process or systemic variables—such as lubrication pressure or mill feed rate—that could correlate with and potentially explain these fluctuations.

Figure 8 shows the overall vibration trends for Gearbox #2, which exhibits a similar profile to Gearbox #1. In this case, some periodic excursions into the red alarm region can also be appreciated, with amplitudes exceeding 0.36 in/s. In accordance with Gearbox #1 results, the most pronounced vibration spikes occur during startup sequences. This parallel in behavior between the two gearboxes reinforces the hypothesis of a common underlying cause and underscores the value of a unified data analysis approach for both units.

The vibration spectrum for Shaft #1 in Gearbox #2 features a prominent peak around 418 Hz at 0.25 in/s, a value comparable to Gearbox #1's characteristic frequency (albeit slightly shifted due to speed variations), as seen in Figure 9. This close alignment across two distinct plants suggests a shared failure mode. Consequently, leveraging advanced analytics to thoroughly investigate these recurring vibration frequencies becomes essential for preempting gearbox damage and optimizing maintenance strategies.

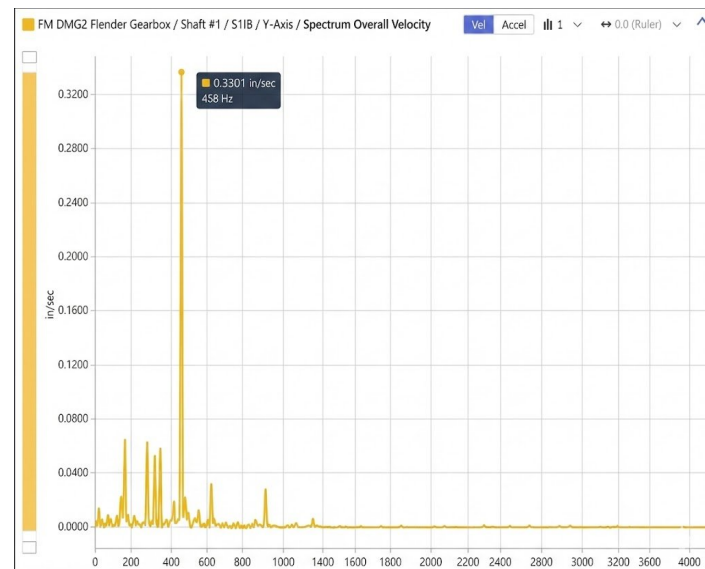


Figure 7. Mechanical vibration spectrum in Gearbox #1.

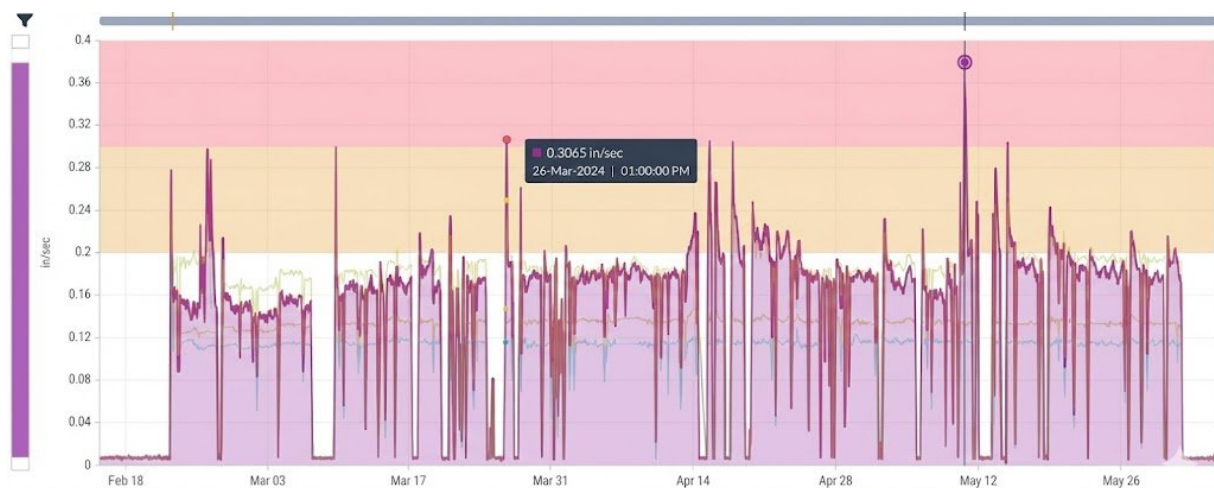


Figure 8. Mechanical vibration trends in Gearbox #2.

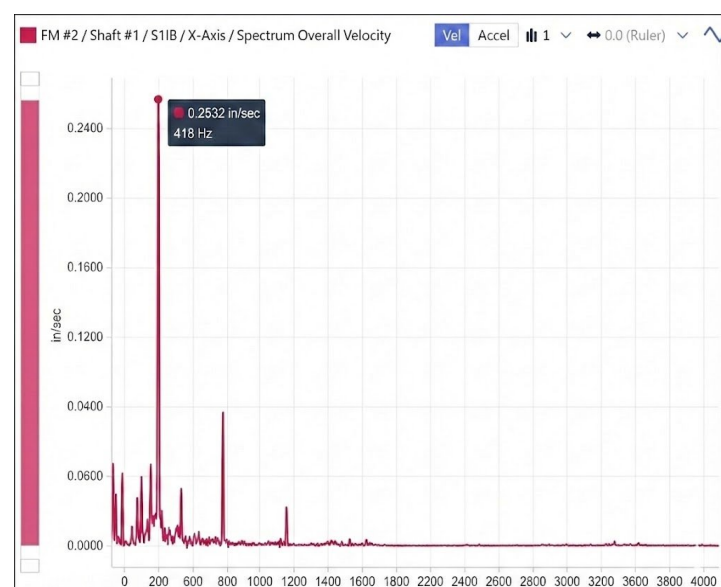


Figure 9. Mechanical vibration spectrum in Gearbox #2.

3.2. Results Interpretation Based on the Evaluated Models (Neural Boosted, Boosted Tree, and k-Nearest Neighbors)

By applying the models in JMP Pro 17 with a random holdback split (~67/33), consistent evidence is obtained that mill feed (T/h) is the dominant driver of gearbox vibration. Variable-importance tables show mill feed with the largest Main and Total Effects, while lubrication pressures and lube-system temperature contribute at much smaller scales. This pattern is consistent across both gearboxes (G1 and G2) and axes (S1OBX and S1OBY). On validation, boosted trees achieved the highest R^2 and lowest RMSE in Plant 2 targets and were competitive in Plant 1, leading to their selection as the primary model for scoring and diagnostics. Boosted neural networks provided strong complementary performance, particularly in capturing interactions, see Tables 2 and 3.

Table 2. G1 (Plant 1)—Model Comparison (Validation metrics).

Target	Model	Valid N	Validation R^2	Validation RMSE
S1OBX	Neural (boosted)	333	0.9883	0.0037
S1OBX	Boosted Tree	333	0.9940	0.0046
S1OBX	k-Nearest Neighbors	333	0.9707	0.0102
S1OBY	Neural (boosted)	333	0.9926	0.0053
S1OBY	Boosted Tree	333	0.9934	0.0080
S1OBY	k-Nearest Neighbors	333	0.97012	0.01713

Table 3. G2 (Plant 2)—Model Comparison (Validation metrics).

Target	Model	Valid N	Validation R^2	Validation RMSE
S1OBX	Neural (boosted)	333	0.9878	0.0036
S1OBX	Boosted Tree	333	0.9928	0.0028
S1OBX	k-Nearest Neighbors	333	0.9689	0.0058
S1OBY	Neural (boosted)	333	0.9911	0.0055
S1OBY	Boosted Tree	333	0.9936	0.0047
S1OBY	k-Nearest Neighbors	333	0.9718	0.0099

In Gearbox 1, mill feed ranks first overall, with lubrication pressure next, and then lube temperature. A very similar behavior is observed in Gearbox 2, where mill feed ranks first by a wide margin, while lubrication feed-end high pressure and lube temperature appear as secondary contributors, with smaller Main Effects and interaction-driven Total Effects. This indicates that controlling feed rate is the most direct lever, while stabilizing lubrication pressure and temperature helps mitigate excursions under load or during transients. For model results comparison, see Figure 10.

Baseline model context:

- k-Nearest Neighbors (kNN): k sweeps yielded competitive training fit in some targets, but consistent holdback validation was not available in these outputs. kNN did not surpass the Neural model on validated comparisons.

The numerical results reported in Tables 1 and 2 motivated the selection of boosted trees as the reference model (based on the best overall balance of predictive performance and practical interpretability).

MFNN

Overall				
Column	Main Effect	Total Effect	0.2	0.4 0.6 0.8
G1 Mill Feed (T/h)	0.984	0.993		
G1 Lube Discharge End HP	2×10^{-5}	5×10^{-5}		
G1 Lube System Temp. (°F)	2×10^{-5}	4×10^{-5}		
G1 Lube Feed End HP	2×10^{-5}	4×10^{-5}		

Overall				
Column	Main Effect	Total Effect	0.2	0.4 0.6 0.8
G2 Mill Feed (T/h)	0.978	0.984		
G2 Lube System Temp. (°F)	1×10^{-4}	3×10^{-4}		
G2 Lube Feed End HP	1×10^{-4}	2×10^{-4}		
G2 Lube Discharge End HP	1×10^{-4}	2×10^{-4}		

BT

Summary Report				
Column	Main Effect	Total Effect	0.2	0.4 0.6 0.8
G1 Mill Feed (T/h)	0.984	0.997		
G1 Lube System Temp. (°F)	8×10^{-18}	2×10^{-17}		
G1 Lube Feed End HP	8×10^{-18}	2×10^{-17}		
G1 Lube Discharge End HP	8×10^{-18}	2×10^{-17}		

Summary Report				
Column	Main Effect	Total Effect	0.2	0.4 0.6 0.8
G2 Mill Feed (T/h)	0.981	0.995		
G2 Lube System Temp. (°F)	1×10^{-17}	2×10^{-17}		
G2 Lube Feed End HP	1×10^{-17}	2×10^{-17}		
G2 Lube Discharge End HP	1×10^{-17}	2×10^{-17}		

KNN

Overall				
Column	Main Effect	Total Effect	0.2	0.4 0.6 0.8
G1 Mill Feed (T/h)	0.984	0.993		
G1 Lube Discharge End HP	2×10^{-5}	5×10^{-5}		
G1 Lube System Temp. (°F)	2×10^{-5}	4×10^{-5}		
G1 Lube Feed End HP	2×10^{-5}	4×10^{-5}		

Overall				
Column	Main Effect	Total Effect	0.2	0.4 0.6 0.8
G2 Mill Feed (T/h)	0.978	0.984		
G2 Lube System Temp. (°F)	1×10^{-4}	3×10^{-4}		
G2 Lube Feed End HP	1×10^{-4}	2×10^{-4}		
G2 Lube Discharge End HP	1×10^{-4}	2×10^{-4}		

Figure 10. Model comparison (variable-importance metrics).**3.3. Root Cause Failure Analysis (RCFA)**

A structured fault-tree perspective was combined with evidence from the validated boosted neural model in JMP Pro 17 (see Figure 11). The goal was to separate process-regime drivers from purely mechanical contributors and to identify the conditions under which vibration excursions are most likely.

Key findings:

1. Process regime (primary driver): The most consistent driver of gearbox vibration is the mill feed (T/h). Neural variable-importance results show mill feed with the largest Main and Total Effects across gearboxes (G1 and G2) and axes (S1OBX and S1OBY). Practically, the highest risk windows occur at very low or near-zero feed during startups and ramp-ups. Under these conditions, small disturbances can trigger disproportionate vibration responses. This finding contradicts the initial intuition that heavy load would be the dominant cause.
2. Lubrication system effects (secondary but material): Transient pressure spikes and unstable lubrication conditions can amplify vibration, particularly when coincident with low-feed operation. Mechanistically, unstable film formation and short-term changes in oil flow/pressure can increase tooth contact variability and excite mesh dynamics. While the absolute effect sizes of lube variables are smaller than feed, their interaction with feed is meaningful (Total Effect > Main Effect), indicating non-additive behavior.
3. Mechanical contributors (context): Classic mechanical factors such as alignment, backlash, bearing condition, and gear mesh quality remain credible contributors. However, within the scope of this dataset, their influence appears largely mediated by the operating regime (feed) and lubrication stability. This does not rule them out; rather, it suggests they are less frequently the initiating cause of the observed excursions.

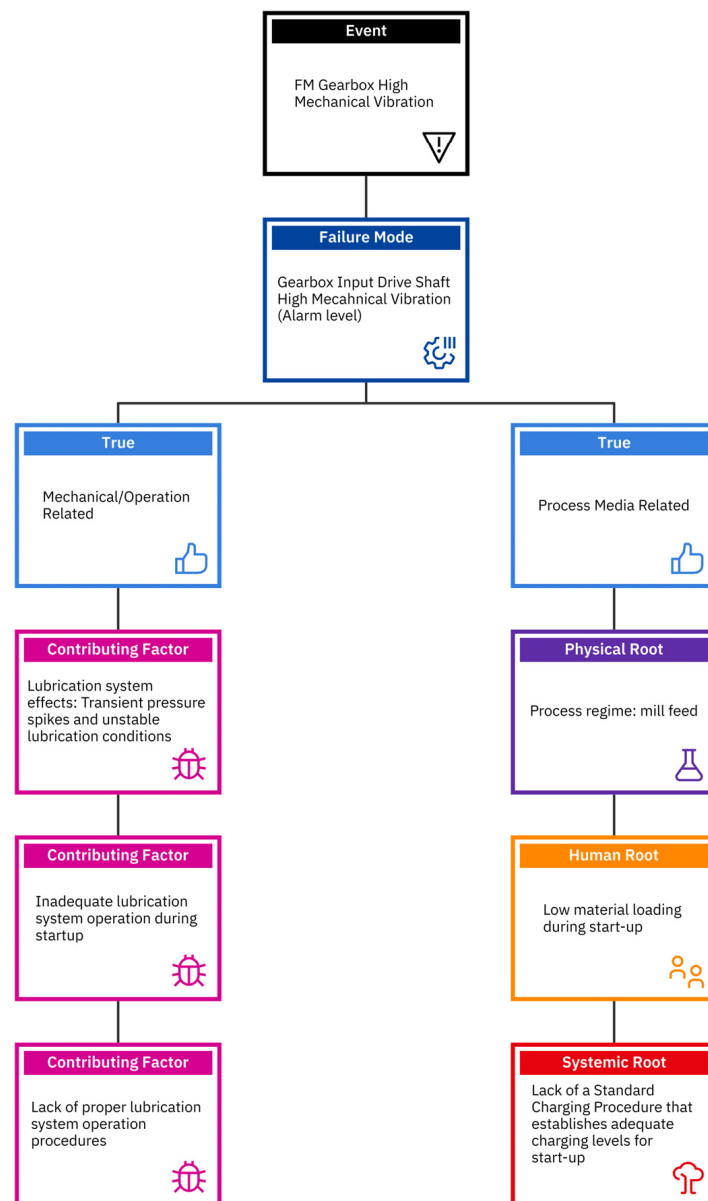


Figure 11. Failure root cause analysis—Validation.

Interaction insight: The consistent gap between Main and Total Effects indicates that variables do not act in isolation. In practice, a low or rapidly changing feed combined with small lubrication pressure fluctuations can yield a vibration response larger than the sum of each factor alone. This supports a control strategy focused on stabilizing the operating regime during startups and transients.

Operational recommendations from the RCFA:

- **Startup and ramp strategy:** establish minimum feed set-points before releasing to normal operation; apply controlled ramps to avoid low-feed dwell times; and monitor for rapid feed oscillations.
- **Lubrication stability:** enforce pressure stability targets, verify pump performance curves at the expected operating points, and maintain oil quality and temperature within tighter bands.
- **Monitoring and governance:** add operator prompts and interlocks for low-feed startups; pair feed control with real-time lube pressure checks to suppress excursions; and document exceptions and review them weekly.

Limitations and confidence: Our results are based on the present sensors and operating envelopes. The evidence base is strong for the process-regime driver (feed) and supportive for lubrication interactions, but causal confirmation for purely mechanical hypotheses will benefit from targeted inspections, controlled tests, or additional instrumentation.

4. Conclusions

Integrating IoT-grade vibration trends with a validated boosted tree model in JMP Pro 17 clarified the primary drivers of gearbox vibration in this mill service. Contrary to the original hypothesis, excursions are most prone to occur at low or near-zero feed conditions (startups and early ramp-ups), not at sustained heavy load. Lubrication pressure stability acts as an important secondary modifier that can amplify responses under sensitive regimes. Taken together, these findings point to a process-first mitigation strategy: stabilize feed during startups and enforce lubrication pressure control while continuing to verify mechanical health via routine inspection.

Immediate operational impact:

- Feed governance: implement minimum feed thresholds before transition to normal operation; define ramp-rate guardrails; and flag prolonged low-feed dwell.
- Lubrication control: set narrower pressure and temperature bands for startup and ramp; verify pump health and control loop tuning; and add alarms for fast pressure transients.
- Alarming and human-in-the-loop: convert the model's signals into clear operator prompts and priority alerts during startups and high-risk regimes.

Future work:

- Integrate axial measurements for certain fault mechanisms such as misalignment, axial loading or mounting issues to complete the diagnostic assessment.
- Model robustness and scope: add k-fold cross-validation and out-of-time validation; expand the feature set (torque, shaft load, oil temperature at critical points, and gear mesh indicators); and evaluate multi-target models for X/Y axes simultaneously.
- Sensing and data quality: consider higher-frequency accelerometers at mesh and bearing locations; ensure synchronized timestamps among process and vibration channels; and standardize data preprocessing and health checks.
- Real-time deployment: implement streaming model scoring with simple rules for RASE- and residual-based anomaly flags; publish alerts to the control room with recommended operator actions.
- Process optimization studies: design small, controlled ramp experiments to quantify how specific feed profiles and lubrication set-points affect vibration; update standard operating procedures and training materials accordingly.
- Mechanical verification: when the model flags persistent anomalies outside of known process regimes, it triggers targeted inspections (alignment, backlash, and bearing condition) to confirm or dismiss mechanical root causes.

Overall, a combined focus on process regime (feed) and lubrication stability, supported by a validated predictive model, offers a practical path to reduce vibration excursions, extend gearbox life, and improve plant reliability.

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Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

VIBRATION SENSOR NODE SPECIFICATIONS	
Mechanical	
Weight	6.6 oz (188 g)
Enclosure Material	303 Stainless Steel and Radel R 5800
Environmental	
Storage Temperature	-40 to 238 °F (-40 to 120 °C)
Min. Operating Temp.	-4 °F (-20 °C)
Max. Operating Temp.	230 °F (110 °C) surface @ 72 °F (22 °C) ambient 212 °F (100 °C) surface @ 105 °F (40 °C) ambient 167 °F (75 °C) surface @ 167 °F (75 °C) ambient
IP Rating	IP68, dust-tight and water-tight
Impact Resistance	Survives 5-ft drop onto concrete surface
Hazardous Certification	Class I, Division 2, Groups A-D, T5 (model SD-VSN-3N)
Wireless Radio	
Radio	KCF DART™ Wireless 2.4GHz ISM band, FCC ID #Z5ISD2
Range	800ft (240m) in open field 200ft (60m) in congested industrial space (site survey recommended for installation) Repeater SD-R adds up to 2400ft (730m) of range
Antenna	Internal dipole antenna
Power	
Power Source	3-Volt Lithium Manganese Dioxide (CR123A)
Battery Life	Full spectrum acquisition every: • 60 minutes – 8 years • 15 minutes – 6 years • 2.5 minutes – 2 years Note: battery life is somewhat reduced at extremely cold temperatures
Accelerometer	
Range	+/- 19 g typical, +/- 16 g nominal
Resolution	0.866 mg nominal w/ individual NIST-traceable calibration
Noise Floor	1.496 mg RMS @ 64 Hz / 13.01 mg RMS @ 8192 Hz
Transverse Sensitivity	10% Typical
Frequency Response	+/- 5% 0-2700 Hz, +/- 3 dB 2700-4000 Hz
Samples per Acquisition	4096 (standard) or 1650 (battery saver)
Spectral Lines	2048 (standard) or 825 (battery saver)
Anti-Aliasing Filter	4000 Hz low-pass cut-off, 3rd-order Sallen-Key
Sampling frequency	64 Hz – 8192 Hz configurable (see table)
Temperature Sensor	
Range	-4 to 167 °F (-20 to 75 °C)
Resolution	+/- 1 °F (+/- 0.5 °C)

Figure A1. Vibration Sensor Node SD-VSN-3.

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