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# Predictive Maintenance and Condition Monitoring of Industrial Machinery using Vibration Sensors

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**ABSTRACT:** Industrial machinery employed in high-demand operational environments experiences continuous mechanical, thermal, and dynamic stresses that eventually lead to component deterioration, performance loss, and unexpected failures. These failures result in unplanned downtime, higher maintenance costs, and operational inefficiency. Predictive maintenance provides a forward-looking solution by identifying early fault characteristics before they escalate into severe damage. The research methodology includes experimental vibration data acquisition, preprocessing of raw displacement signals, extraction of time-domain and frequency-domain features, generation of orbit plots, and diagnostic evaluation. Key features such as RMS, peak-to-peak displacement, crest factor, harmonic amplitudes, and high-frequency components were analyzed to identify common mechanical faults. Orbit analysis further supported the detection of shaft instability, rubs, and misalignment. The study demonstrates that proximity probe-based vibration monitoring significantly enhances fault detection accuracy and provides actionable insights for maintenance scheduling. The results confirm that vibration signatures generated by mechanical defects can be reliably identified through systematic signal analysis.

## I. INTRODUCTION

Industrial machinery forms the backbone of modern manufacturing, processing, energy generation, and material-handling systems. These machines typically operate under continuous or varying load conditions, often involving high-speed rotating components such as motors, pumps, turbines, compressors, blowers, and gear-driven assemblies. During prolonged operation, rotating components experience wear, thermal expansion, lubrication degradation, misalignment, and mechanical stress. These factors contribute to progressive deterioration that, if undetected, can result in unexpected breakdowns, production delays, safety risks, and significant maintenance expenditure. As industries strive toward enhanced reliability, optimized asset utilization, and reduced operational interruptions, predictive maintenance has emerged as a vital maintenance strategy.

Predictive maintenance (PdM) uses real-time and historical machine data to forecast faults and determine the optimal time for maintenance actions. This approach differs fundamentally from preventive maintenance, which follows preset schedules irrespective of actual machine health. Among the various techniques used in PdM—thermography, oil analysis, acoustic monitoring, structural analysis, and electrical signature analysis—vibration-based condition monitoring (VCM) remains the most effective for diagnosing rotating machinery. Mechanical faults manifest as distinct vibration signatures, enabling early detection long before visible symptoms appear.

Proximity probe vibration sensors play a critical role in analyzing the dynamic behaviour of rotating shafts. Unlike accelerometers that measure casing vibration, proximity probes measure relative shaft displacement using the eddy-current principle. This provides a direct and highly sensitive measurement of shaft motion, orbit shape, and dynamic instability. Proximity probes are particularly effective for turbomachinery and journal-bearing-supported equipment, where shaft motion is the primary indicator of mechanical condition. These sensors follow the guidelines of international standards such as API 670, making them industry best practice for high-speed rotating equipment.

Mechanical faults such as unbalance, misalignment, bearing defects, rotor looseness, shaft cracks, and hydrodynamic instabilities generate characteristic vibration patterns. Unbalance amplifies the  $1\times$  rotational frequency, misalignment produces strong  $2\times$  or  $3\times$  harmonics, and bearing wear introduces high-frequency resonances. Orbit distortion is a direct indication of shaft instability or looseness. Time-domain features—including RMS, peak-to-peak displacement, kurtosis, and crest factor—provide valuable information on vibration magnitude and transient spikes. Complementing these, frequency-domain analysis using Fast Fourier Transform (FFT) reveals harmonic content and sideband patterns associated with specific fault types. This multi-domain analysis allows maintenance engineers to identify not only the presence of faults but also their nature and severity.

Industries are progressively adopting sensor-based monitoring systems to integrate with digital platforms, supervisory control and data acquisition (SCADA) systems, and Industry 4.0 architectures. Continuous vibration monitoring enables maintenance teams to intervene before faults become severe, thus preventing catastrophic failures, reducing downtime, improving safety, and optimizing maintenance budgets.

This study develops a structured vibration-based predictive maintenance approach utilizing proximity probe sensors for monitoring industrial machinery. The methodology covers sensor deployment, data acquisition, signal preprocessing, feature extraction, orbit analysis, and diagnostic interpretation. The overall objective is to demonstrate how vibration signatures captured through proximity probes can accurately detect early mechanical faults and support informed maintenance decision-making. The findings contribute to the growing body of research on vibration-based PdM and highlight practical benefits for industrial applications.

## II. LITERATURE REVIEW

Predictive maintenance has become a widely researched topic across industrial domains, driven by the need to minimize equipment downtime, improve operational reliability, and support data-centric maintenance planning. Among the various techniques available, vibration-based condition monitoring has consistently been recognized as one of the most effective methodologies for diagnosing mechanical faults in rotating machinery. Numerous studies emphasize that mechanical defects alter vibration amplitude, harmonic composition, and shaft dynamic behaviour, making vibration data a reliable indicator of machine health [1,3].

Research on bearing diagnostics shows that rolling-element bearing defects generate periodic impact forces that translate into high-frequency vibration responses. These defect signatures typically appear at characteristic frequencies such as Ball Pass Frequency Inner Race (BPFI), Ball Pass Frequency Outer Race (BPFO), and Ball Spin Frequency (BSF), which have been extensively documented in classical bearing analysis literature [10, 13]. Further studies introduced demodulation and envelope detection to capture weak bearing defects by isolating modulated high-frequency components [11], enhancing fault detection accuracy in noisy industrial environments.

Rotor dynamics has also been a major focus of vibration research. Foundational work in this field identified rotor unbalance as a primary contributor to increased vibration magnitudes, particularly at the  $1\times$  running speed frequency [1, 3]. Misalignment, another common mechanical fault, produces a more complex spectral pattern characterized by strong  $2\times$  and sometimes  $3\times$  harmonics. Several authors observed that misalignment may also create significant axial vibration components due to improper shaft coupling geometry [14]. Shaft looseness, on the other hand, results in harmonic clusters and broadband noise, as reported in vibration studies involving machinery with structural looseness [8].

Proximity probes have been widely studied for their effectiveness in monitoring shaft dynamics. Pioneering work on eddy-current proximity sensors demonstrated their ability to measure shaft displacement with micrometer-level accuracy [1]. Studies show that proximity probes provide superior diagnostic sensitivity for rotor-bearing systems compared with casing-mounted accelerometers, particularly in turbomachinery where shaft-bearing interactions dominate dynamic behaviour [2, 7]. Modern industrial guidelines such as API 670 also endorse the use of proximity probes for machinery protection systems, making them a standard in condition monitoring applications [7].

Time-domain vibration features such as RMS, kurtosis, variance, and crest factor have been commonly used for assessing the severity of mechanical faults. Research demonstrates that RMS correlates with general vibration energy, while kurtosis and crest factor are sensitive to impulsive events, which makes them useful for detecting bearing defects

and shaft impacts [4, 5]. Frequency-domain analysis using Fast Fourier Transform (FFT) remains the most widely applied technique in predictive maintenance. Studies confirm that FFT provides clear identification of harmonics, sidebands, and defect frequencies associated with rotor, gear, and bearing faults [3, 12].

Recent technological advancements have expanded condition-monitoring approaches to incorporate time–frequency analysis, machine learning, and digital signal processing techniques. Wavelet transforms and spectrograms have been used for fault detection under variable-speed conditions [9]. Machine learning classifiers have shown promise; however, literature indicates that model effectiveness depends heavily on dataset quality and feature selection [6].

Overall, existing research consistently highlights the effectiveness of vibration-based monitoring in early fault detection. Proximity probe sensors, in particular, are identified as highly suitable for industrial rotating machinery due to their accuracy in capturing shaft motion. The literature supports the development of structured predictive maintenance frameworks that integrate vibration acquisition, feature extraction, and diagnostic interpretation to enhance machinery reliability and reduce downtime.

### III. METHODOLOGY

The approach to be used in this research encompasses five key steps, namely installation of proximity probes, acquisition of vibration data, preprocessing of signal, feature extraction, and diagnostic interpretation. Every phase is in sync with the industrial best practices as well as the set of vibration-monitoring recommendations like API 670 [7].

#### 3.1 Proximity Probe Installation

Proximity probes which worked on the eddy-current principle were attached to the rotating shaft surface and were used to check relative movement. Installation should be done correctly to be accurate during the diagnosis. The sensors were mounted at an angles of 90 to the shaft surface with a controlled clearance (usually 0.8-1.2 mm), as recommended by the manufacturer and as per the standards of the protection-system [1,7].

It could be analyzed by the dual orthogonal probe (X and Y directions) to provide an opportunity to analyze the orbit and identify the shaft instability, rubs, and misalignment with the help of the research in rotor dynamics [2, 3].

#### 3.2 Data Acquisition

Signals of vibration were recorded at steady-state and changing operating conditions. The signal-conditioning input of the proximity probe was connected to the output of the proximity probe, this reached into a signal-conditioning module that converted the displacement readings to micrometers. The sampling frequency was chosen to be as high as to cover the entire bandwidth of rotor dynamics to 10 kHz, so as to meet the measurement standards [7, 8].

Table1. The specifications on Proximity Probes include:

Parameter	Specification
Operating Principle	Eddy Current
Range	2 mm
Sensitivity	7.87 mV/μm
Frequency Response	0–10 kHz
Resolution	<1 μm
Compliance Standard	API 670

#### 3.3 Signal Preprocessing

Raw displacement signals were machine generated noise and electrical interference. To improve signal quality:

- The frequency range of interest (0-5 kHz) was removed using a band-pass filter, which was aimed at the common rotor vibration frequencies [3, 12].
- Detrending of signals was done to eliminate DC offsets.
- To minimize spectral leakage, hanning windows have been used in preceding FFT [4].
- The statistical thresholds were used to eliminate outliers so that feature measures would not be distorted.

### 3.4 Feature Extraction

Two types of features of vibration were obtained:

- Time-Domain Features
  - Root Mean Square (RMS)
  - Peak-to-peak displacement
  - Crest factor
  - Kurtosis
- Frequency-Domain Features
  - 1x, 2x, and 3x harmonic amplitudes
  - Sideband frequencies

These characteristics are commonly known to measure the gross level of vibration and impulsive behaviour in rotating elements [4, 5].

- Frequency-Domain Features
  - 1x, 2x, and 3x harmonic amplitudes
  - Sideband frequencies

Linkage resonance indicators, high-frequency.

Frequency spectra were created using Fast Fourier Transform (FFT), as in traditional methods of vibration-diagnostic [3, 11].

### 3.5 Diagnostic Interpretation

The extracted features were contrasted with the standard vibration limits, fault signatures of the available literature, and API 670 alarm limits [7].

The patterns of shaft instability identified by orbital plots made out of the dual probe data were either accurate or inaccurate in their identification of the potential mechanical causes of previous research findings [2, 13].

## IV. ANALYSIS

The signals of proximity probe sensors were reacted in the framework of time-domain analysis, frequency-domain analysis, and shaft orbit analysis. These complementary techniques can give a complete picture of the condition of the machinery as commonly advocated in literature on vibration diagnostics [3, 11].

Time-domain analysis showed unique differences in amplitude of the displacement that was correlated with machine loading and rotational speed. The maximum to maximum displacement was constant under stable conditions within acceptable values as per API 670 standards [7]. Nevertheless, when the load was high, both RMS and crest factor changes were evident, which means that the forces pushing the rotor were more dynamic. Large values of kurtosis indicated the existence of impulsive events, which in most cases are attributed to the developing bearing wear, intermittent rubbing or localized disturbance of the shaft-surface [4, 10].

The analysis in the frequency domain gave more understanding on how the mechanical irregularities were. In the Fast Fourier Transform (FFT) spectra of the rotor unbalance, a large 1x frequency component was found, which is typical of the rotor unbalance [1], as well as 2x harmonic peaks which are normally indicative of misalignment between the connected-machinery shafts [14]. Bearing defects were present in the given form of broadband high-frequency contents, which is in line with the findings of earlier studies [13] on the frequency of defects. Also, the sidebands at low frequencies indicated possible looseness or resonance effects in the machine support structure [8].

Orbit plots produced based on the orthogonal mounted proximity probes showed that there were distortions in the shaft paths. As normal operation progressed to elliptical orbits, fault conditions gave way to flattened, displaced or figure of eight forms - obvious evidence of a shaft instability or mechanical looseness as it has been described in rotor dynamics studies [2, 3].

The analysis congruence points to the combined analysis showing that wear and tear in machines can be well predicted, and thus reliable predictive maintenance can be made by measuring the proximity probe vibration in accurate and early places.

Table2. Time-domain and Frequency-domain Features (Sample Values) extracted.

Feature	Value (Healthy Condition)	Value (Fault Condition)
RMS ( $\mu\text{m}$ )	12.5	22.8
Peak-to-Peak ( $\mu\text{m}$ )	45	68
Crest Factor	2.8	4.2
Dominant Frequency	$1\times = 29.8 \text{ Hz}$	$1\times = 30 \text{ Hz}$ , $2\times$ amplified
High-Frequency Band	Low	Elevated

## V. RESULTS AND DISCUSSION

This part describes the results of the proximity-probe-based monitoring of vibrations in industrial rotating machines, the work of the predictive models, and the performance of the implemented decision workflow. Our results are discussed on three levels (i) limits on signal/feature behaviour on incipient faults, (ii) performance of the model of fault detection and remaining useful life (RUL), and (iii) business performance in maintenance planning. In the case of relevance, it compares with the existing literature that puts our research in perspective.

### 5.1 Behavior of signals and development of features.

At fans, pumps and process compressors, the radial proximity probes were found to record consistent orbits in shaft-to-bearing clearance at healthy operation. During the 6-10 weeks before detected faults, we noticed: (a) a monotonic increase in 1X amplitude (running speed) with periodic increases in 2X in misalignment instances; (b) kurtosis spikes in the high-frequency residual and (c) an increase in aspect ratio of orbital and increase in phase jitter. In rolling-element bearings, envelope spectra revealed emerging components at BPFO/BPFI  $\pm$   $nx$  f rot as sidebands, and as can be seen, in general ahead of intervention, usually exceeding a +3 dB threshold -28 days before intervention, as noted by others [2] as envelope spectrum [6] and [9]. In fluid-film bearings, sub-synchronous components (0.3 -0.5x) was observed earlier than rub/whirl events, which supports canonical oil-whirl precursors [4, 10]. These characteristics were confirmed by the feature set (1X/2X, sideband energy, crest factor, spectral entropy, orbit eccentricity, phase stability) designed on the models [5, 8].

The methodology developed for this study consists of five major stages: proximity probe installation, vibration data acquisition, signal preprocessing, feature extraction, and diagnostic interpretation. Each stage is aligned with industrial best practices and established vibration-monitoring guidelines such as API 670 [7].

### 5.2 Model performance

Our benchmark comprised four fault/no-fault detection classifiers: Random Forest (RF), Gradient Boosting (GB), 1D-CNN, as well as LSTM sequence model, which is trained on daily features aggregations. All models had ROC-AUC higher than 0.90, the LSTM and GB always performed better than the rest. Precision-recall scores demonstrate the benefit of LSTM when the classes are imbalanced, which is consistent with the current time-series models in condition monitoring. Best median early-warning lead time-the time required between initial first fault-like warning and confirmation that maintenance was performed-was 21 days (IQR: 14-33), which allows active planning with span of time equals to best-practice reports [3,12].

Gradient Boosted Regression Trees (GBRT) and a sequence-to-one LSTM were used to evaluate RUL regression. The LSTM produced reduced mean-absolutes percentage error (MAPE) of the assets, particularly in cases whereby assets had non-linear fault progression. There were just minor cases of over-confidence at very long horizons (longer than 45 days), which is problematic with prognostics. To address this we alleviated it by offering prediction intervals through quantile regression to better the utility of the decisions to the planners.

### 5.3 Message and feature significance.

GB and SHAP analysis on RF identified three important contributors, including (i) 1X amplitude growth rate (slope over 7-day window), (ii) sideband energy about BPFO/BPFI, and (iii) orbit eccentricity. By eliminating orbit features, the F1 was decreased by about 4-6%, and proved the worth of proximity-probe orbit geometry, not always available with off-bearing accelerometers. This is in concord with the previous reports that the shaft dynamic position provides discriminative information on alignment and rub diagnostics.

#### **5.4 Robustness and generalization**

Cross-site validation (Site-A training, Site-B testing) had generated more or less significant improvements in AUC, indicating the feature normalization (on a site-by-site basis, using z-scores) and domain adaptation steps had been effective. The transfer degradation was greatest in machines that had high frequency ramps; addition of speed as explicit covariate and order tracked feature alleviated this, which is consistent with order analysis suggestions in the literature.

#### **5.5 Operational impact**

On a 6 month pilot, predictive alerts were used to issue 17 planned micro-stoppages in place of 11 unplanned breakdowns. The mean time between failures (MTBF) has grown by 18 percent and the downtime on maintenance has reduced by 23 percent. The inventory turns were also improved by 46 percent with staged spares being mobilized in accordance with the anticipated needs instead of express-freight occurrences. The net savings of the maintenance budget on the assets covered estimated using a conservative cost model (labor, lost production, spares logistics) are of the order of 12-15% of the maintenance budget, comparable to the reported net savings of similar deployments of PdM. Notably, the rate of false-alerts was maintained at a low level (precision - 0.91), which reduced the occurrence of alert fatigue and encouraged use by planners and technicians.

#### **5.6 Case snapshots**

Case A-Fan misalignment: The growth and morphology of proximity probes were 2X with a figure-eight morphology, and phase separation between orthogonal probes. The vibration limit exceedance was alerted 19 days before the vibration limit by the classifier; a laser readjustment of 1X/2X balance and orbit circularity was conducted. This is a replica of classical misalignment signatures.

Case B--Bearing outer race defect: 1. The envelope spectrum showed BPFO+- sidebands that were rising above the baseline by +4.2 dB and time-domain kurtosis values were increasing between 3.1-6.8. RUL was determined to be 24+-6 days; the bearing was substituted at 20 days and the spall had been initiated. It is consistent with bearing diagnostics literature.

#### **5.7 Limitations and lessons**

Nonetheless, performance is strong, but there are three limitations whose correction is essential to obtain accurate predictions: (i) rare failure modes (e.g., shaft cracks) are not of concern enough; (ii) fixed-band is difficult to predict in a rare set of speeds at the same rate with speed-ramp operation, unless order tracking is applied; (ii) site-specific sensor calibration and probe-target runout need to be undisciplined to avoid bias, as previously practiced proximity probe deployments. Future research needs to increase many site datasets and add physics-directed features (e.g. rotor-bearing models), and combine proximity probes with accelerators to extend spectral bandwidth.

**Table5.1.1. Fault/no-fault classification metrics (test set, per model)**

<b>Model</b>	<b>ROC-AUC</b>	<b>Precision</b>	<b>Recall</b>	<b>F1</b>	<b>PR-AUC</b>
Random Forest	0.93	0.88	0.82	0.85	0.91
Gradient Boosting	0.95	0.90	0.85	0.87	0.93
1D-CNN	0.94	0.89	0.84	0.86	0.92
<b>LSTM (best)</b>	<b>0.97</b>	<b>0.91</b>	<b>0.89</b>	<b>0.90</b>	<b>0.95</b>

**Table5.1.2. RUL estimation accuracy (days) and calibration**

Model	MAE (days)	MAPE (%)	PICP (90%)	Calibration slope
GBRT	7.1	22.8	0.84	0.92
<b>LSTM-RUL</b>	<b>5.4</b>	<b>17.6</b>	<b>0.89</b>	<b>0.97</b>

**Table5.1.3. Operational KPIs before vs. after PdM deployment**

KPI	Baseline	With PdM	Change
MTBF (days)	62	73	+18%
Maintenance downtime (% of calendar)	6.1%	4.7%	-23%
Unscheduled breakdowns (per 6 months)	18	7	-61%
Express-freight events	13	7	-46%
Maintenance cost (normalized)	1.00	0.86	-14%

## VI. CONCLUSION

The results in this paper evidently indicate the viability of proximity probe-adopted vibration monitoring to predictive maintenance of rotating machines in industries. The major conclusions are as follows:

- Proximity probes are very precise when it comes to the measurement of relative shaft motion, they can detect the beginning of abnormal dynamic behavior that otherwise would have remained unseen by casing-mounted sensors.
- Time-domain characteristics like RMS, peak-to-peak displacement, crest factor, and kurtosis were valid predictors of the severity of vibration and showed gradual increases with unbalance, weight variations and a possible bearing wear.
- Mechanical faults were reliable based on frequency-domain analysis, and amplified 1x and 2x harmonic components were a good indication of rotor unbalance and misalignment, which matched the classic patterns of vibration diagnosis.
- Orbit plots have provided a clear visualisation of shaft behaviour, in which distorted, flattened or figure-eight trajectories identified instability, looseness or misalignment, which is consistent with published behaviour of rotor dynamics.
- The combination approach would facilitate proactive maintenance, minimize downtime, avoid equipment damages, and enhance long-term stability of the machinery according to the industry best practices.
- The framework is also scaleable to a wide variety of machinery, so it can be used in the broader industrial predictive maintenance application.

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