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CLASSIFICATION OF VIBRATION DIAGNOSTICS METHODS FOR ROTARY DEVICES AND THEIR ANALYTICAL CAPABILITIES

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Annotation. This article classifies vibration diagnostics for rotary machinery into time-domain, frequency-domain, and model-based methods. It evaluates each approach's analytical capabilities for detecting faults such as imbalance and bearing defects, and discusses their integration into predictive maintenance systems.

Keywords: Vibration diagnostics, rotary machinery, condition monitoring, signal processing, fault detection, predictive maintenance.

ROTORLI QURILMALAR VIBRODIAGNOSTIKA USULLARINING TASNIFI HAMDA ULARNING TAHLILIY IMKONIYATLARI

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Annotatsiya. Ushbu maqolada rotorli qurilmalar uchun tebranish diagnostikasi vaqt sohasi, chastota sohasi va modelga asoslangan usullarga tasniflanadi. Unda har bir yondashuvning nomutanosiblik va podshipnik nuqsonlari kabi nosozliklarni aniqlash uchun analitik imkoniyatlari baholanadi va ularning bashoratli texnik xizmat ko'rsatish tizimlariga integratsiyasi muhokama qilinadi.

Kalit so’zlar: Tebranish diagnostikasi, rotorli qurilma, holatni kuzatish, signalni qayta ishlash, nosozliklarni aniqlash, bashoratli texnik xizmat ko'rsatish.

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1. Introduction

Rotating machinery—including turbines, pumps, compressors, fans, and spindles—forms the backbone of modern industrial processes. Unexpected failure of these assets leads to costly downtime, safety hazards, and production losses. Vibration analysis has emerged as the most prevalent and effective technique for non-invasive condition monitoring due to the direct relationship between mechanical forces and vibratory response. When a fault develops in a rotating component, it alters the dynamic forces within the machine, producing characteristic changes in the vibration signature [1].

The core principle of vibration diagnostics is fault signature isolation: distinguishing the signal component generated by a specific fault from background noise and other vibration sources. The effectiveness of this process depends on the chosen signal processing method. While numerous techniques exist, a clear classification based on the domain of analysis and underlying principles is essential for methodological selection.

2. Methods: Classification of Vibration Diagnostics Techniques

Vibration diagnostics methods can be classified into three fundamental domains, each with distinct analytical capabilities. Analysis in the time-domain involves the direct processing of the raw vibration waveform $x(t)$. This approach forms the foundation of machine condition monitoring, prized for its computational efficiency and the direct physical interpretability of its results. It is particularly effective for initial fault screening and assessing the overall degradation state of rotating machinery.

A primary set of tools in time-domain analysis are statistical indicators. These are scalar values derived from the vibration signal that quantify its amplitude distribution and dynamic characteristics, providing immediate, condensed insights into machine health without the need for complex transformation [2].

Root Mean Square (RMS) is the fundamental measure of the signal's power or overall energy content. It is calculated as:

$$X_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

RMS is highly sensitive to sustained, energy-increasing faults. A rising RMS trend is a clear indicator of progressive deterioration, such as developing imbalance, misalignment, or generalized wear across components, as these conditions increase the average dynamic forces within the machine.

Crest Factor refines the analysis by comparing the most extreme signal peaks to its overall energy level. It is defined as the ratio of the peak absolute value to the RMS:

$$\text{Crest Factor} = \frac{|\, x_{\mathrm{peak}} \,|}{X_{\mathrm{RMS}}}$$

This metric is specifically designed to detect transient, impulsive events. A high Crest Factor signifies the presence of sharp, high-amplitude shocks against a relatively moderate background vibration—a classic signature of localized defects like a bearing spall or a gear tooth crack in its early stages. As the fault worsens and generates more continuous noise, the Crest Factor often decreases while RMS increases [2].

Kurtosis is a statistical measure of the "tailedness" or impulsivity of the signal's probability distribution. Its formula is:

$$\beta_2 = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2\right)^2}$$

For a normal distribution (typical of healthy, random vibration), kurtosis has a value of 3. A kurtosis value significantly greater than 3 indicates a distribution with heavy tails and a sharp peak, meaning the signal contains frequent impulsive outliers. This makes kurtosis an exceptionally sensitive tool for identifying the very early onset of rolling element bearing faults, where microscopic surface defects generate repetitive, low-energy impacts before they significantly affect the overall RMS level.

Additional indicators like Skewness (which measures distribution asymmetry) and the Shape Factor provide further nuance in characterizing waveform morphology, aiding in distinguishing between different fault modes and severities.

For isolating periodic vibration components buried in noise, Time-Synchronous Averaging (TSA) is a powerful pre-processing technique. It requires a reference signal, typically from a tachometer, synchronized with the shaft rotation [3].

The method works by segmenting the vibration signal into consecutive blocks, each exactly equal to one or multiple rotation periods T, and then averaging these blocks coherently. The averaged signal $\bar{x}(t)$ is given by:

$$\bar{x}(t) = \frac{1}{M}\sum_{m=0}^{M-1} x(t + mT)$$

where M is the number of averaged rotations. Vibration components that are perfectly synchronous with the shaft (e.g., from imbalance, shaft bow, or a specific gear) reinforce themselves during averaging. In contrast, non-synchronous components (e.g., bearing noise, electrical interference, or vibrations from other shafts) tend to cancel out as random noise. The primary capability of TSA is, therefore, the dramatic enhancement of the signal-to-noise ratio for synchronous events. It is indispensable in gearbox diagnostics for extracting the clean meshing vibration of an individual gear from a chaotic mixture of signals, and for separating shaft-related fault signatures from general background machinery vibration.

Frequency-domain techniques involve the transformation of the time-domain vibration signal $x(t)$ into a representation of its frequency content. This transformation is crucial because different mechanical faults excite distinct characteristic frequencies within the machine's structure. Analyzing these spectral signatures allows for precise fault identification and isolation that is often impossible in the time domain alone [3].

The cornerstone of frequency-domain analysis is the Fourier Transform, which decomposes a signal into its constituent sinusoidal frequencies. For digital signal processing, the Discrete Fourier Transform (DFT) and its efficient algorithm, the Fast Fourier Transform (FFT), are used. The DFT is defined as:

$$X(f_k) = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N}, k = 0,1, \dots, N-1$$

where x_n are the discrete-time samples and $X(f_k)$ represents the complex amplitude at frequency bin f_k. The resulting spectrum plots magnitude versus frequency, revealing dominant tonal components. Its primary capability is the unambiguous identification of faults related to shaft rotation. For instance, mass imbalance produces a dominant peak at the fundamental rotational frequency (1× RPM), while misalignment typically generates significant peaks at twice (2× RPM) and sometimes three times (3× RPM) the rotational frequency. A series of harmonics can indicate mechanical looseness or rubs [4].

To statistically estimate the power distribution across frequencies in a signal, especially for random vibration components, the Power Spectral Density (PSD) is employed. It is calculated as:

$$S_{xx}(f) = \lim_{T\to\infty} \frac{1}{T} \mid X_T(f) \mid^2$$

The PSD is exceptionally useful for identifying the machine's resonant frequencies, where the structure amplifies vibration. It is also critical for analyzing the background noise floor and characterizing non-tonal, broadband vibration sources, providing a complete picture of the dynamic forces at play.

Envelope analysis is a sophisticated technique specifically designed to detect low-energy, repetitive transients—such as those generated by incipient bearing defects—that are often masked by higher-energy vibration in a standard spectrum. The process involves two key steps. First, the raw signal is band-pass filtered around a high-frequency structural resonance of the bearing housing or machine casing; this resonance is excited each time a rolling element hits a defect. Second, the filtered signal is processed using the Hilbert Transform to extract its amplitude envelope, $A(t)$, which contains the lower-frequency repetition pattern of the impacts:

$$A(t) = \mid x(t) + i\mathcal{H}\{x(t)\} \mid$$

where $\mathcal{H}$ denotes the Hilbert transform. A final FFT is then performed on this envelope signal $A(t)$. The resulting envelope spectrum clearly reveals the fundamental bearing defect frequencies—such as Ball Pass Frequency Outer Race (BPFO) or Inner Race (BPFI)—free from contaminating noise. This method's superior capability for diagnosing rolling element bearing faults (spalls on inner/outer races, balls, or cage) makes it the industry standard for early bearing failure detection [4].

When standard spectral analysis proves insufficient for diagnosing subtle, transient, or complex fault conditions, model-based and high-resolution techniques offer a deeper analytical framework. These methods either incorporate a physical model of the machine's dynamics or employ advanced signal processing to achieve superior resolution in time, frequency, or both, making them indispensable for advanced diagnostics and incipient fault detection.

Modal analysis moves beyond simple vibration measurement to characterize the inherent dynamic properties of the mechanical structure itself. It derives these properties—natural frequencies (ω_n), damping ratios (ζ), and mode shapes (ϕ)—from the system's Frequency Response Function (FRF). The FRF, $H(\omega)$, is defined as the ratio of the system's vibration response $X(\omega)$ to an applied force $F(\omega)$. For a linear system with N degrees of freedom, it can be expressed as a sum of its modal contributions:

$$H(\omega) = \frac{X(\omega)}{F(\omega)} = \sum_{r=1}^{N} \frac{\phi_r \phi_r^T}{-\omega^2 m_r + i\omega c_r + k_r}$$

where m_r, c_r, and k_r are the modal mass, damping, and stiffness for the r-th mode. Its primary diagnostic capability lies in detecting changes in structural integrity. A developing crack or corrosion locally reduces structural stiffness k, which manifests as a measurable shift in the system's natural frequencies and a distortion of its mode shapes. This makes modal analysis essential for structural health monitoring and the prognosis of failures in critical components like turbine blades, shafts, and foundations.

Conventional FFT analysis assumes a constant rotational speed, which is often violated in real-world machinery like turbines, compressors, and engines during startup, shutdown, or load changes. Order Tracking solves this by resampling the vibration signal from the time domain into the angular (or order) domain. Using a tachometer signal as a reference, the nonuniformly spaced time samples are converted into samples spaced at constant angular increments of the shaft. This process generates a "speed-corrected" signal where spectral components related to shaft rotation (orders) remain constant. Its critical capability is enabling clear, smear-free vibration analysis of machines with variable rotational speed. It allows for the accurate tracking of order amplitudes (e.g., 1X, 2X) across the entire operating speed range, which is vital for diagnosing faults in applications like wind turbines, aircraft engines, and automotive drivetrains [5].

The Wavelet Transform addresses a key limitation of the Fourier Transform: its inability to provide joint time-frequency localization for non-stationary signals. It decomposes a signal using a set of basic functions called wavelets, which are scaled and translated versions of a finite-length "mother wavelet" $\psi(t)$. The Continuous Wavelet Transform is given by:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\ \psi^* \left(\frac{t-b}{a}\right) dt$$

Here, the scale parameter a dilates or compresses the wavelet (inversely related to frequency), and the translation parameter b shifts it in time. This provides a time-frequency map where one can see not only which frequencies are present but also *when* they occur. This capability is ideal for detecting and analyzing short-duration, transient events that are lost in an average FFT, such as the impulsive shock of a rotor-stator rub, the onset of a crack propagation event, or the transient vibrations during machine startup [4].

Parametric spectral estimation methods model the vibration signal as the output of a linear, time-invariant system driven by white noise. The two common models are the Autoregressive (AR) model and the more general Autoregressive Moving-Average (ARMA) model. The ARMA (p, q) model is defined by the difference equation [5]:

$$x_n = -\sum_{k=1}^{p} a_k\, x_{n-k} + \sum_{k=0}^{q} b_k\, \epsilon_{n-k}$$

where p and q are the model orders, a_k and b_k are the model coefficients, and ϵ_n is a white noise input sequence. By solving for these coefficients from the measured data, a high-resolution spectrum can be estimated. These methods offer a significant advantage over non-parametric methods (like the periodogram) by providing excellent frequency resolution for short data records and for resolving closely spaced spectral peaks. This high-resolution capability is particularly useful for early fault detection, where the initial spectral features of a developing fault are weak and may be closely spaced, allowing for earlier and more precise identification than standard FFT-based approaches [6].

Table 1: Classification of Vibration Diagnostics Methods.

Domain	Primary Methods	Key Faults Detected
Time-Domain	Statistical Indicators, TSA	Severe wear, imbalance, impulsive faults
Frequency-Domain	FFT, Envelope Analysis, Cepstrum	Imbalance, misalignment, bearing/gear faults

Domain	Primary Methods	Key Faults Detected
Model-Based	Modal Analysis, Wavelet, Parametric Models	Cracks, structural defects, non-stationary faults

3. Results: Analytical Capabilities for Specific Faults

Each fault type generates a unique vibration signature, making certain methods more effective than others. Mass imbalance is one of the most common faults in rotating machinery, arising from an uneven distribution of mass about the axis of rotation. The diagnostic signature is characteristically straightforward: a dominant and often elevated vibration peak precisely at the fundamental (1×) rotational frequency in the radial direction [5]. This is because the uneven mass creates a centrifugal force that rotates synchronously with the shaft, exciting the structure once per revolution. For verification and to distinguish pure imbalance from other synchronous faults like bent shaft or eccentricity, orbit analysis plotting the shaft centerline motion within a bearing clearance can be employed; a perfect circular orbit often confirms pure static imbalance.

The physics governing this fault is described by the unbalance force F_u, a centrifugal force proportional to the product of the unbalance mass m_u, its radial eccentricity e, and the square of the rotational angular velocity ω:

$$F_u = m_u e \omega^2$$

This relationship highlights why imbalance becomes critically severe at high speeds. The primary and most effective diagnostic method is FFT spectral analysis of radial vibration. A health assessment involves tracking the amplitude and phase of the 1× component over time. A significant increase in this amplitude, especially if accompanied by a stable phase angle, is a definitive indicator of developing or worsening imbalance, necessitating corrective balancing [6].

Misalignment occurs when the centerlines of two coupled shafts (or a shaft and its driver/load) are not collinear. This condition is typically categorized into angular misalignment and parallel misalignment. The vibrational signature is more complex than imbalance. It is predominantly characterized by high vibration at twice the rotational frequency (2× RPM), as the misalignment forces reverse direction twice per shaft revolution. Significant vibration at three times (3× RPM) is also common. A key diagnostic clue is the prominence of this 2× and 3× vibration in the axial direction, as misalignment induces strong axial shuttling forces, whereas imbalance primarily excites radial modes.

From a physics perspective, misalignment generates oscillating bending moments and reaction forces at the coupling and bearings. These forces are periodic with shaft rotation and have a strong axial component, leading to the observed spectral harmonics and axial vibration. The best diagnostic methods involve a combined approach: FFT spectral analysis of both radial and, critically, axial vibration signals to identify the elevated 2×/3× harmonics, and phase analysis. In a condition of pure misalignment, the phase relationship between radial vibration points on the same shaft (e.g., 0° and 180° positions) will typically show a 180° difference, while axial phase readings across the coupling will be out of phase. This multi-dimensional analysis (spectral amplitudes in radial/axial planes and phase relationships) is essential to conclusively diagnose misalignment and differentiate it from other faults like mechanical looseness, which may also generate harmonics [7].

Defects in rolling element bearings—such as spalls, pits, or cracks on the inner race, outer race, or rolling elements—generate distinctive, impact-induced vibrations. Unlike synchronous faults, their signatures are characterized by specific bearing defect frequencies, which are functions of the bearing's geometry and rotational speed. These frequencies are calculated as follows:

- Ball Pass Frequency of the Inner Race (BPFI): The rate at which rolling elements pass a defect on the inner race, which rotates with the shaft.

$$\mathrm{BPFI} = \frac{n}{2} f_r \left(1 + \frac{d}{D} \cos\ \phi\right)$$

- Ball Pass Frequency of the Outer Race (BPFO): The rate at which rolling elements pass a stationary defect on the outer race.

$$\mathrm{BPFO} = \frac{n}{2} f_r \left(1 - \frac{d}{D} \cos\ \phi\right)$$

- Ball Spin Frequency (BSF): The rotational rate of a rolling element about its own axis.

$$\mathrm{BSF} = \frac{D}{2d} f_r \left(1 - \left(\frac{d}{D} \cos \phi\right)^2\right)$$

where n is the number of rolling elements, f_r is the shaft rotational frequency, d is the ball diameter, D is the pitch diameter, and ϕ is the contact angle [6].

The best method for diagnosing these defects is Envelope (Demodulation) Analysis. This technique isolates the low-frequency repetitive impacts (at BPFI, BPFO, etc.) by band-pass filtering the signal around a high-frequency structural resonance excited by each impact and then extracting the signal's amplitude envelope. For early detection, time-domain statistical indicators are highly sensitive: a rising Kurtosis value ($\beta_2 > 3$) signals the onset of impulsive activity, and an increasing Crest Factor points to growing transient shocks against the vibration background.

The fault progression follows a predictable path: in the early stage, high-frequency impacts occur, raising kurtosis and crest factor while the overall vibration energy (RMS) remains stable. In the advanced stage, the defect worsens, causing a significant rise in RMS as the impacts become more severe and continuous, and the defect frequencies become clearly visible in the envelope spectrum, allowing for precise fault localization [7].

Faults in gears, such as tooth wear, pitting, or cracks, manifest in the vibration signal through the Gear Mesh Frequency (GMF) and its associated sidebands. The GMF is the fundamental frequency generated by the meshing of gear teeth:

$$\mathrm{GMF} = N_{\mathrm{teeth}} \times f_r$$

where N_{teeth} is the number of teeth on the gear in question and f_r is its rotational frequency. A local fault on a single tooth (like a crack) or a distributed fault (like wear) modulates this mesh frequency. This modulation creates a series of sidebands—spectral components spaced at the fault gear's rotational frequency (f_r) above and below the GMF and its harmonics.

The best diagnostic methods for gear faults are specifically designed to isolate these complex signatures from noisy signals:

- Time-Synchronous Averaging (TSA): This technique averages vibration signals over many revolutions, using a tachometer signal from the shaft of interest. It dramatically improves the signal-to-noise ratio, providing a clean waveform of the vibration from a specific gear by eliminating asynchronous components from other shafts and bearings.

- Sideband Analysis: Following TSA or applied to a standard spectrum, this involves a detailed examination of the pattern, spacing, and amplitude of sidebands around the GMF. The spacing identifies the faulty gear, while the amplitude and number of sidebands indicate the severity and type of fault.
- Cepstrum Analysis: This is a powerful tool for detecting and quantifying periodic structures in a spectrum. It excels at identifying the precise spacing (or *quefrency*) of harmonic families, such as sideband clusters. This makes it exceptionally effective for diagnosing faults in complex gearboxes with multiple gears, as it can separate the sideband families caused by different gears [8].

Mechanical looseness is a condition where there is excessive clearance between components in the assembly, such as at bearing housings, foundation bolts, or between rotating and stationary parts. This clearance allows for relative motion, resulting in a distinct and often severe vibration signature. The primary signature is the presence of multiple harmonics of the rotational speed, typically spanning from 1× up to 10× RPM. Furthermore, a strong indicator is the appearance of sub-harmonics (e.g., 0.5×, 0.33× RPM), which result from the nonlinear, impacting nature of the loose connection that can cause the rotor to partially slip or bounce within the clearance.

The physics behind this fault involves nonlinear dynamic behavior. When a component is loose, the restoring force is not a linear function of displacement; instead, impacts occur when the part moves into the clearance gap. This generates a choppy, non-sinusoidal time waveform rich in higher harmonics. The best diagnostic methods combine frequency and time-domain analysis. The FFT spectrum reveals the characteristic harmonic and sub-harmonic "comb" pattern. Simultaneously, inspection of the time waveform often shows a distinct "choppy" or "clipped" pattern with sudden spikes or dropouts, directly visualizing the impacts and reversals of motion caused by the looseness. This dual analysis is crucial to distinguish looseness from misalignment, which also produces harmonics but typically lacks sub-harmonics and the distinctive choppy time signal [8].

A transverse crack in a rotating shaft is a critical fault that significantly alters the rotor's dynamic characteristics due to a local reduction in bending stiffness. The vibration signature is twofold. First, the crack introduces asymmetric stiffness in the rotor's cross-section: the stiffness is lower when the crack is under tension (open) compared to when it is under compression (closed). This asymmetry, which rotates with the shaft, generates a strong synchronous (1×) and, more diagnostically, a prominent twice-per-revolution (2× RPM) vibration component. Second, the overall reduction in structural stiffness leads to measurable changes in the rotor's natural frequencies, detectable through modal testing.

The best diagnostic methods therefore require a multi-faceted approach. FFT spectral analysis is used to monitor the growth of the 2× RPM component, especially during startup or shutdown when the crack opens and closes. More definitively, modal analysis is employed to detect downward shifts in the rotor's natural frequencies (particularly the first and second bending modes) and changes in mode shapes, which are direct indicators of a global stiffness reduction caused by a crack. For critical machinery, periodic modal testing combined with trend analysis of 2× vibration provides a robust strategy for early crack detection [9].

The following table synthesizes the optimal diagnostic technique and key vibrational indicator for each primary fault type, providing a guideline for condition monitoring strategies.

Table 2: Fault-Method Effectiveness Matrix.

Fault Type	Optimal Method	Key Indicator	Sensitivity
Imbalance	FFT Spectrum	1× RPM amplitude	High
Misalignment	FFT (Axial) & Phase	2× RPM, axial/radial ratio	High
Bearing Defects	Envelope Analysis	BPFI, BPFO peaks	Very High
Gear Wear	TSA & Cepstrum	GMF sideband energy	Medium-High
Rotor Crack	Modal + FFT	2× RPM, natural frequency shift	Medium
Looseness	Time Waveform + FFT	Multiple harmonics, sub-harmonics	High

4. Discussion

The classification and analysis presented in the preceding sections demonstrate that vibration diagnostics for rotary machinery is a rich, multi-layered discipline. The effectiveness of any condition monitoring program hinges not on the supremacy of a single technique, but on the strategic integration of complementary methods, a clear understanding of their inherent limitations, and a forward-looking adoption of intelligent technologies [9].

In industrial practice, a singular diagnostic method is insufficient for reliable, predictive maintenance. A staged, hybrid approach has become the standard, leveraging the strengths of each method at different phases of the fault detection and analysis pipeline.

1. Screening and Health Assessment: The first line of defense involves monitoring overall vibration levels. Broadband metrics like Root Mean Square (RMS) velocity or displacement are tracked against international standards (e.g., ISO 10816) to provide a simple go/no-go gauge of general machine condition. This serves as an efficient, low-cost screening tool for an entire plant.
2. Fault Detection and Alerting: When overall levels rise, or as part of a periodic check, basic diagnostic methods are applied. The FFT spectrum is used to detect common synchronous faults like imbalance and misalignment by identifying dominant peaks at 1× and 2× RPM. Concurrently, time-domain statistics like Kurtosis are monitored to provide early warning of incipient bearing faults, often before they significantly affect the overall energy (RMS).
3. Advanced Diagnosis and Fault Isolation: Once a potential fault is flagged, targeted high-resolution techniques are deployed. Envelope analysis is employed to confirm and pinpoint specific bearing defect frequencies. For gear-related issues, Time-Synchronous Averaging (TSA) and Cepstrum analysis are used to isolate the vibration of individual gears and decipher sideband patterns. Transient events are investigated using the Wavelet Transform.

4. Prognosis and Remaining Useful Life (RUL) Estimation: The ultimate goal of predictive maintenance is forecasting failure. This involves trending health indices (HI)—often derived from key features like RMS, kurtosis, or specific harmonic amplitudes—over time. These trends can be modeled mathematically. A common empirical model is the exponential degradation law:

$$\mathrm{HI}(t) = \mathrm{HI}_0 \exp\left(-\lambda t\right)$$

where the degradation rate constant λ is itself a function of operational severity factors like load and speed [$\lambda = f$(load,speed)]. By extrapolating when the HI will cross a predefined failure threshold, an estimate of RUL can be generated, enabling truly condition-based maintenance scheduling [10].

Despite its power, vibration diagnostics faces several persistent challenges that dictate the limits of its applicability and accuracy [11].

- Low Signal-to-Noise Ratio (SNR): Early-stage fault signatures, especially from bearings, are often weak and buried within noise from other machine components and processes. This necessitates advanced signal processing techniques (like the band-pass filtering in envelope analysis) and can limit the earliest possible detection time.
- Variable Speed Operation: Traditional FFT analysis assumes stationary signals, which is invalid for machines that frequently change speed (e.g., wind turbines, traction motors). This causes spectral "smearing." Order Tracking is required to resample the data in the angular domain, but it adds complexity and requires a reliable tachometer signal.
- Multiple Simultaneous Faults: In complex machinery, several faults may develop concurrently, and their vibration signatures can interfere. Disentangling these combined signals requires advanced source separation techniques, such as blind deconvolution or independent component analysis, which are computationally intensive and not yet routine in many industrial settings.
- Cost-Benefit and Complexity Trade-off: While high-resolution methods (e.g., wavelet transforms, parametric ARMA models) offer superior diagnostic insight, they demand greater computational resources, specialized expertise, and longer processing times. The trade-off between diagnostic depth and practical cost/feasibility remains a key consideration for plant engineers [12].

The future of vibration diagnostics lies in transcending these limitations through digitalization and intelligence, moving from diagnostics to autonomous prognostics.

- AI-Enhanced Automated Diagnostics: Machine learning, particularly Deep Learning, is revolutionizing fault recognition. Convolutional Neural Networks (CNNs) can automatically classify faults by analyzing vibration spectrograms or time-frequency maps as "images," reducing reliance on expert analysis. Support Vector Machines (SVMs) and other algorithms can fuse multiple features for robust, automated decision-making.
- Digital Twin Integration: A digital twin—a high-fidelity, physics-based virtual model of the machine—can be continuously updated with real-time vibration data. This allows for virtual health assessment, simulation of fault progression under different loads, and highly accurate, physics-informed RUL prediction, creating a powerful closed-loop prognostic system.
- Industrial IoT and Wireless Sensor Networks: The proliferation of low-cost, wireless vibration sensors enables continuous, pervasive monitoring of large fleets of machinery. Cloud-based analytics platforms can aggregate this data, applying diagnostic and prognostic algorithms at scale to optimize maintenance across entire facilities or corporations.

• Multi-Sensor and Multi-Physics Data Fusion: Vibration analysis is most powerful when combined with other modalities. Sensor fusion—integrating data from vibration, acoustic emission (sensitive to high-frequency crack growth), thermography (for temperature hotspots), and motor current signature analysis (for electrical and mechanical faults)—provides a holistic, multi-physics view of machine health, dramatically improving diagnostic confidence and coverage [13].

5. Conclusion

Vibration diagnostics methods for rotary devices are systematically classified into time-domain, frequency-domain, and model-based approaches, each with distinct analytical strengths. Time-domain statistical indicators provide robust overall health assessment, while frequency-domain techniques like FFT and envelope analysis excel at isolating specific fault signatures. Model-based methods offer high resolution for complex defects such as cracks and non-stationary vibrations.

The selection of a diagnostic method must consider the target fault type, operational conditions, and required sensitivity. In practice, a staged, multi-method approach—from simple RMS monitoring to advanced envelope or wavelet analysis—provides the most reliable fault detection and prognosis [14].

The future of vibration diagnostics lies in the intelligent integration of these methods with artificial intelligence and digital twin technologies, paving the way for fully autonomous predictive maintenance systems that maximize reliability and operational efficiency in industrial applications.

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