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Review

AI-driven intelligent vibration monitoring for predictive maintenance in chemical process plants: Signal processing, diagnostics, and industrial integration

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ABSTRACT

Intelligent vibration monitoring is increasingly important for predictive maintenance (PdM) in chemical process plants, where machinery faults may appear as weak, mixed, nonstationary, or process-dependent signatures. This review examines how vibration measurements can be converted into reliable maintenance intelligence using signal processing, artificial intelligence (AI), and plant-level integration. A structured critical narrative review was conducted using literature identified from Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore, focusing mainly on studies published from 2016 to September 2026. It compares fault signature complexity across pumps, compressors, agitators, turbines, fans, gear-driven systems, and rolling-element bearings and evaluates time- and frequency-domain analysis, wavelet methods, empirical mode decomposition, cepstral enhancement, and time–frequency approaches. AI-based classification, anomaly detection, deep learning, and prognostic modelling were assessed in relation to interpretability, generalisation, benchmark data limitations, uncertainty, and industrial trust. Particular emphasis is placed on process-aware interpretation because vibration responses can be affected by the flow, pressure, hydraulic instability, operating duty, structural transmission, and maintenance constraints. This review proposes a deployment-oriented, tiered PdM framework that aligns analytical depth, AI support, asset criticality, process context, and maintenance workflow integration. A standards-informed distinction between condition monitoring, diagnostic advisories, and machinery protection functions was also introduced. Future studies should prioritise explainability, field robustness, cross-condition validation, and traceable linkages between diagnostic outputs, plant information systems, and maintenance decisions.

Keywords: rotating machinery; condition assessment; machine learning; anomaly detection; prognostics; asset criticality

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1. Introduction

Predictive maintenance (PdM) is increasingly used in chemical process plants (CPPs) because rotating equipment failures can affect production, safety, the environment, and maintenance workload[1,2]. Maintenance studies have also shown that preventive work, turnarounds, and condition-based interventions must be balanced against operating constraints[3,4]. Similar issues arise when maintenance frameworks are applied in day-to-day industrial practices[5]. Vibration monitoring is one of the main condition-monitoring methods for rotating machinery because changes in the dynamic response often occur before functional failure[6,7].

Reviews of vibration analysis and gear or bearing monitoring further support its use for diagnosis[7,8]. However, in process plants, hydraulic instability, flow and pressure changes, thermal conditions,

load variation, structural transmission, and sensor location can alter the measured response without indicating fault growth[9,10]. An increase in vibration should be interpreted in the context of the operating state rather than being automatically considered evidence of mechanical deterioration.

The analytical response to this difficulty has expanded in several directions. Conventional time- and frequency-domain methods remain the baseline for physically interpretable vibration assessment[11]. Wavelet and time–frequency methods are widely used when transient or non-stationary content must be resolved[12,13], while adaptive decomposition provides a data-driven route for separating mixed oscillatory behaviour[14,15]. Cepstral processing is more specialised and is mainly used to expose repetitive modulation that is difficult to observe in ordinary spectra[16,17]. Machine learning (ML) and deep learning (DL) have extended these methods toward automated fault classification[18,19], and anomaly detection or prognostic modelling can support early warning and degradation assessment when labelled fault data are limited[19,20].

For clarity, condition monitoring is used to identify changes in machine state; diagnosis attributes those changes to probable fault mechanisms; prognosis estimates future degradation; and PdM uses this evidence to support the timing and prioritisation of maintenance intervention.

1.1. Literature review and review gap

The recent literature on reviews can be grouped into several complementary streams, but each stream addresses only a part of the deployment problem considered here. Sensor-centred reviews describe accelerometer technologies, measurement principles, and practical condition-monitoring considerations; however, downstream interpretation and maintenance decision pathways are usually secondary topics[6]. Broader reviews of vibration analysis compare time-domain, frequency-domain, and time–frequency techniques across multiple machinery classes; however, process-variable coupling and plant workflow integration are not normally the organising problem[7].

Component-focused reviews provide deeper knowledge of particular fault families. Gear-wear reviews explain the progression from conventional spectral features to enhanced diagnostic and prognostic methods[8]. Bearing-focused work similarly shows how localised defects can require specialised feature extraction and fault-frequency interpretation[21]. These reviews are valuable for mechanism-level diagnosis; however, their intentionally narrow scope does not resolve how different equipment classes should be monitored within one chemical-process maintenance strategy.

A second stream concentrates on artificial intelligence (AI). Reviews of DL and ML fault diagnosis show rapid progress in representation learning, classification, and automated feature extraction[18,19]. Condition-monitoring reviews also demonstrate the breadth of supervised, unsupervised, and hybrid data-driven approaches[22]. However, model performance is commonly reported using controlled datasets, so benchmark accuracy does not by itself establish robustness to process variation, sensor relocation, machine-to-machine differences, or incomplete fault labels.

A third stream addresses PdM and prognostics at a wider system level. Data-driven prognostic reviews emphasise degradation assessment and remaining useful life support[20]. Reviews of PdM implementation highlight recurring difficulties associated with data quality, organisational adoption, and uncertain maintenance value[23]. More recent work on critical machinery and digital twin (DT)-enabled PdM has further increased attention to explainability, integration, and deployment readiness[24]. Industrial studies also show that maintenance forecasting and workflow linkage influence whether diagnostic information leads to timely intervention[25,26]. To further clarify the positioning of the present review, **Table 1** compares its principal focus with three representative reviews addressing data-driven prognostics, AI-based prognostics and health management, and DT-enabled PdM.

Table 1. Comparison of representative predictive maintenance reviews and the present study.

Reference	Primary focus	Main contribution	Distinction from the present review
Wen et al. [20] (2022)	Data-driven prognostics	Reviews prognostic methods, remaining useful life prediction, and applications across industrial sectors	The present review places greater emphasis on vibration interpretation under process-dependent operating conditions and its connection to plant maintenance decisions.
Fernandes et al. [27] (2026)	AI-based prognostics and health management for critical machinery	Reviews AI/ML applications, diagnostic and prognostic methods, and technological challenges in critical machinery	The present review focuses more specifically on vibration measurement, process-induced variability, diagnostic evidence, and practical deployment in CPPs.
Abd Wahab et al. [24] (2024)	PdM and DT technologies	Examines DT applications, implementation challenges, opportunities, and maintenance-related practices across industries	The present review examines the diagnostic chain from vibration measurement and signal interpretation to maintenance action, rather than primarily focusing on DT technologies.
Present study	Process-aware vibration-based PdM in CPPs	Integrates measurement integrity, machinery-specific vibration signatures, signal processing, AI reliability, operating context, and maintenance decision-making	Proposes a deployment-oriented interpretation framework linking diagnostic evidence, operating conditions, asset criticality, and maintenance response.

The comparison in **Table 1** indicates that existing reviews have made substantial contributions to data-driven prognostics, AI-based machinery diagnostics, and DT-enabled PdM. However, these studies differ in their primary objectives and do not specifically organise vibration-based PdM around the combined challenges of process-dependent operating conditions, measurement reliability, diagnostic interpretation, and maintenance decision-making in CPPs. The contribution of the present review therefore lies in connecting these elements within a unified, deployment-oriented interpretation framework. Rather than comparing diagnostic algorithms solely by their reported accuracy, the review examines how vibration evidence should be evaluated against machinery behaviour, operating context, AI reliability, asset criticality, and maintenance requirements. This perspective provides a practical basis for determining when an observed vibration change warrants further diagnosis and how the resulting evidence can support a defensible maintenance decision.

This review addresses the following practical question: How can vibration signals from chemical-process equipment be converted into maintenance decisions that are technically defensible and useful in plant operations? The discussion is organised around four issues: difficulty in obtaining machinery-specific fault signatures; amount of signal processing needed to recover useful evidence; generalisation, interpretability, and field-data limitations of AI diagnostics; and the manner in which diagnostic results are carried into plant information and maintenance workflows. The objective is to provide engineers with a basis for selecting the analytical depth according to machine behaviour, process interaction, and maintenance consequence.

For CPP applications, the reported algorithm accuracy is only one part of the evidence. A method must also separate mechanical deterioration from process-related variability, remain sufficiently stable for repeated monitoring, and produce results that can be interpreted within the maintenance constraints. The methods are compared mainly based on what they add to the diagnosis and the conditions under which they can be trusted.

A technique that performs well on a bearing test rig may have limited value in service if it is highly sensitive to speed changes, difficult to explain, or dependent on fault labels that are rarely available. Conversely, a simpler method can be preferable when its behaviour is transparent and repeatable. This review treats signal processing, AI, and plant integration as linked stages of the same diagnostic workflow.

2. Materials and methods

2.1. Review design and scope

This study used a structured critical narrative review because the topic spans rotating machinery dynamics, vibration signal processing, AI diagnostics, sensing infrastructure, and maintenance implementation. The scope was restricted to vibration-based PdM for rotating equipment relevant to CPPs, with an emphasis on

how measurement evidence is transformed into maintenance-relevant information. The review was designed for thematic and engineering-oriented synthesis, rather than statistical aggregation.

A statistical meta-analysis was not attempted because the reviewed studies differed substantially in terms of machinery type, sensor arrangement, operating regime, fault severity, dataset balance, preprocessing, model architecture, and validation strategy. A direct numerical comparison would be misleading. The synthesis is qualitative and engineering-oriented, with an emphasis on transferability to realistic plant conditions, interpretation in the process context, availability of explainable evidence, and the extent to which a method can support a maintenance decision.

The scope was deliberately limited to avoid transforming this paper into a general survey of sensing hardware. Accelerometer types, wireless protocols, and sensor networks are discussed only when measurement fidelity, sensor placement, harsh-environment operation, or data availability affect the diagnostic results. AI methods are grouped by maintenance function rather than by architecture. This keeps the discussion focused on how vibration evidence is converted into maintenance information while retaining the supporting literature required to evaluate data quality and field deployment.

2.2. Literature search and study selection

Studies were included if they focused on vibration-based machinery monitoring, fault signature interpretation, signal processing, AI diagnosis, anomaly detection, prognostics, or maintenance decision support, specifically in the context of rotating equipment in process industries. Civil, seismic, and unrelated vibration applications were excluded unless the method provided a directly transferable principle.

Evidence from adjacent vibration-monitoring domains was included only when the measurement or diagnostic principle was directly transferable to the process machinery; such evidence was treated as methodological support rather than direct CPP field validation.

Literature was identified primarily through Scopus, Web of Science, ScienceDirect, SpringerLink, and IEEE Xplore. The principal search horizon covered 2016 to September 2026, while earlier landmark studies were retained where necessary to establish classical vibration and diagnostic principles. Search terms were combined across three concept blocks: (i) asset and plant context, including pumps, compressors, agitators, turbines, fans, gears, bearings, process plants, and rotating machinery; (ii) diagnostic method, including vibration, spectral analysis, wavelet, decomposition, anomaly detection, ML, DL, and prognostics; and (iii) deployment context, including PdM, industrial monitoring, process integration, computerised maintenance management systems (CMMS), field validation, and maintenance decision support. As the present study was designed as a structured critical narrative review rather than a systematic review or meta-analysis, the literature selection was guided by technical relevance and the contribution of individual studies to the critical synthesis. A formal PRISMA screening procedure was therefore not adopted. Instead, emphasis was placed on identifying representative and technically relevant evidence across the selected research themes. This approach was considered appropriate given the multidisciplinary scope and substantial heterogeneity of machinery configurations, operating conditions, diagnostic methods, and industrial applications.

2.3. Evidence classification and critical synthesis

The synthesis was thematic rather than chronological and was organised around four connected themes: (1) machinery-specific fault signature complexity, (2) signal processing routes for improving diagnostic visibility, (3) AI-based diagnosis, anomaly recognition, and degradation assessment, and (4) industrial integration and maintenance decision-making. Sensor technology was addressed solely in contexts where the quality of measurement or the positioning of sensors significantly influenced diagnostic interpretation; it was not examined as a standalone hardware topic.

To improve traceability, the literature was evaluated according to the role played by each source in the synthesis. Broad review papers were used mainly to establish the state of practice and identify recurring technical themes, whereas experimental and field studies were used when specific claims were made about measurement behaviour, fault signatures, signal-processing performance, or deployment constraints. Greater interpretive weight was given to evidence that included realistic operating variation, field measurements, cross-condition validation, and a clearly described measurement chain. Laboratory studies were retained where they demonstrated a transferable diagnostic principle; however, benchmark accuracy alone was not treated as evidence of plant readiness.

This review also distinguished between detection and deployment evidence. A method could be considered technically promising if it improved fault visibility or classification under controlled conditions; however, stronger deployment relevance required evidence of repeatability, sensitivity to operating state, sensor-position effects, robustness to noise or domain shift, and a plausible route from diagnostic output to maintenance action. This distinction was used throughout the synthesis to avoid comparing methods solely by headline accuracy. The resulting review is therefore structured as an engineering decision framework rather than as a ranking of algorithms, and it deliberately retains negative factors such as ambiguity, false alarms, transfer limitations, and measurement-chain uncertainty when judging practical usefulness.

For synthesis, the evidence was interpreted at three practical levels. Level A evidence refers to laboratory or benchmark studies that demonstrate a diagnostic principle under controlled conditions. Level B evidence includes cross-condition, pilot-scale, or transfer-oriented studies that expose the method to changing load, speed, sensor position, or operating domain. Level C evidence refers to field or workflow evidence in which the diagnostic output is connected to real equipment condition, operational context, or maintenance action. These levels are not quality scores; they indicate how directly a study can support a claim about plant deployment. This distinction is used later to separate method sensitivity from implementation readiness.

The classification was intended as an interpretative framework for comparing evidence across different research settings, rather than a formal study-quality grading system. Accordingly, the levels were assigned according to the type of validation reported and its relevance to practical deployment, rather than through a systematic risk-of-bias assessment. Review articles and technical standards were used primarily to establish the broader research context and engineering requirements, and were not treated as direct experimental or field-validation evidence. This distinction allows the review to consider findings from laboratory studies, cross-condition investigations, and industrial applications without implying that they provide equivalent levels of deployment evidence.

3. Results and discussion

3.1. Vibration signatures and fault-interpretation challenges in process equipment

3.1.1. Process-coupled variability in pumps, compressors, and agitators

In CPPs, the first diagnostic challenge is that process conditions can modify vibration independently of mechanical damage. Pumps may exhibit imbalance, misalignment, looseness, and bearing degradation, while cavitation and off-design hydraulic operation can generate overlapping broadband or irregular responses[9,28]. Bearing-related changes may also be embedded within the overall pump response[21,29]. A rise in root mean square (RMS) vibration or broadband energy can therefore reflect deteriorating machinery, hydraulic disturbance, or both. Field-oriented pump monitoring studies have shown that transducer choice and installation should be interpreted together with process duty[30,31]. In the context of pumps, it is essential to interpret vibration in conjunction with flow, pressure, operating point, and historical baseline, particularly when process coupling is significant.

Experimental evidence further demonstrates the influence of operating conditions on centrifugal pump vibration. Han et al.[32] investigated off-design operation and cavitation using vibration and motor stator current measurements, demonstrating the complementary value of mechanical and electrical signals in identifying hydraulic operating abnormalities. More recently, Kong et al.[33] reported a horizontal radial RMS vibration velocity of 4.060 mm/s under a low-flow, off-design operating condition (0.6Q) in a high-specific-speed centrifugal pump, with the 73–92 Hz instability band accounting for approximately 73.8% of the excitation energy. These findings provide quantitative evidence that considerable changes in vibration characteristics can arise from hydraulic operating conditions. Nevertheless, the relationship between the operating point and vibration response remains dependent on pump design, hydraulic behaviour, and measurement configuration.

In particular, deviations from the best efficiency point (BEP) should not be directly equated with shifts in theoretical bearing characteristic frequencies, which are primarily governed by bearing geometry and rotational speed. Although practical frequency deviations may arise from speed variation, slip, and dynamic interactions, changes in hydraulic loading are more directly reflected in vibration amplitude, broadband energy, and spectral characteristics. Consequently, a universal relationship between a specified percentage deviation from BEP and bearing characteristic frequency drift cannot be established without machine-specific evidence.

Compressors create a more mixed signal environment. Depending on the type and speed, the measured response can include running-speed harmonics, modulation, valve or impact events, bearing-related components, rotor-dynamic behaviour, and process/load effects[10,34]. Shaft and bearing responses do not always carry the same information, particularly when imbalance or support conditions change[35,36].

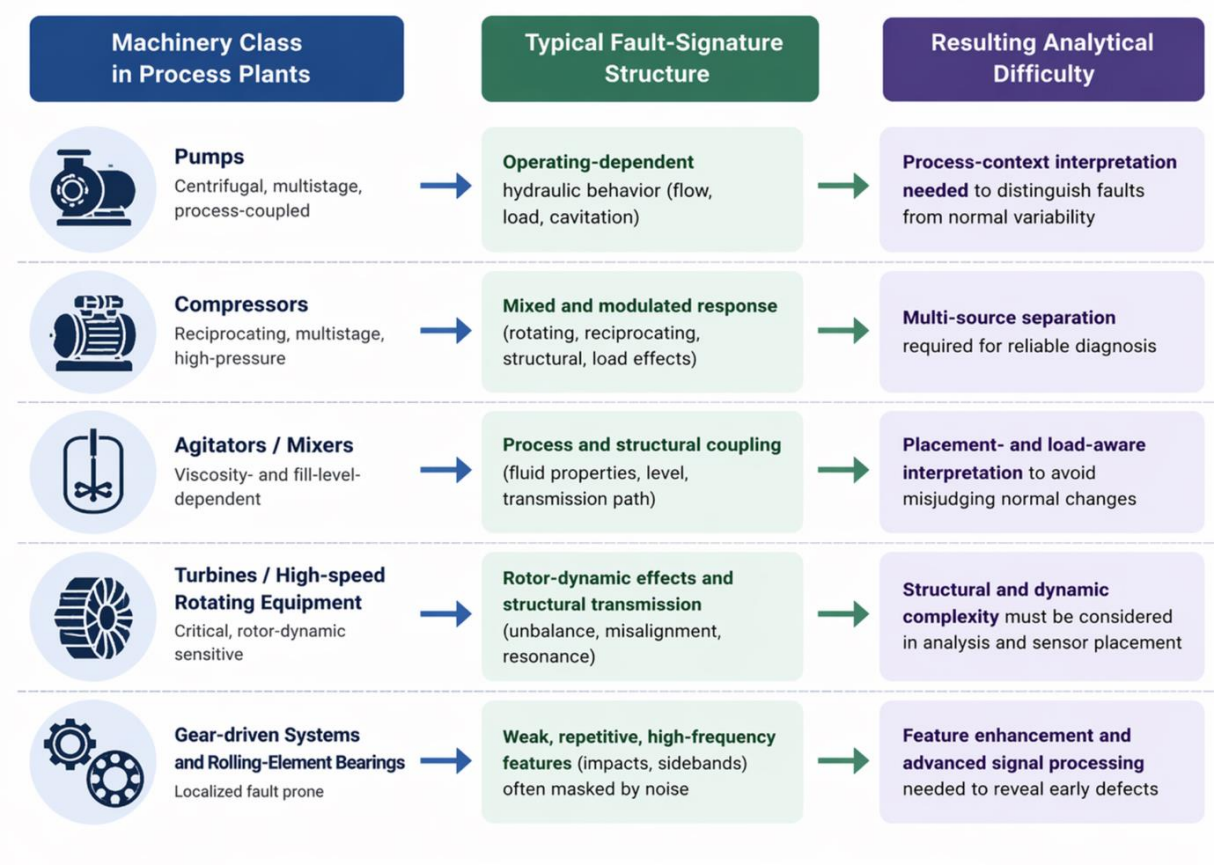


Figure 1. Conceptual relationship between machinery class, fault signature structure, and analytical difficulty in vibration-based predictive maintenance for chemical process plants.

Recent dual-rotor work also shows how alignment and assembly errors can alter the vibration pattern[37]. In high-speed trains, the motion of the shaft may provide more informative data than the casing vibration. Conversely, reciprocating machines may exhibit transient-rich signatures. Agitators and mixers add long

transmission paths and process-dependent loading: viscosity, fill level, blade condition, gearbox behaviour, shaft alignment, and support stiffness can all shift the measured baseline. For these assets, the key engineering task is attribution, determining whether a change represents fault growth, process variation, or an interaction between the two. **Figure 1** summarises the main differences in fault-signature structure and the associated analytical difficulty across representative equipment classes.

Misinterpreting process-related vibration as mechanical deterioration can lead to unnecessary inspection or shutdown work, while dismissing a developing fault as process variability can delay the intervention. Comparing the machine-specific baseline under similar operational conditions provides more informative insights than using a fixed absolute threshold. The apparent fault features should also be checked against the operating variables. For example, broadband energy that increases as the pump suction pressure decreases may support a hydraulic explanation, whereas increasing synchronous or bearing-related components under stable process conditions provide stronger evidence of mechanical deterioration.

The same reasoning applies to compressors and agitators, where the load, throughput, viscosity, and process state can shift the normal vibration envelope. Generic alarm limits are useful for screening, but process-coupled equipment often requires an operating-state context before a maintenance decision is made.

Distinguishing process-induced vibration variation from developing mechanical faults therefore requires operating-condition-aware analysis. A practical approach is to establish condition-specific vibration baselines by grouping measurements within comparable rotational speed, flow, pressure, and load ranges. For variable-speed machinery, order tracking and speed-normalised spectral analysis can reduce the influence of rotational speed variation on fault-frequency interpretation. Wu and Lin[38] demonstrated the potential of amplitude normalisation to reduce the coupling between vibration energy and rotational speed under varying operating conditions. More advanced approaches, including load-invariant feature extraction and domain adaptation, may further improve diagnostic consistency when operating conditions differ from those represented in the original monitoring data. However, these techniques should not be regarded as substitutes for physical interpretation. For chemical process equipment, the most defensible approach is to evaluate vibration trends together with relevant process variables, fault-specific spectral evidence, and maintenance history. This allows process-related fluctuations to be distinguished more reliably from persistent mechanical deterioration and reduces the risk of unnecessary maintenance interventions.

3.1.2. Structural and rotor-dynamic effects

Turbines, high-speed rotating equipment, and large fans illustrate a second problem: the measured signal is filtered by the machine structure before reaching the transducer. Shaft dynamics, support conditions, and misalignment can change the measured response substantially[36,37]. Proximity probe and accelerometer measurements may also emphasise different aspects of rotor behaviour[29,34]. Source separation and beamforming studies further show that overlapping vibration sources can complicate fault localisation[39,40]. Sensor mounting is not a neutral detail; damping and mounting structure can alter the transmitted vibration[41,42], while contact conditions can affect high-frequency measurements with portable or heavy sensors[43]. Multidirectional or multipoint monitoring is justified when structural transmission or rotor dynamics materially change fault visibility.

A related concern is that structural amplification can create apparently severe vibrations at one location, whereas another location better represents the actual fault source. A resonance-sensitive casing point may exaggerate a modest excitation, whereas a poorly coupled measurement point may attenuate a developing defect. In high-speed machinery, the analysis of shaft relative vibration, phase information, orbit behaviour, and casing response can provide complementary evidence.

The implication for PdM is that signal quality begins with a physically meaningful measurement path. Advanced algorithms cannot fully correct a measurement strategy that consistently observes the wrong

structural response. Consequently, sensor placement and channel selection should be based on expected fault transmission, bearing arrangement, support stiffness, and the dynamic behaviour of the machine, rather than on installation convenience alone.

3.1.3. Localised gear and bearing fault signatures

Gear-driven systems and rolling-element bearings present different forms of difficulty. Early defects often appear as weak repetitive impacts, modulation sidebands, mesh-related changes, or high-frequency energy that can be masked by stronger machine-level vibration[8,21]. Gear wear progression and localised gear damage are particularly dependent on feature visibility and trend consistency[44,45]. Bearing studies similarly show that defect-related frequencies and statistical indicators can shift with fault location and operating condition[46,47].

Recent work combining microelectromechanical systems (MEMS) sensing with ML also illustrates the growing use of compact sensing with data-driven classification[48]. These features may exist long before overall vibration becomes severe, but their visibility depends on bandwidth, signal quality, operating speed, structural transmission, and suitable feature enhancement. This is the strongest justification for advanced processing because localised defects often require it, as the relevant information is present but poorly separated.

Localised faults also illustrate why early detection and reliable diagnosis are not the same problem. High-frequency energy or impulsiveness may indicate that something has changed, but fault localisation requires stronger evidence. The bearing characteristic frequencies can shift with slip, speed variation, or load, and the gear sidebands can be influenced by several forms of modulation.

A useful industrial workflow separates screening from confirmation: a broad indicator identifies abnormal behaviour, targeted spectral or envelope-related evidence supports localisation, and the conclusion is then checked against the speed, load, lubrication, and maintenance history. This staged logic reduces the risk that an isolated mathematical feature is interpreted as a confirmed defect. It also supports more efficient plant deployment because advanced processing can be reserved for assets or time periods in which conventional trends indicate a credible need for deeper diagnosis.

3.1.4. Comparative interpretation across equipment classes

Equipment classes require different diagnostic strategies. Process-coupled machines require operating context information; high-speed machines require attention to structural transmission and rotor dynamics; and gear- or bearing-dominated systems depend on the adequate visibility of weak localised features. Conventional trends may be sufficient for many low-criticality fans and general pumps, whereas critical compressors, turbines, gearboxes, and bearing-dominated assets often justify deeper analysis. **Table 2** summarises these differences and links machinery behaviour to the level of analysis typically required.

Table 2. Comparative interpretation of fault-signature behaviour across representative process equipment classes in chemical process plants.

Equipment class	Dominant vibration behaviour	Main source of interpretation difficulty	Typical analytical requirement	Practical monitoring emphasis
Pumps	Combination of rotating fault response and hydraulic-condition-dependent vibration	Mechanical faults may be masked or modified by cavitation, recirculation, or operating-point variation	Requires contextual interpretation beyond simple severity increase	Combine signal assessment with basic hydraulic operating context

Table 2. (*Continued*).

Equipment class	Dominant vibration behaviour	Main source of interpretation difficulty	Typical analytical requirement	Practical monitoring emphasis

Compressors	Multi-source vibration involving rotor behaviour, impacts, modulation, and process/load effects	Overlapping fault sources and machine-type dependence complicate diagnosis	Often requires advanced feature extraction and structured interpretation	Use multi-directional and multi-point analysis where possible
Agitators/mixers	Mixed mechanical and process-coupled response with strong structural transmission effects	Signal visibility depends heavily on vessel load, support stiffness, and measurement location	Requires placement-aware interpretation and comparison across locations	Interpret with awareness of process variability and structural amplification
Turbines/high-speed rotating equipment	Running-speed, harmonic, shaft-motion, and rotor-dynamic response	Casing vibration alone may not capture the most critical instability behaviour	May require integration of casing vibration and shaft-motion monitoring	Prioritise high-confidence trend analysis and rotor-dynamic interpretation
Fans and general rotating assets	Predominantly running-speed, looseness, and flow-related vibration	Mechanical and aerodynamic effects may coexist but are often broadly interpretable	Conventional trending may be sufficient in many cases	Focus on scalable early identification of imbalance, looseness, and bearing change
Gear-driven systems and bearings	Localised, repetitive, high-frequency, and modulation-rich signatures	Early fault features are weak, masked, or superimposed on broader machine vibration	Strong candidate for enhanced signal processing and AI-assisted diagnosis	Emphasise feature visibility, localisation, and early defect detection

3.1.5. Diagnostic confidence and evidence escalation

Across the equipment classes discussed above, the main diagnostic challenge is not simply to detect a change but to decide how much confidence should be attached to it. A useful distinction is made between three evidence levels: screening, attribution, and maintenance confirmation. Screening asks whether the machine response has moved away from its established baseline. Attribution asks whether the change is consistent with a particular mechanical or process mechanism. Maintenance confirmation asks whether the evidence is sufficiently coherent, repeatable, and consequential to justify inspection, intervention, or a change in monitoring intensity. Treating these levels separately reduces the tendency to interpret every abnormal indicator as a confirmed fault.

For screening, overall vibration, simple statistics, and broad spectral trends are often sufficient. Attribution requires more specific evidence, such as coherent running-speed harmonics, bearing-related components, modulation sidebands, transient features, and agreement across measurement directions and locations. Source-separation and spatial-diagnostic studies show why this second step becomes important when several excitation mechanisms overlap[39,40]. For gears, progressive wear should be checked against consistent changes in mesh-related or modulation features rather than accepted from a single transformed signal[44,45]. Bearing-related indicators likewise require confirmation against the expected defect mechanism and operating condition[46,47].

The final escalation step should include the process state and consequence. A vibration change that appears only during a particular hydraulic duty may require a different response from the same change observed under stable process conditions. Similarly, weak but repeatable evidence on a critical compressor can justify earlier verification than a comparable indication on a redundant utility fan. This evidence-escalation logic provides a common interpretation framework across heterogeneous plant equipment: simple methods identify where attention is needed, targeted analysis establishes whether a mechanically credible pattern exists, and operating context plus asset consequence determine the maintenance response. The objective is not to delay action but to make the path from signal change to intervention technically auditable.

3.2. Signal-processing foundations for vibration-based diagnostics

The choice of signal-processing method should follow the diagnostic problem identified in Section 3. Industrial vibration records may contain running-speed components, harmonics, broadband energy, transient

impacts, modulation, process-driven variation, and structural filtering[11]. Studies on source separation and modulation analysis have shown that weak fault information can remain hidden even when the raw signal contains it[39,49].

More elaborate processing is useful only when it reveals information that conventional analysis cannot resolve. The main requirement is to retain a clear link between the processed features and the underlying machine behaviour. **Figure 2** shows the progression from conventional analysis to feature enhancement, time-frequency interpretation, and decomposition-based processing.

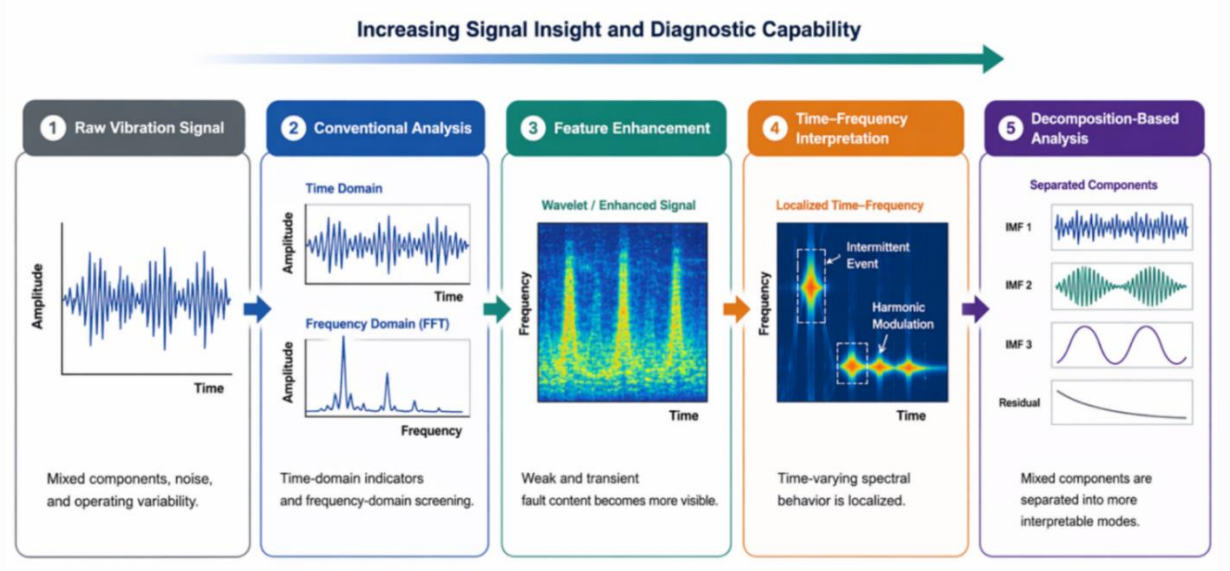


Figure 2. Conceptual progression of vibration signal processing in predictive maintenance, from conventional time-domain and frequency-domain analyses to advanced feature enhancement, time–frequency interpretation, and decomposition-based methods.

3.2.1. Conventional time- and frequency-domain analysis

Time-domain indicators, such as RMS, peak level, crest factor, and kurtosis, remain valuable for plant-wide screening because they are computationally light, easy to trend, and familiar to maintenance personnel[11]. Their value is also supported by quality-control studies showing that even basic vibration metrics can vary with measurement conditions and test repeatability[47]. RMS is useful for severity change, while peak-related statistics can support the detection of impulsive behaviour. Their limitation is low fault specificity: the same increase may arise from imbalance, cavitation, looseness, load change, or a transient event. These indicators are strongest when interpreted against historical baselines and operating states rather than used as standalone fault labels.

Fast Fourier transform (FFT)-based spectral analysis remains the primary physical language for rotating machine diagnosis. Enhanced FFT methods are widely used to resolve bearing-related frequency content[11,50], and embedded implementations show that spectral analysis can be performed even on relatively low-cost acquisition platforms[51].

The running-speed components, harmonics, gear-mesh frequencies, sidebands, and characteristic bearing frequencies are easier to interpret in the frequency domain. Its weakness is the assumption of stationarity. Intermittent cavitation, compressor events, speed changes, and process-dependent agitator responses can be diluted in the global spectrum. In the context of CPPs, conventional analyses should serve as the initial layer. This approach offers transparent evidence and facilitates a broad screening. However, it should prompt a more in-depth analysis when critical fault information is characterised by temporal variability, weakness, or superimposition.

The continued value of conventional methods is sometimes underestimated in AI-centred literature. In real plants, a method that is slightly less sensitive but highly repeatable, explainable, and easy to trend can be more useful than a complex transformation that is difficult to validate. Classical indicators also provide an important reference layer for checking advanced outputs. If an AI model reports a worsening condition while basic spectra, waveform behaviour, and operating history show no consistent change, the discrepancy should trigger an engineering review rather than automatic escalation. Conversely, a clear growth in harmonics, sidebands, or impulsive content can provide the physical evidence needed to justify deeper analysis. Conventional methods therefore act as both a diagnostic tool and a verification layer for more sophisticated analytics.

3.2.2. Time-frequency and feature-enhancement methods

Wavelet methods and the short-time Fourier transform (STFT) extend the analysis into the time-varying domain. Wavelet-based diagnosis has been applied to shaft misalignment and transient fault features[13,52], while improved wavelet methods can also support the denoising of weak vibration signals[53,54]. STFT provides a direct spectrogram-based view of changing frequency content and is well suited to transient rotating-machine behaviour[55,56].

Application studies also demonstrate its usefulness for rotor unbalance under time-varying conditions[57]. The main limitation of both routes is parameter dependence: window length, wavelet family, decomposition depth, and reconstruction strategy can materially change the result. Reproducibility therefore matters as much as visual sensitivity.

Cepstral and related spectral enhancement methods address a narrower but important problem: repetitive modulation that exists in the spectrum but is masked by dominant harmonics or transmission effects. Hybrid cepstral preprocessing has been used to enhance bearing fault features[16,17], whereas cepstrum analysis has been applied to rotating aeroengine vibrations[58].

By emphasising the periodicity in the spectral structure, these methods can improve the sideband and repetitive fault visibility in gears and bearings. However, they are not universal tools for broad process noise; their values are highest when the target mechanism is repetitive and localised. Across these methods, the engineering criterion is whether the added processing reveals evidence that changes the diagnostic decision.

The choice between wavelet and STFT routes should be driven by the expected signal behaviour. STFT is often preferable when the analyst needs a transparent view of the frequency evolution over time, particularly during start-up, coast-down, or changing load. Wavelet analysis is more flexible when events occur over multiple time scales or when short transients must be separated from broader background content. In both cases, parameter selection should be documented because different windows, scales, or mother wavelets can produce materially different visual emphasis.

For review and deployment purposes, reproducibility is as important as sensitivity. A plant diagnostic method should specify how the parameters are selected, how the results are compared across machines, and what evidence constitutes a meaningful change. Without such rules, time–frequency plots can become visually persuasive but are operationally inconsistent.

3.2.3. Adaptive decomposition for mixed and non-stationary signals

Empirical mode decomposition (EMD) and its variants are useful when the measured vibration contains several overlapping oscillatory behaviours that cannot be cleanly separated using fixed-basis methods[14,15]. Hybrid empirical/variational decomposition and multi-axis EMD studies have demonstrated how the method can be adapted when the signal contains complex or mixed components[59,60]. Ensemble variants have also been developed for high-speed transient acceleration signals[61].

EMD derives intrinsic mode functions from the data itself, making it attractive for compressors, pumps, and agitators, where mechanical and process excitations coexist. Classical EMD is susceptible to challenges such as mode mixing, end effects and sensitivity to noise. In practical PdM, decomposition is best treated as a targeted preprocessing or feature-structuring step for genuinely mixed signals, not as a default replacement for FFT or time-domain analysis.

Decomposition-based methods should also be evaluated based on whether the separated modes retain physical meaning. A mathematically clean intrinsic mode is not automatically a fault component, and mode selection can become subjective when multiple sources overlap. For industrial use, decomposed components should be related to known machine frequencies, transient events, process changes, and repeatable condition trends.

Hybrid methods may improve separation, but additional processing steps can increase parameter sensitivity and reduce interpretability. In CPP PdM, decomposition therefore plays a selective role: it can help separate difficult signal components and expose weak information, but the final diagnosis should remain anchored to machine physics and operating context.

3.2.4. Matching processing depth to diagnostic need

Table 3. Comparative role of major vibration signal-processing routes in the predictive maintenance of chemical process plants.

Signal-processing route	Best suited signal condition	Main analytical strength	Main limitation	Typical practical role
Conventional time-domain indicators	Broad condition change and severity variation	Simple, scalable, low computational burden	Low fault specificity	First-line screening and trend monitoring
FFT-based spectral analysis	Stationary or near-stationary periodic fault content	Strong physical interpretability for classical rotating faults	Limited for transient or mixed-source behaviour	Baseline diagnostic tool for general rotating machinery
Wavelet-based analysis	Transient and non-stationary localised features	Strong time–scale localisation and denoising capability	Sensitive to parameter choice	Early localised fault enhancement and non-stationary feature analysis
STFT and time–frequency analysis	Time-varying spectral behaviour	Useful visualisation of evolving frequency content	Time–frequency resolution trade-off	Transient event analysis and process-dependent signal interpretation
EMD and decomposition-based analysis	Mixed, nonlinear, and process-variable signals	Data-adaptive mode separation	Higher complexity and sensitivity to decomposition quality	Preprocessing and advanced signal restructuring for difficult machinery
Cepstrum and spectral enhancement	Weak repetitive fault content masked by dominant spectral components	Improves visibility of modulation and repetitive defect structure	More specialised and less general-purpose	Early gear and bearing fault visibility enhancement

A practical analysis sequence starts with simple, interpretable screening and adds processing only when the signal characteristics require it. Conventional indicators and FFT are appropriate for broad condition changes and classical periodic faults; wavelet and STFT methods are useful for transient or non-stationary behaviour; cepstral enhancement can expose weak repetitive modulation; and adaptive decomposition is valuable when several signal components overlap. **Table 3** summarises these roles. Such staged use of the methods limits unnecessary complexity and ensures that the maintenance conclusion is traceable to the measured signal.

3.3. AI-based diagnostics, anomaly detection, and prognostic intelligence

AI-based methods extend vibration analysis from feature extraction to automated classification, anomaly recognition, and prognostic support. Reviews of ML and DL in rotating machinery describe rapid progress in

these areas[18,19], while more recent work has shifted attention toward generalisation, few-shot learning, prognostics, and industrial deployment[27]. For CPP use, the limiting issue is rarely benchmark accuracy alone. Plant data are often noisy, imbalanced, incompletely labelled, and affected by changing operating conditions; diagnostic outputs must also remain understandable to engineers who are responsible for maintenance decisions. These constraints shape the usefulness of AI more strongly than headline accuracy on a controlled dataset. **Figure 3** illustrates the progression of AI-based vibration diagnostics from fault classification and anomaly detection to degradation assessment and prognostic support, highlighting their respective roles in PdM.

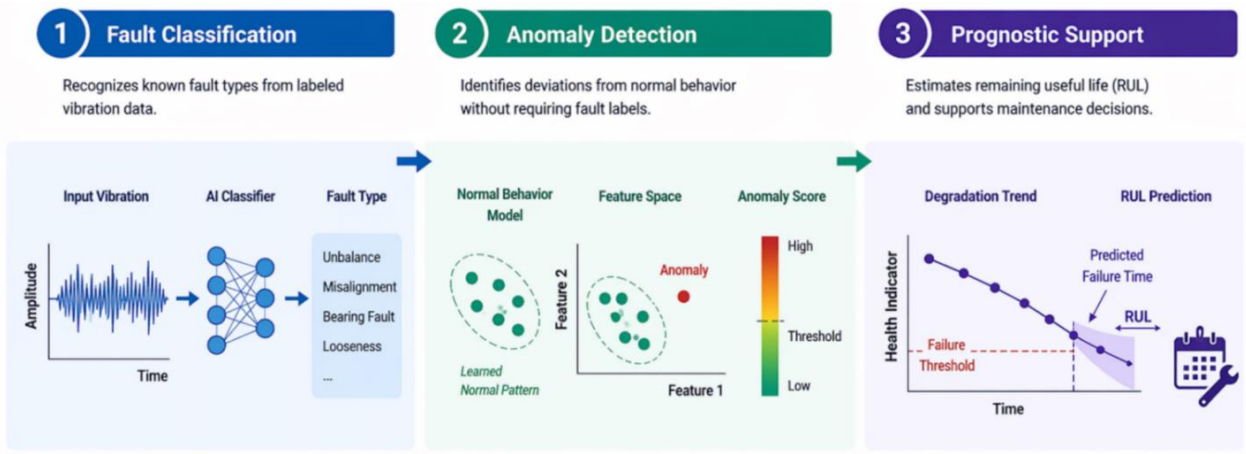


Figure 3. Conceptual progression of AI-based vibration diagnostics in predictive maintenance from fault classification and anomaly detection to degradation-aware prognostic support.

3.3.1. Classification and representation learning

Supervised ML remains effective when labelled examples of healthy and known fault conditions are available[19,62]. Support vector machine (SVM)-based studies on vibration monitoring and bearing diagnosis illustrate how the extracted features can support practical classification[63]. The main limitation is their reliance on representative labels and specific deployment conditions. Out-of-distribution (OOD) studies have shown that confidence can deteriorate when field data differ from the development domain[64,65]. A model trained on one machine, load, sensor position, or laboratory rig may therefore not remain reliable when the plant conditions change.

DL reduces the need for hand-crafted feature selection and can learn complex representations from raw waveforms, spectra, or time–frequency images[18,66]. Continuous wavelet transform (CWT)-based convolutional neural networks (CNNs) and benchmark studies have demonstrated strong pattern-learning capabilities for machinery faults[13,67].

Domain-adaptation research addresses part of the transfer problem when operating conditions or machines change[68], whereas virtual vibration-sensor work illustrates how convolutional models can also reconstruct or augment vibration information[69]. A higher model capacity generally increases data requirements and can also make the physical basis of a prediction less transparent. For plant use, deep models are most defensible when they demonstrate cross-condition robustness and when the learned output can be connected to signal evidence.

3.3.2. Anomaly detection and prognostic support

Anomaly detection is particularly relevant to CPPs because complete fault libraries rarely exist for all assets. Long short-term memory (LSTM)/SVM and one-class approaches show how to identify deviations without a fully populated fault catalogue[70,71]. This approach is beneficial for detecting rare faults and managing large populations of assets. However, anomaly scores alone do not inherently determine the root

cause. Their value increases when deviations are interpreted in conjunction with vibration features, process conditions, and maintenance history.

Prognostic modelling moves beyond present-state diagnosis toward degradation trajectory and remaining useful life. Gear-wear and rolling-bearing studies have shown how condition features can be linked to progression or life prediction[44,72]. Broader prognostic reviews emphasise that useful forecasting depends on repeated degradation data and appropriate validation[27,67]. In process plants, these conditions are often weak because duty changes and intervention histories are incomplete. Prognostic outputs should therefore be treated as uncertainty-aware decision support rather than deterministic failure dates.

Anomaly detection also requires careful baseline management. Normal behaviour in a process plant is rarely a single compact state; it may include several legitimate operating regimes associated with throughput, speed, temperature, or product grade. OOD and transfer-learning studies have shown why models can fail when the operational domain changes[64,65].

Practical anomaly systems should therefore incorporate operating-state segmentation, adaptive baselines, or contextual variables, as appropriate. Prognostic systems face the same issue at a longer time scale: a degradation rate estimated under one duty may not remain valid after operating conditions change. For both applications, uncertainty should be communicated explicitly because maintenance planning depends on prediction confidence as well as numerical output.

3.3.3. Generalisation, interpretability, and deployment readiness of AI diagnostics

The central limitation of AI-based vibration diagnostics is the domain shift. Many published models have been developed using controlled datasets with fixed speeds, seeded defects, balanced classes, and consistent sensor locations. Reviews of small/imbalanced data diagnosis and domain adaptation both identify this mismatch as a major obstacle to transfer[68,73].

CPPs introduce variable loads, process disturbances, sensor drift, maintenance changes, incomplete labels, and mixed mechanisms. High within-dataset accuracy can overstate field performance. Stronger evidence comes from cross-machine, cross-load, cross-sensor, or plant-to-plant validation, and from testing under realistic noise and operating variation.

Interpretability is important because maintenance decisions have operational consequences. Reviews of condition-monitoring ML emphasise the need to connect model outputs to engineering evidence rather than accuracy alone[18,22]. Engineers are more likely to act on a diagnosis when it is supported by familiar evidence, such as $1\times/2\times$ behaviour, sidebands, impulsive growth, spectrogram changes, and deviation from a machine-specific baseline. The diagnostic workflow should therefore retain these links between the model output and vibration evidence. **Table 4** compares the practical roles of classification, deep representation learning, anomaly detection, and prognostic support.

Table 4. Comparative role of AI-based diagnostic routes in vibration-based predictive maintenance for chemical process plants.

AI route	Main purpose	Main strength	Main limitation	Most realistic industrial role
Supervised machine learning	Classify known fault categories from extracted features	Good structured discrimination when labelled data are representative	Strong dependence on label quality and limited ability to handle unknown fault behaviour	Known-fault recognition in reasonably well-characterised assets
Deep learning	Learn high-dimensional discriminative representations directly from signal data	Strong capability for complex nonlinear pattern recognition	High data demand and reduced interpretability	Scalable diagnostics for complex signal classes when data realism is strong
Anomaly detection	Identify meaningful deviation from expected normal behaviour	Useful when fault labels are sparse or incomplete	Sensitive to operating variability and false-alert risk	Early warning and attention prioritisation in plant-wide monitoring

AI route	Main purpose	Main strength	Main limitation	Most realistic industrial role
Prognostic modelling	Estimate degradation progression or condition evolution	Supports maintenance planning beyond current-state diagnosis	Harder to generalise and more sensitive to uncertainty	Decision-support layer for critical assets with sufficient historical condition data

Industrial validation should report how performance changes with load, sensor position, machine identity, and noise, in addition to conventional metrics such as accuracy, precision, and F1 score. Domain-adaptation work also shows why transfer performance should be reported explicitly when training and deployment conditions differ[65,68]. Failure cases are equally informative because they reveal when a model becomes uncertain or incorrect.

A more useful way to evaluate industrial AI is to treat validation as a ladder rather than a single test score. The lowest level is within-dataset validation under the same rig, sensor position, and operating regime. Higher levels test cross-load and cross-speed performance, followed by cross-sensor or cross-machine transfer, and finally performance on data collected under real plant conditions. OOD research shows how confidence can deteriorate when the field input no longer resembles the validated development domain[64]. Transfer-learning and domain-adaptation studies similarly show that changing the machine or operating regime can expose failure modes that random train/test splits do not reveal[65,68]. For process-plant deployment, evidence from the higher levels should carry greater weight than a marginal improvement in benchmark accuracy.

Uncertainty should also be reported as part of the diagnostic performance. When a model is exposed to an unfamiliar operating state, a low-confidence or OOD indication can be more useful than an apparently precise but unsupported fault label[64]. For anomaly detection, useful measures include false-alarm persistence, sensitivity to operating-state transitions, and the stability of the anomaly score over repeated healthy operations. For prognostic applications, lead time, trend stability, and consistency of health indicators after maintenance intervention are as important as point-estimate errors. Small and imbalanced industrial datasets further strengthen the case for confidence-aware evaluation rather than accuracy-only reporting[73]. Benchmark datasets remain valuable for reproducible model comparison[66,67], but they cannot substitute for industrial field validation. Deployment readiness should be assessed according to the level of validation achieved, remaining uncertainties, and suitability for maintenance decision support.

The selection of AI-based diagnostic methods should ultimately depend on the asset characteristics, available data, and maintenance decisions being supported. Conventional spectral analysis may remain sufficient for machinery with well-established fault signatures, whereas anomaly detection may provide greater value when labelled fault data are limited. Supervised learning and prognostic modelling can support critical equipment when sufficient operating history is available and model performance has been evaluated across representative conditions. Analytical sophistication should be justified by the diagnostic objective, asset criticality, operating variability, and required level of interpretability rather than by algorithm accuracy alone.

3.4. Industrial integration and maintenance decision-making

Vibration analytics have operational value only when their results reach the maintenance workflow. Edge-enabled monitoring can move processing closer to the asset[74], while distributed control-system integration provides an operating context for interpreting condition changes[75]. CMMS records can then link diagnostic findings to inspection history, work orders, and follow-up actions[76].

Research on the early warning of unplanned shutdowns also shows why intervention timing matters in process operations[77]. A technically sound diagnosis can still have little effect if it remains isolated from process information or maintenance systems; the usefulness of the analysis depends on how clearly it is connected to plant actions.

3.4.1. From signal intelligence to maintenance action

A vibration alert should be interpreted according to the asset criticality, redundancy, process duty, shutdown opportunity, and the consequence of failure. Lower-criticality assets can often be managed with route-based measurements, conventional trends, and exception reporting, whereas critical compressors, turbines, and major pumps may require permanent sensing and closer diagnostic oversight. Studies on unplanned-shutdown risk and maintenance policy selection support linking intervention timing to consequences and operating contexts[77,78]. In practice, the same numerical change can lead to different actions depending on whether the equipment is redundant, process-critical, or approaching an available shutdown window.

A tiered monitoring strategy also avoids unnecessary analytical complexities. The required evidence should reflect the consequences of such failures. Broad screening can identify changes; deeper analysis can determine whether the change is technically credible; process data can show whether it is associated with operating conditions; and the maintenance system can then convert a confirmed finding into an action. This sequence provides a clearer escalation path than applying the same diagnostic depth to each asset.

The same tiered approach can be used to define when automated outputs require an engineering review. Routine changes in low-risk equipment may be managed through trend dashboards and scheduled follow-ups, whereas a rapid change in a critical train should prompt immediate assessment. Work-system studies of PdM show that adoption depends on how people, roles, and automated recommendations are integrated into maintenance practices[79]. Escalation should consider the condition evidence, rate of change, process state, and consequence, rather than a single alarm value. AI can support evidence screening and prioritisation; however, the responsibility for approving maintenance actions should remain explicit.

The tiered monitoring approach described here represents a maintenance escalation process, in which vibration abnormalities are progressively evaluated through diagnostic verification, operating-condition assessment, and asset criticality before an appropriate maintenance action is determined. This decision-making process should be distinguished from the standards-informed alarm and machinery protection functions discussed in Section 3.5.

3.4.2. Process context, plant information systems, and trust

Integration with process and maintenance systems should be purpose-specific. Distributed control systems can provide the operating-state variables needed to interpret process-coupled vibration[75]. CMMS databases add intervention history, work orders, inspection outcomes, and repair records that can be used to verify whether a diagnostic conclusion is correct[76]. For CPP equipment, integrating vibration measurements with operating-state information and maintenance records can support the identification of nuisance alarms and improve the interpretation of mechanical deterioration relative to process-induced vibration variations.

Recent industrial studies provide further evidence of the practical application of PdM in process-related environments. Anshori and Dhini[80] investigated fault detection in petrochemical rotating machinery using historical plant data collected between 2015 and 2024. Their WGAN–TabNet approach achieved an accuracy of 96.01% and an F1-score of 93.20%, demonstrating the potential of data-driven fault detection for critical rotating machinery in petrochemical applications. In a separate refinery application, Riyandwita et al.[81] used vibration spectral analysis and phase-based diagnostics to identify impeller imbalance in a centrifugal pump. Following corrective balancing, the reported vibration velocity decreased from 11.61 to 3.59 mm/s, providing a direct connection between diagnostic evidence and verified mechanical intervention. These studies demonstrate different forms of industrial validation, although retrospective classification performance and successful fault correction should not be interpreted as equivalent evidence of sustained PdM deployment.

For process-coupled machinery, vibration measurements should be time-aligned with relevant operating variables, including rotational speed, flow rate, suction and discharge pressure, temperature, and load. Where vibration data are acquired at substantially higher sampling rates than process historian records, diagnostic

features should first be extracted over defined measurement windows and then associated with the corresponding operating-state information. Consistent timestamps, appropriate aggregation intervals, and consideration of sensor response times and data acquisition delays are important for preventing incorrect attribution of process-induced vibration changes to mechanical faults. In practical applications, time-aligned vibration trends and process variables can support condition-specific baselines, improve alarm interpretation, and provide more reliable evidence for maintenance decisions.

Measurement chain and sensor fitness

The measurement chain is the first diagnostic model in any vibration-monitoring system, as it determines which parts of the machine response are physically available for later signal processing and AI. Sensor selection should begin with the expected fault frequencies, required dynamic range, machine speed, measurement quantity, and asset criticality rather than with device cost alone. Piezoelectric accelerometers remain a strong choice where broad bandwidth, low noise, and sensitivity to localised high-frequency content are important[82,83]. Broader piezoelectric-sensing reviews also show that transducer material and configuration affect the usable bandwidth and sensitivity[84,85]. Low-cost MEMS accelerometers are attractive for scalable or wireless monitoring because they can support compact edge nodes and large asset populations, provided that their bandwidth, noise floor, linearity, and saturation limits are verified for the intended machine[86,87]. Shaft-relative motion may require proximity or other non-contact measurements when casing acceleration does not adequately represent rotor behaviour[29,34].

Sensor placement and acquisition quality remain important, but they are treated here as enabling conditions rather than separate review topics. Low-cost MEMS and wireless acquisition can support scalable condition monitoring[86], whereas piezoelectric accelerometers remain important when sensitivity and bandwidth are critical[82,83]. Broader piezoelectric-sensing reviews have also shown how transducer characteristics influence the usable vibration signal[84,85].

Sensor fitness also depends on the diagnostic task. A transducer that is adequate for overall severity trending may be unsuitable for early bearing-impact detection, while a high-bandwidth channel may add little value if the objective is only to track stable running-speed vibration. The sampling frequency, anti-aliasing, analogue conditioning, channel synchronisation, and the duration of each record should be selected together with the sensor rather than after installation. This is particularly important when time–frequency or AI methods are planned, because apparently sophisticated analytics cannot reconstruct information that was never captured by the measurement chain. For critical assets, the selected sensor and acquisition configuration should therefore be treated as part of the diagnostic specification, not merely as instrumentation hardware.

Placement, mounting, and harsh-environment reliability

The measurement accuracy and mounting dynamics can materially alter the recorded response[87,88]. Proximity probes are particularly relevant when shaft-relative motion is required[29]. Distributed fibre-optic systems offer multipoint coverage; however, their response depends on the sensing architecture and installation[89,90]. Sensor-location studies across different structures have consistently shown that placement changes observability[91]. Similar findings have been reported for ground and tunnel monitoring[92,93] and industrial robot and damage localisation applications[94,95].

Data acquisition design and sampling strategy further affect the information available for diagnosis[50]. Harsh hydrocarbon environments and severe mounting conditions introduce additional reliability constraints. Alternative sensing concepts, including self-powered accelerometers and magnetic sensors, continue to expand the available measurement options[96].

Recent fibre-optic studies have illustrated several distributed vibration architectures[97,98], whereas interferometric and low-power multi-sensor approaches have highlighted the trade-offs in bandwidth,

sampling, and robustness[99,100]. Field-oriented optical systems have also been demonstrated for vibration monitoring and pipeline leakage detection[101,102].

Placement and mounting define the mechanical transfer path between a fault source and the measured signal. A sensor located close to the bearing load zone may reveal weak localised impacts that are attenuated at a remote casing point, whereas a structurally resonant location may amplify a narrow frequency band and exaggerate apparent severity. Experimental work shows that the mounting interface can materially alter the dynamic response of an accelerometer[88]. Sensor placement studies likewise show that observability changes with location and the selected optimisation criterion[91,94]. Evidence from ground and tunnel monitoring is used here only for the transferable placement principle, not as direct process-plant validation[92,93]. Damage localisation studies provide a similar methodological basis for selecting locations that preserve diagnostic sensitivity[95]. Permanent installations offer repeatable geometry and trending, whereas route-based measurements can introduce additional variability through contact pressure, orientation, surface condition, and repeated positioning.

Distributed and alternative sensing architectures can extend coverage where conventional point accelerometers are difficult to deploy. Distributed fibre-optic vibration sensing provides electrical isolation and extended spatial coverage; however, its diagnostic value depends on the interrogation architecture, spatial resolution, frequency response, and installation quality[89,90]. More recent fibre-optic architectures have illustrated how the sensing range and transduction principle influence the available vibration information[97,98]. Interferometric and low-power multi-sensor approaches introduce additional trade-offs in bandwidth, sampling, synchronisation, and robustness[99,100]. Field-oriented optical systems have also been demonstrated for vibration monitoring and pipeline-leakage applications[101,102]. Wireless and low-power nodes can reduce cabling and support wider asset coverage, but they introduce trade-offs in power budget, data rate, communication reliability, and local processing[100,103]. For chemical-process environments, the practical question is which architecture can preserve repeatable diagnostic information over the required service interval and under the actual mechanical and environmental constraints. **Table 5** compares the practical suitability of representative vibration measurement technologies, considering their diagnostic applications, measurement capabilities, and limitations under industrial operating conditions.

Table 5. Practical fit of representative vibration measurement routes for predictive maintenance in chemical process plants.

Measurement route	Main strength	Principal limitation	Typical best fit	Deployment emphasis
Piezoelectric accelerometer	High sensitivity and broad usable bandwidth; strong for impulsive and high-frequency vibration	Mounting quality, cabling, and installation path can affect response	Critical pumps, compressors, gearboxes, bearings, and fixed monitoring points	Use when diagnostic bandwidth and repeatable trend quality are priorities
MEMS accelerometer / smart node	Compact, low cost, low power, and suitable for edge or wireless deployment	Noise floor, bandwidth, dynamic range, and saturation must match the machine	Large populations of pumps, fans, auxiliary assets, and scalable monitoring networks	Verify sensor performance before using low-cost data for advanced diagnosis
Proximity / shaft-relative measurement	Direct observation of rotor displacement and shaft dynamic behaviour	Requires suitable target geometry, gap control, and dedicated installation	Turbines, high-speed compressors, and fluid-film-bearing machinery	Use where casing acceleration alone cannot represent rotor stability
Distributed fibre-optic sensing	Electrical isolation and long-range or multi-point coverage	Higher interrogation complexity; spatial and frequency performance depend on architecture	Extended structures, pipelines, remote areas, and distributed monitoring	Treat installation design and interrogation settings as part of diagnostic qualification
Wireless / low-power multi-sensor node	Reduced cabling and easier expansion across dispersed assets	Power, communication reliability, synchronisation, and bandwidth constraints	Low- to medium-criticality assets and exception-based plant-wide screening	Prioritise local feature extraction or event-driven transmission when raw-data bandwidth is limited

Human oversight, traceability, and maintenance feedback

Human review remains important for consequence-sensitive rotating equipment. Abnormal vibration may result from changes in process conditions, mixed fault mechanisms, or limitations in the measurement chain. Full automation may therefore be difficult to justify when operating conditions are variable, model confidence is low, or the consequence of an incorrect action is high. Intelligent monitoring is better used to prioritise evidence, show the basis of an alert, and support engineering judgment. Human review is especially important when model confidence is low, operating conditions are unusual, or the proposed action has significant production or safety implications.

Plant data integration can also improve the monitoring system over time. Industrial PdM studies have shown that implementation is more useful when diagnostic outputs are linked to maintenance history and follow-up actions[25,26]. When an alert leads to inspection, repair, or a decision to take no action, the outcome can be linked back to the original signal. This creates machine-specific evidence connecting vibration patterns with confirmed equipment condition. Historian and CMMS records can therefore support threshold refinement, model evaluation, and separation of nuisance alarms from useful precursors[76].

A closed feedback loop is especially important for preventing diagnostic systems from becoming detached from the maintenance reality. Every confirmed inspection, repair, replacement, and no-fault-found outcome provides information on whether the preceding vibration alert was useful. Industrial PdM studies show why maintenance history and follow-up actions are important for evaluating whether monitoring outputs actually support interventions[25,26]. DT and PdM reviews further emphasise the value of connecting diagnostic outputs with persistent asset and maintenance information[24]. Over time, this evidence can be used to refine machine-specific baselines, identify nuisance alarm conditions, adjust escalation rules, and evaluate whether the model performance remains stable after equipment or process changes.

Evidence of maintenance workflow integration remains more limited but is particularly important for evaluating deployment readiness. Embarki et al.[104] reported an industrial implementation of vibration-based PdM for a reverse osmosis system in a continuous-process beverage plant. The system integrated vibration measurements, historical data management, condition-based alarm logic, predictive modelling, and CMMS functions. Following deployment, the proportion of failure-free operating days increased from 72.8% to 84.5%, while the reported operational assessment also indicated a reduction in unplanned downtime. Although the application was outside the chemical and petrochemical sectors, its implementation provides transferable evidence of how diagnostic information can be connected to maintenance execution and performance monitoring. The findings should nevertheless be interpreted cautiously because the study involved a single industrial site and a before-and-after evaluation without a contemporaneous control group.

The feedback loop should preserve the original sensor location, operating state, analytical result, engineering decision, and final maintenance finding so that subsequent model or threshold changes can be audited.

Traceability is also a governance requirement. An AI-generated condition label should not be treated as an isolated technical truth; it is one piece of evidence within a decision process that also includes process conditions, asset history, inspection findings, and consequences. Establishing clear ownership is essential for the confirmation of alerts, approval of changes to thresholds or models, and documentation of instances where engineering judgment supersedes automated recommendations. Such records are valuable because they reveal not only successful detections but also the conditions under which the monitoring system is uncertain or misleading.

3.4.3. Deployment barriers and a plant-level framework

Several barriers repeatedly limit plant deployment. Reviews have identified data quality, incomplete labels, weak integration, and uncertain maintenance value as recurring PdM problems[23,24]. Work-system

research has added organisational factors, including role clarity and the way automated recommendations are incorporated into routine work[79].

Sensor reliability and environmental survivability remain additional constraints in harsh process settings[105]. These findings point to five linked requirements for implementation: reliable measurement, signal-processing depth suited to fault visibility, AI support consistent with the available data, validation against process context, and an escalation rule matched to asset consequence.

The PdM performance is best judged at the system level. High-quality sensors and sophisticated models do not guarantee useful monitoring if alerts are not reviewed, responsibilities are unclear, or work order feedback is missing. A simpler system can provide greater value when its limits are understood and aligned with asset criticality, operating context, and maintenance execution. In process mechanical engineering, the purpose of the monitoring system is to reduce uncertainty about the equipment condition at the point where a maintenance decision must be made.

Deployment readiness can therefore be judged using a small set of system-level questions: Is the measurement repeatable? Is the diagnostic feature physically credible? Does the model recognise when operating conditions fall outside its validated range? Can the alert be traced to a responsible engineering review? Is there a defined maintenance response proportional to asset criticality? And is the outcome fed back into the monitoring history? These questions expose weaknesses that may be invisible in algorithm-level metrics. For example, a highly accurate classifier can still create little value if sensor drift is not detected, if alerts cannot be associated with process state, or if maintenance teams cannot distinguish advisory information from a protection-level warning. Conversely, a simpler monitoring route can be deployment-ready when its measurement limits, escalation rules, and response ownership are explicit.

Table 6 summarises the main integration issues. For industrial PdM, the ability to trace a diagnosis from measured evidence through the operating context to maintenance action is more informative than algorithm accuracy considered in isolation.

Table 6. Main industrial integration issues affecting the deployment of intelligent vibration monitoring in chemical process plants.

Integration issue	Why it matters	Typical consequence if weakly handled	Practical implication for deployment
Weak connection to maintenance workflows	Diagnostic outputs do not automatically become maintenance decisions	Monitoring remains informational rather than actionable	Link analytics to triage, inspection planning, and work-order logic
Limited integration with process and plant information systems	Vibration changes may be misread without operating context	False alarms or ambiguous interpretation in process-coupled assets	Combine vibration data with operating and maintenance context
Lack of asset-criticality differentiation	Same analytical depth is applied to all machines regardless of consequence	Inefficient monitoring architecture and weak prioritisation	Use tiered monitoring strategies matched to asset importance
Poor interpretability	Engineers cannot relate model outputs to recognizable machine behaviour	Low trust and weak adoption	Preserve explainable links between signal evidence and diagnostic output
Domain shift and data-quality variability	Real plant signals differ from development datasets	Reduced model robustness and weak transferability	Evaluate and adapt models under realistic plant variability
Overreliance on full automation	Diagnostic outputs are treated as autonomous decisions	Misalignment with engineering practice and consequence-sensitive operations	Position intelligent monitoring as decision support within human-guided workflows

3.5. Standards-informed assessment, protection, and alarm governance

A deployment-ready vibration programme should distinguish between condition monitoring, diagnostic interpretation, and machinery protection. ISO 17359 provides a general framework for establishing a machine

condition-monitoring programme and emphasises a structured process rather than isolated measurement activity[106]. This is consistent with the tiered logic used in this review, where screening, diagnosis, contextual verification, and maintenance escalation are treated as connected but different functions.

For many industrial machines, ISO 20816-3 provides guidance for evaluating in situ broadband vibrations under steady-state operating conditions and can support both acceptance and operational monitoring[107]. Importantly, its scope is vibration evaluation rather than a detailed diagnosis of the condition of internal gears or rolling element bearings[107]. Exceeding a severity zone or threshold should be regarded as an indication necessitating further assessment rather than an automatic identification of a specific fault mechanism.

Machine-specific standards further illustrate why one universal vibration threshold is inappropriate. ISO 20816-8 provides measurement and classification guidance for reciprocating compressor systems, particularly for vibration and fatigue-related concerns; however, the standard explicitly states that its guidelines are not intended for condition-monitoring purposes[108]. ISO 20816-9 addresses enclosed gear units and includes housing and shaft vibration measurements for acceptance and operational monitoring, while specialist techniques for evaluating gear condition remain outside its diagnostic scope[109]. These distinctions reinforce the need to match the monitoring rule to the machine type, measurement quantity, operating state, and diagnostic objective.

For petroleum, chemical, and gas industry services, machinery protection requirements create an additional boundary around PdM analytics. API Standard 670:2025 defines minimum requirements for machinery protection systems that monitor quantities such as radial shaft vibration, casing vibration, axial position, rotational speed, and critical machinery temperatures[110]. The existence of this protection layer means that an AI or PdM platform should not be designed as an informal replacement for an established trip or protection function. Instead, condition-monitoring analytics should complement protection systems by providing earlier interpretation, fault discrimination, and maintenance planning before protection limits are reached.

A practical governance model is therefore to distinguish three functions: machinery protection alarms, condition-monitoring alarms, and diagnostic advisories. Protection alarms are consequence-driven and require controlled configuration, testing, and documented response ownership. Condition alarms identify statistically or physically significant deviations from an established baseline and should trigger a review rather than immediate fault labelling. Diagnostic advisories provide a more specific interpretation based on spectra, time–frequency features, process context, or AI outputs and should communicate the evidence and uncertainty supporting the conclusion. This separation reduces the risk that a probabilistic model output is treated as equivalent to a hard protection limit.

Standards-informed governance also changes how thresholds should be managed. Broadband vibration severity limits can provide an initial reference for condition assessment; however, fault-specific diagnostic thresholds should be interpreted separately and evaluated against the operating state, machine characteristics, and historical vibration trends[107]. Changes to baselines, alarm limits, model thresholds, or sensor configurations should be traceable because each change alters the evidence chain used for maintenance decisions[106]. In critical services, the most defensible architecture is therefore layered: standards and protection systems define safety and monitoring boundaries, vibration analytics improve diagnostic specificity, and maintenance workflows determine the final intervention according to condition evidence and asset consequence[106].

The distinction between maintenance escalation and alarm governance is particularly important in industrial PdM. While Section 3.4 addresses how vibration evidence is evaluated and translated into maintenance decisions, the present section defines the functional boundaries between condition monitoring, diagnostic advisories, and machinery protection. ISO 17359 provides the general framework for condition-

monitoring programmes, the applicable parts of ISO 20816 support vibration evaluation within their specified equipment scopes, and API 670 establishes requirements for machinery protection systems. The proposed approach therefore complements these established standards by supporting process-aware diagnostic interpretation and maintenance decision-making without replacing independent machinery protection functions.

3.6. Evidence limitations and future research directions

3.6.1. Evidence-base limitations and comparative readiness

A major limitation of current vibration-based PdM research is the continued reliance on controlled datasets. Reviews of intelligent diagnosis have highlighted the difficulty of obtaining small, imbalanced, and domain-shifted datasets[65,73]. More convincing validation would include changing loads and process conditions, realistic noise, incomplete labels, intervention history, and confirmed maintenance outcomes. Cross-machine and cross-site testing is also required because a model that works on one installation may not transfer to another. Benchmark datasets remain useful for method development but should be treated as a starting point rather than evidence of plant readiness.

Uncertainty and explanations also require stronger treatment. Trustworthy diagnosis research indicates the importance of indicating when predictions fall outside the confidence supported by training data[64]. Future studies should test whether linking diagnostics to historians and CMMS actually changes inspection timing, work order quality or maintenance decisions. Recent PdM reviews increasingly argue for evaluating the complete chain from sensing and signal interpretation to process context and maintenance outcomes[23,24].

Reporting practice is another weakness. Instances of false alarms, missed detections, sensor failures, model drift, and situations where engineers dismiss automated recommendations all serve as indicators of deployment performance. However, these occurrences are seldom documented with the same level of detail as successful classifications. Studies should clearly state the operating range, sensor location, sampling configuration, train/test separation, maintenance ground truth, and decision thresholds for another plant to judge transferability. This emphasis on field constraints is consistent with recent reviews of PdM implementation and would make it easier to distinguish laboratory performance from evidence that is relevant to process-plant qualification[23,25].

The second limitation is the comparability of the studies. Published studies differ in fault-severity definition, sensor location, mounting, sampling rate, operating regime, preprocessing, train/test separation, and the method by which maintenance ground truth is established. The accuracy value reported may thus be as indicative of the dataset's construction as it is of the diagnostic capability. Cross-paper ranking by accuracy is particularly misleading when one study uses a fixed-speed seeded-fault benchmark, while another uses changing loads, naturally occurring degradation, or unlabelled plant data.

Deployment readiness should be interpreted based on the type of evidence provided by a study. Controlled classification studies are valuable for method development, but their main contribution is their analytical sensitivity. Cross-condition and domain-adaptation studies provide stronger evidence of robustness because they test whether the diagnostic representation survives a change in the operating or measurement domain[64,68]. Field and workflow studies provide different forms of evidence by showing whether alerts, forecasts, or diagnostic outputs can be linked to inspection, maintenance, or operating decisions[26,77].

The evidence streams should be considered complementary rather than competitive. Laboratory studies answer whether a fault signature can be detected; transfer studies answer whether the method remains stable when the domain changes; and field studies answer whether the information is useful within an operating and maintenance context. **Table 7** summarises representative evidence streams and the deployment questions that they can and cannot answer.

Table 7. Representative evidence streams and their implications for deployment readiness in vibration-based predictive maintenance.

Evidence stream	Representative source(s)	Evidence setting	What it demonstrates	Main deployment limitation
Measurement and sensor field validation	[30]	Field test / asset-specific	Shows that the measurement chain can operate on real machinery	Limited evidence of transfer to other assets, mounts, or process states
Edge and MEMS feasibility	[74]	Pilot / process-simulation facility	Demonstrates compact sensing and near-asset analytics	Pilot conditions may not reproduce long-term plant variability
Benchmark ML and DL	[62,66]	Controlled labelled datasets	Useful for comparing feature and model capability	High accuracy may not survive domain shift or realistic class imbalance
OOD and domain-transfer diagnostics	[64,68]	Cross-domain / transfer-oriented studies	Addresses confidence and generalisation when data distribution changes	Still requires field confirmation and maintenance ground truth
Anomaly and signal-integrity detection	[70,71]	Healthy-baseline or abnormality-focused studies	Useful when comprehensive fault labels are unavailable	Abnormality detection does not automatically identify cause or required action
Process-risk and early-warning studies	[77]	Operational / process-oriented evidence	Links condition information to shutdown or operational consequence	Often asset- or process-specific and may not expose detailed vibration mechanisms
Industrial maintenance forecasting and implementation studies	[25,26]	Industry / maintenance-workflow evidence	Shows how forecasts and diagnostic information enter maintenance practice	Sensor and algorithm details may be less complete than in laboratory studies

Table 7. (*Continued*).

Evidence stream	Representative source(s)	Evidence setting	What it demonstrates	Main deployment limitation
DT and PdM integration reviews	[24]	System-level synthesis	Highlights integration, data, and implementation requirements	Broad conclusions still depend on relatively limited field-validated deployments
Petrochemical rotating machinery diagnostics	[80]	Historical plant data; compressors and steam turbines	AI-based fault detection using industrial data; 96.01% accuracy and 93.20% F1-score	Retrospective validation; sustained deployment benefits and downtime reduction not established
Refinery pump fault diagnosis and intervention	[81]	Refinery centrifugal pump; field diagnosis and corrective balancing	Vibration reduced from 11.61 to 3.59 mm/s following intervention	Single-asset case; no longitudinal false-alarm or downtime evaluation
Industrial monitoring-to-maintenance integration	[104]	Continuous-process beverage plant; vibration-based monitoring and CMMS integration	Failure-free operating days increased from 72.8% to 84.5% after deployment	Adjacent industrial sector; single-site observational evidence

3.6.2. Minimum reporting and validation priorities

A practical priority is the development of minimum reporting requirements for field-oriented vibration PdM studies. At a minimum, reports should identify the sensor type and mounting, measurement direction and location, sampling configuration, operating range, asset and fault ground truth, preprocessing steps, model development and test separation, alarm or decision threshold, and the maintenance outcome used to verify the diagnosis. Without these details, another plant cannot judge whether a reported method is transferable or whether high performance depends on an unusually favourable measurement condition.

Future studies should also report deployment failures more systematically. False alarms, missed detections, sensor faults, model drift, communication losses, and cases in which engineers reject an automated recommendation are not peripheral observations; they define the operational limits of the system. Reporting them alongside successful classifications would support a more realistic comparison of methods and help differentiate laboratory maturity from plant maturity. Consequently, the most valuable research will integrate algorithm performance with measurement fidelity, operating context, human review, and verified maintenance outcomes rather than addressing these elements as separate topics.

Validation should also follow an explicit escalation ladder. Within-dataset testing is suitable for initial method comparison, followed by cross-load or cross-speed evaluation and cross-sensor or cross-machine transfer testing. Field validation should assess diagnostic performance against independently confirmed equipment conditions or maintenance findings, while sustained deployment readiness requires additional evidence of operational reliability and maintenance effectiveness. Uncertainty-aware and OOD methods are particularly useful at the transition between development and deployment because they can indicate when the input no longer resembles the validated domain[64]. Transfer-learning research can reduce the performance loss created by machine or operating-condition changes, but successful adaptation should not be treated as a substitute for independent field verification[65].

Evaluation metrics should be expanded accordingly. Accuracy, precision, recall, and the F1 score remain useful for labelled classification; however, plant qualification should also consider the false-alarm rate, missed-event rate, detection delay, stability across operating states, diagnostic lead time, and the proportion of alerts that result in a confirmed maintenance finding. At the workflow level, useful measures include avoiding unnecessary inspections, earlier intervention, reduced unplanned downtime, and the quality of work-order prioritisation. These metrics connect analytical performance to the operational value that PdM is intended to create[23,25].

3.6.3. Priority research directions for chemical process plants

The first priority is process-aware modelling. Pumps, compressors, and agitators can change the vibration response because of flow, pressure, viscosity, load, or operating-point variation, even when the mechanical condition is stable. Future models should therefore evaluate vibration together with the selected process variables rather than treating operating variability only as noise. Edge-enabled architectures already provide a route for synchronising local vibration analysis with plant-state information[74]. Process-risk research further shows the value of relating condition evidence to the probability and consequence of unplanned shutdown[77].

The second priority should be trustworthy AI rather than progressively larger models. Critical-machinery reviews increasingly identify interpretability, uncertainty, and robustness as central deployment requirements[27]. OOD detection can help identify data that fall outside the conditions represented during development[64]. Future work should combine these ideas with physically recognisable vibration evidence so that an engineer can see both the model conclusion and the signal features supporting it.

The third priority is longitudinal validation through maintenance feedback. PdM systems should be evaluated over enough time to capture sensor drift, process changes, repeated alarms, inspection outcomes, and maintenance interventions. CMMS and DT research suggest that the value of PdM increases when diagnostic outputs are linked to the history of actions and outcomes rather than retained as isolated analytics[24]. Industrial implementation studies similarly show that forecasting becomes useful only when it is connected to actual planning and execution[26].

Finally, future studies should report unsuccessful as well as successful deployments. A false alarm caused by a changed process state, a missed defect caused by poor sensor placement, or a model that loses confidence after overhaul can provide more transferable engineering knowledge than another near-perfect benchmark classification. A mature evidence base will therefore require publication practices that expose the operating

envelope, failure modes, and governance limits of the monitoring system, not only its best-case analytical performance.

4. Conclusion

Vibration-based PdM in CPPs is best treated as a process-aware diagnosis and maintenance decision problem. The main sources of difficulty are not the same for every asset: process-coupled variability dominates some pumps and agitators, structural and rotor-dynamic effects are more significant in high-speed machinery, and weak localised features are critical in gears and rolling-element bearings. The analytical depth should follow the signal problem. Conventional indicators provide the first level of evidence, with time-frequency analysis, feature enhancement, decomposition, or AI added only when the signal cannot be interpreted reliably at that level.

The main challenge is to translate analytical performance into dependable plant-level decisions. This requires field-representative data, interpretable AI outputs, checks against process conditions, escalation according to asset criticality, and integration with plant information and maintenance systems. A stratified methodology ensures transparency in the progression from vibration evidence to maintenance action. This approach prevents the indiscriminate application of advanced algorithms in situations where simpler and more comprehensible methods are adequate.

For plant deployment, the strongest architecture is layered rather than algorithm-centred. Standards-informed monitoring and machinery-protection functions establish measurement and response boundaries, conventional vibration analysis provides transparent baseline evidence, advanced processing improves weak or non-stationary feature visibility, and AI supports classification or anomaly prioritisation when its validated domain is understood. The final decision still depends on the process context, asset consequence, and a traceable maintenance response. This layered interpretation provides a more realistic path from high-performing vibration analytics to reliable PdM in CPPs.

Ethical approval

Not applicable.

Informed consent statement

Not applicable.

Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist with English language refinement, manuscript formatting, and the preparation of conceptual illustrations. All AI-assisted materials were carefully reviewed, revised, and verified by the authors. The scientific content, technical interpretations, literature evaluation, and final illustrations were independently checked and approved by the authors, who take full responsibility for the accuracy, scientific integrity, and final content of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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