

Fault Diagnosis of Centrifugal Pumps under Hydraulic Excitation and Flow Noise: A Critical Review of Vibration, Motor-Current, Acoustic-Emission, and Data-Driven Methods

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ABSTRACT

Centrifugal-pump diagnosis is complicated by flow-induced excitation from pressure pulsation, recirculation, rotating stall, cavitation, and turbulence, which can produce periodic, modulated, impulsive, and broadband components that overlap the signatures associated with bearing, shaft, impeller, and seal faults. This review covers 103 traceable publications on vibration, motor-current, audible-sound, acoustic-emission, signal-processing, and data-driven methods. The included evidence is classified as direct centrifugal-pump evidence, transferable rotating-machinery evidence, or contextual review evidence. It shows that signal processing is not equally robust across all pump configurations and operating conditions, and that the frequency position alone is insufficient to support a diagnostic opinion. Harmonics, sidebands, envelope content, time-domain waveform behavior, speed, and flow context each provide important information. Methods such as envelope analysis, spectral kurtosis, mode decomposition, modulation signal bispectrum, motor current analysis, acoustic emission, and deep learning may provide meaningful results with varying reliability depending on the fault-transmission path, sensor location, operational range, and validation scheme. Higher-order spectral methods and data-driven approaches show promise but have not been iterated widely among pumps or different operating conditions. An example workflow is to perform healthy baselines covering the intended envelope, and diagnostic reports with uncertainty boundaries and evidence boundaries. Limitations include non-exhaustive literature discovery, heterogeneity in test rigs and labels, restricted access to some primary data, and reliance on transferable evidence where pump-specific validation is unavailable. The results therefore support condition-aware, multi-indicator diagnosis rather than universal thresholds or a single preferred algorithm.

Keywords: Acoustic emission, Centrifugal pump fault diagnosis, Critical review, Hydraulic noise, Machine learning.

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1. INTRODUCTION

Condition monitoring of centrifugal pumps includes vibration, electrical, acoustic, pressure, flow, and performance measurements. Vibration- and acoustic-based condition-monitoring techniques are well established for rotating machinery. Motor- current analysis is a nonintrusive technique that provides an electrical view of electromechanical loading (**Tandon and Choudhury, 1999; Thomson and Fenger, 2001; Jardine et al., 2006; Randall and Antoni, 2011**). In the case of a pump, these methods cannot be applied as simply as they can to an isolated bearing or motor because the measured response incorporates not only structural vibration from the rotating elements and bearings but also fluid-induced forces transmitted from the impeller and volute through the casing, shaft, bearings, foundation, and connected pipework.

Hydraulic excitation can be periodic, quasi-periodic, transient, or broadband. Pressure pulsation tied to rotational or blade-passing processes can occur because of impeller–volute or blade–tongue interactions. Changes in low-frequency and broadband content can also result from flow separation, recirculation, and stall (**Guelich and Bolleter, 1992; Chu et al., 1995; González et al., 2002; Parrondo-Gayo et al., 2002; Spence and Amaral-Teixeira, 2009; Barrio et al., 2010; Pei et al., 2012**). Cavitation may also generate broadband and impulsive vibration, audible sound, fluid-borne noise, and acoustic-emission activity, although the observed frequency band and amplitude depend on pump geometry, speed, flow, cavitation stage, sensor bandwidth, and transmission path (**McNulty and Pearsall, 1982; Neill et al., 1997; Alfayez et al., 2005; Čudina, 2003; Al-Obaidi, 2020b; Dong et al., 2019b; Mousmoulis et al., 2019a**).

This can make fault attribution ambiguous. A peak near a characteristic frequency may arise from a mechanical fault, hydraulic forcing, structural resonance, or modulation between them. Similarly, an increase in broadband content may result from cavitation, turbulence, friction, impact, or a change in the measurement chain. This means that frequency location alone is not necessarily useful for diagnosis, as harmonics, sidebands, demodulated signals, impulse content, sensor coherence, and external operating conditions must also be considered.

Earlier reviews analyzed rotating machinery signals, pump pressure fluctuations, fluid-induced excitation, artificial intelligence applications, and motor-driven pump diagnostic methods (**Bagri et al., 2024; Khalid et al., 2024; Zheng et al., 2023; Wu et al., 2023; Sunal et al., 2022**). This review article focuses on the impact of hydraulic-induced excitation and variations in operating conditions on the diagnostic evidence analyzed, subsequently increasing the reliability of the evidence. It is a critical review and not a systematic review or meta-analysis and does not claim to be thorough or to provide a statistically pooled estimate.

The review delineates pump faults, hydraulic states and measured response, so that for example pressure pulsation and noise do not overlap as two different fault classes when occurring on the same system. Evidence (in the form of frequency, harmonics, sidebands, envelope, waveform behavior and machine operating condition) and diagnostic techniques (vibration, motor current, acoustic emission, higher-order spectral, independent component and data driven) are compared using these evidence tiers. A condition-aware diagnostic workflow is recommended, not making assumptions about frequency bands or confidence thresholds, nor assuming superiority of one method over another.



2. CRITICAL REVIEW METHOD

2.1 Discovery and Bibliographic Verification

The literature was found in Scopus, Web of Science, IEEE Xplore, and Google Scholar, with some additional discovery capabilities taken from SciSpace and Elicit. These methods were not meant to replace bibliographic databases or other forms of verifying primary sources. The searches combined centrifugal pump or rotodynamic pump with fault diagnosis, condition monitoring, vibration, acoustic emission, sound, motor current, pressure pulsation, cavitation, recirculation, flow variation, denoising, time-frequency analysis, higher order spectra, machine learning, transfer learning, domain adaptation, and references were identified using backward chaining and forward chaining from certain articles identified as key. Only papers published during the period 2000-2025 are mainly considered; additionally, pre-2000 papers are included when the research establishes a foundation for future work on pump cavitation beginning, pressure pulsation, blade-tongue interaction, acoustic-emission detection, pump bearing kinematics, or empirical mode decomposition. After the bibliography was checked against DOI-registry metadata, the resulting bibliography contained 103 unique titles and 103 unique DOI records.

2.2 Relevance Rules and Evidence Tiers

Sources were eligible when they contributed evidence on at least one defined area, including pump-fault mechanisms, flow-induced excitation, pump-specific diagnostic experiments, transferable signal-processing principles, sensing modalities, the effects of operating conditions, model transfer or generalization across pump designs, operating conditions, or sensing domains. Sources were excluded if the DOI resolved to a different publication, the corresponding Scopus record could not be located, or the topic fell outside the scope of this review. This evidence was then divided into three tiers:

1. Direct centrifugal-pump evidence: experiments, simulations, databases, case studies, or review articles concerning centrifugal pumps themselves.
2. Transferable machinery evidence: bearing, motor, gearbox, hydraulic-pump, or more general rotating-machinery work is used to explain a method or physical signature but is not used to validate the pump.
3. Contextual review evidence: reviews used to present trends and limitations rather than to support a specific pump result.

The final evidence base comprised 51 studies providing direct evidence on centrifugal pumps, four pump-specific reviews, one transferable hydraulic-machinery study, 36 transferable rotating-machinery or methods studies, and 11 contextual rotating-machinery reviews. These categories total 103 studies. Conference papers were retained only when directly relevant and traceable. Their findings were treated as study-specific unless corroborated by independent evidence.

2.3 Synthesis and Claim Control Procedure

Each source was assigned an admissible role, and the quantitative/comparative statements were only included when the source referenced the same machine class, fault, operating condition, method, and outcome. Tests not directly comparable were not compared. Statements containing words such as best, only, universal or always were cut unless supported by evidence in the reviewed studies. The synthesis is therefore mainly qualitative, aimed at explaining mechanisms and limitations of individual studies, rather than providing

a false performance league table.

Because of the limited way searches were conducted and our inability to access search logs, we were not able to provide reproducible PRISMA numbers and do not report on record counts, duplicate counts, PRISMA flow diagrams, or exhaustive screening statements. Some data are from laboratory pumps, some from transferable rotating machinery datasets. Test rig and data differ in type of pump, rpm, flowrate, fault implantation method, sensor locations and types, sampling time and duration, drawback and validation method. These differences make meta-analysis impractical, and hamper attempts to directly compare the reported classification performance.

3. FAULTS, HYDRAULIC STATES, AND MEASURED RESPONSES

3.1 Corrected Taxonomy

Mechanical and rotor dynamic faults include unbalance, misalignment, bent shafts, looseness, and rolling-element bearing defects. Impeller and rotor structural faults include blockage, erosion, wear, cracking, blade damage, and asymmetric mass or loading. Seal and clearance faults include mechanical-seal damage, wear-ring clearance changes, leakage-induced disturbance, and rotor–seal interaction. Hydraulic states include cavitation, recirculation, rotating stalls, off-design operation, and transients. These states can damage components or mask their signatures and should be distinguished from component faults. Pump-rig studies have applied statistical features, wavelets, support-vector machines, decision trees, and other classifiers to bearing, seal, impeller, cavitation, and compound conditions (Sakthivel et al., 2010a; Sakthivel et al., 2010b; Muralidharan and Sugumaran, 2012; Sakthivel et al., 2012; Muralidharan and Sugumaran, 2013a; Muralidharan and Sugumaran, 2013b; Muralidharan et al., 2014; Sakthivel et al., 2014). While these studies show diagnostic feasibility for their respective test rigs, they do not establish condition-independent performance for industrial pumps. The corrected taxonomy is shown in Fig. 1.

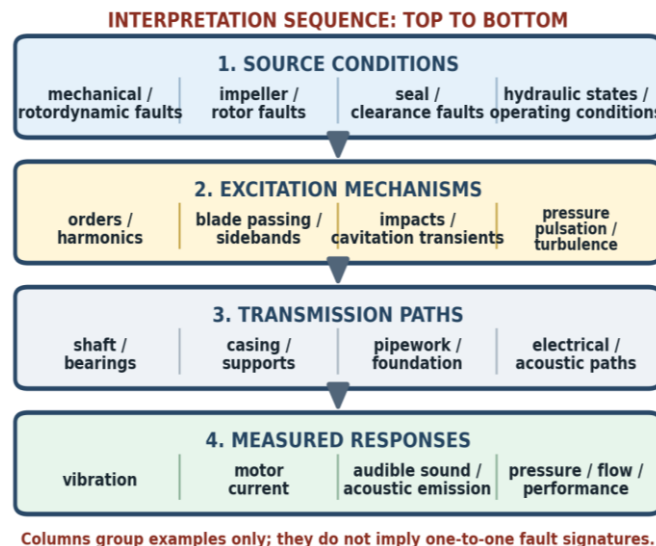


Figure 1. Top-to-bottom taxonomy linking pump conditions to excitation mechanisms, transmission paths, and measured responses. Author-created conceptual synthesis.

Fig. 1 uses a top-to-bottom causal sequence from faults and hydraulic states, through excitation mechanisms and transmission paths, to measured responses. This sequence



synthesizes pump-excitation and pressure-fluctuation evidence (**Guelich and Bolleter, 1992; Chu et al., 1995; González et al., 2002; Parrondo-Gayo et al., 2002; Spence and Amaral-Teixeira, 2009; Zheng et al., 2023; Wu et al., 2023**).

3.2 Multi-Indicator Diagnostic Characteristics

The presence of a bearing defect can produce impulses at the frequency of the defective geometry, the kinematic frequencies, but the effect may be modulated or smeared by slip on the surface, the load, structural resonances and hydraulic excitation (**McFadden and Smith, 1984; Randall and Antoni, 2011; Smith and Randall, 2015; Kumar and Kumar, 2018**). Unbalance and misalignment spectra tend to be confined to the harmonics of the rotational frequency and may be affected by hydraulic radial forces and structure dynamics. Damage to the impeller will impact the rotational, blade-passing, sideband content of the vibration, as well as the performance of the pump. Seals and clearances will impact structural and hydraulic coupling. The cavitation and off-design flows may create intermittent, broadband, and condition-dependent responses instead of establishing only one unique signature. **Table 1** provides a non-exhaustive list of signatures that should be considered.

Table 1. Diagnostic characteristics that should be interpreted jointly.

Fault or hydraulic phenomenon	Frequency-domain evidence	Harmonics and sidebands	Envelope/time-waveform evidence	Operating-condition dependence and caution
Localized rolling-element bearing defect	Geometry-dependent bearing components may appear within structural resonance bands	Harmonics and modulation by shaft speed may occur	Repetitive impacts can be enhanced by envelope analysis; impulsiveness varies with load and transmission path	Pump hydraulic excitation can mask impacts; confirm with shaft-speed order, waveform, and preferably more than one sensor (McFadden and Smith, 1984; Randall and Antoni, 2011)
Unbalance, misalignment, bent shaft, or looseness	Rotational orders and structural resonances may change	Harmonic pattern and directional response can help discrimination	Waveform may show periodicity, impacts, or modulation depending on fault and looseness	Hydraulic radial force and foundation resonance can produce similar components; no sensor position is universally optimal (Sinha and Rao, 2006)
Impeller damage, wear, blockage, or asymmetry	Rotational, blade-passing, and broadband components can change	Shaft-frequency modulation and sidebands may reflect non-uniform loading	Waveform and demodulated features may change, but the response depends on the transmission path	Interpret with head, flow, efficiency, speed, and a healthy impeller baseline (Albraik et al., 2012; Hamomd et al., 2017; Daraz et al., 2019)
Seal damage or wear-ring/clearance change	Rotational and broadband content may change with altered leakage and fluid force	Sideband changes can accompany rotor–seal interaction	Statistical and decomposed components may track severity on a given rig	Clearance influences both hydraulics and vibration; the diagnostic direction can change with design and flow (Liu et al., 2015; Tang et al., 2024)



Blade–tongue and impeller–volute interaction	Blade-passing-related pressure and vibration components are expected	Shaft-frequency modulation and harmonics can occur	Usually periodic or quasi-periodic rather than isolated impact evidence	Strongly dependent on operating point, geometry, and measurement location (Chu et al., 1995; González et al., 2002; Parrondo-Gayo et al., 2002)
Recirculation or rotating stall	Low-frequency, blade-related, and broadband components can coexist	Modulation may reflect rotating structures and unstable stall cells	Amplitude and intermittency may change over time	Primarily an operating-state diagnosis; verify with flow, pressure, and proximity to the intended duty point (Ren et al., 2019; Wang et al., 2018)
Cavitation	Broadband, tonal, and redistributed energy may coexist	Blade-passing and rotational content may be strengthened, weakened, or modulated	Intermittent impacts and non-stationary bursts can occur	Signature depends on inception/severity, speed, flow, net positive suction head (NPSH), fluid, sensor, and bandwidth; avoid universal bands (Alfayez et al., 2005; Zhang et al., 2015; Mousmoulis et al., 2019a)

4. HYDRAULIC EXCITATION AND OPERATING-CONDITION DEPENDENCE

4.1 Why Frequency Bands Overlap

Although hydraulic excitation does not occur at only high frequencies, the causes of periodic pressure fluctuations include rotation of the machinery and passage of the blades. Low- and intermediate-frequency bands may be affected by stall and recirculation. Broadband noise can result from turbulence, and impulsive and broadband noise can come from cavitation. The structure-transmission, or measurement chain, through the casing, bearings, supports, piping and sensor mounting will influence the response. Thus, exactly the same source can look very different at different locations, and different sources can be seen even at the same frequency. These relationships can be schematically represented in the form of the model shown in **Fig. 2 (Guelich and Bolleter, 1992; Chu et al., 1995; Barrio et al., 2010; Cui et al., 2020; Zheng et al., 2023; Wu et al., 2023)**.

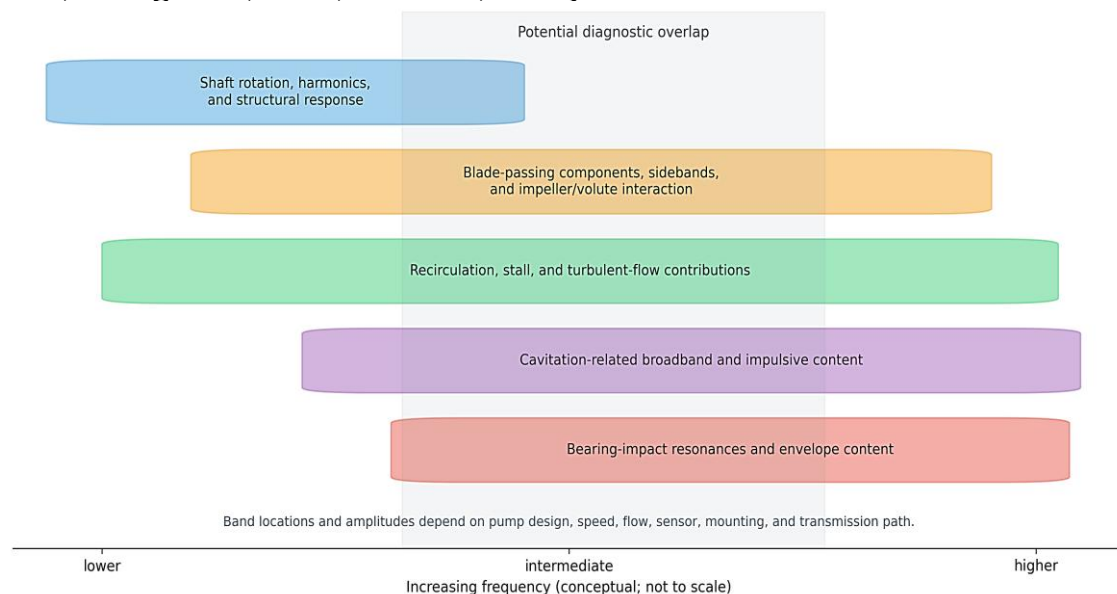


Figure 2. Conceptual overlap of centrifugal-pump vibration contributions. Author-created synthesis; locations and widths are not to scale.



4.2 Flow, Speed, and Transient Operation

The operating condition can be both a confounding variable and an input to the diagnosis. Experimental and numerical studies show that pressure fluctuations, vibration, stall, cavitation response, and prognostic features can vary with flow and rotational speed (**Mele et al., 2014; Bai et al., 2019; Al-Obaidi, 2019; Wang et al., 2019; Cui et al., 2020**). Changes in these conditions can alter feature distributions even if the health state of the components remains unchanged. Hence, a classifier trained to recognize a fault at a particular duty point may misclassify a different operating condition as a fault or fail to recognize a genuine fault when its pattern changes under the new condition.

This review does not define the operating range as a fixed percentage of the best efficiency point (BEP). Instead, the required operating range should be determined from the actual pump curve, the control strategy being employed, process demand, and known transient conditions. Healthy baseline data should be collected across this intended operating envelope. When flow or speed cannot be measured directly, these conditions should be estimated or represented by suitable process variables before spectral or learned features are interpreted.

4.3 Sensor Location and Transmission Path

Conventional accelerometers are normally mounted on stationary structures such as bearing housing, casing locations, supports, or other accessible monitoring points with a defensible transmission path. Conventional wired accelerometers should not be mounted directly on a rotating shaft. When shaft-mounted measurements are required, purpose-designed telemetry, secure mechanical retention, and an appropriate risk assessment are necessary. There is no universally applicable ranking of drive-end, non-drive-end, axial, radial, or casing locations. Observability depends on the layout, bearing arrangement, casing stiffness, coupling, piping, foundation, fault location, and sensor direction. Multi-location and multi-sensor studies show why sensor selection should be validated for the specific asset rather than assumed from another rig (**Safizadeh and Latifi, 2014; Bruinsma et al., 2024**).

5. SIGNAL-PROCESSING METHODS

5.1 Time-Domain and Spectral Indicators

Root-mean-square level, variance, peak measures, crest factor, kurtosis, entropy, and related statistics summaries pump condition. Decision trees, fuzzy systems, neuro-fuzzy inference, and support-vector machines (SVMs) have been used to classify pump conditions based on statistical features (**Farokhzad, 2013; Sakthivel et al., 2010a; Xue et al., 2014**). The advantage of these methods is their simplicity; the disadvantage is their lack of specificity. A change may be caused by a fault, hydraulic condition, process transient, sensor remounting, or background disturbance. Statistical indicators are therefore better suited to change detection than to isolated fault identification unless supported by operating condition and spectral information. Fast Fourier transform (FFT) spectra can show rotational orders, blade-passing components, harmonics, resonances, and broadband redistribution. Spectrum analysis remains useful because many pump mechanisms are linked to shaft and blade kinematics. Fixed-frequency comparisons may become unreliable when speed varies or when fault-related and hydraulic components overlap. Order tracking, synchronous resampling, sideband analysis, and normalization for operating conditions should therefore be considered when comparing spectra collected at different speeds.



5.2 Time–Frequency and Adaptive Decomposition

Because wavelets provide localized time–frequency information, they have been used extensively for rotating-machinery diagnosis (**Feng et al., 2013; Yan et al., 2014**). Wavelet-decomposed features have also supported pump classification on controlled laboratory rigs (**Muralidharan and Sugumaran, 2012; Muralidharan and Sugumaran, 2013a; Muralidharan and Sugumaran, 2013b**). The selected wavelet, scale, window, sampling rate, and operating condition influence the extracted features. The method must therefore be specified and validated rather than treated as an invariant preprocessing step.

Empirical mode decomposition (EMD) and ensemble EMD (EEMD) can be applied to non-stationary signals, although they are subject to mode mixing, end effects, and sensitivity to noise and stopping rules (**Huang et al., 1998; Wu and Huang, 2009**). EEMD-based entropy features have supported controlled motor-bearing diagnosis, but this remains transferable rather than pump-specific evidence (**Zhao et al., 2016**). Variational mode decomposition (VMD) uses an optimization framework to formulate band-limited modes, but the number of modes and penalty parameters remain influential (**Dragomiretskiy and Zosso, 2014**). Pump-specific research has employed VMD for multistage-pump bearing diagnosis. Fault-information-guided variational mode decomposition (FIVMD) and feature mode decomposition (FMD) are transferable developments that still require pump-specific validation (**Zhang et al., 2017; Ni et al., 2022; Miao et al., 2023**). Decomposition should not be equated with successful denoising unless the retained modes preserve the fault mechanism across operating conditions.

5.3 Envelope Analysis, Spectral Kurtosis, and Deconvolution

Envelope analysis is applicable when repetitive impacts excite a resonance that can be separated from the rest of the signal. Spectral kurtosis and the kurtogram can be used to identify frequency bands containing non-stationary impulsive content (**Antoni, 2006; Antoni, 2007**). Adaptive spectral-kurtosis and filter-selection methods extend this idea. Autocorrelated envelopes or cepstrum pre-whitening may improve the visibility of periodic components under specific forms of interference (**Barszcz and Jabloński, 2011; Wang and Liang, 2011; Borghesani et al., 2013; Xu et al., 2021**). Maximum correlated kurtosis deconvolution and optimized filtering are transferable techniques for enhancing repetitive impulses (**McDonald et al., 2012; Wodecki et al., 2018**).

These methods can be effective for pumps when their assumptions are checked. Hydraulic transients and cavitation can also be impulsive and may dominate kurtosis-based band selection. A selected band may therefore maximize non-Gaussian flow activity rather than a bearing or impeller fault. Verification should include the expected repetition pattern, speed dependence, sidebands, multiple operating conditions, and preferably another sensing modality.

5.4 Higher-Order Spectral Analysis and Modulation Signal Bispectrum

Higher-order spectra can characterize nonlinear coupling and modulation that are not fully described by a power spectrum. Modified bispectrum analysis of motor current has been used for downstream mechanical diagnosis, while modulation signal bispectrum (MSB) has been investigated for bearing and pump signals (**Gu et al., 2011; Hamomd et al., 2017; Tian et al., 2018; Daraz et al., 2019**). The pump evidence shows that MSB is a promising feature representation for particular experimental faults, but it does not establish MSB as the best or only reliable method for impeller-fault diagnosis.



Computational cost cannot be inferred from method labels or unsupported exact complexity expressions. Practical comparisons should instead report implementation choices, sample length, parameter selection, processing time, repeatability, and performance across flow and speed. Independent pump-specific replication outside the limited group of available studies remains important.

5.5 Independent Component Analysis and Blind Source Separation

Independent component analysis (ICA) estimates latent components that are as statistically independent as possible. Dynamic ICA has been evaluated on the Tennessee Eastman industrial-process benchmark, while combined FFT-ICA has been explored using multichannel vibration measurements from a general rotating machine (**Stefatos and Hamza, 2010; Shari et al., 2019**). These studies provide transferable evidence for process monitoring and rotating machinery, not direct validation for centrifugal pumps. ICA may help separate mixed signals when several sensors record different linear combinations of the sources, but it does not ensure separation of mechanical and hydraulic contributions. Its interpretation also depends on assumptions about source independence, source number, stationarity, and the physical meaning of the recovered components.

The limitations include the need for informative multichannel observations, uncertainty about the number of sources, scaling and permutation indeterminacy, dependence on preprocessing, and imperfect source independence and stationarity in actual pumps. Given these limitations, ICA is better presented as a potential source-separation technique. Its output should be corroborated by physical source identification and cross-condition testing rather than treated as evidence that the method is immune to hydraulic noise.

6. SENSING MODALITIES

6.1 Vibration

Vibration is the most widely represented modality in the reviewed pump literature and is sensitive to structural response. It has been used for industrial diagnosis, cavitation detection, impeller assessment, multistage-pump monitoring, and machine-learning classification (**Sinha and Rao, 2006; Albraik et al., 2012; Al-Obaidi, 2020a; Ahmad et al., 2020; Bai et al., 2019**). The same sensitivity that makes vibration useful also makes it susceptible to structural transmission, mounting variation, and hydraulic excitation. Vibration reporting should include sensor type, direction, mounting, location, sampling rate, anti-aliasing, speed, flow, load, and fault-implementation method.

6.2 Motor-Current and Electrical-Signature Analysis

Motor-current signature analysis (MCSA) uses stator-current modulation caused by mechanical loading and electromagnetic interactions and does not require a sensor on the pump casing. Foundational motor-current research explains its use for induction-motor faults, while pump-specific studies combine current with vibration or use electrical signatures for pump-fault classification (**Thomson and Fenger, 2001; Pandarakone et al., 2017; Mohanty et al., 2012; Araste et al., 2022**). MCSA may be attractive when mechanical sensors cannot be fitted. However, its sensitivity to a downstream pump fault depends on the motor, coupling, drive, load, supply, and control system.

The publicly described motor-current and vibration dataset of (**Bruinsma et al., 2024**) may support development across multiple operating conditions and fault classes. Recent pump



platforms and reviews also illustrate growing interest in MCSA-based diagnosis (**Sunal et al., 2022; Adaika et al., 2025**). The evidence reviewed here does not establish that this is the only public pump dataset because dataset availability was not surveyed exhaustively.

6.3 Audible Sound and Acoustic Emission

Audible sound, fluid-borne noise, and acoustic emission (AE) occupy different measurement chains and bandwidths and should be distinguished from one another. Audible and fluid-borne sound have been used to collect data for cavitation diagnosis, whereas AE captures stress waves and rapid surface or fluid–structure events (**Čudina, 2003; Dong et al., 2019a; Dong et al., 2019b**). Pump-specific AE studies have examined incipient cavitation, behavior around the BEP, and cavitating operation using sensors mounted on stationary structures (**Neill et al., 1997; Alfayez et al., 2005; Mousmoulis et al., 2019a; Mousmoulis et al., 2019b**). No universal AE band is imposed because transducer response, mounting, acquisition bandwidth, material, pump size, and cavitation stage differ. AE can complement vibration through its sensitivity to high-frequency transient activity, but attenuation and installation repeatability remain important. Multi-sensor fusion of vibration, current, acoustic, pressure, and flow require synchronized and calibrated acquisition, transparent handling of missing data, and leakage-resistant validation to support interpretable results (**Song et al., 2024; Bruinsma et al., 2024**).

7. MACHINE LEARNING, DEEP LEARNING, AND TRANSFER

Traditional machine-learning methods, such as decision trees, fuzzy classifiers, neuro-fuzzy systems, Bayesian classifiers, and support-vector machines, have been applied to statistical, spectral, wavelet, and decomposed pump features (**Farokhzad, 2013; Sakthivel et al., 2010a; Muralidharan and Sugumaran, 2012; Xue et al., 2014**). These studies have shown that controlled fault classes can be separated within specific datasets. Reported classification values are not compared here because differences in data segmentation, sample independence, fault severity, operating condition, and validation design can dominate the numerical results.

Deep learning can learn representations from waveforms, spectra, time–frequency maps, or multiple sensors. Rotating-machinery research has examined convolutional neural networks (CNNs), residual structures, attention, adversarial learning, and transfer learning (**Han et al., 2019; Hoang and Kang, 2019; Li et al., 2019; Liu et al., 2020; Jiao et al., 2020; Zhao et al., 2019; Zhao et al., 2020**). However, these findings provide transferable methodological evidence, not proof of pump robustness.

Pump-specific work has applied discriminant feature extraction, transfer learning, wavelet-coherence images, digital twins, and contrastive learning (**Ahmad et al., 2020; Sunal et al., 2024; Ullah et al., 2023; Xu et al., 2024; Wu et al., 2025**). The studies addressed representation and generalization, but their results remained sensitive to how the source and target domains were defined. For reproducibility, studies should report the pump, sensor, speed, flow, fault classes, training domain, test domain, and whether target labels were used.

Source-free and multi-source domain-adaptation methods developed for rotating machinery may also be applicable when source data cannot be shared or when operating domains differ (**Chen et al., 2020; Gao et al., 2024; Zhang et al., 2023**).

The normalized diagnostic feature-gram with a CNN remains bearing-specific transferable



evidence and should not be described as centrifugal-pump validation (Alsalaet et al., 2023). Likewise, research on attention mechanisms and noise-corrupted bearing signals shows methodological potential but cannot support pump-specific accuracy claims (Zhang et al., 2018; Li et al., 2019). Data leakage is a major concern. Segments cut from the same run can be highly correlated, and a random segment-level split may place near-duplicate observations in the training and test sets. More credible evaluation separates run, operating conditions, fault installations, pumps, or sites. Calibration, class imbalance, uncertainty, out-of-distribution detection, and independent replication should accompany reported accuracy metrics. These requirements are consistent with broader machine-diagnosis roadmaps and benchmark concerns (Lei et al., 2020; Smith and Randall, 2015; Zhao et al., 2020).

8. COMPARATIVE EVIDENCE SYNTHESIS

Table 2 compares the method families using the same dimensions of evidence instead of undocumented numerical scores. **Table 3** lists typical direct pump sources and the inference limit for each evidence area.

Table 2. Evidence-based comparison of diagnostic method families.

Method family	Principal observable	Direct pump support in this review	Main strength	Main limitation under hydraulic excitation
Time-domain statistics	Overall level, distribution, impulsiveness, entropy	Yes	Simple trending and low computational burden	Non-specific; sensitive to flow, speed, remounting, and transients
FFT, order, harmonic, and sideband analysis	Periodic components tied to rotation and blade processes	Extensive	Physically interpretable when speed and geometry are known	Frequency overlap and smearing under variable speed or flow
Wavelet and time–frequency analysis	Localized transient and evolving frequency content	Yes	Represents non-stationary behavior	Results depend on basis, scale, window, and parameter choice
EMD/EEMD/VM D/FIVMD/FMD	Adaptive or optimized signal modes	Limited direct pump support plus transferable evidence	Can isolate components without fixed bands	Mode mixing, parameter sensitivity, and uncertain physical meaning
Envelope analysis and spectral kurtosis	Repetitive impacts within resonant bands	Strong transferable bearing evidence; pump use requires verification	Effective for periodic impact mechanisms	Hydraulic impulsiveness can select the wrong band or obscure repetition
Higher-order spectra and MSB	Nonlinear coupling and modulation	Limited direct pump studies	Represents coupling beyond the power spectrum	Parameterization, implementation reporting, and independent replication are limited
ICA and blind source separation	Latent statistically independent components	No direct pump-specific validation identified in the selected sources; transferable process	May separate multichannel mixtures	Source independence, number of sources, and stationarity



		and rotating-machine evidence only		assumptions are restrictive
MCSA and electrical signatures	Electromechanical load modulation	Direct pump studies and dataset evidence	Noninvasive and useful when casing access is difficult	Fault information may be attenuated by the drive, motor, coupling, and control system
Audible sound/fluid-borne noise/AE	Airborne, fluid-borne, or stress-wave response	Direct cavitation evidence	Complementary sensitivity to fluid and transient phenomena	Bandwidth, attenuation, mounting, and environmental noise differ substantially
Machine learning, deep learning, and transfer	Learned combinations of engineered or raw features	Growing direct pump evidence	Handles multivariate nonlinear patterns	Dataset shift, leakage, calibration, and limited external validation

Table 3. Representative direct centrifugal-pump evidence and allowed inference.

Evidence area	Representative pump sources	What the evidence supports	Boundary of inference
Pump and impeller vibration diagnosis	(Sinha and Rao, 2006; Sakthivel et al., 2010a, 2010b; Albraik et al., 2012; Sakthivel et al., 2012, 2014; Muralidharan and Sugumaran, 2012, 2013a, 2013b; Muralidharan et al., 2014; Xue et al., 2014)	Feasibility of feature-based classification and physical diagnosis on studied rigs	Does not establish cross-pump or cross-condition accuracy
Hydraulic pressure, interaction, stall, and clearance	(González et al., 2002; Parrondo-Gayo et al., 2002; Spence and Amaral-Teixeira, 2009; Barrio et al., 2010; Liu et al., 2015; Wang et al., 2018; Liu et al., 2019; Ren et al., 2019; Cui et al., 2020; Tang et al., 2024)	Operating point, geometry, clearance, and flow structures alter pressure and vibration	No universal amplitude, frequency band, or BEP threshold
Cavitation, sound, and AE	(Čudina, 2003; Alfayez et al., 2005; Dong et al., 2019a, 2019b; Mousmoulis et al., 2019a, 2019b; Al-Obaidi, 2019, 2020a, 2020b; Zhang et al., 2015; Song et al., 2024)	Multiple modalities can detect cavitation-related changes	Response depends on cavitation stage, sensor, pump, speed, flow, and NPSH
Higher-order and decomposition methods	(Hamomd et al., 2017; Daraz et al., 2019; Zhang et al., 2017)	Pump-specific examples of MSB, acoustic bispectrum, and VMD-based analysis	Limited independent replication; no universal superiority claim
Motor current, multimodal sensing, and datasets	(Mohanty et al., 2012; Araste et al., 2022; Bruinsma et al., 2024; Adaika et al., 2025)	Electrical and complementary sensing can reveal pump conditions	Sensitivity depends on electromechanical transmission and dataset design
Data-driven and transfer methods	(Ahmad et al., 2020; Wang et al., 2019; Sunal et al., 2024; Ullah et al., 2023; Xu et al., 2024; Wu et al., 2025)	Pump-specific examples of learned features, prognosis, transfer, digital-twin assistance, and generalization	Deployment requires run/pump/site-separated validation and uncertainty reporting

The evidence map also contains additional transferable evidence on bearing-feature classification, hydraulic-pump signal demodulation, and spectral-kurtosis methods (Sharma et al., 2014; Jiang et al., 2015; Wang et al., 2016). Although these studies help explain the methods and their limitations, they are not treated as direct centrifugal-pump validation.

9. RESEARCH GAPS AND PRACTICAL WORKFLOW

9.1 Research Priorities

What is needed most is not another high reported accuracy based on randomly divided signal segments from a single rig, but evidence that remains valid when flow, speed, load, fault severity, sensor mounting, pump design, or site changes. This need leads to the priorities presented in **Table 4**.

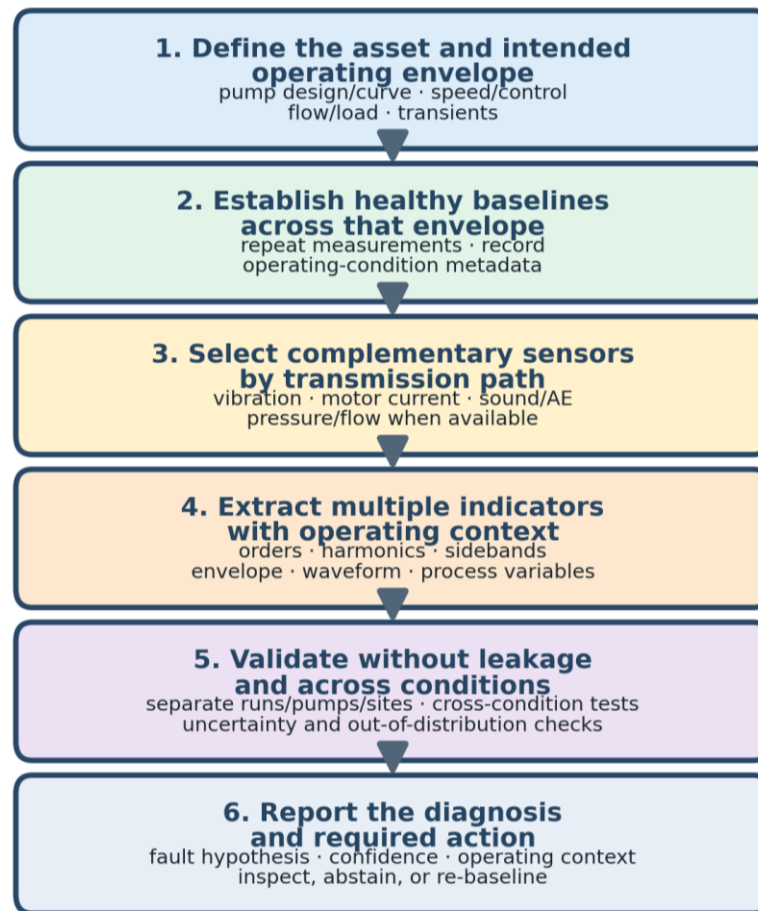
Table 4. Research and reporting priorities.

Priority	Required evidence	Reason
Operating-envelope validation	Healthy and faulty data across intended flow, speed, load, and transient conditions	Separates condition change from health change
Independent replication	A different pump, installation, research group, or industrial site	Tests whether the method is pump-specific or generally transferable
Multi-indicator interpretation	Frequency, harmonics, sidebands, envelope, waveform, and process condition	Reduces misclassification caused by overlapping signatures
Transparent sensor reporting	Sensor model, bandwidth, mounting, direction, location, sampling, synchronization	Enables reproducibility and explains transmission-path differences
Leakage-resistant validation	Run-, installation-, pump-, or site-separated test data	Avoids optimistic results from correlated signal segments
Uncertainty and abstention	Calibrated confidence, out-of-distribution checks, inspection triggers	Supports safe decisions when the operating state is unfamiliar
Shared pump datasets and metadata	Raw signals, speed, flow, load, fault implementation, severity, and baseline history	Enables fair comparison and transfer studies
Physics-data integration	Features or constraints tied to pump kinematics, pressure fluctuation, and flow state	Improves interpretability and may reduce spurious learning

9.2 Diagnostic Workflow

The workflow in **Fig. 3** describes the pump layout and operating context before considering the algorithm. Baselines must be captured across the expected operating range. Complementary measurements are selected according to fault-transmission paths and sensor access. Multiple indicators are then extracted and validated across flow, speed, load, and repeated runs. The diagnosis should include the fault hypothesis, confidence, operating context, and conditions under which inspection is required. The sequence synthesizes

variable-condition, transfer-learning, and pump-diagnostic evidence (Wang et al., 2019; Sunal et al., 2024; Ullah et al., 2023; Xu et al., 2024; Wu et al., 2025).



If the operating domain changes materially, re-establish the baseline or revalidate before deployment.

Figure 3. Condition-aware workflow for centrifugal-pump monitoring. Author-created synthesis; no universal thresholds are implied.

10. LIMITATIONS OF THE REVIEW

Due to methodological limitations and incomplete access to the original search records, a reproducible PRISMA count could not be established for this non-exhaustive review. Therefore, no screening-flow statistics are reported. English-language works with traceable DOI records were prioritized, which may have underrepresented some regional and non-DOI literature. The evidence set includes component tests, whole-pump test rigs, simulations, industrial cases, datasets, and transferable methods from other rotating-machinery systems. These studies use different definitions and validation procedures for the faults. Direct pump evidence is largely in vitro, and some methods may have poor reproducibility. Transferable bearing and motor experiments can provide perception into underlying mechanisms and algorithms but not pump performance. We have not pooled classification scores across these datasets, because some used training/validation/test splits that differ in their leakage control or construction, training/validation protocols, and operating conditions. Rapidly evolving research areas such as deep learning and domain adaptation may have active and recently published literature.



11. CONCLUSIONS

Hydraulic excitation is one of the main confounding factors in centrifugal-pump diagnosis. It is not simply a high-frequency noise process. Pressure pulsation, stalls, recirculation, turbulence, cavitation, structural response, and mechanical faults can overlap in both time and frequency. Frequency position alone is therefore insufficient to distinguish bearing, shaft, impeller, seal, and hydraulic states. No one approach is uniformly superior. Time-domain and spectral methods remain useful when interpreted within the operating context. Wavelet and decomposition analyses describe non-stationary content but introduce uncertainty through parameter and mode selection. Envelope analysis and spectral kurtosis can reveal repetitive impacts, although hydraulic impulsiveness can mislead the analysis. MSB and other higher-order methods show promise for modulation, but direct pump evidence and independent replication remain limited. ICA is a candidate multichannel separation method that relies on restrictive assumptions. MCSA, audible-sound, and AE sensing provide complementary information. Machine-learning and transfer methods require leakage-resistant, cross-condition validation. In summary, a defensible engineering approach is condition-aware and uses multiple indicators. It begins by defining the operating envelope and establishing healthy baselines across it. Sensors should be located on stationary structures according to the fault-transmission path. Frequency, harmonics, sidebands, envelope, waveform, and process variables should then be considered together, and uncertainty should be reported. Future work should focus on external validation, shared datasets with complete operating metadata, and more interpretable ways of combining pump physics with data-driven models.

NOMENCLATURE

Symbol	Description	Symbol	Description
AE	Acoustic emission	FMD	Feature mode decomposition
BEP	Best efficiency point	ICA	Independent component analysis
CNN	Convolutional neural network	MCSA	Motor-current signature analysis
EEMD	Ensemble empirical mode decomposition	MSB	Modulation signal bispectrum
EMD	Empirical mode decomposition	NPSH	Net positive suction head
FFT	Fast Fourier transform	SVM	Support-vector machine
FIVMD	Fault-information-guided variational mode decomposition	VMD	Variational mode decomposition

Credit Authorship Contribution Statement

Sharad R. Bhadane: Conceptualization, Methodology, Investigation, Writing – original draft, Visualization. Kasi Raja Rao: Supervision, Validation, Writing – review & editing. Sanjay T. Purkar: Validation, Resources, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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تشخيص أعطال المضخات الطاردة المركزية تحت تأثير الإثارة الهيدروليكية وضوضاء الجريان: مراجعة نقدية لطرائق الاهتزاز وتيار المحرك والانبعث الصوتي والطرائق المعتمدة على البيانات

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الخلاصة

يتعمّد تشخيص أعطال المضخات الطاردة المركزية بسبب الإثارة الناجمة عن الجريان، ومنها نبضات الضغط وإعادة دوران الجريان والانفصال الدوّار والتكهف والاضطراب؛ إذ قد تولّد هذه الظواهر مكوّنات دورية ومضمّنة ونبضية وعريضة النطاق تتداخل مع البصمات المرتبطة بأعطال المحامل والعمود والدقّاعة وموانع التسرب. تستعرض هذه المراجعة 103 منشورات قابلة للتتبع تتناول الاهتزاز وتيار المحرك والصوت المسموع والانبعث الصوتي ومعالجة الإشارات والأساليب المعتمدة على البيانات. وصُنّفت الأدلة إلى أدلة مباشرة خاصة بالمضخات الطاردة المركزية، وأدلة قابلة للنقل من دراسات الآلات الدوّارة، وأدلة مستمدة من مراجعات سياقية. وتبيّن النتائج أن مئاة أساليب معالجة الإشارات تختلف باختلاف تصميم المضخة وظروف التشغيل، وأن موضع التردد وحده لا يكفي لإسناد حكم تشخيصي. وتوفّر التوافقيات والحزم الجانبية ومحتوى الغلاف وسلوك شكل الموجة في المجال الزمني وسياق السرعة والتدفق معلومات متكاملة. كما يقدّم تحليل الغلاف والتقلطح الطيفي وتقنيك الأنماط والطيف الثنائي لإشارة التضمين وتحليل تيار المحرك والانبعث الصوتي والتعلم العميق معلومات مفيدة بدرجات متفاوتة من الموثوقية، تبعاً لمسار انتقال العطل وموقع المستشعر ومجال التشغيل وتصميم التحقق. وتُظهر الأساليب الطيفية عالية الرتبة والأساليب المعتمدة على البيانات إمكانات واعدة، إلا أن كثيراً منها لم يُكرّر بعد على أنواع متعددة من المضخات ولم يُتحقق منه عبر ظروف تشغيل متنوعة. وينبغي أن يتضمن سير العمل العملي خطوط أساس للحالة السليمة تغطي مجال التشغيل المقصود، وأن توضح التقارير التشخيصية عدم اليقين وحدود الاستدلال. وتشمل قيود المراجعة عدم شمول البحث في الأدبيات لجميع المنشورات، وتباين منصات الاختبار وتسميات الحالات، ومحدودية الوصول إلى بعض البيانات الأولية، والاعتماد على أدلة قابلة للنقل عند غياب التحقق الخاص بالمضخات. لذلك تدعم النتائج تشخيصاً متعدد المؤشرات ومراعياً لظروف التشغيل، بدلاً من اعتماد عتبات عامة أو خوارزمية واحدة مفضلة.

الكلمات المفتاحية: الانبعث الصوتي، تشخيص أعطال المضخات الطاردة المركزية، المراجعة النقدية، الضوضاء الهيدروليكية، التعلم الآلي.