Signal Processing Techniques and Mathematical Modeling for Analyzing and Diagnosing Cavitation in Centrifugal Pumps

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Abstract: *Cavitation remains a critical issue in centrifugal pump operation, leading to performance degradation, structural damage, and increased maintenance costs. Effective cavitation detection and modeling are essential for improving pump reliability and efficiency. This review integrates two key aspects of cavitation research: signal-based fault detection methods and mathematical modeling approaches. First, we review various cavitation detection techniques based on vibration, acoustic emission, noise, and pressure pulsation signals. Each method's advantages and limitations are discussed, focusing on their effectiveness in early-stage detection, robustness, and implementation feasibility. Next, we compare different mathematical models used to simulate cavitating flows, highlighting their assumptions, strengths, and limitations in accurately predicting cavitation behavior. By bridging experimental detection techniques with computational modeling, this review provides a perspective on cavitation analysis, offering insights into future research directions that combine advanced sensing, intelligent algorithms, and improved multiphase flow simulations.*

Keywords: *Cavitation detection, Centrifugal pump, Intelligent algorithms, Fault diagnosis, Mathematical modeling, Multiphase flow, Signal processing*

1. Introduction

Hydraulic systems are indispensable in various industries, enabling the efficient and controlled transmission of power through fluid movement, which provides precise control over machinery and equipment. This allows for the execution of critical tasks such as lifting, pressing, and driving complex systems with high efficiency and reliability [1-3]. The design and study of hydraulic systems [4, 5], along with mathematical modeling and simulation of their operation [6], further enhance the understanding and optimization of these systems, allowing for accurate prediction of performance, energy consumption, and system behavior under varying operational conditions [7].
Pumps, as integral components of hydraulic systems, play a fundamental role in various industrial, agricultural, and domestic applications by ensuring efficient fluid circulation, pressure regulation, and energy conversion [8-10]. Despite their widespread utilization, pump systems are inherently susceptible to various operational inefficiencies and mechanical failures [8]. Recent developments in intelligent diagnostic methods for hydraulic piston pumps have provided valuable insights into detecting and mitigating such faults, enhancing pump systems' overall reliability [11, 12].
Centrifugal pumps are extensively used in industries including manufacturing, agriculture, oil and chemicals, and aerospace. Pump systems are inherently vulnerable to various problems, with cavitation being one of the most damaging [13, 14]. Cavitation, a complex multiphase flow phenomenon, arises when local static pressure drops below the vapor pressure of the working fluid, leading to the formation of vapor bubbles. As these bubbles travel into regions of higher pressure, they undergo rapid implosion, generating high-intensity pressure waves that result in severe material erosion, flow disturbances, noise, and excessive vibration. Over time, the persistence of cavitation leads to significant degradation in pump performance, reduced energy efficiency, and increased maintenance costs, making it a critical subject of investigation in hydraulic machinery [15]. The transient and highly nonlinear nature of cavitation poses significant challenges in both its detection and predictive modeling. The collapse of vapor cavities introduces unsteady flow characteristics that complicate conventional diagnostic approaches. Additionally, the unpredictability of cavitation initiation and development due to factors such as flow velocity, system pressure, temperature variations, and pump geometry further complicates its analysis. Traditional detection methods rely on physical inspection and performance monitoring; however, these

techniques often fail to provide early warnings or quantify the severity of cavitation in real time. In response to these limitations, modern signal processing techniques have emerged as powerful tools for cavitation diagnosis. By leveraging acoustic emission, vibration analysis, noise monitoring, and pressure pulsation measurements, researchers have developed advanced methodologies to characterize cavitation-induced fluctuations and identify early warning indicators [15, 16]. The integration of artificial intelligence (AI), machine learning (ML), and deep learning (DL) algorithms further enhances the capability of these techniques by enabling automated feature extraction, pattern recognition, and state classification with improved accuracy and robustness [17-21].

In parallel, mathematical modeling has played a crucial role in understanding the fundamental mechanisms governing cavitating flows [22]. Theoretical frameworks based on fluid dynamics, such as the Bernoulli equation and Navier-Stokes formulations, provide a foundation for simulating cavitation dynamics under varying operational conditions. Computational Fluid Dynamics (CFD) models have been extensively developed to predict cavitation inception, bubble dynamics, and flow field variations [23-25]. These models incorporate multiphase flow representations, including homogeneous and heterogeneous cavitation models, to capture the phase transition phenomena with greater fidelity. Despite significant advancements, challenges remain in achieving computational efficiency, model validation, and adaptability to real-world pump systems.

This review explores cavitation detection methods utilizing signal processing techniques, providing a comparative analysis of existing mathematical models for cavitation simulation. The discussion encompasses the principles, methodologies, and recent developments in vibration-based, acoustic, noise, and pressure pulsation detection approaches. Furthermore, a critical evaluation of different cavitation models is provided, highlighting their applicability, accuracy, and computational constraints. By integrating experimental and theoretical perspectives, this review aims to bridge the gap between empirical diagnostics and predictive modeling, offering insights into future research directions in cavitation analysis of centrifugal pumps.

2. Research methodology

A comprehensive survey was conducted to evaluate the increasing research focus on signal processing techniques and mathematical modeling for centrifugal pump cavitation analysis and diagnosis. Recognizing the practical significance of this domain, the investigation covers studies published between 2011 and 2024. This review examines a range of journal articles exploring key concepts and their applications in cavitation detection and modelling for centrifugal pumps.

2.1 The common mathematical formulations for cavitation modelling

Cavitation modeling plays a crucial role in understanding and predicting the behavior of multiphase flows, particularly in hydraulic systems and turbomachinery. Cavitation can lead to three distinct and unfavorable consequences: (1) a reduction in head-capacity and efficiency performance, (2) impeller deterioration due to pitting and erosion, and (3) structural vibrations accompanied by increased noise levels. Due to the complex nature of cavitation, various mathematical models have been developed to simulate its dynamics with varying levels of fidelity.

1) Multiphase flow modeling

Multiphase flow modeling describes the behavior of two or more coexisting phases within a fluid system. The classification of multiphase flows includes:

• Gas–liquid and liquid–liquid flows, which encompass cavitation phenomena where vapor bubbles form and collapse within a liquid medium.
• Gas–solid flows, involving dispersed solid particles in a gaseous carrier fluid.
• Liquid–solid flows, where solid particles interact with a surrounding liquid phase.

Cavitation is a subset of gas–liquid multiphase flows, specifically categorized as bubbly flow, in which discrete gaseous bubbles are suspended in a continuous liquid phase. The accurate modeling of cavitation requires capturing phase interactions, bubble dynamics, and mass transfer mechanisms. Cavitation models are typically categorized into two-fluid and one-fluid models, each with its own advantages and limitations [22]. Additionally, cavitation modeling approaches can be broadly classified into two primary categories: direct models and averaged models [26].

2) Two–fluid models

Two-fluid models are employed to separately resolve the conservation equations governing both the discrete and continuous phases in cavitating flows. These models provide a detailed representation of phase interactions, enabling a more accurate prediction of cavitation dynamics. The solution of these conservation equations can be achieved using one of the following approaches:

• Euler approach: This method involves solving the conservation equations for each phase by considering the flow properties at a fixed spatial location while monitoring the transport of individual phases. This approach is particularly useful when treating both phases as interpenetrating continua, where phase interaction terms, such as momentum and mass exchange, must be carefully modeled.

• Lagrange approach: In this method, the conservation equations for the continuous phase are solved using the Eulerian framework, whereas the discrete phase (e.g., cavitation bubbles) is tracked along individual trajectories using a Lagrangian formulation. This allows for a more detailed representation of bubble dynamics, including coalescence, breakup, and transport, but requires substantial computational resources due to the necessity of tracking numerous discrete elements.

While these methods offer high accuracy in modeling cavitating flows, they become computationally expensive when the vapor volume fraction exceeds a critical threshold. In practical simulations, alternative modeling approaches may be preferred to reduce computational costs while maintaining acceptable accuracy.

3) One–fluid models

One-fluid models provide a simplified yet effective approach to modeling cavitating flows by assuming that the conservation equations govern a homogeneous mixture of liquid and vapor phases. Unlike two-fluid models, where the individual phases are treated separately, the one-fluid framework integrates the two phases into a single continuum with averaged properties. Given that cavitating flows are typically assumed to be isothermal, only the mass and momentum conservation equations are considered, while energy conservation equations are often omitted.

$$\rho = \alpha\rho_v + (1-\alpha)\rho_l \tag{1}$$

$$(\rho u) = \alpha(\rho u)_v + (1-\alpha)(\rho u)_l \tag{2}$$

where: ρ, ρ_v, ρ_l represent the densities of the mixture, vapor phase, and liquid phase, respectively [$kg \cdot m^{-3}$]; (ρu), $(\rho u)_v$, $(\rho u)_l$ denote the momentum of the mixture, vapor phase, and liquid phase, respectively [$kg \cdot m^{-2} \cdot s^{-1}$]; u is the velocity of the mixture [$m \cdot s^{-1}$]; α is the vapor volume fraction, a dimensionless parameter ranging from 0 (pure liquid) to 1 (pure vapor).

Several variations of one-fluid models exist, each differing in their assumptions regarding phase interactions and the additional equations required to close the system:

• Zero-equation models

Zero-equation models take an even more simplified approach by solving only the mixture conservation equations without introducing any additional transport equations. Instead of explicitly modeling phase interactions, these models rely on a barotropic state law, which defines the relationship between density and pressure. The density of the mixture is directly computed as a function of pressure, eliminating the need for additional conservation equations.

• One-equation models

One-equation models assume that there is no slip between the phases, meaning that both the liquid and vapor phases move with the same velocity. Instead of solving separate conservation equations for the individual phases, these models introduce a single additional equation governing the conservation of vapor mass, expressed as:

$$\frac{\partial \alpha\rho_v}{\partial t} + \nabla(\alpha\rho_v u) = R_e - R_c \tag{3}$$

where: R_e and R_c represent the source terms corresponding to vapor generation (evaporation) and condensation, respectively [$kg \cdot m^{-3} \cdot s^{-1}$]. The primary distinction among different one-equation models lies in the formulation of these source terms, which govern the rate of phase transition between liquid and vapor.

Several one-equation models have been developed to describe cavitation phenomena, primarily based on transport equations for vapor volume fraction. These models incorporate phase change

dynamics using source terms derived from bubble dynamics equations, such as the Rayleigh-Plesset equation.
- Kunz model. The Kunz model is a one-equation cavitation model where the vapor volume fraction is governed by a transport equation. The source terms, R_e and R_c, represent the mass transfer between liquid and vapor and are determined empirically. This model is widely used due to its simplicity and computational efficiency. However, its reliance on empirical coefficients makes it less adaptable to complex cavitation phenomena.
- Singhal model. The Singhal model incorporates the Rayleigh–Plesset equation, providing a more physics-based approach to cavitation modeling. It includes corrections for turbulent pressure fluctuations, making it suitable for a wide range of flow conditions. However, the model requires additional parameters such as the turbulent kinetic energy (k), which can increase computational cost.
- Zwart–Gerber–Belamri (ZGB) model. The ZGB model also relies on the Rayleigh–Plesset equation but introduces nucleation site volume fraction (α_{nuc}) to model cavitation inception. This model is particularly useful for industrial applications due to its balance between accuracy and computational efficiency. However, it requires careful calibration of the nucleation site volume fraction and bubble radius.
- Schnerr and Sauer model. The Schnerr and Sauer model uses a bubble dynamics-based approach, where the number of bubbles per unit volume is a key parameter. This model is highly effective in simulating cavitation in high-speed flows and turbine applications. However, it can be computationally expensive due to its detailed bubble tracking mechanism.
A comparative analysis of one-equation cavitation models are shown in Tables 1 and 2.

Table 1: A comparative analysis of one-equation cavitation models

Model	Governing equation	Advantages	Limitations
Kunz Model	One-equation transport model	- Computationally efficient - Simple implementation	- Empirical nature limits accuracy in complex flows - Less physics-based
Singhal Model	Rayleigh–Plesset equation with turbulence correction	- More physics-based than Kunz - Accounts for turbulent fluctuations	- Requires additional turbulence parameters - Higher computational cost
ZGB Model	Rayleigh–Plesset equation with nucleation site correction	- Balances accuracy and computational efficiency - Suitable for industrial applications	- Requires calibration of nucleation site parameters
Schnerr and Sauer Model	Bubble dynamics-based approach	- Detailed cavitation representation - Suitable for high-speed flows	- Computationally intensive due to bubble tracking

Table 2: Comparison of one-equation cavitation models in terms of computational efficiency, stability, accuracy, and applications

Model	Computational efficiency	Numerical stability	Accuracy in predicting cavitation	Applications
Kunz Model	High (fastest)	High	Moderate	Fast simulations with moderate accuracy
Singhal Model	Moderate	Moderate	High	Turbulent cavitating flows
ZGB Model	Moderate to High	Moderate to High	High	Industrial applications
Schnerr and Sauer Model	Low (most expensive)	Moderate to Low	Very High	High-speed, detailed cavitation studies

• Two-equation models
Two-equation models account for slip between the liquid and vapor phases, meaning that each phase can move at different velocities. In addition to the conservation equations of the mixture, two additional equations are introduced to govern the conservation of either the liquid or vapor phase. These models allow for a more accurate representation of phase interactions, but at the cost of increased computational complexity.

Advantages and limitations of one-fluid models

One-fluid models offer computational efficiency and simplicity compared to two-fluid models, making them attractive for simulating cavitating flows in engineering applications such as hydrofoils, pumps, and nozzles. However, their reliance on averaged properties and simplified phase interaction assumptions may lead to inaccuracies in highly dynamic cavitating flows where phase separation, slip velocity, and bubble dynamics play a significant role. The choice between different one-fluid modeling approaches depends on the required accuracy and computational resources available for the simulation.

2.2 Principles and approaches in cavitation detection

Several methods are employed to detect cavitation of pumps based on different physical principles such as vibration, acoustic emission, noise, and pressure pulsation (Table 3). These methods are distinguished by their ability to monitor different parameters, which help identify cavitation onset, progression, and severity. Each method has its own strengths and weaknesses depending on the specific pump system, operating conditions, and desired level of sensitivity. Combining multiple techniques can enhance the reliability and accuracy of cavitation detection [15].

Table 3: Overview of common detection cavitation methods

Method	Parameters monitored	Detection principle	Advantages	Limitations
Vibration method	Vibration acceleration, frequency, RMS, variance	Vibration signals detected by accelerometers	- High sensitivity - Suitable for real-time detection	- Requires placement of sensors - May not detect early cavitation
Acoustic emission	Signal energy, amplitude, rise time, duration	Microjet or shockwave induced acoustic signals	- Sensitive to high-frequency cavitation signals - Non-invasive	- Requires high-quality sensors - Signal attenuation in air
Noise method	Noise intensity, frequency spectrum	Noise generated by cavitation bubble formation and collapse	- Useful for early detection - Simple and cost-effective	- Difficult to distinguish from other types of noise - Limited to detectable noise frequency range
Pressure pulsation	Pressure fluctuations, frequency spectrum	Pressure pulsations caused by cavitation-induced flow field disturbances	- Effective in varying pump flow conditions - High signal-to-noise ratio	- Complex data interpretation - Requires high precision sensors

a) Vibration signal processing methods

Vibration signal processing techniques employed for cavitation detection and analysis primarily fall into three broad categories: time-domain analysis, frequency-domain analysis, and time–frequency domain analysis. These methodologies play a crucial role in extracting meaningful information from vibration signals, enabling the identification and characterization of cavitation phenomena in pumping systems. Time-domain analysis focuses on the direct examination of vibration signals over time, capturing transient characteristics and statistical parameters such as root mean square (RMS), peak values, crest factor, and kurtosis. These features provide essential insights into the severity and evolution of cavitation-induced vibrations. Frequency-domain analysis involves transforming time-domain signals into their spectral representations using techniques such as the Fast Fourier Transform (FFT) and Power Spectral Density (PSD). This approach facilitates the identification of dominant frequency components associated with cavitation, distinguishing them from other mechanical or hydraulic disturbances. Time–frequency domain analysis integrates both time and frequency characteristics, allowing for the assessment of non-stationary signals. Methods such as Wavelet Transform (WT), Short-Time Fourier Transform (STFT), and Hilbert-Huang Transform (HHT) enable the precise localization of cavitation-induced transient events across different frequency bands. These techniques are particularly advantageous in detecting early-stage cavitation, where signal characteristics dynamically evolve over time.

A comprehensive summary of the latest advancements and applications of these vibration signal processing methodologies in cavitation diagnosis is shown in Table 4.

Table 4: Comprehensive overview of vibration signal processing methods

Analytical method	Techniques used	Advantages	Limitations
Time-domain analysis (Refs. [27], [28])	Correlation analysis, amplitude range analysis, statistical feature extraction (RMS, peak values, kurtosis, crest factor)	Simple and intuitive; directly reflects cavitation-induced variations; effective for periodic signals	Limited to stationary signals; lacks frequency-related insights; susceptible to noise
Frequency-domain analysis (Ref. [28])	Fourier Transform (FT), Power Spectral Density (PSD), envelope analysis, difference frequency analysis, cepstral analysis	Provides insight into dominant frequency components related to cavitation; useful for steady-state conditions	Inability to capture transient, time-varying characteristics; requires pre-filtering for accuracy
Time–frequency domain analysis (Ref. [29], [30])	Short-Time Fourier Transform (STFT), Wavelet Transform (WT), Empirical Mode Decomposition (EMD), Wigner–Ville Distribution (WVD), Hilbert-Huang Transform (HHT)	Suitable for non-stationary signals; enables localized analysis of transient events; effective for cavitation detection and diagnosis	Computationally intensive; choice of transformation parameters affects accuracy

Figure 1 illustrates the relationship between cavitation states and their corresponding vibration characteristics in centrifugal pumps.

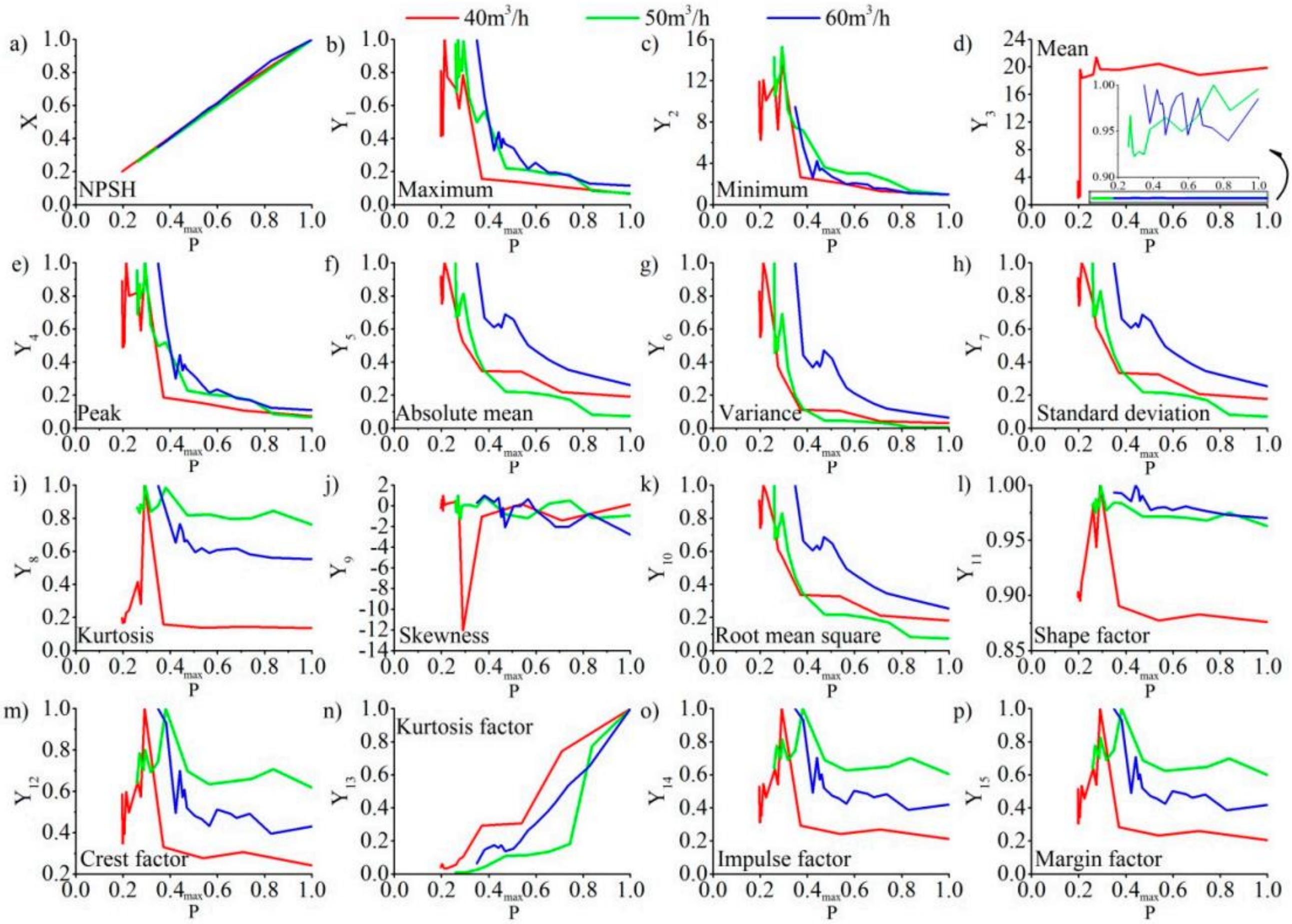

Fig. 1. Normalization value: (a) The net positive suction head (NPSH), (b) Maximum, (c) Minimum, (d) Mean, (e) Peak, (f) Absolute mean, (g) Variance, (h) Standard deviation, (i) Kurtosis, (j) Skewness, (k) Root mean square, (l) Shape factor, (m) Crest factor, (n) Kurtosis factor, (o) Impulse factor, (p) Margin factor. (Reprinted from ref. [27] with permission of MDPI AG publisher).

Figure 2 illustrates the cavitation-induced vibration signal at 40 Hz for a centrifugal pump, shown in time and frequency domains, with random high-frequency components indicating cavitation [28].

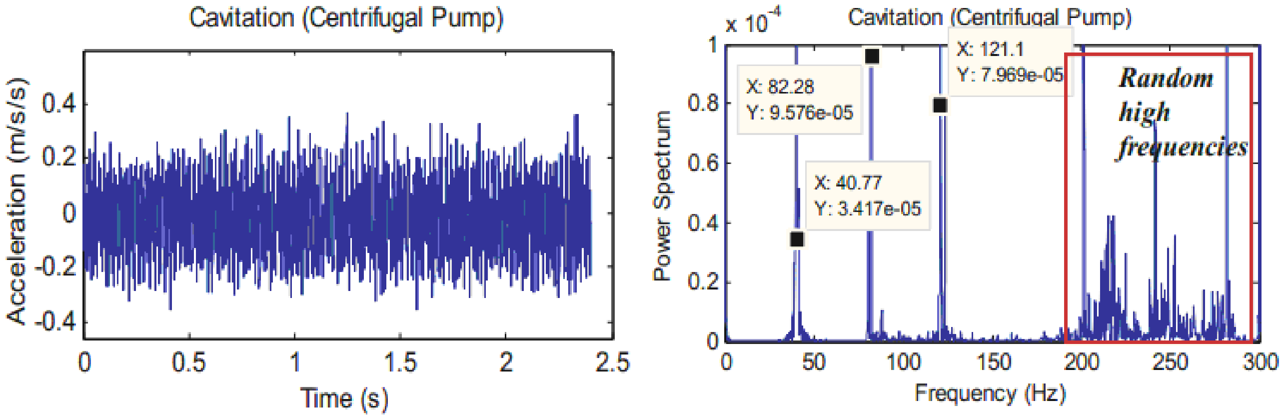

Fig. 2. Cavitation-induced vibration signal at a rotational speed of 40 Hz for a centrifugal pump. (a) Time-domain representation. (b) Frequency-domain representation, where random high-frequency components indicate cavitation. (Reprinted from ref. [28] with permission of Springer Nature Switzerland AG publisher).

Figure 3 illustrates the time-domain representation of signal x(t) and the corresponding results of three computational methods (time–frequency algorithms) for a centrifugal pump: (a) time-domain diagram of x(t), (b) time–frequency algorithm (Wigner–Ville distribution method), (c) time–frequency algorithm (short time Fourier transform method), and (d) time–frequency algorithm (United algorithm of STFT–WVD method) [29].

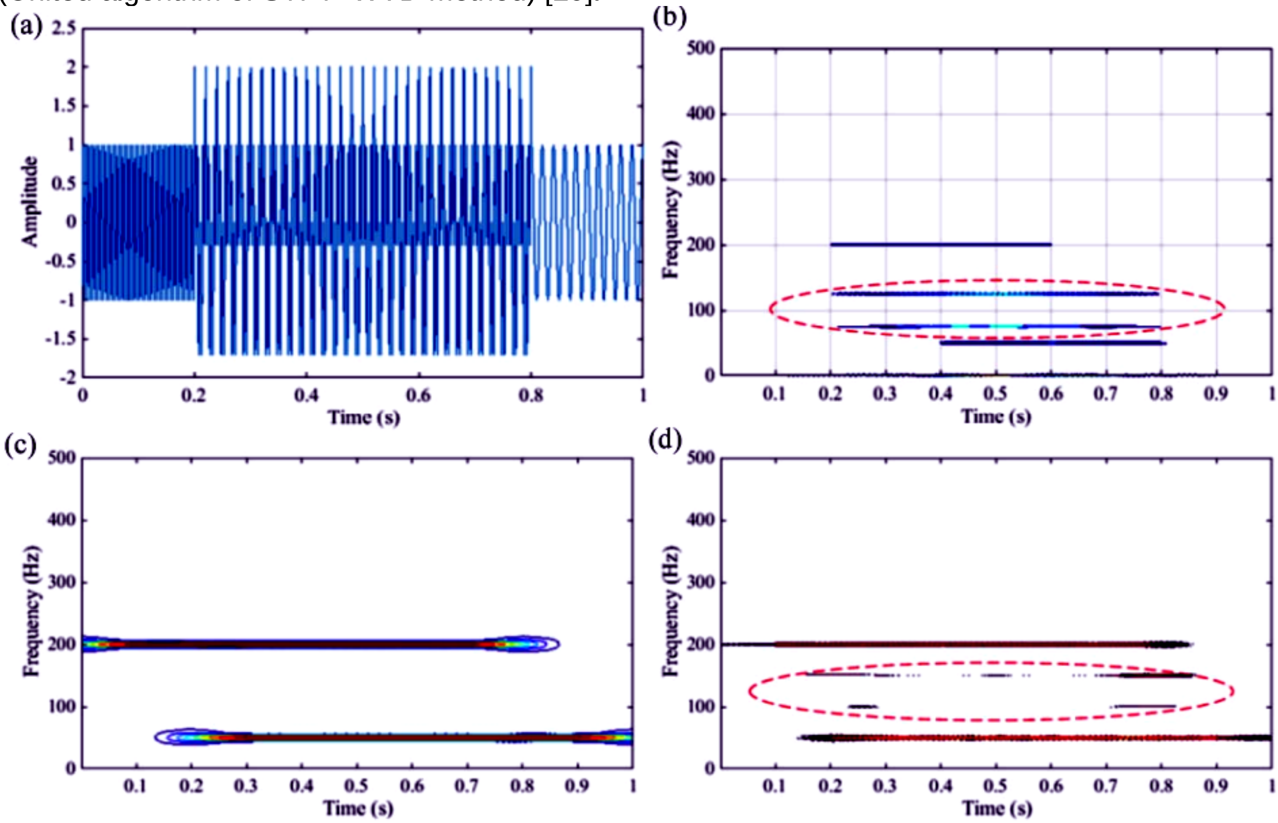

Fig. 3. Cavitation-induced vibration signal for a centrifugal pump. Time-domain representation of signal x(t) and corresponding results of three time–frequency algorithms. (a) Time-domain representation of x(t). (b) Wigner–Ville distribution (WVD) method. (c) Short-Time Fourier Transform (STFT) method. (d) Combined STFT–WVD method. (Reprinted from ref. [29] with permission of Springer Nature Switzerland AG publisher).

Table 5 provides a comparative analysis of various frequency-domain techniques used for cavitation diagnosis, highlighting the advantages such as the ability to identify dominant frequency components and the limitations like difficulty in capturing transient characteristics. Similarly, Table

6 shows a review of time-frequency domain techniques, emphasizing the strengths of adaptability to non-stationary signals and the challenges, such as the trade-offs in time-frequency resolution or issues like mode mixing in some methods.

Table 5: Comparative analysis of frequency-domain techniques for cavitation diagnosis

Method	Key Principle	Advantages	Limitations	Common Applications
Fourier Transform (FT)	Decomposes the signal into its frequency components	Simple and well-established; identifies dominant frequencies	Inability to capture transient, time-varying characteristics	Identifying steady-state cavitation frequencies
Power Spectral Density (PSD)	Measures the power distribution of the signal across frequencies	Provides a clear representation of frequency components	Requires steady-state conditions; cannot handle transient events	Monitoring dominant frequencies in cavitating pumps
Envelope Analysis	Analyzes the modulation of the signal amplitude	Effective for detecting low-frequency cavitation signatures	Can miss high-frequency cavitation details	Detecting cavitation-induced vibration signatures
Difference Frequency Analysis	Analyzes the difference between peak frequencies in the signal	Highlights cavitation-induced low-frequency variations	Sensitivity to signal noise can reduce accuracy	Detecting cavitation by evaluating frequency shifts
Cepstral Analysis	Uses the inverse Fourier transform of the log-spectral representation	Helps separate periodic components from a signal's noise	Less effective for non-stationary signals	Identifying cavitation by examining harmonic components

Table 6: Comparative analysis of time–frequency domain techniques for cavitation diagnosis

Method	Key principle	Advantages	Limitations	Common applications
Short-Time Fourier Transform (STFT)	Segments the signal and applies FT to each segment	Provides a time-localized frequency representation	Fixed time-frequency resolution trade-off	Detecting cavitation onset and transient events
Wavelet Transform (WT)	Uses scalable wavelets to analyze signals at multiple resolutions	Adaptive resolution; effective for both transient and periodic signals	Requires appropriate wavelet selection for optimal performance	Identification of cavitation-induced broadband noise
Empirical Mode Decomposition (EMD)	Decomposes signals into intrinsic mode functions (IMFs) using adaptive filtering	Suitable for non-linear and non-stationary signal analysis	Mode mixing issues can affect interpretation	Feature extraction in cavitation pattern recognition
Hilbert-Huang Transform (HHT)	Combines EMD with Hilbert spectral analysis	High adaptability for analyzing complex, non-stationary signals	Computationally expensive; requires robust mode decomposition	Time-localized cavitation feature analysis
Wigner–Ville Distribution (WVD)	Provides high-resolution time-frequency representation	Superior energy concentration; precise localization of transients	Prone to cross-term interference	High-resolution cavitation impact signal analysis

The frequency distribution of cavitation-induced vibrations spans a broad spectrum, predominantly concentrated in high-frequency bands, with distinct sensitivity characteristics observed across these frequency ranges [15]. Cavitation, being a dynamic and nonlinear phenomenon, interacts differently with various frequency bands, leading to variations in vibration patterns. The high-

frequency vibrations are often associated with the rapid formation and collapse of cavitation bubbles, which generates sharp, high-energy pulses. These pulses typically manifest as significant peaks in the vibration signal at frequencies ranging from several kilohertz to tens of kilohertz. However, the interaction between cavitation and low-frequency components, especially below 1 kHz, has also been of significant interest in the literature, as these frequencies are often linked to broader system responses, such as mechanical resonances and pump rotor behavior. Studies have shown varying responses of cavitation to different frequency ranges, with some researchers emphasizing high-frequency bands for fault detection, while others point to the importance of low-frequency signals in capturing early-stage cavitation and identifying subtle pump instabilities [31-36]. These findings highlight the complexity of cavitation vibration characteristics and the need for comprehensive frequency-domain analysis to fully understand its impact on pump performance.
In recent years, machine learning has emerged as a pivotal tool within artificial intelligence for extracting meaningful insights from vast and intricate datasets. Fault classification algorithms, such as Support Vector Machines (SVM), Extreme Learning Machines (ELM), and their enhanced variants, are among the prominent methodologies employed in this domain. The integration of machine learning with vibration analysis has further enhanced its efficacy, becoming a powerful approach for detecting pump cavitation faults [37-39]. Artificial neural networks (ANNs), have significantly advanced in fault detection applications. Techniques such as nonlinear autoregressive models, support vector machines, and random forests are commonly employed for cavitation detection. Among these, the extreme learning machine (ELM) has demonstrated superior accuracy compared to other methods like BP neural networks and random forests. While machine learning approaches have evolved, challenges remain, including the inability of shallow neural networks to handle complex nonlinear relationships without expert input. The advent of deep learning models, particularly deep neural networks like SAE, LSTM, and CNN, has enhanced the ability to process large datasets with high precision. CNN, in particular, has outperformed other methods in cavitation diagnosis, showing higher accuracy in analyzing vibration signals. Despite the success of deep learning, challenges such as resource limitations and the need for multi-channel sensor inputs remain. Traditional methods, however, continue to hold value in specific scenarios, and the choice of method should be tailored to the working conditions [40-43].
In cavitation detection, recent advancements have focused on improving both accuracy and speed, with various innovative methods demonstrating significant progress. Techniques such as hybrid feature selection combined with empirical modal decomposition and generalized regression neural networks (GRNN) have achieved near-perfect detection accuracy, while also enhancing speed [44]. Additionally, noise reduction methods, like time-frequency image denoising and convolutional neural networks (CNN), have proven effective in improving detection accuracy in noisy environments. Other strategies, including artificial immune algorithms, bispectral analysis with transfer learning, and the constant false alarm rate (CFAR) criterion, have demonstrated superior accuracy compared to traditional methods, particularly in the early stages of cavitation detection [45-47]. The location of vibration measurement points significantly influences the accuracy of cavitation detection, with certain areas, such as near the volute tongue, proving most effective for capturing reliable signals [30]. Research shows that sensors positioned closer to the cavitation zone yield higher detection accuracy, while optimizing sensor placement can reduce costs and improve inspection efficiency [15].

b) Acoustic emission signals processing methods
Acoustic emission (AE) refers to releasing elastic waves when particles within a material experience relative motion, thereby discharging strain energy in the form of these waves. This phenomenon provides a means of evaluating materials' internal condition or structural integrity. The application of AE technology in detecting equipment faults is closely linked to the discovery of the Kaiser effect, which demonstrated that materials have the ability to 'remember' previous stress events. In pumps, the primary sources of AE signals are associated with the following conditions [48-50]:
- Low-pressure zones: These are typically located behind the pump blade inlet, an area particularly prone to cavitation due to significant pressure drops.

- Pressure instability: Unstable conditions within the pump lead to irregular pressure fluctuations, which contribute to AE emissions.
- Shear stress: Large shear forces generated within the fluid flow also induce AE signals, particularly in turbulent regions.

When cavitation occurs, microjets and shock waves are generated by the collapse of vapor bubbles, interacting with the pump's components, such as the impeller and pipe walls. These interactions create AE signals that predominantly fall within the medium to high-frequency range, spanning from 1 kHz to 1 MHz. These signals propagate through the pump system, enabling sensitive detection of cavitation-related phenomena. AE signals are particularly effective for detecting impulsive pressure variations within the pump, which are indicative of cavitation, especially in large-scale systems. Acoustic emission sensors are strategically placed in high-risk areas, such as near the impeller, inlet, and outlet of the pump, to capture the AE signals generated during cavitation events. However, since AE signals attenuate rapidly in air, the use of couplants is essential for ensuring effective signal transmission. Several characteristics of AE signals, such as amplitude, energy, rise time, duration, and event counts, can be extracted and analyzed to assess the presence and severity of cavitation. These parameters are crucial for identifying cavitation faults and can significantly enhance diagnostic accuracy in pump monitoring systems. By leveraging AE technology, cavitation can be detected at an early stage, allowing for timely maintenance and preventing potential damage.

c) Noise processing methods

The acoustic emissions produced by a centrifugal pump are intrinsically influenced by its geometric configuration, including size and structural design, as well as the operational parameters such as rotational speed and load conditions. Additionally, hydrodynamic instabilities within the pump significantly contribute to elevated noise levels. These instabilities may arise due to phenomena such as flow separation (stall), system-wide oscillations (surge), and cavitation, each of which induces fluctuating pressure fields and turbulence, thereby amplifying acoustic disturbances [51].

It is known that cavitation-induced noise in centrifugal pumps is a type of hydrodynamic noise distinct from mechanical noise, characterized by a unique frequency differing from the blade passing frequency. This noise results from the formation and collapse of bubbles, with the collapse generating radiation noise that is transmitted through the pump body and detected by sound sensors, although the precise mathematical model of this process remains under experimental investigation [51-54]. Figure 9 illustrates the impact of cavitation on noise characteristics in a centrifugal pump, comparing noise spectra before and after cavitation inception and analyzing the relationship between noise levels, specific frequency components, and total delivery head under varying NPSH conditions.

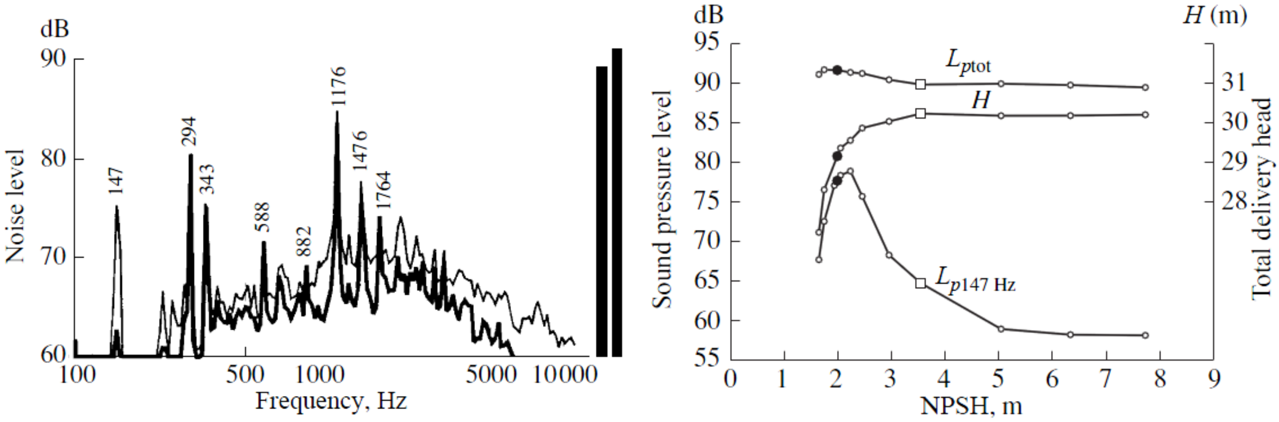

Fig. 4. (a) Noise spectra before cavitation inception (thick line) and after full development (thin line) for a centrifugal pump. (b) Comparison of total noise level (L_{ptot}), noise level at 147 Hz (L_{p147} Hz), and total delivery head (H) for different available NPSH values. (Reprinted from ref. [51] with permission of Springer Nature Switzerland AG publisher).

Noise measurements are frequently integrated with other signal analyses, particularly vibration signals, to enhance the accuracy and reliability of cavitation detection.

d) Pressure pulsation methods
Research on cavitation-induced pressure pulsation in centrifugal pumps focuses on key locations such as the inlet, outlet, volute, and impeller [15]. Studies indicate that inlet pressure pulsations are more sensitive to cavitation, with frequency components shifting from low to high as cavitation progresses [55]. At the volute tongue, cavitation leads to broadband pulsation and reduced main frequency amplitude. Severe cavitation increases high-frequency components, while pressure pulsation amplitudes vary across different pump sections. For cavitation detection, pressure pulsation signals, being nonlinear and non-stationary, require advanced signal processing techniques. Methods like wavelet analysis, singular value decomposition, and deep learning improve fault diagnosis accuracy. While pressure-based detection is less comprehensive than vibration or acoustic methods, it is cost-effective, resistant to interference, and crucial for monitoring pump faults [56-60]. Figure 5 compares pressure pulsation amplitudes at at f_{BPF} under non-cavitation and critical $NPSH_c$ conditions (a) and shows angular distributions for different cavitation numbers at the nominal flow rate (b).

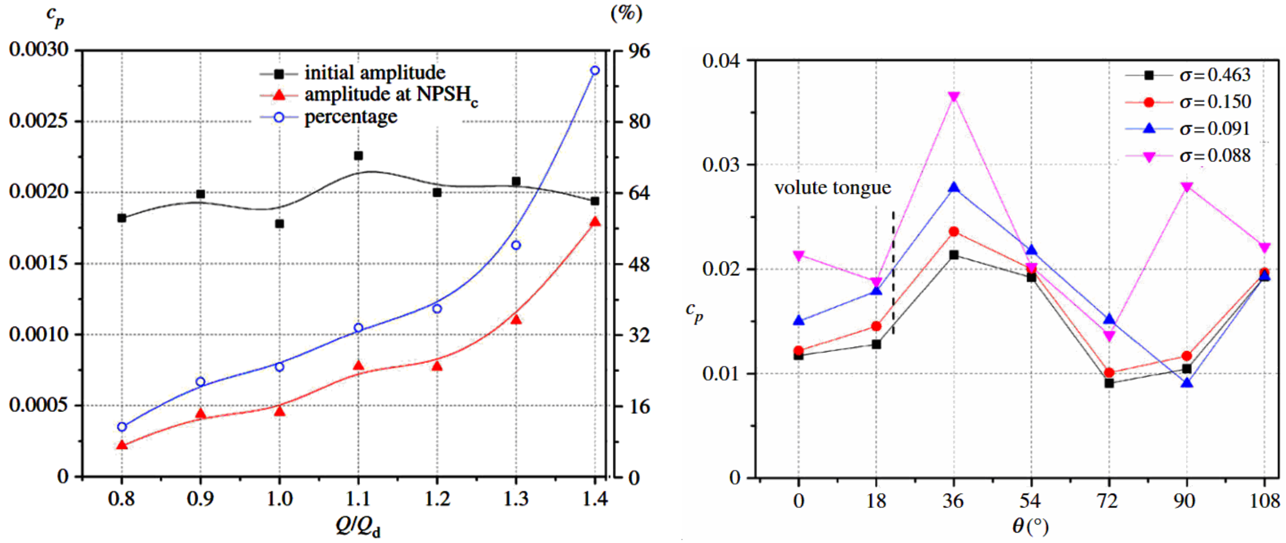

Fig. 5. a) Comparison of amplitudes at f_{BPF} for In1 under non-cavitation and critical point $NPSH_c$ conditions. b) Angular distributions of pressure amplitudes at f_{BPF} for different cavitation numbers at nominal flow rate. (Reprinted from ref. [55] with permission of Royal Society publisher).

3. Analysis, limitations, comparison of methods and future challenges

Acoustic emission and noise methods excel in early cavitation detection, particularly in non-contact settings, but are hindered by noise reduction challenges and high sensor costs. Acoustic emission is effective in complex, harsh environments but remains underexplored in industrial applications. Vibration-based detection faces signal attenuation and lower accuracy for early cavitation detection, while pressure pulsation methods are more resistant to interference but less accurate and difficult to implement in practical settings due to sensor installation complexity.
Signal-based cavitation detection methods are evolving to address challenges such as noise interference and complex signals. Key trends include:
- Advancement in signal acquisition: while pump systems complicate signal acquisition, advancements in sensing and signal processing are improving cavitation fault detection.
- Optimization of existing methods: many current methods can be refined, with ongoing research focusing on enhancing algorithms and detection accuracy.
- Integration of AI: AI and machine learning, particularly reinforcement learning, are enhancing the efficiency and precision of cavitation detection.
- Cross-field innovations: techniques from other fault detection fields are being adapted to improve cavitation detection through innovative signal processing and computational models.
- Versatility in detection systems: cavitation detection systems need to be more versatile, as current methods are often pump-specific. Future research should aim for generalized solutions applicable to various pump types.

4. Conclusions

This review examines various fault detection methods based on different signals, providing valuable insights into centrifugal pump cavitation detection. It highlights advancements in vibration, noise, acoustic emission, and pressure pulsation methods, emphasizing their contributions to improving detection accuracy and reliability. Despite progress, challenges such as sensor costs, noise reduction, and feature extraction remain, requiring further research to fully realize the potential of these methods. Additionally, the integration of advanced technologies, such as artificial intelligence, could significantly enhance the effectiveness of these detection systems. With continued development, signal-based cavitation detection methods will find substantial applications in fault detection systems, ultimately contributing to the optimization of pump performance and the prevention of costly mechanical failures.

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