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Review

A Review of Pump Cavitation Fault Detection Methods Based on Different Signals

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Abstract: As one of the research hotspots in the field of pumps, cavitation detection plays an important role in equipment maintenance and cost-saving. Based on this, this paper analyzes detection methods of cavitation faults based on different signals, including vibration signals, acoustic emission signals, noise signals, and pressure pulsation signals. First, the principle of each detection method is introduced. Then, the research status of the four detection methods is summarized from the aspects of cavitation-induced signal characteristics, signal processing methods, feature extraction, intelligent algorithm identification of cavitation state, detection efficiency, and measurement point distribution position. Among these methods, we focus on the most widely used one, the vibration method. The advantages and disadvantages of various detection methods are analyzed and proposed: acoustic methods including noise and acoustic emission can detect early cavitation very well; the vibration method is usually chosen first due to its universality; the anti-interference ability of the pressure pulsation method is relatively strong. Finally, the development trend of detecting cavitation faults based on signals is given: continue to optimize the existing detection methods; intelligent algorithms such as reinforcement learning and deep reinforcement learning will be gradually integrated into the field of cavitation status identification in the future; detection systems still need to be further improved to accommodate different types of pumps; advanced sensing devices combined with advanced signal processing techniques are one of the effective means to detect cavitation in a timely manner; draw on other fault detection methods such as bearing faults and motor faults.

Keywords: artificial intelligent; fault detection; cavitation state recognition; feature extraction; sensors; signal processing

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1. Introduction

Pumps are widely used in industry and daily life as a kind of fluid machinery. They are used to provide the energy required to transfer fluids. They are inseparable from household and agricultural applications [1]. Various faults may occur during actual operation. Cavitation is an inevitable multiphase flow complex phenomenon including phase transition [2–4]. In general, cavitation occurs when the static pressure at some point within a pump is lower than the liquid vapor pressure at the working temperature. In this case, a large number of bubbles are created, and these bubbles will collapse as the liquid reaches the high-pressure zone. The mechanism of cavitation has yet to be fully revealed due to its randomness and multi-phase characteristics [5]. Once the cavitation occurs, the energy exchange between the impeller and the fluid is damaged, the head-flow rate curve drops, and the surface of the flow passage parts is severely worn and corroded [6,7]. Also, it will cause noise and pump body vibration [8–10]. When the frequency reaches the natural frequency of the pump, resonance may occur, and even not normal operation [11]. Therefore, cavitation is a significant scientific issue in the field of pumps and a point of current concern. Cavitation detection has become an urgent problem to be solved, which has very important safety and economic significance [12].

The signal-based cavitation fault detection method is based on the fact that the accompanying cavitation phenomenon will change the acoustic, vibration, and pressure pulsation signals inside the pump. There is a certain relationship between the change in the signal and the occurrence of cavitation. Signal sensors are installed in different positions of the pump, collecting the data signal in the pump's operating state for analysis. At the same time, artificial intelligence algorithms such as machine learning and deep learning are used to achieve feature extraction and state recognition. The basic process of cavitation fault detection is shown in Figure 1. Compared with other detection methods, the cavitation detection method based on different signals can be applied to complex and nonlinear systems and has low requirements of the field environment. At the same time, signal methods are helpful to improve the performance of the detection system. Hence, researchers have carried out extensive work in this area.

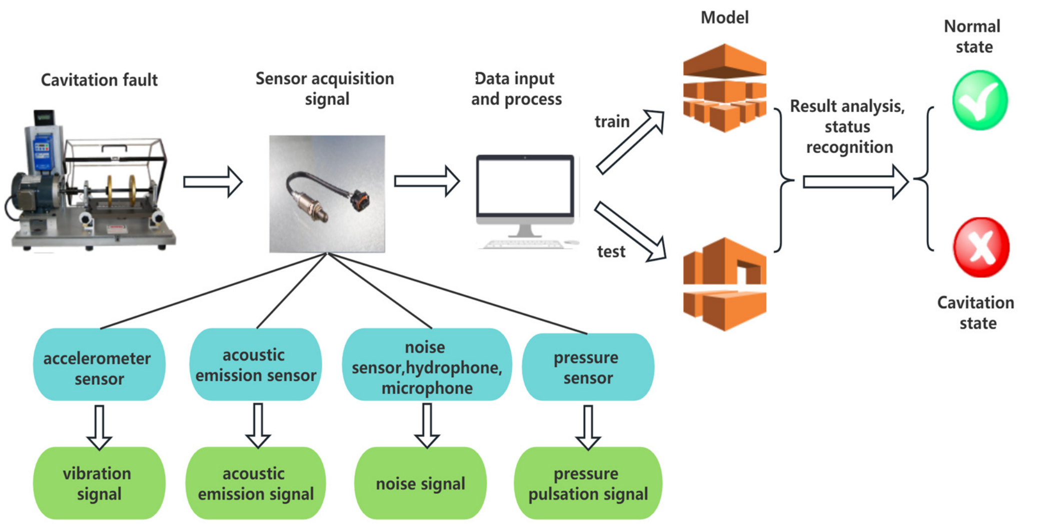


Figure 1. Basic flowchart of cavitation detection based on different signals.

This paper discusses the four cavitation detection approaches in depth. The principles of the detection methods are first clearly introduced. Then, an overview of the current research progress of the vibration method is given, with emphasis on five aspects—signal processing, signal frequency distribution range, application of artificial intelligence, detection efficiency, and distribution of measurement points—and the current status of the acoustic and pressure pulsation methods is analyzed. Then, the advantages and disadvantages of different methods are compared. Finally, the development prospects are provided. The detailed information in this paper can provide a reference for further research to find the best anti-cavitation design for pumps. This is a motivation for the current research.

The main content of the paper is shown in Figure 2. Section 2 enumerates the commonly used cavitation detection methods and explains their principles. Section 3 details the research status of each method. Section 4 gives a comparative analysis of different methods. Section 5 presents several future directions for detecting cavitation based on different signals. Finally, Section 6 concludes the work.

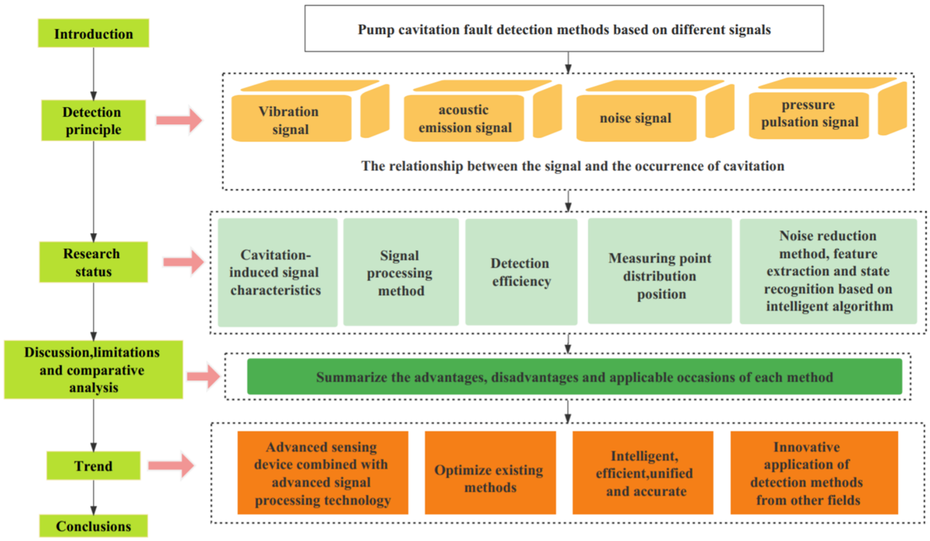


Figure 2. Diagram of the main research content of the article.

2. Common Cavitation Detection Methods and Principles

Cavitation detection is one of the contents of fault detection. Energy methods, high-speed photography [13], surface coating methods, resistance methods, ultrasonic detecting methods [14], and optical methods have been used in cavitation detection. However, the continuous advancement of technology and the continuous complexity of pumps have led to certain limitations of the above methods. In recent times, signal-based fault detection has shown certain advantages in the field of cavitation. According to the existing reference materials for cavitation detection research in pumps, commonly used signals are vibration, acoustic emission, noise, and pressure pulsation. The causes of them in the pump are extremely complex [15]. In addition, the motor current can also be used as an indicator of the occurrence of cavitation [16], but few are studying it. In the next subsections, the principles of the four detection methods are described.

2.1. Vibration Method

When a fault occurs, the most direct reflection is often that the vibration of the mechanical equipment has changed abnormally. If the pump cavitation is the same, the pump will have abnormal vibration after the occurrence of cavitation. Vibration signals contain a lot of cavitation fault information. The vibration frequency induced by cavitation will exceed BPF, and vibration data are usually collected by means of acceleration sensors, which are installed in various parts near the pump [17,18], including the base, inlet, outlet, and pump body, as shown in Figure 3. The general installation is divided into three directions: axial, radial, and vertical. Whether it is the variance and RMS in the time domain or the spectrum in the frequency domain, the vibration signal caused by cavitation is different from the vibration signal during normal operation. In Figure 4, the vibration signals in the time and frequency domains are significantly different in the cavitation and non-cavitation states [19].

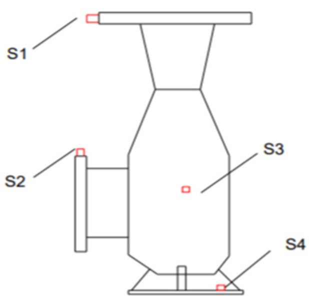
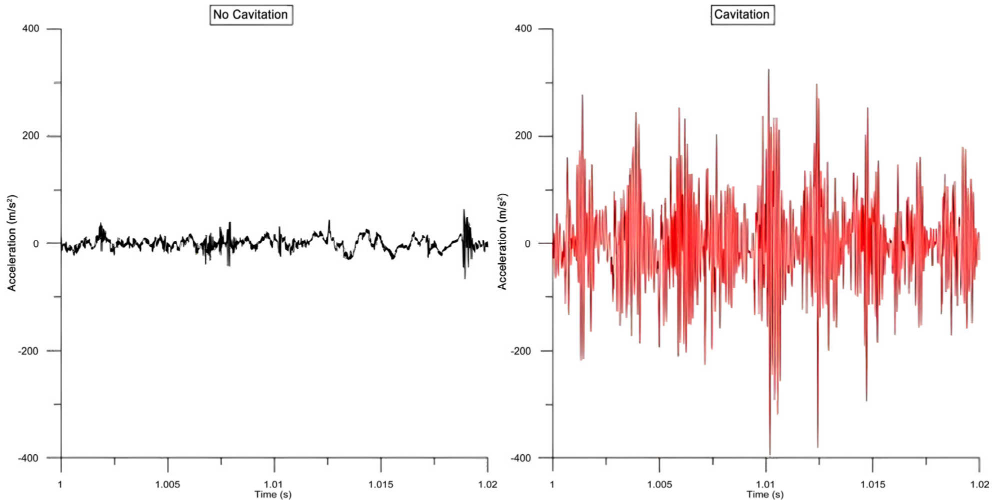


Figure 3. Four accelerometer installation positions. S1: outlet, S2: inlet, S3: pump body, S4: base.



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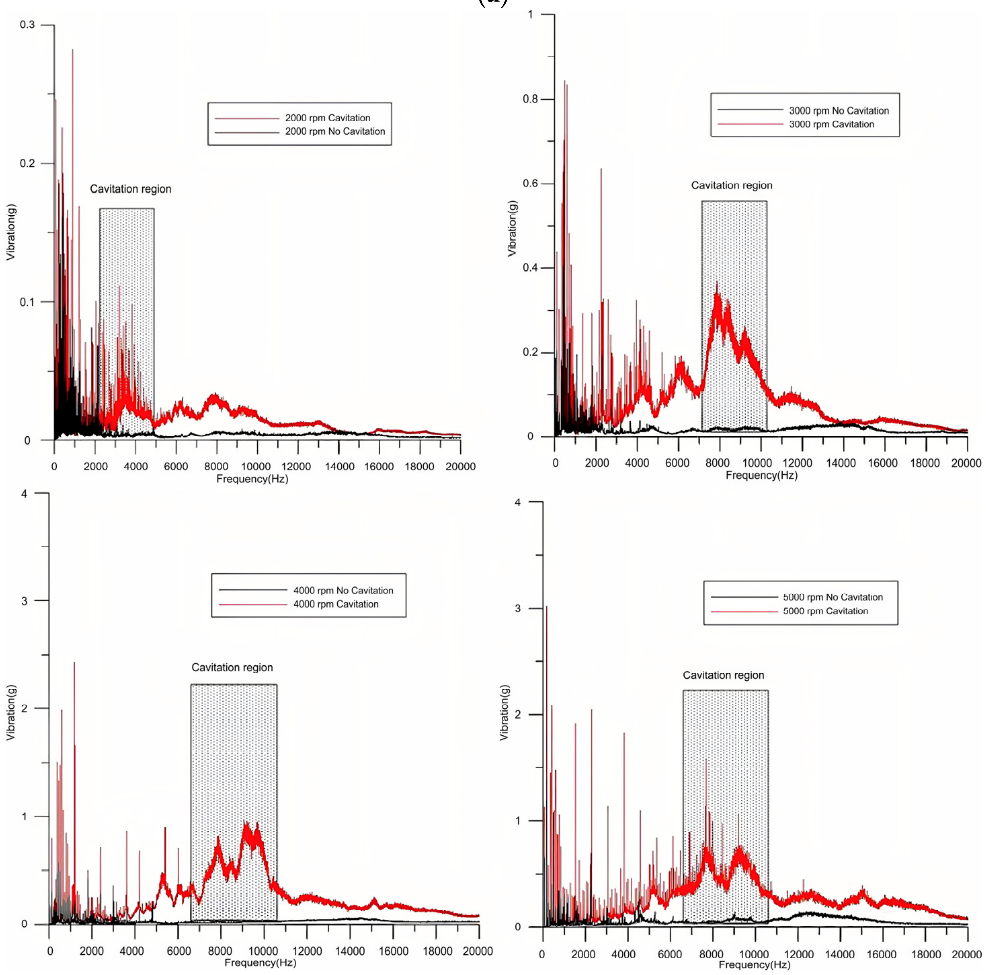


(**b**)

Figure 4. (**a**) Time domain acceleration signals in cavitation and non-cavitation states. (**b**) Vibration signal spectrum under different rpm [19].

With the continuous development of technology, vibration testing and analysis technology theories and methods are relatively mature. Many researchers have made good progress in the domain of cavitation detection by focusing on vibration analysis methods, combining intelligent algorithms and advanced signal processing technology.

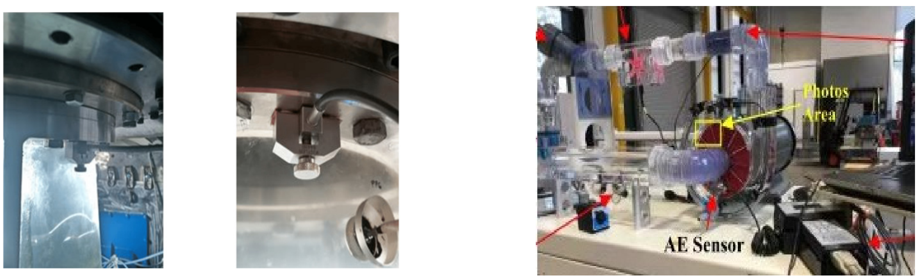
2.2. Acoustic Emission Method

Acoustic emission is when the particles inside a substance generate elastic waves after relative motion and then release strain energy in the form of elastic waves, thereby realizing the identification of the internal state of the material or structure [20,21]. Acoustic emission technology for detecting faults in static equipment has been used since the 1970s [22]. Its rapid development originated from the discovery of the Kaiser effect by the scientist Kaiser. The main sources of acoustic emission signals in the pump are as follows:

1. The lowest pressure point when the pump is operating, generally the position behind the inlet end of the blade, which is also the most prone to cavitation;
2. Irregular fluctuations in pressure under unstable conditions;
3. Large shear stresses in the water flow.

In the process of cavitation, a large number of microjets or shock waves are generated, which act on some components of the pump, such as impellers, the wall of the pipe, etc., forming medium- and high-frequency AE signals in the range of 1 kHz~1 MHz, and propagating along the pump system [23].

The frequency of acoustic emission signals is high and has a strong sensitivity to impulse pulsations caused by fluid in the pump, especially in larger pumps [24]. As shown in Figure 5, acoustic emission sensors are typically installed at the inlet and outlet of the pump, near impellers [25,26]. AE signals are strongly attenuated in air, so a suitable couplant is required to ensure adequate signal transmission [27]. Many acoustic emission characteristic parameters can be extracted from the acoustic emission signal, as shown in Figure 6, including energy, amplitude, rise time, duration, counts, and so on. These parameters can reflect cavitation in the pump [28,29].



(**a**) (**b**)

Figure 5. (**a**) AE sensors collect signals in pump test system [25]. (**b**) AE sensors are installed on the flange [26].

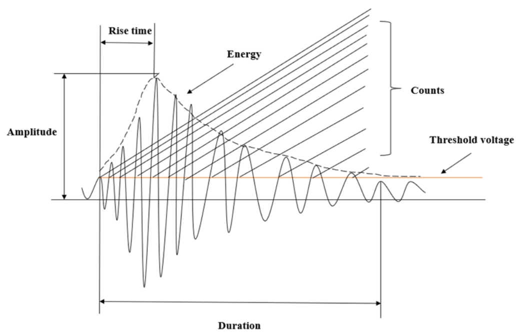


Figure 6. Acoustic emission signal characteristic parameters.

2.3. Noise Method

The noise generated by the pump during operation is divided into mechanical noise and hydrodynamic noise, and the noise caused by cavitation belongs to hydrodynamic noise. The composition is shown in Figure 7. When cavitation occurs, noise of a unique frequency is generated, which is very different from the blade passing frequency. Cavitation noise is relatively complex, with monopole noise source characteristics, and the mathematical model of its mechanism needs to be established. The current research is mainly experimental [30]. It is inseparable from the generation and collapse of bubbles. When cavitation begins, bubbles form at the inlet of the blade. When cavitation develops to a certain extent, the flow channel is filled with bubbles, and the high pressure makes these bubbles collapse. The radiation noise generated is transmitted to the outside of the pump through the pump body, and the signal is picked up by the sound sensor.

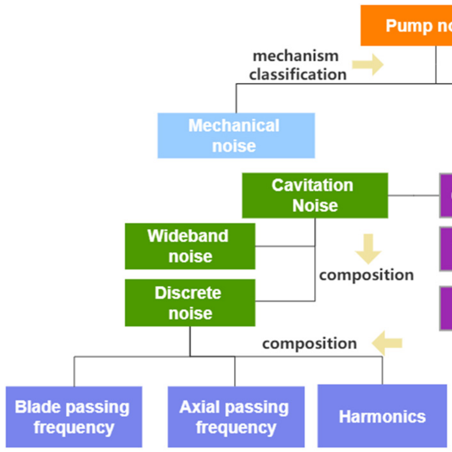


Figure 7. Composition of pump noise.

Noise is a fundamental consequence of cavitation and can also be used as an indication of the onset of cavitation. The noise method is promising for detecting the beginning of cavitation, and it can be applied to any flow condition, so there has been extensive research on the application of acoustic-based methods for detecting cavitation [31,32].

2.4. Pressure Pulsation Method

The pump will produce a pressure difference under a stable flow to transport the medium. In this process, a static pressure component is generated along with a dynamic pressure component, that is, pressure pulsation. The pressure pulsation inside the pump is especially complex, and much work has been carried out to study its mechanism [33,34]. The pulsation of different pumps under different working conditions is distinctive and caused by many factors like dynamic and static interference, secondary flow, rotating stall, cavitation, etc. [35,36]. The flow field inside the pump changes with the occurrence of cavitation, and the pressure pulsation also changes in the inlet and outlet, volute tongue, and impeller flow channel. The pressure sensor is usually installed on the inlet and outlet of the pump near the flange for dynamic testing, and the collected pressure pulsation signal is analyzed spectrally to detect cavitation. The manifestation of the signal may be a periodic signal or a random signal, and its components are blade frequency and its harmonics, axis frequency and its harmonics, and random pulsation close to white noise [37]. Because of the complexity, it cannot be eliminated theoretically, thus stimulating many scholars to study and analyze the pressure pulsation generated by cavitation.

After cavitation, the flow field is affected first. As a signal characteristic describing the flow field, pressure pulsation is closely related to the occurrence of cavitation, so it is necessary to carry out cavitation detection by the pressure pulsation method.

3. Research Status of Cavitation Fault Detection

3.1. Vibration-Signal-Based Cavitation Detection

The vibration method is the most commonly used mechanical fault detection method by researchers. The vibration inside the pumps will provide a strong indicator of cavitation.

3.1.1. Vibration Signal Processing Methods

The current vibration signal processing methods are generally based on time domain analysis, frequency domain analysis, and time–frequency domain analysis. The relevant research is shown in Table 1. In time domain analysis, the mean, root, RMS, peak, peak-to-peak, etc., can be used for feature extraction. Cavitation causes an increase in the amplitude of the vibration signal, and the RMS will also increase. Compared to RMS and variance, peaks and peak-to-peak values are the most sensitive for detecting pump cavitation [38]. Cao and Yuan [39] adopted the method of gray slope correlation analysis to explore the relevance between vibration and cavitation and incorporated mathematical standards into the selection of characteristic targets. It can be concluded that kurtosis factors, variance, and root mean square are related to cavitation intensity. Later studies found that the vibration signal of cavitation is more obvious in the frequency domain than in the time domain. The results obtained by relying only on time domain analysis are one-sided. To some extent, most researchers prefer to study the vibration characteristics of the frequency domain or time–frequency domain, and the time domain image is only used as reference data. He et al. [40] installed accelerometers on both sides of the pump casing to obtain the vibration signal. In order to better extract the band characteristics of the vibration signal, on the basis of the standard octave band, the improved octave band is combined with a BP neural network, which can effectively identify four cavitation states. However, the method of frequency domain analysis has certain defects. The spectral analysis results of different time periods under the same signal are different, and sometimes even the signal needs to be filtered, leading to the loss of information, which cannot extract the characteristics of cavitation completely. To address this problem, Liang et al. [41] used the MFDFA algorithm for feature extraction of vibration signals, which can reflect the fractal characteristics of the signal in different states. A new feature vector composed of multiple fractal spectral feature parameters as the input to the BP neural network provides a new development idea for cavitation fault detection. Time–frequency analysis is now considered the most accurate method; it can be applied to nonlinear and non-stationary signals. The main methods for extracting cavitation features based on time–frequency analysis are spectral kurtosis, short-time Fourier transform, empirical modal decomposition, wavelet transform, and Wigner–Ville distribution [42]. Mousmoulis et al. [43] used spectral kurtosis methodology to effectively detect the pulse shock waves generated by bubbles when they collapsed.

Table 1. Common processing methods for vibration signals.

Analytical Method	Including	Disadvantages and Advantages	Ref.
Time Domain Analysis	Correlation analysis and amplitude range analysis	Simple, intuitive, one-sided, only suitable for stationary signals	[38,39]
Frequency Domain Analysis	Difference frequency analysis, cast frequency analysis, envelope analysis, spectrum analysis	Only frequency domain information can be obtained, cannot be completely extracted to the cavitation characteristics, and cannot meet the noise reduction requirements	[40]
Time–Frequency Domain Analysis	Spectral kurtosis, short-time Fourier transform, empirical mode decomposition, wavelet variation, Wigner–Ville	Ability to handle complex, non-stationary, and nonlinear signals	[41,43]

3.1.2. Frequency Distribution of Cavitation Vibration Signal

The vibration characteristics of cavitation are distributed in a wide frequency band, mainly in high frequencies. Cavitation has different sensitivities to different frequency bands [44]. Duan et al. [45] found through frequency domain analysis that the vibration signal has significant peaks around 2 kHz, 4 kHz, 6 kHz, and 8 kHz. Gong et al. [46] performed a time–frequency analysis of the vibration signal. They concluded that the vibration signal in the high-frequency band could be used as a basis for detecting pump cavitation faults. Nevertheless, other studies have pointed out that cavitation is more sensitive to the low-frequency range. Gao et al. [47] studied the vibration characteristics caused by cavitation, mainly analyzing the relationship between cavitation and vibration in the 10 to 500 Hz frequency band. Compared with the high-frequency band, the vibration change trend of the low-frequency band is different. Zhang et al. [48] studied the vibration characteristics of the slope volute centrifugal pump under cavitation conditions, installed seven acceleration sensors on the surface of the volute, divided the collected vibration signal spectrum into four different frequency bands, and revealed that the cavitation process had a great influence on the low-frequency signal. Luo et al. [49] collected the vibration signals of the centrifugal pump under normal working conditions and cavitation conditions and compared the spectrum under the two conditions through frequency domain analysis. It was concluded that the spectrum during cavitation was a continuous wide-band vibration. The vibration was significantly strengthened, and the change was more obvious in the middle- and low-frequency bands. Lu et al. [50] studied the vibration signal of mixed-flow pumps. He presented that high amplitude vibration occurred in the range of 1200 Hz to 1400 Hz after the occurrence of cavitation. Meanwhile, Al-Obaidi [51] installed vibration sensors on the volute tongue and used MATLAB to analyze the vibration signal in the time and frequency domains. In further investigation and research, it was found that the low-frequency range of 1 kHz and 2 kHz was the most sensitive to cavitation. Table 2 provides information on the above studies.

Table 2. Research on frequency distribution range of cavitation vibration signal.

Research Object and Related Parameters	Vibration Signal Acquisition Location	Based on Frequency Range	Conclusion	Ref.
Single-stage, single-suction centrifugal pump; blade number: 6; type: PWF-125	Case	0~20 kHz	The detection of cavitation in the bandwidth range of 8~12 kHz conforms to the law of sound pressure	[44]
Single-stage, single-suction centrifugal pump; rotating speed: 1440 r/min; nominal flow rate: 100 m^3/h	Bearing housing and pump casing	0~20 kHz	The vibration signal has obvious peaks around 2 kHz, 4 kHz, 6 kHz, and 8 kHz, and the trend is obvious above 5 kHz	[45]
Single-stage, single-suction centrifugal pump; type: IS-50-160-00; rotating speed: 2900 r/min; nominal flow rate: 50 m^3/h	Base and axial, longitudinal, and transverse directions	0~5 kHz	The axial vibration signal during cavitation is mainly concentrated at 3.6 kH~4.7 kHz	[46]
Low-specific-speed centrifugal pump; nominal flow rate: 55 m^3/h; rotating speed: 1450 r/min	Three locations near the surface of the volute	10~52.1 kHz	The trend of vibration signal change in the low-frequency range of 10~500 Hz is special	[47]
Centrifugal pump with slope volute; nominal flow rate: 48 m^3/h; rotating speed: 1450 r/min	Slope volute surface	0~25 kHz	The 10~25 kHz high-frequency signal is more sensitive to the occurrence of cavitation, and the cavitation process also has a certain impact on the low-frequency signal	[48]
Single-stage, single-suction centrifugal pump; type: IS-50-160; nominal flow rate: 25 m^3/h; rotating speed: 2900 r/min	Pump case radial horizontal direction	0~12,800 Hz	In the range of 0~12,800 Hz, the bottom of the spectrum line has a certain degree of elevation, and the change in medium- and low-frequency vibration signal is more significant	[49]

Table 2. *Cont.*

Research Object and Related Parameters	Vibration Signal Acquisition Location	Based on Frequency Range	Conclusion	Ref.
Mixed-flow pump; flow rate: 0.035 m^3/s; rotating speed: 1450 r/min	Near blade tip	0~2000 Hz	After cavitation, high-amplitude vibration occurs in the range of 1200~1400 Hz	[50]
Centrifugal pump; type: F32/200 H; rotating speed: 2755 r/min	Volute tongue	0~15 kHz	The low-frequency range of 1 kHz and 2 kHz is most sensitive to cavitation	[51]

In the process of studying the frequency distribution range of cavitation vibration signals through experiments, the research results also have certain differences due to the different size parameters of the test pumps and signal processing methods. In addition, the type of test bench will also affect the conclusion. Generally speaking, the accuracy of the open test bench will be lower than that of the closed one.

3.1.3. Application of Artificial Intelligence in Cavitation Detection

The combination of machine learning and the vibration method has become one of the effective means of pump cavitation fault detection.

Artificial neural networks were first introduced by McCulloch and Pitts [52], and after continuous development and improvement, they are now more mature in the application of fault detection. Siano and Panza [53] proposed a nonlinear autoregressive method based on an artificial neural network (ANN) to process the vibration signal of the pump. In addition to artificial neural networks, there are also support vector machines [54,55], BP neural networks, random forests, etc., which are also extensively adopted in cavitation detection. The extreme learning machine (ELM) model can also be used to detect cavitation, and the findings show that the accuracy of this model is higher than that of BP neural networks and random forests [56].

Machine learning has been widely used in the field of detection, from the beginning of simple models to the present continuous optimization, but at the same time, there are shortcomings. Ordinary neural network architecture is shallow, cannot learn complex nonlinear relationships, and even needs to rely on the prior knowledge of experts. The development of artificial intelligence shows that data classification algorithms based on deep learning can process large datasets with high accuracy, so they are gradually applied to cavitation fault detection [57]. The three deep learning techniques of SAE network, LSTM network, and CNN are used in the cavitation diagnosis for the axial flow pump, and the vibration signal is used as the input dataset of the three networks. The results show that the accuracy of CNN is much higher than that of the other two networks [58].

Chao et al. [59] applied deep learning to cavitation detection of high-speed aviation hydraulic pumps for the first time, and converted the vibration signals of X, Y, and Z channels collected on the pump casing into RGB images as input to a two-dimensional convolutional neural network. Moreover, they also used a one-dimensional convolutional neural network model to identify the four levels of cavitation intensity of the piston pump [60]. However, only the vibration signals in different directions are collected as the input of the CNN model. Different types of sensor signals can be explored as multi-channel inputs of the model in the later work. One-dimensional and two-dimensional convolutional neural networks are also some of the most popular deep learning methods in recent years, with a strong ability to extract feature information from images. As diagnostic techniques for cavitation, one-dimensional and two-dimensional convolutional neural networks were poorly adopted by researchers in the past. Gradually, they can also be extended to tasks of fault detection. Although deep learning technology can process a large amount of data, it causes some problems for researchers in the face of resource conservation [61]. In many cases, traditional methods will also retain some advantages. Thus, it is vital to make a wise choice when choosing an approach based on the actual working conditions.

3.1.4. Detection Efficiency

In cavitation detection, accuracy and speed have received more and more attention from scholars. In recent years, many scholars have devoted themselves to improving the detection speed under the premise of ensuring accuracy and have achieved certain research results, as shown in Table 3. In order to improve the detection accuracy and speed, a centrifugal pump cavitation severity detection system based on hybrid feature selection technology is proposed [62]. In this research, the empirical modal decomposition is combined with the generalized regression neural network. The collected vibration signals are decomposed by the EMD, and GRNN for cavitation fault classification. The hybrid feature selection algorithm can select the best features from a large set of features. The finding showed a possible accuracy of up to 100% and a faster detection speed. The vibration signal is sensitive to noise. In the industrial environment, many methods to detect cavitation due to background noise are often unsatisfactory. Hence, denoising is also a key factor to improve detection accuracy. The vibration signal can be converted into a two-dimensional spectrum by a short-time Fourier transform, and the denoised spectrum is used as the input image of the convolutional neural network. The finding demonstrates that the method improves the accuracy of cavitation recognition in the noise environment [63]. In addition, the artificial immune algorithm proposed by Matloobi and Riahi [64], the transfer learning and bispectral analysis presented by Hajnayeb and Qin [65], and the adaptive cavitation detection method based on the constant false alarm rate (CFAR) criterion suggested by Chu et al. [66] can have an accurate detection of cavitation faults, and the accuracy is higher than that of multilayer artificial neural networks and nonlinear support vector machines under the same conditions.

Table 3. Research on improving the accuracy and speed of cavitation detection.

Pump Types	Main Method	Purpose	Ref.
Centrifugal Pump	Hybrid Feature Selection Technique, EMD is combined with GRNN	To improve accuracy and speed	[62]
Axial Poston Pump	Time–Frequency Image Denoising, Convolutional Neural Networks	To improve the accuracy of cavitation recognition in noisy environments	[63]
Centrifugal Pump	Artificial Immune Algorithm	To improve the accuracy of detecting cavitation in the initial stage	[64]
Centrifugal Pump	Bispectral Analysis, Transfer Learning, Convolutional Neural Networks	Accurate detection of cavitation with fewer data	[65]
Centrifugal Pump	Constant False Alarm Rate	To improve the detection rate of initial cavitation	[66]

3.1.5. Vibration Measuring Point Location

At present, there is a lack of research on the sensitivity of the distribution of measurement points for cavitation detection. The position of the measurement point also has a certain impact on the acquisition of vibration signals, and the vibration signal characteristics of different positions and even different frequency bands are distinctive. Studies have shown that the position near the volute tongue area is the most suitable position to obtain vibration signals, as shown in Figure 8a; because of the high degree of interaction between the rotating part impeller and the fixed part volute, the position has a positive effect [67]. Tong et al. [68] studied the relationship between pump performance, vibration signal, and cavitation image; they installed eight sensors at different positions of the pump body, and the measurement point distribution is shown in Figure 8b. The results show that the vibration signal measured by the sensor near the cavitation zone can better detect the cavitation faults, while the sensor far from the cavitation zone has the lowest accuracy (from high to low: #5, #2, #4, #3, #7, #1, #8). The accelerometers are also placed at the rolling bearings that support the overhung impeller near the suction of the pump [69].

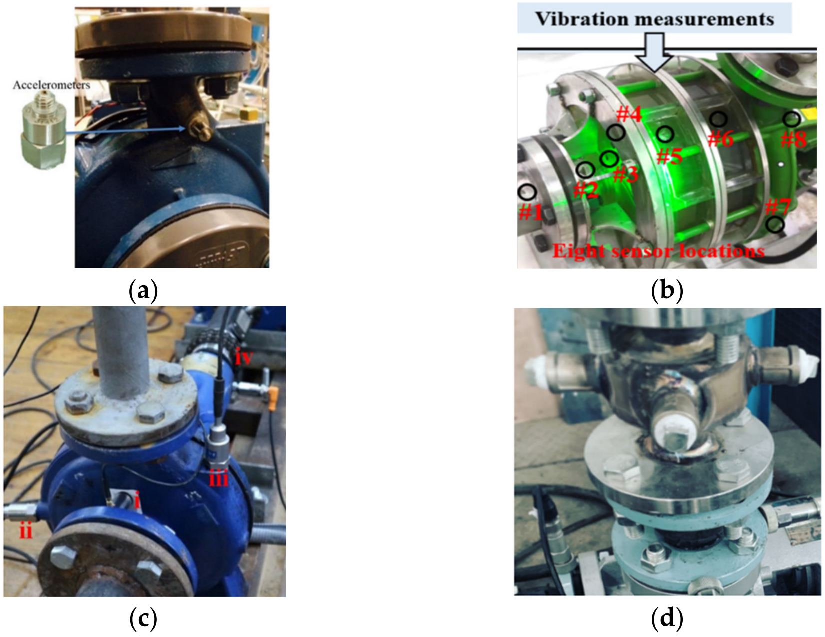


Figure 8. (**a**) The accelerometer is located at the tongue of the volute. (**b**) Eight acceleration sensors measuring point distribution. (**c**) AE sensor i and accelerometers ii, iii, iv installation position. (**d**) Distribution of eight vibration measuring points [67–70].

As shown in Figure 8c, Zhou et al. [70] installed eight vibration sensors in the horizontal and vertical directions of the inlet and outlet flanges, pump axial and radial, pump foot, and bearing housing, as shown in Figure 8d, measuring signal characteristics at different positions under different conditions. At the stage of cavitation not occurring, the pump radial vibration acceleration is greater than the axial vibration acceleration. With the deterioration of cavitation, the pump axial vibration acceleration significantly exceeds the radial, while the overall acceleration level of the pump foot is small, the signal distribution is sparse, and the spectral changes are not obvious enough and less sensitive to the occurrence of cavitation.

Determining the best vibration measurement point can optimize the inspection system and reduce the number of sensors, reducing test costs while having a better inspection result.

3.2. Acoustic Emission Signal-Based Cavitation Detection

Although acoustic emission detection technology has developed in the past ten years, there are still few related studies applied to cavitation detection.

3.2.1. Previous Research Results

Neill et al. [71] detected cavitation by acoustic emission signals at a very early stage and preliminarily concluded that it was possible to detect cavitation before the head dropped by three percent. In the study by Alfayez and Mba [72], acoustic emission sensors were placed in five different positions near the pump. According to the experimental results, the acoustic emission sensor worked best on the pump casing near the impeller. Meanwhile, researchers pointed out that cavitation caused a decrease in acoustic emission levels. The acoustic emission technique provided the possibility to determine the optimal efficiency point for centrifugal pumps [73]. Ylönen et al. [74] studied the relationship between the distribution of AE peak voltage value and the diameter of pits on the material surface caused by cavitation and indirectly explored the correlation between acoustic emission signal and cavitation intensity, which laid a foundation for the application of acoustic emission detection cavitation in pumps in the future. The characteristic parameters of the acoustic emission signal, such as ringing count, frequency center, energy, etc., can serve as a basis for determining the occurrence of cavitation [75]. The waveform and spectrum of the signal can also be used to visualize the distinction between the normal state and the cavitation state [76]. Existing studies generally agree that combining quantitative analysis of parameters and waveforms can achieve better outcomes. The above studies show that it is feasible to use this non-invasive means to detect early cavitation.

3.2.2. Noise Signal Reduction Method

Since the collected cavitation signal is usually medium-high frequency, it may be doped with a high-frequency noise signal, so noise reduction treatment is required. The current methods for cavitation acoustic emission noise reduction are using other noise reduction methods in the field of fault detection, such as the wavelet noise reduction method, empirical mode decomposition, and singular value decomposition. The wavelet decomposition cannot realize the adaptive decomposition of signals, and empirical mode decomposition can make up for the shortcomings of wavelet decomposition, but it has problems such as modal aliasing [77]. Singular value decomposition can relatively better solve the noise reduction of the signal and have good stability, but it cannot be decomposed in the face of multiple resolutions of the signal. To address the above issues, multi-resolution singular value decomposition has better results, which can realize the decomposition of signals at different resolutions, and has a certain research value in the noise reduction of cavitation signals [78]. In addition, Liu et al. [79] used the HHO algorithm to optimize the VMD parameters to obtain the optimal parameter combination and then applied it to the noise reduction of cavitation acoustic emission signals of hydraulic turbines. Aiming at the problem of noise reduction and feature extraction difficulties, a joint noise reduction method based on adaptive iterative filter decomposition and singular spectrum analysis is established, which is of great significance for improving the application of acoustic emission technology in cavitation fault detection [80].

3.3. Noise-Signal-Based Cavitation Detection

3.3.1. Cavitation Noise Characteristics

The characteristics of cavitation noise, including intensity characteristics, pulse characteristics, and spectral structure characteristics, were studied in the 1950s. McNulty and Pearsall [81] indicate that cavitation noise is broadband noise, and the main energy is concentrated in high-frequency bands. Gülich [82] pointed out that the decrease in cavitation number leads to an increase in the noise pressure level. Chudina [83] used a microphone to collect the noise of the centrifugal pump, proposed that the noise could be used as the basis for cavitation, and experimentally concluded that the discrete frequency of 147 Hz was the characteristic frequency of cavitation. Later, Liu et al. [84] carried out a detailed analysis of various characteristics of noise, and selected the energy, steepness, and spectral center of gravity above 10 kHz as the characteristic vector composition of the support vector machine. Under large background noise, a good recognition effect was still obtained. The noise signal generated by cavitation is a random and continuous broadband spectrum, and the spectral structure is unique. The effective value and variance cannot detect critical cavitation. On the contrary, the kurtosis can reflect the early cavitation faults, and it shows a satisfactory result in detecting cavitation [85].

In order to prove the effectiveness of noise methods in detecting cavitation, extensive work has been carried out. Hosien and Selim [86] tested in a water tunnel, and the tests showed that the sound pressure level of high-frequency noise would increase significantly with the development of cavitation. When the sound pressure level is higher than the critical frequency of the cavitation noise spectrum, the occurrence of cavitation can be detected by the increase in sound pressure level. Lighthill is widely used in noise calculations for most rotating machinery. The combination of computational fluid dynamics and the Lighthill acoustic analogy was used to investigate the changes in the internal sound field of the pump caused by cavitation. Once the cavitation begins, APF, 10~100 Hz band and 1000~3000 Hz band showed signs of increase, while BPF showed a downward trend [87]. Also, the sound generated by the impellers can be used as an indication of cavitation [88]. Experimental and numerical studies have shown a strong correlation between inlet and outlet noise and cavitation. The signal close to the pump hydrophone test point is more sensitive to cavitation. The inlet noise signal in the range of 6 to 9 kHz is typical of the cavitation band, and as the flow rate increases, the cavitation-induced outlet noise signal moves to a lower frequency band within a certain range [89]. The sound source propagation inside the pump is more complicated, and the noise signal at the inlet and outlet alone cannot fully reflect the internal flow field information. In the study of Duan et al. [90] and Ye et al. [91], the acquisition of noise signals is too local, and the effect is not very ideal. In this case, multi-point noise analysis showed a strong application prospect, which broke through the limitations of the location and number of measurement points and met the requirements of the industry in terms of accuracy and speed [92]. Compared with the vibration signal, the liquid-borne noise signal is proven to be the most sensitive signal to cavitation [93].

3.3.2. Signal Processing

The appropriate processing of the acquired acoustic signal is critical. Spectrum analysis based on Fourier transform has insurmountable limitations for abrupt signals. The combination of wavelet packet decomposition, principal component analysis, and radial basis function neural network has a good reflection of the detection results. WPD performs time–frequency domain analysis on internal flow-borne noise signals, PCA is used for dimensionality reduction, and radial basis function neural network is used for state recognition. Finally, the recognition rate of three cavitation states (non-cavitation, initial cavitation, and severe cavitation) can reach 98.2% [94]. The psychoacoustic method, the science of human perception acoustics, was first used by Murovec et al. [95] for cavitation detection in industrial environments. They used the derivative and logarithm of the signal as input to calculate and extract psychoacoustic indicators and descriptors, such as loudness, roughness, sharpness, tonality, and so on. Compared with other noise methods, its outstanding features are independent of sound pressure level and robustness. In addition, this method can also design a simple cavitation detection alarm system. Although the final result is still a certain deviation, as an emerging technology, it can provide a new way of detecting cavitation in a pump. After reviewing the available literature, we can safely assume that if the noise signal can be processed and manipulated correctly, it carries enough information to characterize the cavitation features.

3.3.3. Combination of Noise Measurement and Vibration

Noise measurements are often combined with other signal measurements to evaluate the accuracy and reliability of cavitation detection, most commonly in conjunction with vibration signals. Battarra and Mucchi [96] combined acoustic vibration measurements with a dedicated signal-processing program to effectively detect primary cavitation in external gear pumps. In another paper, vibration and acoustic analysis techniques were used to evaluate the degree of cavitation inside a centrifugal pump. The analysis of vibration and acoustic signals provides a good indication of how the pump operates under non-cavitation and different cavitation stages [97]. In the study by Dong et al. [98], a test method for detecting cavitation based on liquid-borne noise was proposed, focusing on the changing pattern of vibration and total noise level during the whole cavitation process. It was found that liquid-loaded noise has higher sensitivity to the change in cavitation, and the signal spectrum is concentrated in the 2000~3000 Hz range and below 100 Hz, which is suitable for large pumps.

3.4. Pressure Pulsation Signal-Based Cavitation Detection

3.4.1. Signal Characteristics at Different Positions

The effect of cavitation on pressure pulsation needs to be combined with flow conditions and location [99]. The research on the pressure pulsation characteristics induced by cavitation in the pump mainly focuses on four parts: inlet, outlet, volute, and impeller. Among them, there are more studies on the inlet and outlet. Li et al. [100] studied the relationship between suction inlet pressure and cavitation performance. The difference is that the probability density function is used as a statistical parameter in the process of analyzing the signal, which can be used as an indicator of critical cavitation. The components of the inlet and outlet pressure pulsation change with the cavitation state. It can be observed that the outlet pressure pulsation presents a low-frequency component at the beginning of the cavitation, and as the cavitation develops, the high-frequency component is enhanced, and the axial frequency and its harmonics are more significant, while the inlet pressure pulsation spectrum is dominated by axial and blade frequencies. However, during the study, it was found that inlet pressure pulsations are more sensitive to cavitation [101].

When the pump is operated above the design flow rate, cavitation is more likely to occur in the tongue of the volute, not in the impeller [102]. In recent years, it has also been found that the pressure pulsation caused by cavitation inside the volute has also been of great research significance. Lu et al. [103] studied the cavitation of the volute tongue and its induced pressure pulsation characteristics. Under the operating conditions of large flow, the pressure pulsation around the tongue has the same period in the time domain, the main frequency amplitude of the pressure pulsation decreases, and broadband pulsation occurs in the low-frequency range. Wang et al. [104] took the high-specific-speed centrifugal pump as the research object and analyzed the pressure pulsation characteristics of the pump at the tongue and outlet under different flow rates and different cavitation stages. The main frequency of pressure pulsation is still blade passing frequency with the development of cavitation. In severe cavitation, due to the collapse of the bubbles, the high-frequency component will increase, and the amplitude of pressure pulsation at the tongue and outlet will decrease. According to available research, the amplitude of pressure pulsation in the tongue of the volute decreases when cavitation deteriorates. He et al. [105] concluded that the main frequency of internal pressure pulsation during centrifugal pump cavitation is the blade passing frequency, and the high-frequency component increases from slight cavitation to severe cavitation. However, some studies posit that the characteristics of the axial frequency are the most obvious during cavitation [106]. For ultra-low-specific-speed pumps, it is found that when cavitation does not occur, the main frequency of pressure pulsation in the impeller flow channel is impeller rotation frequencies and its harmonic frequencies, while the main frequency in the volute is blade passing frequencies and its harmonic frequencies. With the development of cavitation, the amplitude of pressure pulsation in the impeller shows a downward trend. On the contrary, the amplitude of pressure pulsation increases in the pump inlet, outlet, and volute [107], which is consistent with the results obtained by Shi et al. [108]. The amplitude of pressure pulsation is more sensitive to the change in cavitation, and the discrete and broadband pulsations in the volute increase with the enhancement of the degree of cavitation.

3.4.2. Feature Extraction and Signal Processing

Pressure pulsation signals are nonlinear and non-stationary, and it is critical to select appropriate algorithms for feature extraction and signal processing. Zhou and Lv [109] studied the pressure pulsation at the outlet of a centrifugal pump. The signals begin to become complex under the condition of cavitation faults, and the average amplitude is improved. For non-linearity and non-stationarity of the signals, the authors aptly and accurately detected early cavitation faults by improving wavelet theory, singular value decomposition, and optimized neural networks. The singular value decomposition method has excellent results for noise reduction and feature extraction of pressure pulsation signals [110]. In addition, Liang et al. [111] extracted features from nonlinear inlet pressure signals based on chaotic theory. The least squares support vector machine model optimized by genetic algorithms is used to recognize cavitation fault diagnosis. However, the collected pressure signal is not filtered, and there will be some interference. Tiwari et al. [112] used pressure signals to identify cavitation in centrifugal pumps based on deep learning algorithms. The cavitation phenomenon was more pronounced at higher velocities and blockages and produced high-pressure pulsations at the radial outlet. But they only studied the time domain, not the frequency and time–frequency domains. Sometimes the industrial environment is more complex, with more interference and conditions that are not allowed. In this case, the pressure signal will be more resistant to disturbances than other signals. The structure is relatively simple and low-cost. Samanipour et al. [113] proposed a simple structure and low-cost cavitation detection method, which relies only on pressure sensors and electrical sensors to obtain the pressure signal of electric pumps. They analyzed the signals in the time domain by self-organizing mapping neural network. Although the accuracy is not as high as in the vibration and acoustic methods, the method is highly resistant to interference. The research on pressure pulsation signals for fault detection is not comprehensive enough, but pressure pulsation is the first-hand information of pump-related faults and is of great significance.

4. Discussion, Limitations, and Comparative Analysis

The effects of four signals to detect cavitation are compared and analyzed from a macro perspective. The pros and cons of the methods are presented in Table 4.

Table 4. Pros and cons of methods.

Based Signal	Pros	Cons
Vibration	1. Mature detection theory 2. Wide range of applications	1. Signal attenuation when propagating through the pump structure 2. Low accuracy for primary cavitation detection
Acoustic emission	1. High tolerance to detection environment and pump structure 2. Have a high accuracy for detecting early cavitation	1. Less noise reduction methods 2. High cost of sensors 3. Less applied to industrial fields, most of the research is performed in the laboratory
Noise	1. High accuracy	1. Interference from background noise
Pressure pulsation	1. High anti-interference	1. The installation of the sensor is complicated 2. The detection accuracy of early cavitation is low

Both acoustic emission and noise methods are acoustic-based detection technologies. They are successful in detecting the occurrence of faults in the field of non-contact measurement. There is an outstanding contribution in terms of improving safety and saving resources. They are widely used in early cavitation detection. The acoustic emission method is suitable for cavitation detection of large pump units with complex structures and harsh working environments. However, research in the field of fault detection is limited by factors such as acoustic sensors and acoustic signal analysis methods. At present, the mechanism of cavitation occurrence still needs to be explored. Research concerning its formation, development, and the source of radiation energy is not perfect. In this case, the development of acoustic emission technology was limited. Moreover, noise reduction methods need to refer to other fields when processing cavitation-induced acoustic emission signals. In most cases, research on the detection of cavitation by acoustic emission signals has been carried out in the laboratory, and the application to industrial fields is relatively less developed. Much exploration work is still required to achieve the combination of theory and practice.

Cavitation fault detection is primarily dependent on vibration. However, there is a possibility that the vibration signal will be attenuated when it propagates through the structure of the pump. At the same time, the spacing between the sensor and the pump, the flow rate setting, and various other factors will create errors during the experiment. Extracting features from the vibration signal is a tedious process. The results obtained have an idealized nature. Also, the detection effect for incipient cavitation is not very effective.

The pressure pulsation method is more resistant to interference and has a higher accuracy in detecting cavitation, but it is less excellent than the vibration and acoustic methods. The installation of the pressure sensors may require a hole in the pipe, which can cause inconvenience in practical applications. It is difficult to detect incipient cavitation.

5. The Development Trend of Signal Methods to Detect Cavitation

Noise signal mixing, non-stationary signals, non-Gaussian signals, etc., will bring certain difficulties to detection. Accurate detection of cavitation faults is a problem that must be solved. With the development of testing instruments and the continuous improvement of technical personnel and fault detection means, the development direction of cavitation fault detection based on signals is as follows:

1. One of the challenges of cavitation fault detection is the complexity of the pump making signal acquisition difficult. Fortunately, the advancement of science and technology has brought diversity to the way of obtaining signals. The combination of advanced sensing devices and advanced signal processing technology is among the powerful means for the timely detection of cavitation faults;
2. The existing detection methods can continue to be optimized. In the literature summary, we can observe that many studies are conducted to improve on the basic approach, such as optimizing several parameters in an algorithm. This aspect is meaningful and valuable. Therefore, in the following research work, it is a development trend to continue improving some cavitation fault detection methods already proposed;
3. Against the background of the rapid development of artificial intelligence, the integration of intelligent algorithms into the identification of cavitation states has become an inevitable trend. The combination of signal-based cavitation fault detection methods with reinforcement learning or deep reinforcement learning may bring a new possibility, which will be more intelligent, more efficient, and more accurate;
4. In the existing papers, many of the methods used by researchers are applied for the first time in the field of pump cavitation detection. Learning from detection methods in other fault fields, including signal processing techniques, computational models, etc., innovatively applied to cavitation fault detection, will attract much attention;
5. There are different ways of cavitation movement in different types of rotating machinery. Cavitation detection methods will be distinctive for different pumps, such as plunger pumps, mixed flow pumps, centrifugal pumps, axial flow pumps, etc. From a general point of view, the current pump cavitation detection system lacks uniformity—most of the methods proposed in the literature are targeted and may only be suitable for specific pumps and specific situations. In subsequent work, signal-based detection methods need to strengthen versatility.

6. Conclusions

This paper provides a detailed review of fault detection methods based on different signals. This review presents theoretical guidance for the technical research of pump cavitation detection and points out the direction for future research. Cavitation fault detection based on different signals has improved accuracy and reliability. The applications of vibration, noise, acoustic emission, and pressure pulsation methods in cavitation detection have been discussed in depth.

(1) Time–frequency analysis is considered to be the most effective in dealing with vibration signals, especially the spectral kurtosis, which can effectively detect shock waves

generated by bubble collapse. Most of the studies have focused on the high frequency range of vibration signals, but cavitation is more sensitive to the low frequency range. Convolutional neural networks have been gradually developed in the field of cavitation detection in recent years. The placement of the sensor is critical to the detection results, and the closer to the region where cavitation occurs, the higher the accuracy.

(2) Although the acoustic emission method can detect the beginning of cavitation well, it has not been widely used due to the limitation of noise reduction method development.

(3) The cavitation noise signal is random and its spectral structure is unique. The liquid-loaded noise signal is promising for detecting cavitation. Psychoacoustic methods, principal component analysis, and radial basis functions have good reflections for dealing with abruptly changing noise signals.

(4) The cavitation-induced pressure pulsation at the worm gear is more valuable to study than that at the impeller.

However, there are still many problems to be solved. A lot of research is still needed before signal methods are widely used. On the one hand, a balance must be found between sensor cost and accuracy. One the other hand, noise reduction methods, feature extraction, signal processing methods, etc., still need to be improved. If these problems can be adequately solved, the future of signal methods is immense. We should pay more attention to developing a complete system for pump cavitation fault detection. Cavitation detection methods based on different signals will have broad application prospects in the field of fault detection.

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