Characterization of cavitation evolution in centrifugal pumps through motor current signal analysis

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Abstract

Cavitation detection is quite significant for safety and stability of centrifugal pump operation. In this research work, motor current signal analysis (MCSA) technique is improved to extract indicators for quantitative characterization of cavitation status. The method of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is preliminarily used for denoising and isolating Intrinsic Mode Functions (IMFs) containing cavitation characteristics from current signals. IMFs revealing pump operation are selected based on the concurrent frequency bands in spectrograms. IMFs are analyzed by Hilbert Transform to select the components that could reveal energy variation, so that the irrelevant components are removed. According to the feature analysis of cavitation, the peak value in marginal spectrum of IMF 6 is extracted to indicate incipient cavitation. And the peak value in marginal spectrum of IMF 7-8 is extracted as the indicator for characterization of cavitation evolution. Results of this research could provide technical assistance for pump cavitation detection.

1 Introduction

Cavitation is a kind of common but unexpected flow situation in centrifugal pumps. And such phenomenon consists of a succession of vapor bubble behavior starting from formation, then subsequently moving to high pressure area, finally condensation and implosion [1]. Usually, inception of cavitation cannot be instantly and accurately detected until its negative influences have induced degradation of pump performance and even erosion of mechanical flow passage components [2]. In order to ensure operation stability and safety of the pump and prolong its service life, extensive research has been conducted to develop pump cavitation detection techniques with high accuracy and reliability.

Generally, pressure pulsation [3], vibration [4], acoustic signals [5] are acquired and analyzed to extract characteristics for detecting cavitation status in pumps. As is shown in plenty of references, those signal-based methods are conducted onsite even without knowing pump information beforehand. Measuring pressure pulsation signals [6–7] is an effective and accurate method with high information integration of cavitation characteristics, but pump casing must be altered since the measurement is invasive. Testing pump vibration signals is non-invasive, but the results might be interfered by structural vibration of the whole pump system. Another non-destructive method is measuring acoustic signals by using microphones placed near the pump. However, the acoustic signal is susceptible to environment background noise which makes denoising difficult for signal analysis. Thus, the signal transmission path from the excitation source to sensors should be simplified to extract distinct frequencies to characterize cavitation status.

MCSA (Motor Current Signal Analysis) technology could bring implications to improve pump cavitation detecting technique. This method is commonly utilized to extract indicators from motor stator current signals of electric motors for fault diagnosis, such as broken bars, eccentric air gap magnetic field, winding short circuit, etc. Recently, MCSA has been extended to be used for fault diagnosis of motor-driven machines such as pumps [8]. MCSA was firstly used by Siegler [9] for erosion diagnosis of

seawater pump impeller. Kenull [10] found the energy density of stator current signals varies in different frequency ranges, which provides information for detection of cavitation and reverse rotation of centrifugal submersible pumps. Afterwards, MCSA is combined with the artificial-intelligence algorithm for pump cavitation diagnosis [11]. To improve the fuzzy rules and membership functions of the recognition system when the structural parameters of detected pump change, Harihara [12] developed the algorithm to detect cavitation by MCSA without prior knowledge of pump design and structural parameters. Luo [13] primarily analyzed both time and frequency domain of current signals under different cavitation status only showing limited few of states without reflecting the whole process of cavitation development.

Previously, only qualitative description of current signal characteristics was clarified for cavitation detection. Sun [14] summarized quantitative relationship between cavitation number and motor current signal characteristics. The indicators are able to depict the transient characteristics of cavitation evolution. But only cavitation under large flow rate can be significantly revealed. Thus, the denoising performance needs to be improved to reveal cavitation under small flow rate and the inception state.

In this research work, MCSA technology is further improved to increase accuracy and sensitivity of incipient cavitation detection. The time-frequency signal analysis method is ameliorated for denoising. Moreover, the influences of pump structural parameters are eliminated and the indicators are normalized. Then the detection adaptability is improved to be applied for cavitation detection of different types of centrifugal pumps under various working conditions.

2 Theory

A. Principle of MCSA technology

MCSA is applicable for cavitation detection since most centrifugal pumps are driven by electric motors. In electric motors, the air-gap magnetic field between stator and rotor is mutually coupled with motor operation conditions [15]. The working principle can be clarified by the following mathematical equations.

(1) Flux equation

In asynchronous motors, the flux of each winding is the sum of its self-induced flux and mutual-induced flux with other windings. And the magnetic flow of each winding is the sum of mutual-induced and leakage-induced magnetic flow. The relative position each three-phase stator (or rotor) winding is fixed. And the relative position between any one phase of the stator and rotor windings keeps changing with the angular displacement θ . The flux equation can be represented by the block matrices [16].

$$\begin{bmatrix} \Psi_s \\ \Psi_r \end{bmatrix} = \begin{bmatrix} L_{ss} & L_{sr} \\ L_{rs} & L_{rr} \end{bmatrix} \begin{bmatrix} i_s \\ i_r \end{bmatrix}$$

$$L_{ss} = \begin{bmatrix} L_{ms} + L_{ls} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & L_{ms} + L_{ls} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ms} + L_{ls} \end{bmatrix}$$

2

$$L_{rr} = \begin{bmatrix} L_{ms} + L_{lr} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & L_{ms} + L_{lr} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ms} + L_{lr} \end{bmatrix}$$

3

$$L_{rr} = \begin{bmatrix} L_{ms} + L_{lr} & -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & L_{ms} + L_{lr} & -\frac{1}{2}L_{ms} \\ -\frac{1}{2}L_{ms} & -\frac{1}{2}L_{ms} & L_{ms} + L_{lr} \end{bmatrix}$$

4

In Eq. (1), $\Psi_s = [\Psi_A \ \Psi_B \ \Psi_C]^T$ is fluxoid of three-phase stator windings. $\Psi_r = [\Psi_a \ \Psi_b \ \Psi_c]^T$ is fluxoid of three-phase rotor windings. $i_s = [i_A \ i_B \ i_C]^T$ is transient three-phase stator current. $i_r = [i_a \ i_b \ i_c]^T$ is transient three-phase rotor current. L_{ss} and L_{rr} represent the self-induction of stator and rotor windings respectively. L_{sr} and L_{rs} are the mutual-induction between stator and rotor windings. And L_{sr} is the transposition of L_{rs} . L_{sr} and L_{rs} change with rotor position θ . The mathematical calculation of L_{ss} , L_{rr} , L_{sr} and L_{rs} are shown as following [16]. In Eq. (2)-(4), L_{ms} is mutual-induction of stators. L_{ls} is leakage-induction of stators. L_{lr} is leakage-induction of rotors.

(2) Voltage equation

Voltage balance of the asynchronous motor can be represented by the Eq. (5) [16].

$$u = Ri + \frac{d\Psi}{dt}$$

5

Through substituting Eq. (1) into Eq. (5), the voltage balance of the motor can be further expressed by Eq. (6) and (7).

$$u = Ri + L \frac{di}{dt} + \frac{dL}{d\theta} \omega i$$

6

$$\theta = \omega t$$

7

In Eq. (6), $L \frac{di}{dt} + \frac{dL}{d\theta} \omega i$ is electromagnetic induction electromotive force. $L \frac{di}{dt}$ is pulse electromotive force resulted from variant current. $\frac{dL}{d\theta} \omega i$ is rotational electromotive force induced by the variant relative position between stator and rotor.

Due to the huge capacity of power grid, the stator voltage of motor is nearly constant. When ω changes with load, stator current also changes to keep the dynamic balance of Eq. (6). Thus, the stator current is directly related with load variation.

(3) Motion equation

Motion control system of the asynchronous motor can be represented by Eq. (8) and (9) [16].

$$T_e = T_L + \frac{J}{p_n} \frac{d\omega}{dt}$$

8

$$\frac{d\theta}{dt} = \omega$$

9

In Eq. (8), T_e is electromagnetic torque. T_L is load torque including friction resistance torque. J is rotary inertia. p_n is motor pole pair number. In the Eq. (9), ω is angular velocity. θ is mechanical angle. Both Eq. (8) and (9) show the dynamic torque balance of asynchronous motor. Rotating shaft fluctuation is induced by load fault causes nonuniform of air-gap magnetic field distribution between stator and rotor. T_L and ω keep changing during operation. T_e is adjusted by stator current to reach the equilibrium of the motion equation.

Based on the mathematical analysis, the working principle of MCSA technology is demonstrated in the upper part of Fig. 1. The fluctuation is transmitted from load side to the motor side via torsional oscillated shaft. The load variation is coupled with electromagnetic torque. The fluctuation of air-gap magnetic field distribution is characterized by stator current signals. Thus, the stator current signal could reflect load operation situation. The implementation of MCSA for pump cavitation detection is shown in the lower half of Fig. 1. Motor current signals are measured and analyzed. Based on the cavitation mechanism, fault characteristic frequencies are ascertained through analysis of time-frequency spectra. Consequently, the indicators are extracted for cavitation characterization.

B. CEEMDAN-based motor current signal analysis method

Traditional signal analysis for fault diagnosis focuses only on time or frequency domain, which is based on the premise that the signal is stationary. But in practical engineering, fault signals are non-stationary.

Traditional techniques may provide false information since transient events cannot be characterized. Empirical mode decomposition (EMD) is an effective time-frequency signal analysis method to deal with non-stationary signals [17]. Based on local characteristics in time scale of the signal, EMD decomposes raw signals into series of Intrinsic Mode Functions (IMFs). IMFs are determined by signal natural oscillatory characteristics, rather than pre-determined kernels. So EMD is a self-adaptive method. However, mode mixing, end effect and susceptibility to noise are nonnegligible defects of EMD [18, 19]. The Ensemble Empirical Mode Decomposition (EEMD) [20] is then proposed. By adding White Gaussian Noise (WGN) to the original signal, the decomposed components are automatically projected onto more new proper scales, which are established by the statistical properties of the white noise. For each trial of EEMD, the raw signal is added with white noise and then decomposed into IMFs. The number of trials is named as ensemble number. Noise contained in IMFs decreases with bigger ensemble number [20].

In this research, noise should be eliminated from current signals to extract cavitation characteristics. In order to completely avert mode mixing of EEMD, the method of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is used for further IMF denoising [21]. For CEEMDAN, the original signal x is added with M numbers of WGN λ to obtain new signals $X^m = x + \epsilon_0 \lambda^m (m=1, \dots, M)$. Then CEEMDAN is conducted for M times with each signal X to extract the first order IMF written as d_1^m . Afterwards, the first order IMF of CEEMDAN is the average of those M IMFs $\tilde{d}_1 = \frac{1}{M} \sum_{m=1}^M d_1^m$. The first order residual component is $r_1 = x - \tilde{d}_1$. The j th IMF is $E_j(x)$. So the $i+1$ th IMF of CEEMDAN is $\tilde{d}_{i+1} = \frac{1}{M} \sum_{m=1}^M E_1(r_i + \epsilon_i E_i(\lambda^m))$, in which the amplitude of WGN is defined as K times of standard deviation of the i th residual component $\epsilon_i = K \text{std}(r_i)$. And $r_i + \epsilon_i E_i(\lambda^m)$ is obtained by adding the i th residual component with the i th IMF [21]. The CEEMDAN is finished when the residual component is monotone function.

Based on the above theoretical analysis of CEEMDAN process, WGN is added with the signal in every trial. But in EEMD the WGN is added with signals in only the first trial. Thus, the adaptability of CEEMDAN is higher than that of EEMD. Thus, the noise contained in IMFs is decreased to avoid mode mixing effectively. CEEMDAN improves the accuracy of denoising to ensure that the cavitation characteristics are effectively extracted from raw signals for analysis.

3 Pump Test Rig

The experiment was carried out on the pump test rig in Fig. 2. As is shown in the closed test rig, there is a steady flow tank. The cavitation tank is used for evacuation to decrease pump inlet pressure. The pump system consists of a pump model IS65-50-160-00, a motor model Y160M-2 B3, a flow regulating valve and pipes. Two static pressure transducers WIKA S-10 are installed at inlet and outlet respectively. Torque sensor SGDN-50 is installed between motor and pump to detect torque and rotating speed. Turbine flowmeter LWGY-65 is installed at the straight pipe. As is shown in Fig. 3, WBI021KB7_1.0 hall sensors are used to detect motor current and voltage signals. In this research, voltage and current signals are acquired to measure the input power of motor. And transient current signals are acquired for further

signal analysis of MCSA. The signal output terminals of all the above transducers are connected with a data acquisition board NI USB-6343. And the sampling frequency is 10kHz. Being filtered and transmitted by the NI data acquisition board, signals are stored in the computer which could be displayed and analyzed.

1. Steady flow tank; 2. Motor; 3. Torque transducer; 4. Pressure transducer at outlet; 5. Centrifugal pump; 6. Pressure transducer at inlet; 7. Cavitation tank; 8. Flow rate regulating valve; 9. Flowmeter; 10. Vacuum pump

4 Results And Discussion

A. CEEMDAN

An IMF (or more) obtained by CEEMDAN needs to be selected to proceed with the cavitation characterization. The spectrograms of current signals are drawn. Those IMFs appearing as concurrent resonance frequencies in spectrogram contain much energy of modulation signature, which are selected to reflect cavitation [22]. Such procedure of signal analysis is shown as in Fig. 4. For example, the current signal acquired under pump normal operation is decomposed by CEEMDAN into IMFs shown in Fig. 5 (a). Fig. 5 (b) shows the spectrogram of current signal. The time scale of x-coordinate corresponds to the sampling time. And the frequency of y-coordinate corresponds to the frequency of Fourier transform of the original signal. The main frequency of each IMF is pointed out by the red arrow. Highlighted IMFs 1-5 appear as concurrent resonance frequencies. The sum of IMFs 1-5 is analyzed for indicator extraction.

B. Noise elimination

In the original signal, the energy of main components keeps basically stable, but the energy of stochastic components is unsteady. As faults getting severer, the modulated fault frequency is more significant. In of Fig. 4, the noise of IMFs should be removed for further indicator extraction. Then the fault frequency is isolated for characterization.

Signal power can be used to reveal the energy preserved in some certain frequency bands, which also provides the basis of eliminating noise. Signal power of each IMF is calculated by $P_i = E_i \bullet \bar{T}_i$ [23]. P_i is signal power of the i th IMF component. $E_i = \frac{1}{N} \sum_{j=1}^N [A_i(j)]^2$ is energy density and $\bar{T}_i = \frac{2N}{O_i}$ is average period. N is the length of IMF. $A_i(j)$ is transient amplitude of the i th IMF. O_i is the number of extreme points of the i th IMF.

According to the research of Wu [23], the signal power of noise IMF components is constant. The coefficient $C_i (i \geq 2)$ is then calculated by $C_i = \left| \frac{P_i - \frac{1}{i-1} \sum_{i=1}^{i-1} P_i}{\frac{1}{i-1} \sum_{i=1}^{i-1} P_i} \right|$ to find out the IMFs with constant signal power. C_i evaluates whether the i th IMF is multiplied compared with the average of previous $i-1$ th IMFs. If

$C_i \geq 1$, then the i th IMF is multiplied and the signal power of the previous $i-1$ th IMFs is constant. Thus, the previous $i-1$ th IMFs are noise components which can be removed. Meanwhile, the residual components in all IMFs are also removed.

C. Cavitation characterization

After the step and in Fig. 4, the sum of all the remaining IMFs is the new reconstructed signal. The modulated characteristic frequencies are further extracted for cavitation detection. As is shown in Fig. 6, spectrograms of motor current signals under cavitation stages are drawn for characterizing the resonance frequency bands. Energy concentration is depicted on several frequency bands. With cavitation getting more significant, the frequency band width of energy distribution is getting broader. And most of the energy is concentrated in the range of 0-500 Hz. The resonance frequency bands are clear for selecting concurrent IMF components.

Based on the spectrograms under various cavitation conditions, IMF 3-9 components appearing as the concurrent frequencies are selected. As is shown in Fig. 7, the normalized signal power values of IMF 3-9 are calculated which reveals the energy variation in the current signal during cavitation development. The whole process is divided into 4 stages by the 3 black dashed lines indicating head drop 1%, 3% and 10% respectively. The black solid line demonstrates cavitation performance. And the red solid line shows the signal power variation of IMF 3-9 during cavitation development. When pump is running under normal operation without cavitation, the signal power value is low at the beginning. As the cavitation coefficient σ decreases during the first stage ($0 < \text{Head drop} < 1\%$), the signal power sharply rises and falls back to the value higher than the initial one. The sudden surge of the energy in IMF 3-9 shows that the indicator in Fig. 7 is sensitive to incipient cavitation. During the second ($1\% < \text{Head drop} < 3\%$) and third stages ($3\% < \text{Head drop} < 10\%$) of cavitation, the signal power keeps rising with slight fluctuation. And the signal power steeply increases within the fourth stage ($\text{Head drop} > 10\%$). It can be seen that the signal power of IMF 3-9 could response to cavitation development. But the indicator cannot be directly used for cavitation detection, because violent fluctuation under cavitation inception and slight rolling under the second and third stages will result in false alarming.

In order to improve the accuracy of cavitation detection, cavitation characteristics are further extracted from IMF 3-9 to remove the interference of irrelevant components. The selected IMFs are processed by Hilbert Transform. Then the integration in time domain of the Hilbert spectrum $H(\omega, t)$ is conducted to obtain the marginal spectrum $H(\omega) = \int_{-\infty}^{\infty} H(\omega, t) dt$ [7]. The amplitude of the marginal spectrum could reveal the energy accumulation at certain frequencies of IMFs.

Elaborated research is conducted on the marginal spectrum of current signals during cavitation development. As is shown in Fig. 8, peak values in marginal spectrum of IMF 6 are extracted as the indicator for cavitation characterization. The mean frequency of IMF 6 is 200Hz. The red solid line shows variation of the indicator. Within the first and second stages, the indicator experiences noticeable increase in the inception of cavitation and increases monotonously as cavitation gets more significant. Thus, this

indicator could be used to reveal incipient cavitation. But when head drop is higher than 3%, the red curve starts to fluctuate. This shows that the stability of severe cavitation characterization of the indicator is limited.

Peak values in marginal spectrum of IMF 7-8 are extracted as another indicator to reveal the cavitation development. The mean frequency values of IMF 7 and IMF 8 are 100Hz and 50Hz respectively. As is shown in Fig. 8, the blue solid line represents this indicator. The curve experiences a slight rise with fluctuation when head drop is closed to 1%. This shows that this indicator is not sensitive to the incipient cavitation. When head drop is higher than 1% within the next three stages of cavitation, the value steeply increases with the cavitation development. The slight fluctuation could be ignored so that the inclination is regarded as monotonous. Thus, this indicator could be used for characterization of cavitation developing stages.

5 Conclusions

This research tries to extract indicators from motor current signals based on the energy variation induced by cavitation. CEEMDAN is applied for isolating the IMFs containing cavitation characteristics from current signals to eliminate noise components. Spectrograms of the current signals are drawn for characterizing concurrent frequency bands to select IMFs embedded with excessive energy induced by cavitation. Through Hilbert analysis, the indicators are extracted for revealing inception of cavitation and the consequent development stages. Some conclusions can be drawn as following.

- (1) Results show that after CEEMDAN and noise elimination, the signal power of selected IMFs could reveal various cavitation status. The energy variation in motor current signals is induced by unsteady operation during cavitation development. Thus, the feasibility of MCSA technology is validated for cavitation detection.
- (2) Elaborated research was conducted for the relationship between cavitation status and IMF selection. Then the IMF 6 is selected for revealing incipient cavitation. And IMF 7-8 are selected for indicating cavitation developing stages.
- (3) Energy amplitude of main frequency corresponding to the peak value in marginal spectrum is used for revealing energy distribution in signals. The peak value in marginal spectrum of IMF 6 is extracted as the indicator of incipient cavitation. And the peak value in marginal spectrum of IMF 7-8 is extracted as the indicator for characterization of cavitation development.

Declarations

Availability of data and materials

Not applicable.

Competing Interests

The authors declare that they have no competing interests.

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Authors' Contributions

Hui Sun carried out the experiments. Qiaorui Si tested and analyzed signals. Ning Chen was a major contributor in writing the manuscript. Shouqi Yuan revised the manuscript. All authors read and approved the final manuscript.

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Figures

Figure 1

Working principle and implementation of MCSA technology.

Figure 2

Scheme of pump test rig

Figure 3

Installation of Hall sensors

Figure 4

Proposed methodology for cavitation detection

Figure 5

Analysis of current signal acquired under pump designed working condition without cavitation. (a) Fourier spectra of IMFs after the original current signal decomposed by CEEMDAN; (b) The spectrogram of the original current signal.

Figure 6

Spectrograms of current signals under different cavitation status. (a) Head drop 0%. (b) Head drop 1%. (c) Head drop 3%. (d) Head drop 10%.

Figure 7

Normalized signal power variation of IMF 3-9 during cavitation development.

Figure 8

Normalized peak values of marginal spectrum of IMF 6 and IMF 7-8 during cavitation development.