Fault Diagnosis for the Hydraulic System by Using Autoregressive Trispectrum and its Slices

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Abstract: This paper addresses the development of a condition monitoring procedure for mechanical parts which involves time series higher-order spectra analysis. Several approaches based on autoregressive (AR) bispectrum, trispectrum and its slices are investigated as data mining techniques in the fault diagnosis of hydraulic control valves. The characteristics of vibration signals obtained from the control valves have been extracted by means of analyzing the 2-dimensional and diagonal slices of bispectrum and trispectrum, with the main goal of detecting a possible working condition including the normal and fault conditions. The experimental analysis shows that there are distinct bump values in the center of the two-dimensional slices of trispectrum space in the fault conditions, on the contrast, the bump values disappear in normal condition. Comparisons have been done between trispectrum and bispectrum. Results show the slices of the trispectrum reveal the corresponding bispectrum and its slices for diagnosing the faults of the hydraulic control valves. The experimental and theoretical results have indicated that trispectrum is a more suitable tool for diagnosing the faults of the hydraulic control valves. Copyright © 2014 IFSA Publishing, S. L.

Keywords: Time series, Trispectrum, Slices, Fault diagnosis, Hydraulic system.

1. Introduction

With the rapid development of hydraulic technology, more and more hydraulic parts are used in the engineering. The hydraulic control valves are the most essential components in the utilization of the hydraulic technology due to the fact that the majority of problems arise from faulty valves. In the paper the pressure relief valve is preferred as the experimental target, because it is used in almost every hydraulic system. The function of the relief valve is to limit the maximum pressure of a system. Under ideal condition, the relief valve should provide alternative flow path to tank for the system fluid while keeping the system pressure constant. Thus, it is important and necessary to monitor the condition of relief valve in order to minimize unnecessary costs and delays caused by the need to carry out unscheduled repairs.

In the working station of the valve, the vibration signals will be produced by the valve body. Vibration-based monitoring techniques have been used here for detection and diagnosis of the pressure relief valve. In the development of fault diagnosis, one important subject is to utilize the fruits of the modern signal processing to explore a new way for fault diagnosis. The difficulty of fault diagnosis dwells on extracting the feature information because the relation between the faults and the signs is sophisticated, and the useful signals of interest may be buried in the stronger background noises. So a key
step is to separate the useful information corresponding with the states of the operating machines from the vast amount of test signals.

In recent years, higher-order spectra, defined in terms of higher-order cumulants of a signal, have proven to be a powerful tool for dealing with nonlinear system and signals. There are three general motivations behind the use of higher-order spectra in signal processing [1]: 1) To suppress Gaussian noise processes of unknown spectral characteristics; the bispectrum and trispectrum also suppress noise with symmetrical probability distribution, 2) to reconstruct the magnitude and phase response of systems, and 3) to detect and characterize nonlinearities in time series. However, power spectrum (whose estimators are second-order statistics) is blind to the existence of quadratic phase coupling (QPC) and is very sensitive to noise. Information of spectral bumps at certain values among the frequency components may be found in the higher-order spectral diagrams. It is acknowledged that different faults generated by mechanical parts can make different frequency components in vibration signals, so bispectrum analysis can be successfully used to identify the faults [2, 3]. Professor De la Rosa J. J. G has successfully used bispectrum and its slices for the detection and characterization of termites’ emission [4, 5] and acoustic emission events in ring-type samples from steel pipes for the oil industry [6]. Recently, the spectral kurtosis has been successfully used for the diagnosis of rotating machines [7-9]. At the same time, some experts and researchers are studying on the trispectrum: Dalle Molle [10, 11] and Kravtchenko-Berejnoi et al. [12] discuss statistical tests based on the trispectrum; Chandran et al. [13, 14] examine the asymptotical statistics of trispectral estimates; Lutes and Chen [15] examine trispectra from specific nonlinear oscillators; Walden and Williams [16] use trispectral-based methods for deconvolution in a geophysical environment; and Collis [17] uses the trispectrum to analyze nonlinear mechanical systems. A. C. McCormick [18] et al. have studied the fine characteristics embodied in the diagnosis for machine condition; Cooray [19] et al. have studied how to utilize trispectrum characteristics to extract CMB-Cosmic microwave background of lensing information; Xiaoqun Shi [20] has studied the application of trispectrum on diesel engine fault diagnosis and classification. Yijian Huang [21] et al have successfully used the trispectrum and its reconstruction spectrum on the Magnetorheological damping system. The conclusions of these works were funded in the advantages of cumulants; in particular, in the capability of enhancing the signal-to-noise ratio of a signal buried in symmetrically distributed noise process.

The aim of this paper is to show the characteristics of trispectrum based on the time series AR model, which is estimated under three frequencies, enhancing the ability of information recognition. We use trispectrum and its slices to characterize the hydraulic control valves, and present

2. AR Trispectrum Model Analysis

2.1. Higher-order Cumulants and Higher-order Spectra

The higher-order statistics are usually interpreted as higher-order moments, higher-order cumulants and their spectra (higher-order moments spectra and higher-order cumulants spectra). What we use most frequently in the higher-order statistics are higher-order cumulants and higher-order spectra. Here, the relation between them will be provided.

2.1.1. High-order Cumulants

A model is depicted in Fig. 1, in this model, a(t) is stationary white noise with finite variance (a(t) may be Gaussian or non-Gaussian); h(τ) is the impulse response resulting from a single impact; u(t) is Gaussian, white or colored; and a(t) and u(t) are statistically independent.

![Fig. 1. The test model of the vibration signal of pressure relief valve.](image)

The problem we are faced with is that of detecting a fault signal x(t) in measurement y(t) in presence of some strong additive Gaussian colored noise u(t). According to the control theory, the output sequence \{y(t)\} is described by

\[ x(t) = \sum_{\tau=-\infty}^{\infty} h(\tau)^* a(t-\tau) \]

\[ y(t) = x(t) + u(t) = \sum_{\tau=-\infty}^{\infty} h(\tau)^* a(t-\tau) + u(t), \]

where \( \tau \) is the delay. Considering y(t) as a linear process, combining with Eq.(2), the kth-order cumulant function of y(t) can be written as
where delays based on the nature of the higher-order cumulants \([22]\) and Eqs. (1), (3), we get
\[
c_{i,k}(\tau_1, \tau_2, \ldots, \tau_{k-1}) = c_{i,k}(\tau_1, \tau_2, \ldots, \tau_{k-1}) \cdot
\]
(3)

If the input signal \(a(t)\) is non-Gaussian, white, i.i.d., with zero-mean, the higher-order cumulants of which can be expressed as
\[
\gamma_{i,j,k} = \text{cum}[a(\tau_i), a(\tau_j), \ldots, a(\tau_{k-1})]
\]
(5)

By putting \(\tau_1 = \tau_2 = \cdots = \tau_{k-1} = 0\) in Eq.(5), we obtain
\[
\gamma_{1,2} = c_{1,2}(0), \quad \gamma_{1,3} = c_{1,3}(0,0), \quad \gamma_{1,4} = c_{1,4}(0,0,0)
\]
(6)

Eq. (6) is the measurement of the variance, skewness and kurtosis of the distribution in terms of cumulants at zero lags. Then we define \(S^2 = \gamma_{1,2}^2, K = \gamma_{1,3}^2\) as normalized skewness, kurtosis \([17]\), respectively. If output signal \(y(t)\) is symmetrically distributed, its skewness necessarily equals zero (but not vice versa); if \(y(t)\) is Gaussian distributed, its kurtosis is zero (but not vice versa).

According to the nature of the higher-order cumulants \([1, 22]\), combined with Eq. (5), Eq. (7) can be simplified as:
\[
c_{i,k}(\tau_1, \tau_2, \ldots, \tau_{k-1}) = \gamma_{i,k} \sum_{i=1}^{\infty} h(i) (i + \tau_1) \cdots h(i + \tau_{k-1})
\]  
\[
= \sum_{i=0}^{\infty} \sum_{t=0}^{\infty} h(i) h(i + \tau) \cdots h(i + \tau_{k-1}) \cdot \text{cum}[a(-i), a(-i), \ldots, a(-i)]
\]
(7)

2.1.2. Higher-order Spectra

Then we'll assume that the cumulant sequences satisfy the boundary condition as follows
\[
\sum_{t=-\infty}^{\infty} \sum_{t_{k-1}=-\infty}^{\infty} \cdots \sum_{t_1=-\infty}^{\infty} C_{i,k}(\tau_1, \tau_2, \ldots, \tau_{k-1}) < \infty
\]
(8)

Under this assumption, the higher-order spectra are usually defined in terms of the \(k\)-th-order cumulants as their \((k-1)\)-dimensional Fourier transforms. Then the higher-order spectra can be obtained from Eq. (8):
\[
S_{\omega,k}(\omega_1, \omega_2, \ldots, \omega_{k-1}) = \sum_{\tau_{k-1}=-\infty}^{\infty} \cdots \sum_{\tau_1=-\infty}^{\infty} c_{i,k}(\tau_1, \tau_2, \ldots, \tau_{k-1})
\]
\[
= \gamma_{i,k} H(\omega_1) H(\omega_2) \cdots H(\omega_{k-1}) F[\omega_1 + \omega_2 + \cdots + \omega_{k-1}]
\]
(9)

where denotes frequency, \(H(\omega)\) denotes the system transfer function \(H(\omega)\), \(S_{\omega,k}(\omega_1, \omega_2, \ldots, \omega_{k-1})\) is defined as the conjugate function of, and are defined as higher-order spectra, also named higher-order cumulant spectra, where \(k=2, 3, \ldots\). The special spectra derived from Eq. (9) are power spectrum \(P(\omega)\) \((k=2)\), bispectrum \(B(\omega_1, \omega_2)\) \((k=3)\) and trispectrum \(T(\omega_1, \omega_2, \omega_3)\) \((k=4)\), respectively. Only the power spectrum is real, the others are complex magnitudes. In this paper, only bispectrum and trispectrum are mainly explained.

2.2. AR Bispectrum and Trispectrum

We assume in the following that system output random vibration signals are generated by non-Gaussian zero-mean white noises \(a(t)\) which contain abundant useful dynamic information, so the AR model is described by:
\[
y(t) + \sum_{i=1}^{p} \psi_i y(t-i) = a(t), (t = 1, 2, \ldots, N),
\]
(10)

where \(\psi_i (i = 1, 2, \ldots, p)\) denotes AR coefficient, \(p\) is the order of AR model in Eq.(10). For \(h(t)\) is casual and stable, considering the model is a non-minimum phase system, the bispectrum function based on AR model, combined with Eq. (9), may be obtained
\[
B_{\omega_i, \omega_2}(\omega_1, \omega_2) = \gamma_{i,k} H(\omega_1) H(\omega_2) F[\omega_1 + \omega_2 + \omega_3],
\]
(11)

and AR trispectrum expression formula can be defined as
\[
T_{\omega_i, \omega_2, \omega_3}(\omega_1, \omega_2, \omega_3) = \gamma_{i,k} H(\omega_1) H(\omega_2) H(\omega_3) F[\omega_1 + \omega_2 + \omega_3]
\]
(12)

In Eqs. (11) and (12) \(|\omega| \leq \pi/2, |\omega_2| \leq \pi/2, |\omega_3| \leq \pi; H(\omega)\) is the frequency transfer function of the system described in Eq.(8), which may be described as
\[
H(\omega) = \frac{1}{1 + \sum_{i=1}^{p} \psi_i e^{-j\omega i}}.
\]
(13)
We use the parametric method to estimate model coefficients $\psi_i$ to represent the coefficient of AR power spectrum alpha, AR bispectrum beta and AR trispectrum gamma (The estimation of phi described in Section 2.5). By putting the coefficients in Eqs. (11) and (12), the magnitude of AR bispectrum is written in the form

$$B^R(\omega_1, \omega_2) = \left| \sum_{j=1}^{p} \beta_j e^{-j\omega_1+\omega_2} \right|$$

and the magnitude of AR trispectrum is

$$T^R(\omega_1, \omega_2, \omega_3) = \left| \sum_{j=1}^{p} \gamma_j e^{-j\omega_1+\omega_2+\omega_3} \right|$$

And the corresponding phase angles are, respectively,

$$\angle B^R(\omega_1, \omega_2) = \arctan\left[ \frac{B^R_{\omega_1}}{B^R_{\omega_2}} \right]$$

$$\angle T^R(\omega_1, \omega_2, \omega_3) = \arctan\left[ \frac{T^R_{\omega_1,\omega_2}}{T^R_{\omega_1,\omega_2}} \right],$$

where $B^R_{\omega_1}$, $T^R_{\omega_1}$ and $T^R_{\omega_1,\omega_2}$ denote the imaginary and the real part of $B^R(\omega_1, \omega_2)$, $T^R(\omega_1, \omega_2, \omega_3)$, respectively.

2.3. The Slice Spectra

Higher-order spectra are multidimensional functions which comprise of a lot of useful information. As a consequence, their computation may be complicated and impractical in some cases [23]. In order to extract clear and visualized useful information, the slice spectra including two-dimensional and diagonal slices of higher-order spectra are employed in non-Gaussian stationary processes.

2.3.1. 2-dimensional (D) Slices of the Trispectrum

When we fix one frequency $\omega$ of AR trispectrum $T^R(\omega_1, \omega_2, \omega_3)$, taking $\omega_3=C_1(const)$ for example, the expression formulation of AR trispectrum can be defined by

$$T^R(\omega_1, \omega_2, C_1) = \gamma_1 H(\omega_1) H(\omega_2) H(C_1) H(2\omega + C_1)$$

(17)

It is more usual in higher-order spectra literature to use Eq. (17) as the definition of 2-dimensional slice of AR trispectrum, also named the reconstruction bispectrum. Hence, the normalized magnitude is

$$|r^R(\omega_1, \omega_2, C_1)| = \frac{|r|}{\sum_{j=1}^{p} \beta_j e^{-j(\omega_1+\omega_2)+C_1}}$$

(18)

Based on the aforementioned observations, we now know that 2-D slices of trispectrum are obtained from the sphere of the trispectrum, so they have 3-D pictures.

2.3.2. The Diagonal Slices of the Trispectrum

It is remarkable that we use the higher-order spectra technique to process nonlinear, non-Gaussian signals. It can suppress the unknown Gaussian noise effectively, and retain the signal phase information. Comparatively speaking, the diagonal slice of trispectrum creates a more direct and visual way for the reflection of the signal energy and the phase information.

1) For $\omega=\omega_1=\omega_2$, according to Eq. (11), the definition of diagonal slice of bispectrum is given by

$$B^R(\omega_1, \omega_1) = \gamma_1 H(\omega_1) H(\omega_1)$$

(19)

Hence, the normalized magnitude of diagonal slice of bispectrum is

$$|r^R(\omega_1)| = \frac{|r|}{\sum_{j=1}^{p} \beta_j e^{-j(\omega_1+\omega_1)}}$$

(20)

2) For $\omega=\omega_1=\omega_2$, $\omega_3=C_1$, according to Eq. (12), the definition of diagonal slice of trispectrum is given by

$$T^R(\omega_1, \omega_1, C_1) = \gamma_1 H^2(\omega_1) H(C_1) H(2\omega_1 + C_1)$$

(21)

Hence, the normalized magnitude of diagonal slice of trispectrum is

$$|r^R(\omega_1, \omega_1, C_1)| = \frac{|r|}{\sum_{j=1}^{p} \beta_j e^{-j(\omega_1+\omega_1)+C_1}}$$

(22)

2.4. The Representation of Trispectrum

A major problem when calculating the trispectrum is that of deciding how to display it. Bispectrum can easily be plotted using three-dimensional space because its modulus function only has two frequency variables. But it is different with
trispectrum, whose modulus function has three frequency variables and so requires four-dimensional space to display it. Previous work on the trispectrum has tended to display slices through the $(\omega_1, \omega_2, \omega_3)$ space. Here it is attempted to display the magnitude of the entire trispectrum to give an overall picture of the trispectral information.

To achieve this, a moveable sphere is drawn in the trispectral space. The color values of the moveable sphere surface represent the magnitude at that point. The size and shade of the sphere also has the ability. Fig. 2 depicts the magnitude of a trispectrum plotted in the above manner.

![The trispectrum plotted in trispectral space.](image)

**Fig. 2.** The trispectrum plotted in trispectral space.

### 2.5. Estimating the AR Model and the Order Determination

The procedure for the higher-order spectra analysis is based on the AR models. Estimating the parameter $\psi_i$ of the model is a key part of the procedure. In practice, in order to deviate from the Gaussianness $u(t)$, the parameter identification method based on higher-order cumulants could be used for this purpose. The following procedure may be adopted

From Eq. (10), the cumulant of the AR model is given by

$$
\sum_{i=0}^{p} \psi_i \text{cum} \{y(t-\tau_i)\ldots y(t-\tau_{i-1})\},
$$

where if the delays $\tau_1, \tau_2, \ldots, \tau_{i-1}$ had at least one which is no less than zero, we can get the nonstationary higher-order Yule-Walker equation based on the higher-order cumulants [24, 25]

$$
\sum_{i=0}^{p} \psi_i c_{i,i} (i-\tau_i,\ldots,i-\tau_{i-1}) = 0, \ \forall \tau > 0
$$

Assuming $p$ is known, from Eq. (24) the following equation may be obtained:

$$
\begin{bmatrix}
\psi_0 & \cdots & \psi_p \\
\vdots & \ddots & \vdots \\
\psi_{p-1} & \cdots & \psi_{2p-2} \\
\end{bmatrix}
\begin{bmatrix}
c_{1,1} (1-1,\ldots,1-1) & \cdots & c_{1,1} (1-p,\ldots,1-p) \\
\vdots & \ddots & \vdots \\
c_{p,1} (p-1,\ldots,p-1) & \cdots & c_{p,1} (p-p,\ldots,p-p) \\
\end{bmatrix}
= -\begin{bmatrix}
c_{1,1} (-1,\ldots,-1) & \cdots & c_{1,1} (-p,\ldots,-p) \\
\vdots & \ddots & \vdots \\
c_{p,1} (-p,\ldots,-p) & \cdots & c_{p,1} (-p,p-p) \\
\end{bmatrix}
$$

Thus, Eq. (25) may be formed in vector:

$$
\psi_i \cdot C = c,
$$

where $C$ is a $(p \times p)$ matrix, which may be a nonsingular matrix by adjusting the value of $\tau$. Thus, the unique solution for the AR model is given by

$$
\psi_i = c \cdot C^{-1}
$$

There are various criteria in the literature concerning the order selection of AR models. However, most of these criteria are based on autocorrelations or Gaussianness assumptions for the residual errors and thus cannot be used here [26, 27]. Model order selection criteria employing higher-order cumulants based on the singular value decomposition method for the determination of matrix rank will be used in this paper, to estimate the orders of the AR $(p)$ model. The details of the procedures can be found in [27, 28].

### 3. The Testing System

#### 3.1. The Testing Target

The hydraulic control valves are used in almost every hydraulic system, taking the relief valve for example, just as Fig. 3 shows: The pilot relief valve is made up of pilot valve and host valve, where 1, 2, 3 denote valve core, pilot valve and the regulating spring, respectively.

![The sketch of the pressure relief valve: 1-valve core, 2-pilot valve, 3-the regulating spring.](image)

**Fig. 3.** The sketch of the pressure relief valve: 1-valve core, 2-pilot valve, 3-the regulating spring.

The function of the relief valve is to limit the maximum pressure of a hydraulic system. Under ideal condition, the relief valve should provide...
alternative flow path to tank for the system fluid while keeping the system pressure constant. Thus, it is important and necessary to monitor the condition of the relief valve in order to minimize unnecessary costs and delays caused by the need to carry out unscheduled repairs.

3.2. Experiment Principle and the Testing Devices

In the experiments the relief is in the normal condition except for five artificial fault conditions:

1) The pressure relief valve with the regulating spring in the state of tensile strain;
2) The pressure relief valve with hard scrip enwinding the regulating spring;
3) The pressure relief valve in which the valve core was removed;
4) The pressure relief valve in which the valve core was substituted by the regulating spring;
5) The pressure relief valve with the combination of fault conditions 2 and 4.

In the course of testing, the oil pressure varies from 1 MPa to 6 MPa.

In the experiments, the eddy current displacement sensor combined with the high-speed data acquisition card PCI-MIO-16E-1 is used for the data acquisition. Signals gathered are sent to dynamic signal analyzer NI-4552 for processing. The whole data acquisition system is under the management of programs developed by the software platform LabVIEW. The A/D converter has 12 bits. It is written by G language given by software LabVIEW and executed with data sampling frequency of 1000 Hz and reading frequency of 500 Hz according to the Nyquist sampling theorem.

4. Experimental Results and Analysis

4.1. The Pretreatment of the Experiment Data

The experimental raw data often embody various interferences and the noises. In order to denoise, we carry on the mean law to preprocess the sampled data.

Then the estimated signals from the mean law will be imported into the analysis program which is compiled by C language and operated on the software MATLAB 7.1.

The principle of the analysis program is based on the aforementioned analysis, especially according to the Eqs. (12), (13), (14), (15), (18), (20), (22), (25). The functions of the program are to calculate the value of skewness and kurtosis, carry on the analysis of trispectrum, bispectrum and their slices, and draw the figures correspondingly.

4.2. The Fault Identification of Relief Valve using 2-D Slices of Trispectrum

The white noise for the slices spectra analysis described in Fig. 5 (a), (b), (c), (d), (e), (f), and the envelopes of the signals are also provided. From the drawings, we can get that there are great difference. When \( C = 0 \) in the Eq. (17), the normalized 2-D slices of trispectrum in the six working conditions of the relief valve can be obtained. In the normal state, the 2-D slice is shown in Fig. 6(a) which is estimated from the treated signal in Fig. 5(a) correspondingly. When \( \omega_1 = \omega_2 = 125 \text{ Hz} \), the bump of the normal condition is almost equal to zero, which illuminates that the components of the valve are harmonious and
the generated vibration signals are stationary and Gaussian; when the regular spring is in tensile deformation, the spring force is increased, and the hydraulic oil is harder to flow back to the tank compared with that in normal state, which generates the unsteady vibration of the valve body and the hydraulic system. 2-D slice is shown in Fig. 6 (b), there is a big bump in the center. So is similar for the fault condition 2, 2-D slice is shown in Fig.6 (c). When we remove the valve core, that is to say, the pressure valve does not work for the system, the hydraulic oil pass through the valve quickly, producing a series of repetitive short and transient forces. The present of the 2-D slice depicted in Fig. 6(d), and the fault conditions 4, 5 are similar. Seen from Fig. 6(b), Fig. 6 (c), Fig. 6 (d), Fig. 6 (e), Fig. 6 (f), the magnitudes and shapes of bumps are different in different conditions, which means with the variations of the inner components of the valve the vibration is changed. The bumps characterize the nonlinearity of the system, the different magnitudes and shapes represent the degree of nonlinearity. From the perspective of energy, the bumps in the fault conditions also reflect the degree of QPC, the more energy concentration, the bigger coupling strength, and which means the higher degree of nonlinearity is in this state. Similarly, fault condition 1 presents the highest degree of nonlinearity, fault condition 4 is minimal, which suggests that the regulating spring in the relief valve has greater effect on the vibration signals than the valve core. So we can tell the working conditions from the bump values and shapes.

Fig. 7 is the bispectrum graph of the relief valve in the same cases as provided in Fig.6, note that the bumps at $\omega_1=\omega_2=125$ Hz present weaker and coarser. Comparatively speaking, 2-D slices of trispectum are more sensitive to the system’s characteristic information.
Fig. 6. The slices of trispectrum in different states.

Fig. 7 (a). The bispectrum in normal condition.  
Fig. 7 (b). The bispectrum in fault condition 1.
4.3. The Fault Identification of Relief Valve Using Diagonal Slices of Trispectrum

The sampled signals are estimated by the diagonal slices of bispectrum $B_{\text{AR}}(\omega_1, \omega_2)$ and trispectrum $T_{\text{AR}}(\omega_1, \omega_2, 0)$, in Fig. 8 (a), (b), (c) are the diagonal slices of bispectrum. Fig. 8 (d), (e), (f) are the diagonal slices of AR trispectrum. They describe the relation between magnitude and frequency. As shown in Fig. 8, in the fault conditions...
vibration signals present obvious QPC when \( \omega_1=\omega_2=125 \) Hz. The slices of \( B^{AR}(\omega_1,\omega_2) \) present the rough relation between the magnitude and the frequency, which is inconvenient to extract the real signals characteristic; The slices of \( T^{AR}(\omega_1,\omega_2,0) \) not only reflect more information of QPC, but also obtain more delicate, comprehensive and accurate magnitude changing information, which can further improve the accuracy of the fault diagnosis.

According to the analysis above, we have known that: the magnitude of 2-D slice of \( T^{AR}(\omega_1,\omega_2,0) \) is equal to zero in normal condition, however, not equal to zero in the fault conditions. The changes of the valve body’s internal structure lead to the unsteady vibration, thus the stability of valve body becomes worse, resulting in the failure of adjusting the working pressures normally.

5. Conclusion

The significance of this contribution lies on the fact of enhancing the characteristic information of the sampled signals in the frequency domain. On the one hand, in order to abstract characteristics of signals more effectively in the mechanical equipment fault diagnosis, it is supposed that the signals are linear and Gaussian, however, the signal should be analyzed in terms of reality. In this way, more information containing more characteristics can be obtained. On the other hand, trispectrum and its slices are quite natural when we try to analyze and characterize nonlinearity of a system operating under a random input, and offer a more effective tool for analyzing nonlinear and non-Gaussian signals. They can not only detect and characterize the nonlinear properties of mechanisms which generate the Gaussian and non-Gaussian vibration signal closely related to mechanical breakdown, but also improve the accuracy of mechanical fault diagnosis greatly. QPC of the trispectrum and its slices is very sensitive to the change of the mechanical equipment’s working conditions. So trispectrum and its slices are suitable for dealing with the mechanical vibration signals, and it is also a powerful tool for fault diagnosis.

Actually, we are working to propose trispectrum as a complementary tool due to its hard presentation and lack of definite physical meaning. In order to confirm the presence of the higher-order components, the slices of trispectrum can realize it intuitively.

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