The Slow-Changing Alarm system of condition monitoring for rotating machinery

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Abstract: - This paper mainly deals with the issue of early fault diagnosis for rotating machinery. An alarm strategy called the slow-changing alarm (SCA) is proposed to predict early fault of equipment timely and effectively. Meanwhile, the SCA system is the integration of adaptive lifting de-noising scheme, adaptive learning algorithm and decision-making strategy of alarm monitoring and diagnosis for the early fault of rotating machinery. In the paper, both the theories and realization of SCA system are thoroughly researched. Firstly, an adaptive lifting de-noising scheme is proposed to eliminate noise, and then the features of early fault are extracted from de-noised signal. Secondly, the key problem to implement on the SCA system is successfully resolved through adaptive learning algorithm and the decision-making strategy of SCA. To be specific, the alarm threshold of SCA system is obtained based on a novel adaptive learning algorithm, and the alarm based on features of vibration signals is activated according to decision-making strategy of SCA, while the relevant alarm log and data of SCA are instantly saved into database to analyze the causes of faults effectively, acquiring the early fault result synchronously. The proposed system has been applied in some petrochemical projects. In an engineering case, this system can preferably capture the early fault signal of rotating machinery, and considerably enhance the capability of predicting and diagnosing early fault.

Key-Words: - rotating machinery; condition monitoring; early fault; adaptive lifting de-noising scheme; adaptive learning; decision-making strategy; slow-changing alarm

1 Introduction

Rotating machinery is extremely important and widely-used in industrial applications, such as turbines and compressors, which are the key equipments in oil refineries, power plants, chemical engineering plants and so on. However, an unexpected fault in these machines may cause enormous economic loss and personnel casualty [1-2]. With the development of condition monitoring and fault diagnosis technique, rotating machinery condition monitoring system are not only required to monitor real time (RT) operational conditions of plants, but also should decide whether the whole or only parts of the plant are in normal condition or not. As a result, early fault and its cause should be detected effectively and efficiently [3-5]. At the present time, various methods of condition monitoring and fault diagnosis have been developed and applied to detect the early stage faults in the machinery.

In the last few years, numerous new methods have been proposed to address warning and diagnosis of early fault for rotating machinery. Zhao et al. [6] considered that signal of the early fault of the hydraulic pump was a periodic weak signal, so an intermittent chaos, sliding window symbol sequence statistics-based method was proposed to detect the early fault of one single piston loose shoes of hydraulic pump on a hydraulic tube tester, and a control limit was introduced to realize automatic early fault alarm. Hu et al. [7] presented a study of application of duffing oscillator for extracting the features of early mechanical failure signal, which could be used to detect weak signal, such as the feature signal of early machinery fault. An example was presented here to demonstrate the utility of this method by analyzing the early rub-impact signal appearing in a rotor. And Hu et al. [8] also introduced a new method to detect weak useful signal buried in noise. This method was based on stochastic resonance (SR) theory and the model is applied to detect the weak frequency component signals characterizing the inception of rub-impact fault of rotor system. The result showed that this method was simple, robust and reliable. C.Capdessus [9] introduced the theory of cyclostationary processes as a powerful tool for the diagnosis of rotating machines. Dieter-Heinz Hellmann [10] explained how the use of easily measured parameters in combination with suitable mathematical algorithms could provide early diagnosis of faults. But these methods mainly focused on the signal processing, and what's more, those researchers didn't take enough account of the process of early fault.

Generally speaking, the generation of most faults in rotating machinery is always a slow-changing process, but the early features of the faults are often ignored. When alarm of RT monitoring system occurs and thus makes the equipment stop, some components of this equipment may have already been broken seriously, which might cause huge economic loss, so capturing symptom signals in the early stage of the fault is very crucial to prevent it. This paper mainly deals with the design of SCA system, which can be well applied into RT monitoring system. It can capture the early fault symptom signal timely, and save it to the database in order to facilitate the analysis of the cause and overcome the fault before it become more severe [11]. In an example of engineering application case, The SCA system is applied in a machine-set in a petrol-chemical enterprise, which has proven the feasibility of this system.

2 Theoretical analysis

2.1 The features of early fault signal

The features of early fault signal of rotating machinery are often weak and diversified [12], and the most valuable signal feature of early fault may be buried in noise. So the first step, which is quite important, is to find an effective way of de-noising.

In this paper, an adaptive lifting de-noising scheme which is based on lifting wavelet transform is proposed to perform de-noising of the signal. After de-noising, the method of FFT-based spectrum analysis is adopted to extract the features of signal, which can help obtain the features of early fault signal effectively.

Just from the aspects of time domain or frequency domain alone, it is difficult to achieve accurate warning and diagnosis of early faults. FFT-based spectrum analysis method is the most mature and stable method; literature [13] studied the FFT analysis method in detail. But few of researchers systematically combined the changing of spectrum features of vibration signals with the warning and diagnosis of early faults, which can reflect the changing state of the equipment.

As reflected in the frequency domain, features of the fault signal are more obvious, which could activate warning and diagnosis timely. Therefore, this paper mainly deals with the issue of capturing the early fault symptom through continuous changing of the spectral features of vibration signals in time domain.

2.2 Lifting wavelet transform and de-noising

2.2.1 Lifting wavelet transform

Wavelet analysis, which is a new time-frequency analysis methods, is rapidly developing in recent years. It is especially effective in noise reduction, which can improve the extraction of features in weak signals.

The lifting method was proposed by Wim Sweldens in 1995 [14] , which not only can realize the filtering operation fast and effectively, but also can construct biorthogonal wavelet through space domain and it does not depend on Fourier Transformation. Wavelet basis function is not generated by translation and expansion of a function. Every operation is done in the time domain, and can get the same result as those gained from traditional wavelet transformation, which means that the signal can be separated in different frequency bands and thus achieving the goal of multi-resolution. This algorithm comprises of subdivision, prediction and updating [15], as Fig. 1 shows.

(1) Subdivision : Separate the original data into two uncorrelated subset, which are even sample subset $x_e[n]$ and odd sample subset $x_o[n]$.

$$x_e[n] = x[2n] \quad (1)$$

$$x_o[n] = x[2n+1] \quad (2)$$

(2) Prediction : Prediction error $d[n]$ (which can be deemed as wavelet coefficient) can be gained by subtracting the product of $x_e[n]$ and prediction operator P from $x_o[n]$.

$$d[n] = x_o[n] - P(x_e[n]) \quad (3)$$

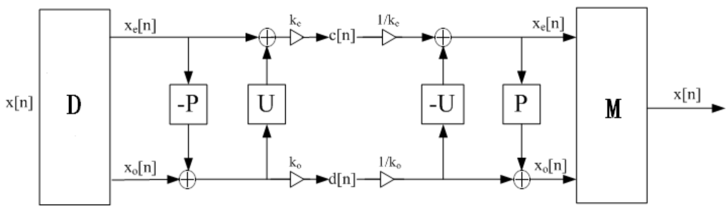

Fig.1 Framework of lifting wavelet decomposition and reconstruction

(3) Updating : Scale coefficient $c[n]$ is the approximation of the original signal $x[n]$, which is gained by adding the product of update operator U and wavelet coefficient $d[n]$ to $x_e[n]$.

$$c[n] = x_e[n] + U(d[n]) \quad (4)$$

The three steps above formulate a lifting process, by iterations of which a complete multi-resolution wavelet transformation can be achieved. Just as Fig. 1 shows, the lifting method can be easily reconstructed, which can also be adaptable when even P and U are non-linear or space-variant functions. All we need to do is just rearrange the orders of formula (3) and (4). The reconstruction steps are (5) and (6).

$$x_e[n] = c[n] - U(d[n]) \quad (5)$$

$$x_o[n] = d[n] + P(x_e[n]) \quad (6)$$

In regard to the frequency domain, detail signal (wavelet coefficient) reflects the high frequency component of the original signal, while the approximation signal reflects the low frequency component. In formula (3) and (4), the choice of P should reflect the correlation of the original data, while the choice of U aims at reducing aliasing effect of subdivision. As a result, wavelet functions and scale functions which have some specific kinds of properties can be constructed.

2.2.2 Adaptive lifting de-noising scheme

Currently, the most widely used de-noising methods are based on hard-threshold or soft-threshold, which were proposed by Donohue [16].The core idea of wavelet threshold de-noising is to concentrate the energy extracted from the signal to some few wavelet coefficients, while noise signals are distributed in all the wavelet coefficients. This means that the better the matching degree of the wavelet and the extracted signal is, the better it will be [17]. To improve the de-noising effect and extract the features of the pulse signals much better, we conduct the de-noising as follows:

(1) Construct the prediction coefficient and updating coefficient of the lifting wavelet transformation according to the adaptive lifting method proposed in 2.2.1

(2) Perform the lifting wavelet transformation using the prediction coefficients and updating coefficients constructed above. The iterative decomposition can be done to the Jth layer, resulting the approximation coefficients $c_{j,k}$ and detail coefficients $d_{j,k}$;

(3)According to the threshold criterion, expansion should be done from the 1st to the Jth scaling wavelet coefficient, so the estimated value of wavelet coefficient $a_{j,k}$ can be obtained.

(4) Reconstruct the approximation coefficient of scaling signal J and estimation value $a_{j,k}$ of scaling wavelet coefficient 1 to J, and the de-noised signal can be obtained.

2.2.3 Simulation data analysis

In order to verify the effect of the adaptive lifting wavelet construction method of de-noising mentioned above, simulation of data analysis is conducted, comparing the results from both adaptive lifting scheme de-noising and the traditional de-noising method.

As shown in Fig. 2, the noise is added to the simulation signal, In order to compare the effect of de-noising from the two techniques, the db4 wavelet is adopted. The results of de-noising are shown in Fig. 3, Fig.4, and Fig. 5.

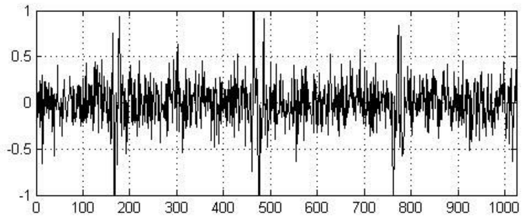

Fig 2 the simulation signal of vibration signal after adding noise

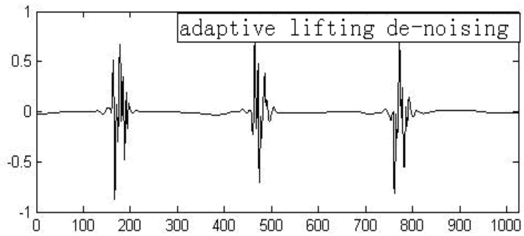

Fig 3 the result of de-noising using the adaptive lifting wavelet

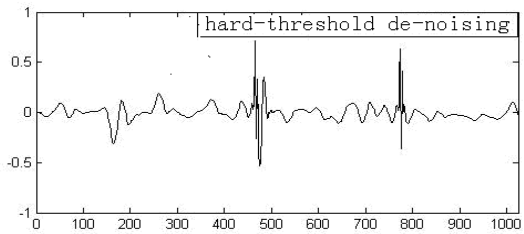

Fig 4 the results of de-noising using db4 wavelet hard-threshold

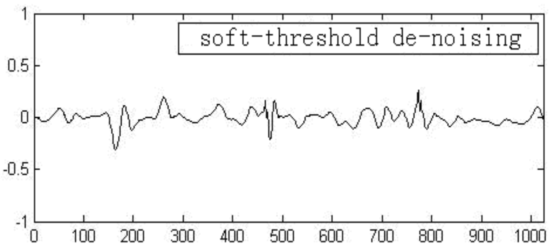

Fig 5 the results of de-noising using db4 wavelet soft-threshold

For the results above, the effectiveness of de-noising using the adaptive lifting de-noising scheme has been proved.

2.3 Basic principles of SCA system

After adaptive lifting de-noising scheme of signal, the features of signal would be obtained through the FFT-based spectrum analysis method effectively. But first of all, the meaning of slow-changing must be clarified.

In brief, the notion of slow-changing means "to change slowly", which has two implications [18]: one is that the operational condition of the machinery changes slowly, such as rotor scaling, bearing wearing in rotating machinery, and the deposit of catalyst on the rotor, causing the change of operational condition from normal to abnormal through slow-changing accumulation for the whole machine, the other is the slow-changing trend which occurs in machine vibration signal because of the change of its condition. For instance, when rotating machinery rotor scales, bearing wear and tear and the deposit of catalyst on the rotor would happen, one or more features of the vibration signal may increase or decrease slowly.

Generally speaking, when early fault occurs in machine sets which are in normal conditions, the variation of operational condition of plants can be described as: stage of smooth operation⟶stage of fault deterioration⟶ stage of smooth operation, just as shown in Fig 6.

In the stage of fault deterioration, which lasts from the starting point of alarm to ending point of alarm as shown in Fig 6, different kinds of slow changes will cause machine vibration signals to have a slow-changing trend during a period of time. Vibration signals which exist in certain duration before and after the SCA occur are very crucial to analyze the slow-changing fault. As a result, capturing and saving these signals will be of great significance to condition monitoring and fault diagnosis. These vibration signals are called Slow-Changing Signals (SCS).

SCS can be quantitatively described by slow-changing value, which is defined as follows. The difference between current and former (which is usually several minutes earlier) machine condition is minute-level changed information amount[19-20], which can describe the changing trend of machine set in a particular period, and is very important to capture early fault signal and prevent the fault from happening.

3 The realization of SCA system

3.1 System design

According to the basic principle of SCA, the accurate capturing of SCS is the key to its realization. The exact moment or time interval must be ascertained when the machine condition slowly changes. Therefore, physical quantity that can be accurately measured should be found to describe the slow-changing events. As to the description of the events, specifically to the rotating machinery, amplitude and initial phase of the overall, 1X, 2X, 3X and 1/2X frequency etc (where NX denotes the N-th harmonic) of the vibration signal can be acquired[21]. If these features exceed the threshold for some times, it can be deemed that the signals change slowly. These thresholds are obtained through a certain adaptive leaning algorithm before the slow change occurs [22]. When adaptive leaning procedure is completed, we should decide if SCA should be confirmed according to its result, and save alarm log and alarm data to the database so as to analyze the cause of the faults

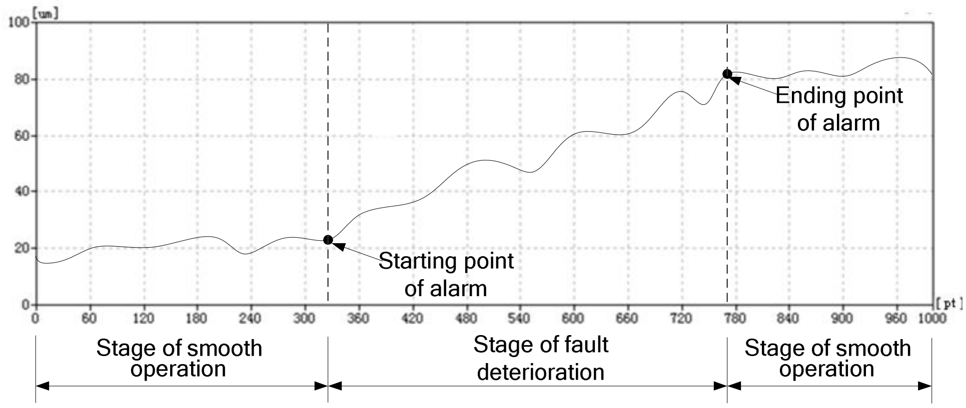

Fig.6 Schematic rig of equipment running status with fault in early stage

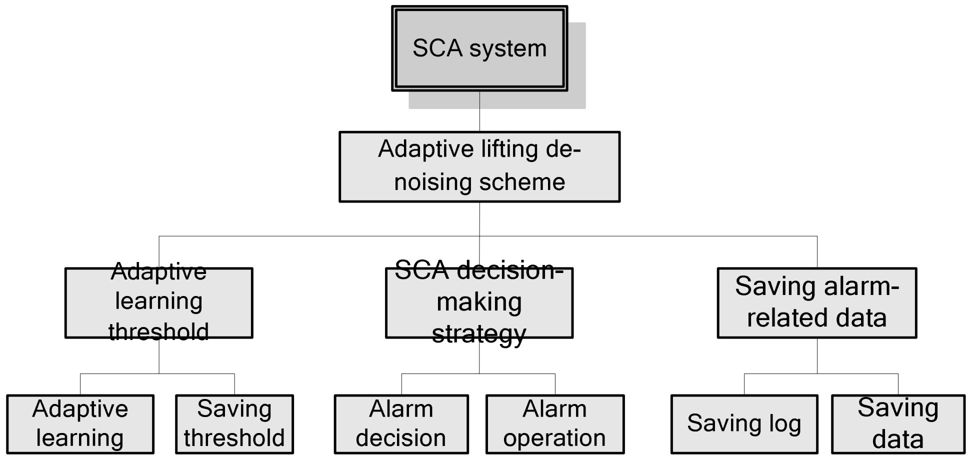

Fig.7 Framework of SCA system

As shown in Fig 7, this SCA system is made up of four parts: Adaptive lifting de-noising scheme, adaptive learning threshold, SCA decision-making strategy and saving alarm-related data.

Currently, the issue of how to realize the functions of SCA by software is the bottleneck on how to implement it. This paper proposes a novel adaptive threshold algorithm to perform SCA judgment and operation, and save alarm-related data. This algorithm is realized by object-oriented C++ language according to the structure of SCA system, and it can successfully resolve the critical problem of realizing SCA system. As shown in Fig 8, the overall flow chart of the software of SCA system is as depicted.

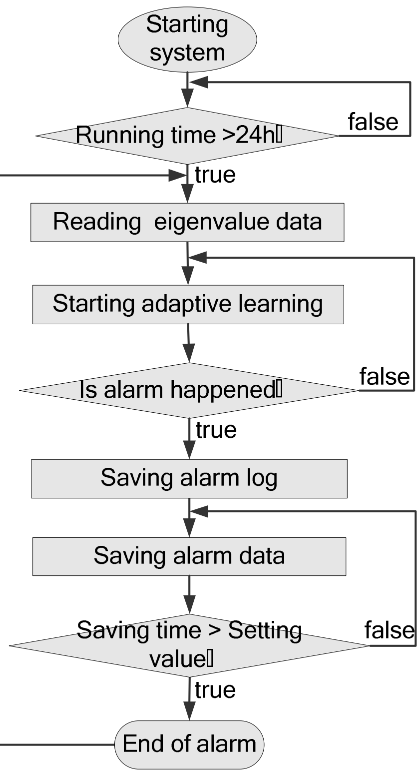

Fig.8 Flow chart of procedure

3.2 Adaptive learning threshold

At first, when the machine set is in normal and smoothly operational condition, a set of length-assigned feature signals series can be kept by saving them in an array-buffer, as shown in Fig 9.

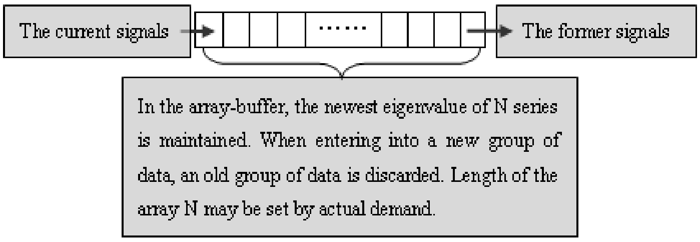

Fig.9 Schematic rig of adaptive learning threshold

About 24 hours after the machine starts running, if it is thought to be in stationary condition, the threshold of SCA can be acquired by a certain adaptive learning algorithm. As to the amplitude of vibration signals of rotating machine, the feature series signal can be manifested as [23-24]:

$$X_{iN} = (x_{i1}, x_{i2}, x_{i3} \ldots x_{in}) \qquad (7)$$

i denotes type of features, including overall, 1X, 2X, 3X, 1/2X and other multiple frequency and fractional frequency, while n is the n-th feature of all the feature type.

Based on Eq. (7), the mean-variance standardization of the different type of features can be represented as:

$$\overline{X}_{iN} = \frac{\sum_{N=1}^{n} x_{iN}}{n} \qquad (8)$$

Furthermore, Based on Eq. (8), the deviation of the different type of features can be represented as:

$$\partial_{iN} = \left| X_{iN} - \overline{X}_{iN} \right| \qquad (9)$$

Therefore, on the basis of both Eq. (8) and Eq. (9), the corresponding matrix S which represents the intensity of variation of the different types of features can be presented as follows:

$$S = \begin{bmatrix} \overline{X}_{1N} + \partial_{1N} \\ \overline{X}_{2N} + \partial_{2N} \\ \overline{X}_{3N} + \partial_{3N} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \overline{X}_{iN} + \partial_{iN} \end{bmatrix} \qquad (10)$$

Generally speaking, the value of matrix S may be affected by interference signals and some other external factors. And it could be modified by expectation coefficient and amplification coefficient, which are set in advance based on practical experience. So the expectation coefficient matrix Hope and amplification coefficient matrix Zoom are described in Eq. (11) and Eq. (12):

$$Hope = \begin{bmatrix} H_1 \\ H_2 \\ H_3 \\ \ldots\ldots \\ H_i \end{bmatrix} \qquad (11)$$

$$Zoom = \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \\ \ldots\ldots \\ Z_i \end{bmatrix} \qquad (12)$$

As a result, the adaptive learning threshold matrix Th, Esq. (13) is as follows:

$$Th = S \bullet Hope \bullet Zoom \qquad (13)$$

As to the actual situation of the machine set, it can reset the expectation coefficient and amplification coefficient repeatedly, and thus the adaptive learning threshold can be optimized, improving the robustness of system.

3.3 The decision-making strategy of SCA

After the threshold is acquired through adaptive learning algorithms, the moment when the slow change event occurs can be obtained by alarm judgment.

The key to realize it is to capture the time when feature of signal changes slowly, that is to say, when the amplitude of vibration signal becomes smaller, it will cause no significant effect to device running normally, but when it becomes larger, some early faults may occur. As a result, the core thought of the SCA decision-making of this system is that [25]: when signal feature becomes smaller, no SCA is activated; while on the contrary, it is activated. As shown in Fig 10, if activated, check if feature of the current signal exceeds the threshold acquired by adaptive learning algorithm. Once the threshold is exceeded, the counter will be added by 1 automatically. When the total count exceeds the specified value, slow-changing event is believed to have happened, so that new slow-changing instruction is send.

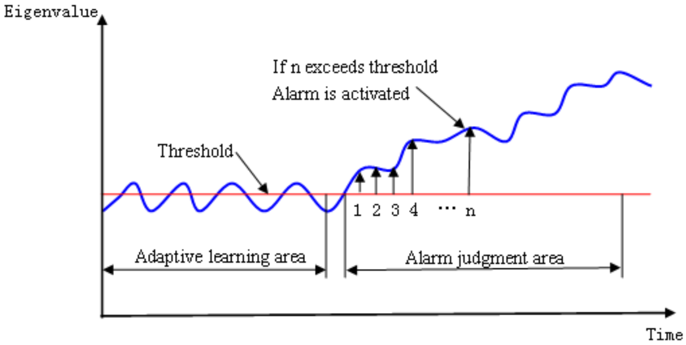

Fig.10 Schematic rig of slow-changing alarm judgment

After the alarm is activated, it means there must be some kinds of faults that cause the alarm. Based on the historical or expert experience of early fault diagnosis of SCA, as shown in Table1, the early fault types could be acquired from SCA system [26-28]. It is effective to predict and diagnose the typical early fault.

Table.1 The early fault result of SCA diagnosis

The early fault result of SCA diagnosis	1/3X	1/2X	1X	2X	3X
rotor imbalance	Good	Good	Alarm	Good	Good
rotor misalignment	Good	Good	Good	Alarm	Good
shaft cracking	Good	Good	Alarm	Alarm	Good
pedestal looseness	Good	Good	Good	Alarm	Alarm
oil whirl	Good	Alarm	Alarm	Good	Good
oil whip	Good	Alarm	Good	Good	Good
rotor rub impact	Good	Good	Alarm	Alarm	Alarm
rotor friction	Alarm	Alarm	Alarm	Good	Good

4 An application case

In a domestic petroleum-chemistry enterprise in China, a SCA system was applied in RT condition monitoring system in a compressor machine set.

At first, the adaptive lifting de-noising scheme of signal was performed to help extract the features of signal. The waveform of original signal was shown in Fig. 11, and the result of adaptive lifting de-noising was shown in Fig. 12.

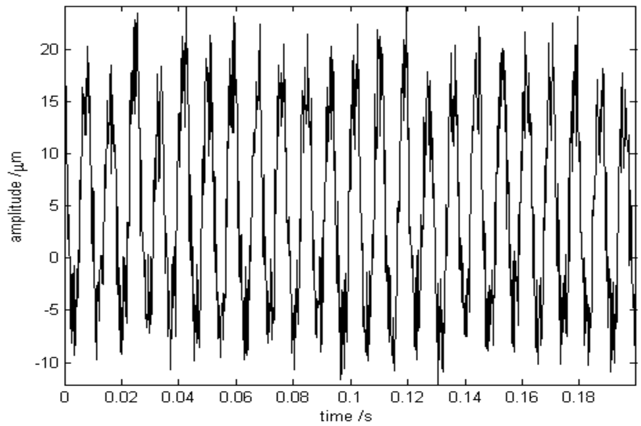

Fig.11 Waveform of original signal

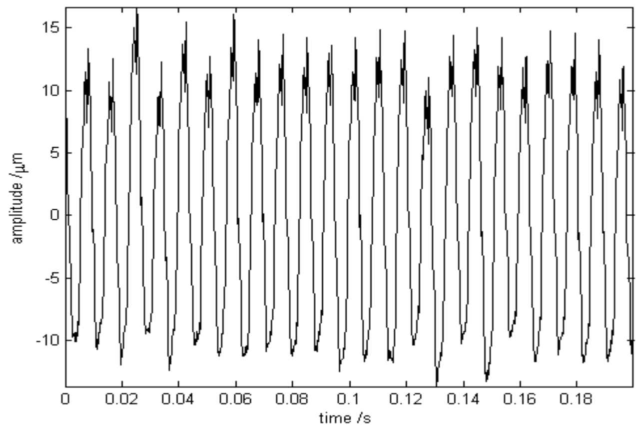

Fig.12 Waveform of signal after adaptive lifting de-noising

When the machine set run stably, after adaptive lifting de-noising, the parameters of SCA were ascertained, and the thresholds were acquired through adaptive learning algorithms. The results were shown in Table 2.

Table.2 Thresholds and parameters of SCA

The N-th harmonic	Adaptive learning Threshold /um	Expectation coefficient	Amplification coefficient
Overall	34.39	0.9	1
1X	27.50	0.9	1
2X	4.52	0.9	1
3X	2.50	0.9	1
1/2X	3.02	0.9	1
1/3X	2.85	0.9	1

Over a period of time, The SCA occurred in vibration channel 1H of the machine through RT monitoring. At this time, the value of Overall frequency in this channel was 40.67um, which had not exceeded regular alarm limit assigned by the machine itself, and it could still operate normally. However, the SCA had occurred, which indicated some kinds of faults or abnormities existed. The next step was to find out what kind of fault it is.

We could acquire historical trend of alarm when SCA took place in channel 1H through diagnosis analysis function of the system, inquiring alarm log and alarm database. Just as shown in Fig 13, the Overall frequency value trend in channel 1H had little change during this period of time, but the 2X frequency value had an apparent growing trend, this value grew from 4.94um to 11.86um slowly, which caused the occurrence of SCA. After that, it was restored to a new stable value. This signified that some potential abnormity or fault had existed in the machine set.

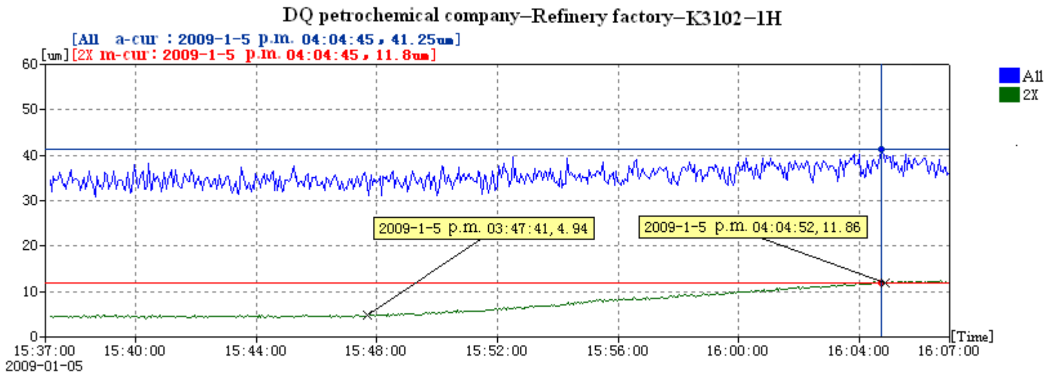

Fig.13 History tendency chart of alarm

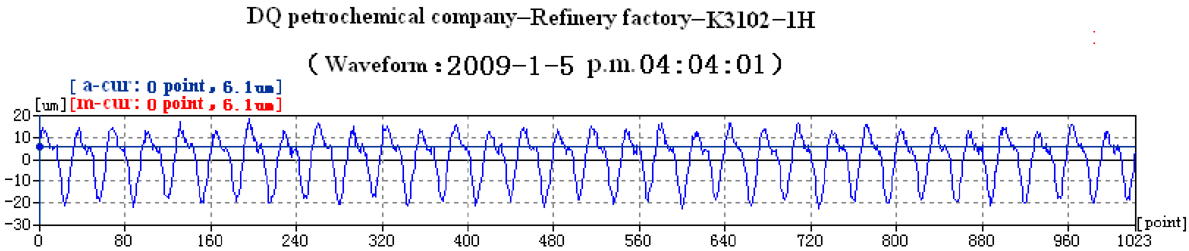

Fig.14 the waveform graph of channel 1H

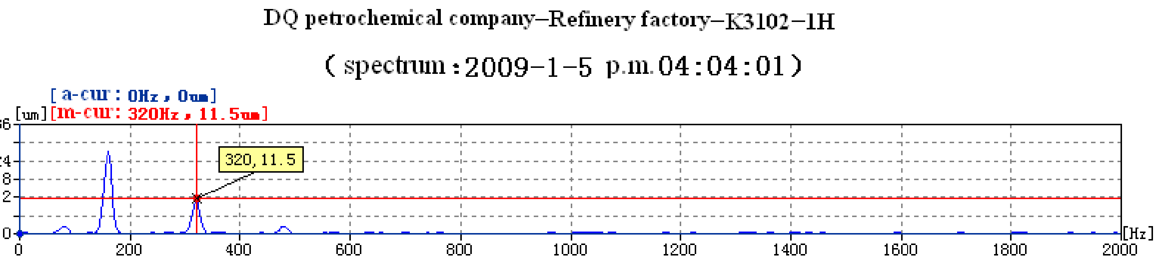

Fig.15 the spectrum graph of channel 1H

Through analysis of the historical alarm waveform, the waveform shape of channel 1H had an abnormal shape, as shown in Fig 14.

In addition, based on the spectrum graph as shown in Fig 15, the value of 2X frequency in channel 1H became larger, which was up to 11.5um. It was evident that the machine had some potential fault.

Then the specific diagnosis result could be acquired from the SCA diagnosis table as Table 1 shows, which could be deemed as early fault in rotor misalignment. The result was consistent with the fact when we check it afterwards. It had been proved that by adopting some solutions in time would overcome the hidden danger, and ensured the long term stable operation of the machine set.

5 Conclusion

Early fault prediction and diagnosis in condition monitoring of rotating machinery has always been a tough problem. The SCA system using a novel adaptive learning algorithm and decision-making strategy is developed to address this issue in this paper. Some of the conclusions are summarized as follows:

(1) Through monitoring real time changing trends of features of vibration signal in each channel, to capture the slow-changing signals, a novel adaptive learning algorithm is proposed to acquire alarm threshold, and based on the running status, the threshold can be optimized by the expectation coefficient and the amplification coefficient.

(2) The decision-making strategy can activate slow-changing alarm to predict the occurrence of early fault when the machine set has potential abnormity, thus it can prevent the fault from becoming apparent or even causing breakdown.

(3) Through an example of engineering application, it has been proved that the SCA system can be successfully applied in the field of condition monitoring system, and it can be quite effective in predicting early fault of rotating machinery and directing the maintenance and management of the equipment.

(4) Further research is needed regarding how to combine the advanced expert system with the SCA system to diagnose and predict early fault of rotating machinery more effectively. In such circumstance, the SCA system can perform this task optimally and effectively.

Acknowledgements

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