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Fault Diagnosis of Centrifugal Pumps based on the Intrinsic Time-scale Decomposition of Motor Current Signals

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Abstract—Centrifugal pumps are widely used in various manufacturing processes, such as power plants, and chemistry. However, pump problems are responsible for large amount of the maintenance budget. An early detection of such problems would provide timely information to take appropriate preventive actions. This paper investigates the application of Machine Learning Techniques (MLT) in monitoring and diagnosing fault in centrifugal pump. In particular, the focus is on utilising motor current signals since they can be measured remotely for easy and low-cost deployment. Moreover, because the signals are usually produced by a nonlinear process and contaminated by various noises, it is difficult to obtain accurate diagnostic features with conventional signal processing methods such as Fourier spectrum and wavelet transforms as they rely heavily on standard basis functions and often capture limited nonlinear weak fault signatures. Therefore, a data-driven method: Intrinsic Time-scale Decomposition (ITD) is adopted in this study to process motor current signals from different pump fault cases. The results indicate that the proposed ITD technique is an effective method for extracting useful diagnostic information, leading to accurate diagnosis by combining the RMS values of the first Proper Rotation Component (PRC) with the raw signal RMS values.

Keywords-Centrifugal Pump; Current Signal Analysis; Intrinsic Time-scale Decomposition.

I. INTRODUCTION

Centrifugal pumps are key components of various technical processes, like in power generation and chemical industries, used for the purpose of manufacturing, heating, air-conditioning and cooling of engines. They are used for fluid delivery and mostly driven by electrical motors. The centrifugal pumps may fail during their operation that can lead to an interruption of the manufacturing process; pumps problems are responsible for a significant amount of the maintenance budget, the damage of centrifugal pumps occurs either in the hydraulic or the mechanical parts. Key parts of pumps including bearings and impellers are subject to different faults which lead to a major retreating of pump performances and causes production breakdown. Therefore, it is important and necessary for monitoring of these machines which has been gradually investigated for developing further advanced techniques, to avoid any unexpected failure and shutdowns. As a result of both early detection and precise diagnosis of incipient faults, this has resulted in fast unscheduled maintenance, reduce maintenance expenses and extend the lifetime of the machines [1]. Numerous monitoring techniques have been invested in detecting and diagnosing incipient faults in centrifugal pumps through the analysis of vibration, acoustic sound, acoustic emission, pressure and temperature, however, these techniques require additional sensors to be installed on the system which leads to increase in the cost of the system [2], also in some cases it may be difficult to access the pump to install sensors. Therefore, motor current signature analyses can be used as an effective technique for fault detection due to the advantages over the popular method mentioned above, such as easy installation without interference to the machine operation and where the sensors are difficult to install because of scanty spaces [3, 4].

Sakthivel et al. [5] presented a method that uses decision tree algorithm for diagnosis of faults in the centrifugal pump where the statistical feature are extracted from vibration signals. [6] proposed a vibration based condition monitoring using wavelet analysis and classification using Naïve Bayes and Bayes net algorithm. Alfayez et al [7] applied acoustic emission for detecting incipient cavitation fault in centrifugal pump, Al-Braik et al [8] used the low-frequency components from Fourier spectrum for detecting van tip fault on impellers.

Stopa et al [9] developed method for detecting the phenomenon of cavitation in centrifugal pumps via motor current signature analysis, using Torque Signature Analysis. Tian et al [3] applied Modulation Signal Bispectrum (MSB) for extracting fault from impellers. The current signals from the centrifugal pump have resulted from a complicated nonlinear process, especially for different fault cases, which usually exhibit nonstationary characteristics. Therefore, the conventional data processing methods such as Fourier spectrum analysis has drawbacks, some of which are "spectral leakage", a phenomenon that occurs when the frequency resolution of the current spectrum is not high enough [10]. Hence, advanced signal-processing techniques and data algorithms are important such as the time-frequency analysis methods, including wavelet transforms which are often used because they can provide the whole and local characteristics of the signals in time and frequency domains [11] concurrently. However, these methods generally have the deficiency in that they have limited time or frequency resolutions which often affect the ability to find small and local signatures relating to faults. Moreover, the successful application of such methods need to have a rigorous understanding of the likely features in the signal which is often not possible because of the high complicity of machine processes.

Recently, a number of data-driven signal processing methods have received high attention in analysis complicated signals. These methods characterise signals based on the instinct features of data along, without using a basis function such as that of spectrum and wavelet transforms. Empirical Mode Decomposition (EMD) is a typical non-linear signal processing method [12]. In this method which a complicated signal will be decomposed into finite stationary Intrinsic Mode Functions (IMFs) where the features can be extracted from the (IMFs), however, there are some inherent deficiencies of EMD, such as the end effects, mode mixing and the unexplainable negative frequency that cannot be ignored [13, 14]. Local Mean Decomposition (LMD) is an improved method of EMD, which can decompose complicated signal into a number of product functions [15]. Nevertheless, LMD technique undergoes from the contaminated components, mode mixing and time-consuming decomposition [16].

Intrinsic time-scale decomposition (ITD) was proposed by Frei and Osorio[17], ITD is developed for analysing the non-linear and non-stationary signals, with high decomposition efficiency and frequency resolution. It decomposes a complex signal into several (PRCs) and a monotonic residual. ITD has ability to overcome the drawbacks of EMD because of the particular formula of ITD and the process of decomposition [16], where the information of the signal itself can be used, consequently, the end effects and the unexplainable negative frequency can be relieved. Furthermore, the ITD method has higher computational efficiency than EMD [11]. ITD has been used in the field of machinery fault detection and diagnosis. Feng et al. [18] have used ITD to decompose planetary gearbox vibration signals into mono-components for further demodulation and analysis. An et al. [19] applied ITD, for fault diagnosis of the bearing of the wind turbine. This study analysed and decomposed the vibration signals by ITD technique and regarded the frequency centres of the first proper rotation component as fault features vector and applying the nearest neighbour algorithm to distinguish the operation condition of these bearings. In [20] the others presented method fault diagnosis of the wind turbine by combined ensemble ITD, with wavelet packet transform for analysing vibration signals then the correlation dimension was adapted to identify the working conditions and fault types of wind turbine gearbox.

Although ITD show effectiveness of processing vibration signals for machine diagnosis, it has not been found in analysing motor current signals. Therefore, this study focused on analysing the current signals from the centrifugal pump by applying this emerging ITD method.

In addition, there is also a trend to utilise combinations of current signal processing and intelligent analysis approach to produce more reliable centrifugal pump fault diagnosis, it is important to find a meaningful feature extract technique which will lead to extracting the most characteristic features for enhancing the diagnostic efficiency and leading to accurate diagnosis [21]. Therefore, this study focuses on analysing the motor current signals from the pump's electrical control system to characterise pump performance

with different faults under a range of flow rates or operating conditions. Specifically, ITD is applied to examine the current signals to develop diagnostic features that allow the faults to be diagnosed.

The remainder of this paper is structured as follows. Section 2 presents the introduction of ITD, Section 3 describes the experimental setup and data acquisition, Section 4 presents the signal processing results and discussion. Finally, Section 5 is the conclusion.

II. THEORETICAL BACKGROUND

A. Intrinsic Time Scale Decomposition

As a new data-driven method, ITD is self-adaptive and capable of time-frequency analysis, and has been successfully applied for processing the non-linear signals as it can decompose a complex signal into the set of PRCs and a monotonic residual. The decomposition details of a non-linear single can be outlined follows [11, 17]:

For a signal X_t, define a baseline extraction operator L to separate the lower frequency baseline signal, the instantaneous mean curve of the signal is denoted LX_t, which is shortened to L_t. Therefore the signal could be decomposed as $X_t = X_t + H_t$ where $H_t = X_t - L_t$ define as the proper rotation component. The algorithm of ITD is consists of following key steps [18, 22]:

1. Find the extrema point X_t, and the corresponding moment τ_k for the given signal, where $k = 0, 1, 2, \ldots$, and let $\tau_0 = 0$.

2. Assume the operators L_t and H_t are provided over the interval $[0, \tau_k]$, where the signal L_t exists on the interval, then on the range $(\tau_k, \tau_{k+1}]$ between adjacent extrema X_k and X_{k+1}, the piecewise baseline extraction operator is defined as

$$LX_t = L_t = L_k + \left(\frac{L_{k+1} - L_k}{X_{k+1} - X_k} \right)(X_t - X_k), t \in (\tau_k, \tau_{k+1}] \quad (1)$$

where

$$L_{k+1} = \alpha \left[X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k} \right)(X_{k+2} - X_k) \right] + (1 - \alpha) X_{k+1} \quad (2)$$

and $0 < \alpha < 1$, usually α is around 0.5.

3. Base signal L_t is the original signal, then by repeating the previous steps continuously the base signal become a constant or monotone function, or the function that includes fewer than three extremum points. In this case, the decomposition will end and the original signal is decomposed into PRCs and trend as:

$$X_t = \sum_{i=1}^{p} H_t^i + L_t^p \qquad (3)$$

where X_t is the i_{th} layer of the proper rotation, L_t^p is the monotonic baseline signal representing the trend of X_t, and p is the decomposition level.

B. The Diagnosis Approach for the Centrifugal Pump

The data-driven ITD was adapted for analysing the current signal, because the current signals from the centrifugal pump are nonlinear under faulty operations, also the diagnostic features are critical procedures in the analysis of the current signal, therefore. Root mean square (RMS) is calculated which can reflect the current energy and discrete characteristics of the signal and it has a useful information for the detection and diagnosis of the faults. Then a combining the RMS of the raw current signal and the RMS from the 1st PRC of ITD are explained and used for diagnosis of all the cases.

III. TEST FACILITY AND DATA ACQUISTION

The experiment was accomplished based on the test facility as illustrated in Fig. 1. The centrifugal pump under test can deliver the water flow at 250 l/min under a pressure of 10 bar when the driving motor operates at a rated speed of 2900 rpm. The discharge flow can be regulated by the discharge control valve to examine the pump under different head and flow rate, allowing its characteristics to be examined over its full operating range.

In this paper, normal condition (baseline) of the centrifugal pump and three common faults were investigated, as illustrated in Fig. 2, there were two types of faults related to the bearing: inner race (IRF), outer race (ORF), and one type of multi-fault namely, outer race with blockage impeller (ORF&IB). Faults were seeded separately into the centrifugal pump. The performance of the centrifugal pump was examined with only one fault presents at a time, in addition pump performance parameters including flow rate discharge head and motor speed were also measured.
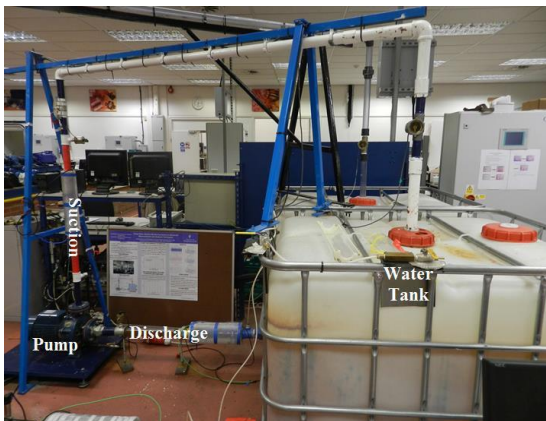

Figure 1. Test rig facility.

Four sets of experiments have been conducted using the test rig described above, the pump was operated at different flow rates 350, 300, 250, 200, 150, 100 and 50 (l/min) for all cases. The Current signals datasets were collected during the experimental work by using a high-speed data acquisition system which is operating at a 96 kHz sampling rate with 24-bit data resolution, under the range of flow rates and the different faults, these datasets and operating settings will help to understand the current characteristics.
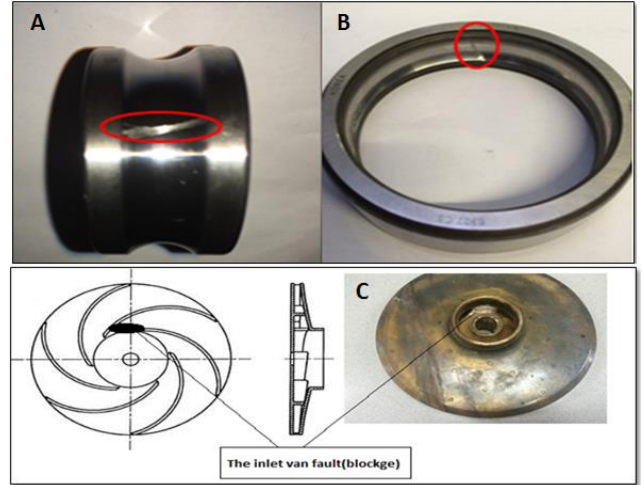

Figure 2. Types of faults (a) Bearing inner race fault (b) Bearing outer race fault, and (c) Impeller fault

The current signal data for different fault conditions including healthy operation BL, IRF, ORF, and ORF&IB, for seven different flow rates, were carried out and analysed to detect and diagnose the operation of the centrifugal pump.

IV. RESULTS AND DISCUSSION

A. Change of Pump Performance

Fig. 3 shows the pump performance curves for all cases. It shows slight pump head drops for the fault cases, visible differences between the fault cases. This means that the seeded faults have been induced effectively to the system. It is also clear that a combined fault ORF&IB reduces more the performance of the centrifugal pump, which is expected.
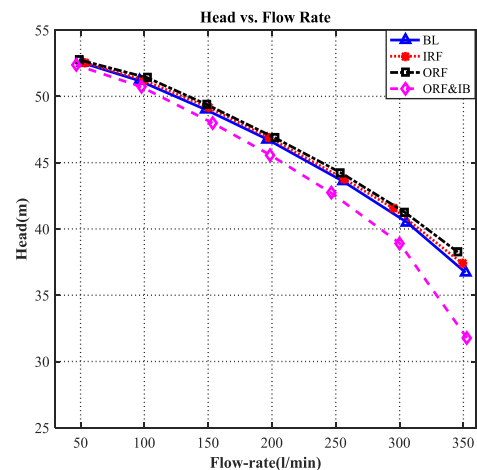

Figure 3. The change of pump performance due to faults

B. Motor Current Analysis

First of all, the measured signal was studied in the time domain. Fig. 4 show the current signals for all cases at the flow rate 351 l/min, it can be found that the values of currents are similar for the baseline case and the bearing fault, at the same flow rate, however some differences in the current value of the combined fault ORF&IB can be noticed.
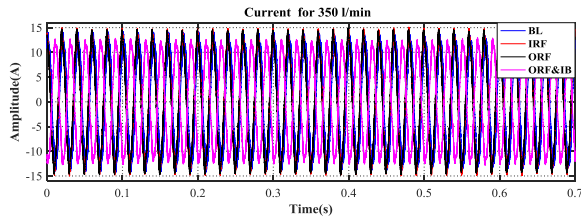

Figure 4. Phase current in time domain for all cases

For more accurate comparison, Fig. 5 presents the RMS values of the raw signal data. Obviously, the RMS is gradually increasing for all cases by increasing the flow rate. Particularly, it shows a difference between BL and ORF&IB over the flow rates higher than 200 l/min, whereas it is unable to separate its BL from other operation condition. This shows that the RMS from the raw signal can differentiate the large faults but have limited performance to separate the small ones.
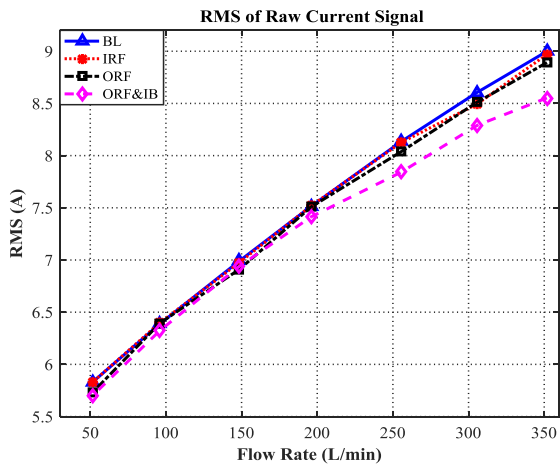

Figure 5. RMS of current with flow rates

To get full separation, then the current signal is decomposed by ITD to different PRCs, resulting in Fig. 6 and Fig. 7. They are for healthy pump BL and inner race bearing IRF respectively. It can be observed that the current signal is adaptively decomposed into five PRCs, which consists of major fluctuations of the signal. In particular, the 1st PRC is of much more fluctuation which can be reflecting more on the nonlinear interactions between the mechanical load and the electrical process. Especially, the distinctive modulations in the 1st PRC are well consistent with the operation process explained in [23] for asymmetrical rotor faults.
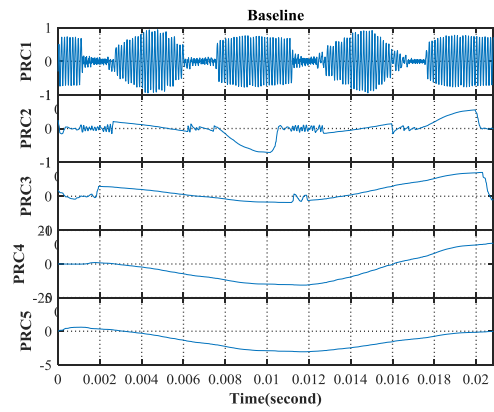

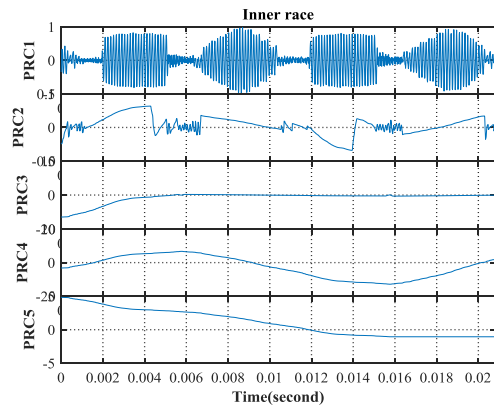Figure 6. ITD decomposition result for the healthy pump at 350 l/min

Figure 7. ITD decomposition results for inner race bearing fault at 350 l/min

By comparing between the two PRCs, it is hard to find clear differences between the baseline and the fault case. However, the modulation profiles show observable differences in that the main profiles of the modulation looks shorter for the fault case. To show accurately the difference the RMS values of the 1st PRCs for all cases are calculated and presented in Fig. 8. It is clear that the RMS values have a useful diagnostic information and leading to separate all operation conditions.
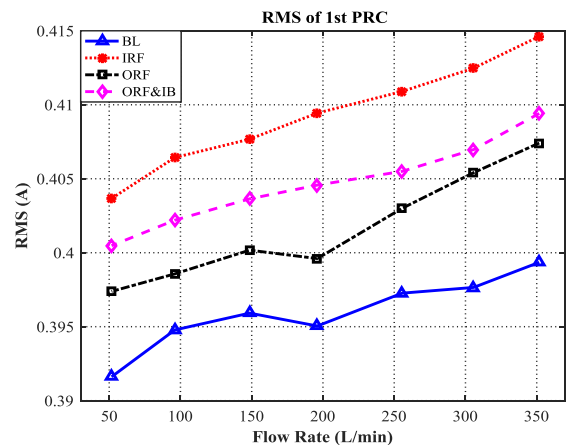

Figure 8. Variation of RMS values of the 1st PRC with flow rates

C. Fault Diagnosis using Motor Current only

Fig. 9 presents the combination of RMS values of the raw data and the RMS of the 1st PRCs. It clearly shows a difference between the healthy condition and all fault cases. It means that the two types of RMS values are able to separate all operating conditions and hence can be based pump diagnosis without the needs any other measurements such as the pressures and the flow rates.
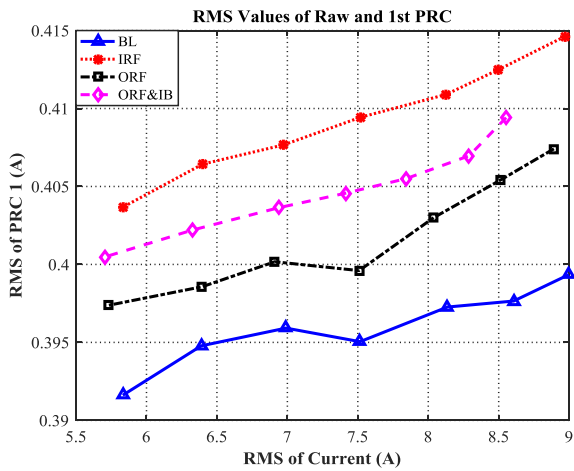

Figure 9. Fault separation based on static and dynamic features from current signals

V. CONCLUSION

In this study, a pump diagnostic approach is developed based on the ITD analysis of motor current signals. As ITD is data-driven signal processing methods, it allows the accurate extraction of the modulation features which is due to nonlinear dynamic effects of various pump faults. Specifically, the study has demonstrated that the 1st PRC extracted by ITD can be explained with motor operation process in that the high-frequency supply components may be altered in a nonlinear modulation way by the dynamic oscillations of the faults. The analysis results show that the proposed approach performs effectively for differencing common pump faults: bearing defects and impeller blockages and as well as their combinations in a wide range pump operating conditions.

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