Generic vibration-based faults identification approach for identical rotating machines installed on different foundations

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ABSTRACT

Vibration-based faults identification (VFI) in rotating machines is well-known and adopted in industries. However, it has proved challenging to directly apply historical measured vibration data from one rotating machine with a particular foundation to another identical rotating machine installed on a different foundation layout during VFI. This is generally due to the different dynamic behaviours exhibited by the identical rotating machines as a result of their different foundation layouts. Hence, VFI could be significantly simplified through the application of a generic approach that enables the sharing of measured vibration data and experience between several identical rotating machines with similar or different foundations. In order to realise this objective, two identical rigs with different flexible foundations were used. Vibration data were collected on the rigs with different foundations under several operating conditions. The measured vibration data were then analysed in the frequency domain to compute poly coherent composite higher order spectra (pCCHOS). pCCHOS is a data fusion method that generates a single composite bispectrum or trispectrum irrespective of the number of vibration measurement locations. The components of pCCHOS were jointly analysed using pattern classification and the results showed clear separation among all considered machine conditions, which is an indication of its ability to satisfy the generic VFI objectives. Sensitivity analysis was also conducted to assess the robustness of the method in case there are faulty measurements and/or sensors from certain locations of the rotating machine.

1. INTRODUCTION

The achievement of complex industrial process objectives usually attracts the installation of numerous rotating machines, owing to their versatility and ability to cope with continuously changing operational parameters. In the past, companies could comfortably afford to achieve similar manufacturing tasks with significantly different rotating machines. For instance, a typical cement process plant could have several pneumatic pumps and blowers from different original equipment manufacturers (OEMs) for transporting pulverised solid fuel to the rotary kilns or fine cement to the storage silos. The implication of such approaches from the maintenance standpoint is that several different spare parts would be required for individual rotating machines. However, the current drive for cost-effectiveness across all industries has led to the shift towards equipment standardisation in order to significantly rationalise spare parts quantities and holding costs. Based on this premise, it has become more and more common for companies to install similar rotating machines (in terms of configuration, components and specification) from the same OEM in different locations on the same plant site. While it is fair to say that such spare parts management strategies have gained tremendous popularity within the past few decades, it is also important to highlight that same cannot be said for the fault detection element of the overall asset management strategy for industrial rotating machines.

Condition monitoring (CM) of rotating machines is a popular asset management strategy that revolves around the initiation of “repair or replace” maintenance decisions based on the analysis of continuously measured machine operational parameters such as vibration, temperature, sound, power consumption, etc. In comparison to other CM techniques commonly used for establishing the health of rotating machines in practice, the existing body of knowledge has overwhelmingly indicated that vibration-based faults identification (VFI) approaches are the most dominant. This dominance is quite evident in the amount of vibration-based fault finding techniques and signatures that have erupted within the past few decades. For instance, Sinha et al. (1), Sekhar (2-3) and Pennacchi et al. (4) respectively explored the ability of theoretical VFI approaches for the detection and analysis of rotor-related faults such as unbalance, shaft misalignment and shaft crack. The positive contributions of theoretical VFI approaches to the understanding of rotating machine faults are undeniable. However, some researchers still believe that it is near impossible to develop a theoretical model that will precisely represent a very complex industrial rotating machine (5). Other researchers have also incorporated artificial intelligence (AI) approaches such as artificial neural networks (ANN) (6-8) and support vector machines (SVM) (9-11) into VFI of rotating machines, so as to reduce the dependence on human interference and judgements. While the research-based applications of AI techniques such as ANN and SVM have continued to flourish, however the deployment of ANN to the field is still restricted by the lack of clearly
identified guidelines for acquiring the training data and the exact approach for training the model while SVM is also limited by a lack of clearly stated standards for selecting its fundamental process (i.e. the Kernel function) (12). It is well known that the application of amplitude spectrum analysis based on power spectrum density (PSD) approach is another commonly used VFI technique due to its relative computational simplicity and ability to respond to the dynamic changes of rotating machines when faults emerge. However, loss of phase information during PSD computation (13) often leads to the combination of amplitude spectrum analysis with other conventional VFI approaches such as rotor orbits analysis (13), full spectrum analysis (14-17), etc., which sometimes complicates the entire fault finding process. Efforts to minimise the complexities that arise from the use of several conventional VFI techniques include the use of higher order spectra (HOS) (18-22) analysis. With HOS, both amplitude and phase information are retained, as well as the establishment of the interrelation that exist between several harmonics of the machine speed.

Besides the highlighted individual limitations associated with some of the currently employed VFI approaches, the authors’ knowledge of the existing body of literature provides a clear indication that rotating machine faults identification and classification are grossly focussed on solitary machines operating at individual speeds. Therefore, when a typical VFI analyst is faced with the task of continuously detecting faults associated with various identical rotating machines operating at different speeds in a typical plant, the entire faults identification process could become convoluted due to the amount of measured vibration data to be analysed. Such scenarios could significantly increase the lead time to accurate fault detection as well as result to costly downtimes. Hence, VFI could be significantly simplified through the application of a generic approach that enables the sharing of measured vibration data and experience between several identical rotating machines with similar or different foundations. In order to realise this, a hybrid (i.e. combination of sensor level and feature level data fusion approaches) data fusion technique that can effectively combine measured vibration data from several vibration-based condition monitoring (VCM) sensors at various speeds for different rotating machines was used. During the current study, vibration data were acquired at different speeds from two identical rigs with different foundations operating at different speeds. The measured vibration data were then analysed in the frequency domain to compute poly coherent composite higher order spectra (pCCHOS) (23). pCCHOS is a data fusion method that generates a single composite bispectrum or trispectrum fault diagnosis features irrespective of the number of vibration measurement locations (23). The pCCHOS features for the identical machines at all speeds are then extracted and fed into a principal components analysis (PCA) based algorithm for classification. Additional, sensitivity analysis was conducted in order to ascertain the robustness of pCCHOS in the event of some faulty measurements and/or sensors from some of the measurement locations on the monitored rotating machines(s).

2. GENERIC VIBRATION-BASED FAULTS IDENTIFICATION APPROACH

The generic vibration-based faults identification (GVFI) approach for identical rotating machines with different foundations and speeds was developed based on three stages of data fusion. Stage 1 of the process is termed multiple sensors single speed single machine (MSSSM) phase whereby measured vibration data acquired from several VCM sensors (say "b") installed on a solitary rotating machine at one speed are combined together in the frequency domain to construct a single pCCHOS (i.e. poly composite bispectrum and trispectrum). The same process is then performed at the different operating speeds of the monitored machine. Equations (1)-(3) respectively provide the mathematical computations of pCCHOS (23-24).

\[ S_{\text{pCCS}}(f_b) = \left( \frac{\sum_{n=1}^{n_b} x_n^2(f_b) y_n^2(f_b) x_n y_n x_n y_n x_n y_n y_n \ldots x_{n-b} y_{n-b} y_{n-b} y_{n-b} y_{n-b} y_{n-b} y_{n-b} y_{n-b}}{n_b} \right)^{1/6} \]  
\[ B(f_i, f_{i+n}) = \sum_{n=1}^{n_b} \left( \frac{S_{\text{pCCS}}(f_{i+n}) X_{n+b} X_{n+b} X_{n+b} X_{n+b} X_{n+b} X_{n+b} X_{n+b} Y_{n+b} Y_{n+b} Y_{n+b}}{n_b} \right) \]  
\[ T(f_i, f_{i+n}) = \sum_{n=1}^{n_b} \left( \frac{S_{\text{pCCS}}(f_{i+n}) X_{n+b} X_{n+b} X_{n+b} X_{n+b} X_{n+b} X_{n+b} X_{n+b} Y_{n+b} Y_{n+b} Y_{n+b}}{n_b} \right) \]  

Equation (1) respectively represent the Fourier transformation (FT) of the rth segment at frequency \( f_b \) of the vibration responses at bearings 1, 2, 3, 4, ..., (b-1) and b. Also, \( Y_{1+b}, Y_{2+b}, Y_{3+b}, \ldots, Y_{(b-1)+b} \) respectively represent the coherence (25) between bearings 1-2, 2-3, 3-4, ...., (b-1)-b. \( S_{\text{pCCS}}(f_{i+n}) \) is the poly-Coherent Composite Spectrum (pCCS) at frequency, \( f_i \). The \( X_{n+b}^2 \) shown in Equations (2)-(3) represents the poly coherent composite FT for a certain segment \( r \) of the measured vibration data from 'b' bearing locations at a certain frequency, \( f_i \), which was computed as (24);

\[ X_{n+b}^2(f_b) = \left( X_1(f_b) Y_1 X_1(f_b) Y_1 X_2(f_b) Y_2 X_3(f_b) Y_3 \ldots X_{n-b-1}(f_b) Y_{n-b-1} X_{n-b}(f_b) \right)^{1/6} \]  

Stages 2 and 3 of the process are based on the application of a PCA-based algorithm to first combine the pCCHOS features generated at individual speeds for a solitary rotating machine so as to develop the multiple sensor multiple speeds single machine (MSMSSM) phase. In stage 3 where it is assumed that several identical rotating machines with different foundations could exist in a typical plant, the pCCHOS features at all speeds
from all identical rotating machines with different foundations are then combined to develop the multiple sensors multiple speeds multiple foundations phase of the process.

Equations (5)-(7) illustrate the PCA feature matrices used to accomplish stages 2-3 of the GVFI approach. Since CM of rotating machines involves the continuous acquisition of vibration data under different machine conditions (healthy and faulty), the PCA feature matrix in Equation (5) assumes that "p" number of vibration data sets were collected from a typical rotating machine \(RM_i\) under a certain machine operating condition \(c_i\), and at a certain rotational speed \(s_i\). \(B_{opp}(c_i,s_i)\), \(B_{opp}(c_i,s_i)\), and \(T_{opp}(c_i,s_i)\) on the other hand respectively denote the \(p\) CCHOS features computed using Equations (2) and (3) for machine operating condition \(c_i\), at speed \(s_i\).

\[
\text{MSSSSM}_{RM_i, s_i} = \\
\begin{bmatrix}
B_{opp}(c_i,s_i) & B_{opp}(c_i,s_i) & T_{opp}(c_i,s_i) \\
B_{opp}(c_i,s_i) & B_{opp}(c_i,s_i) & T_{opp}(c_i,s_i) \\
\vdots & \vdots & \vdots \\
B_{opp}(c_i,s_i) & B_{opp}(c_i,s_i) & T_{opp}(c_i,s_i)
\end{bmatrix}
\] (5)

Assuming that the same rotating machine \(RM_1\) operates at several speeds \(s_1, s_2, ..., s_n\), then MSMSSM feature matrix can be written thus;

\[
\text{MSMSSM}_{RM_k} = \\
\begin{bmatrix}
\text{MSSSSM}_{RM_1, s_1} \\
\text{MSSSSM}_{RM_1, s_1} \\
\vdots \\
\text{MSSSSM}_{RM_1, s_n}
\end{bmatrix}
\] (6)

Stage 3 of the GVFI approach was developed based on the premise that several identical rotating machines with different foundations \(RM_1, RM_2, ..., RM_p\) exists and vibration measurements were acquired from each of them at machine speeds \(s_1, s_2, ..., s_n\). Hence the MSMSMM feature matrix can be written as;

\[
\text{MSMSMM} = \\
\begin{bmatrix}
\text{MSMSSM}_{RM_1} \\
\text{MSMSSM}_{RM_1} \\
\vdots \\
\text{MSMSSM}_{RM_p}
\end{bmatrix}^T
\] (7)

The entire GVFI process is schematically illustrated by Figure 1, so as to enhance visualisation and understanding of the discussed concept.
3. EXPERIMENTAL SETUPS, SIMULATED CASES AND SIGNAL PROCESSING

The measured vibration data used to achieve the objectives of the current study were acquired from 2 very identical (components and configurations) rotating machines with respect to their components and configurations, but are mounted on foundations with different flexibilities. Both RM$_1$ and RM$_2$ consist of 2 rigidly coupled rotors (R1 and R2) as well as 3 identical balance discs (D1, D2 and D3). D1 and D2 are mounted on R1, while D3 is mounted on R2. Rig rotation was achieved through an induction motor (IM) that was flexibly coupled (FC) to R1. RM$_1$ and RM$_2$ rig assemblies were individually supported by 4 anti-friction bearings (AB1-AB4). RM$_1$ bearings were mounted to their respective pedestals via 0.01m diameter threaded bar nuts while RM$_2$ bearings were mounted to their pedestals via 0.006m threaded bar nuts. Figure 2 shows a picture of RM$_1$ experimental rig (which is identical to RM$_2$ except for their differing foundations), while Table 1 provides the specifications of the major components. From RM$_1$ and RM$_2$, 4 accelerometers (A1-A4) were used for acquiring 20 sets of measured vibration data at each of the 3 machine speeds (1200rev/min, 1800rev/min and 2400rev/min) for all 6 experimentally simulated cases (healthy with residual misalignment (C1), bent shaft (C2), shaft crack (C3), loose bearing (C4), shaft misalignment (C5) and shaft rub (C6)) detailed in Table 1. The PCCHOS features (computed as per Equations (2)-(3)) for all data sets was post-processed with a MATLAB.
code using 95% overlap, frequency resolution (df) = 0.6104 Hz, sampling frequency (fs) = 10000 Hz, number of FT data points (N) = 16384 and 148 number of averages.

Table 1: Experimentally simulated cases [23]

<table>
<thead>
<tr>
<th>S/No.</th>
<th>Case</th>
<th>Notation</th>
<th>Severity and Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Healthy with residual misalignment</td>
<td>C1</td>
<td>Possible residual misalignment at couplings (FC &amp; RC)</td>
</tr>
<tr>
<td>2</td>
<td>Bent shaft</td>
<td>C2</td>
<td>0.0034m radial run-out was created at the centre of R1</td>
</tr>
<tr>
<td>3</td>
<td>Shaft misalignment</td>
<td>C3</td>
<td>0.0004m mild steel shim beneath the left-hand-side (LHS) of AB1 foundation</td>
</tr>
<tr>
<td>4</td>
<td>Loose bearing</td>
<td>C4</td>
<td>Loosening some of the threaded bar nuts on AB3</td>
</tr>
<tr>
<td>5</td>
<td>Shaft rub</td>
<td>C5</td>
<td>Rub using a brass sleeve of 0.021m on R1, near D2</td>
</tr>
<tr>
<td>6</td>
<td>Cracked shaft</td>
<td>C6</td>
<td>0.004m (depth) x 0.00025m (width) crack on R1, at 0.16m from AB1</td>
</tr>
</tbody>
</table>

Figure 2: Experimental rig (23)

4. DATA PREPARATION AND FAULTS DIAGNOSIS

The primary objective of GVFI is to develop a technique that can detect and classify rotating machine faults irrespective of speeds and foundation flexibilities (i.e. MSMSMM in Figure 1). However, the process leading to the achievement of this objective was simplified by stratifying the preparation of the MSMSMM feature matrix. Initially, a matrix was constructed for a certain rotating machine at one speed, say RM, at 1200rev/min. In this feature matrix, the 120 sets of measured vibration data (20 data sets for each of the 6 experimentally simulated cases detailed in Table 1) formed the matrix rows (also referred to as observations). Equations (2) - (3) were then used to compute the pCCHOS (i.e. poly coherent composite bispectra (pCCB) and poly coherent
composite trispectra (pCCT) components amplitudes for each of the data sets, which then formed the matrix columns (also referred to as the features). It is worth noting that only the first 2 pCBB (B_{12}, and B_{10}) and pCCT (T_{111} and T_{112}) components were used, as previous studies [26] have already shown their adequacy in the diagnosis of several rotating machine faults at different speeds. Hence, a matrix containing 4 features (B_{11}, B_{12}, T_{111}, and T_{112}) and 120 observations was obtained, as detailed by Equation (8). The second stage (MSMSSM in Figure 1) focuses on fault identification under 3 machine speeds for the same machine (RM_1) where the feature matrix now contains 12 features (i.e. 2 pCBB and 2 pCCT features for each machine speed) and 120 observations. In the final stage the features obtained from stages 1 and 2 for both (RM_1 and RM_2) are then harmonised, thereby generating a feature matrix with 120 observations and 24 features (i.e. 12 features each for RM_1 and RM_2). During each of the stages, the constructed feature matrix is eventually fed into a PCA algorithm that computes the first 2 principal components (PCs). Since maximum representation can be obtained from the first few PCs, a graphical plot of the first and second PCs (Figure 3) is then used for classification of the different cases.

Results of the GVFI approach for MSMSSM (RM_1 and RM_2) are respectively shown in Figures 3(a)-(b). With the exception of the slight overlap between C1 and C3 cases, appreciable separation between all experimentally simulated cases is evident. The observed overlap between C1 and C3 cases was adjudged to be due to the very low severity of induced misalignment (i.e. 0.4 mm) in C3 case and the presence of inherent residual misalignment in the C1 case. On the other hand, the results of the MSMSMM shown in Figure 3(c) provided an even better separation for all considered cases, although a relatively small amount of overlap is still evident between the C1 and C3 cases. Therefore, the GVFI approach offers good potential for significantly reducing the rigour associated with performing separate analysis for solitary rotating machines at different speeds.
5. SENSITIVITY ANALYSIS OF GVFI APPROACH TO DATA AVAILABILITY

The combinations of pCCHOS (i.e. pCCB and pCCT) components have been successfully used to identify and classify various rotor-related faults at different machine speeds (26). For instance, Figure 4 shows how the combination of only $B_{11}$ pCCB and $T_{111}$ pCCT components distinctively separated 100 vibration data sets measured under 5 cases C1-C5 (i.e. 20 data sets per case) at 1800rev/min machine speed into their respective clusters.
While Figure 4 shows good classification for all case, this analysis has always been based on the premise that data from all 4 VCM sensors are available and intact (i.e. ideal scenario (IS)). However, this scenario may not always be obtainable in practice, due to occasional damages to VCM sensors or their accessories at certain measurement locations. In order to assess the sensitivity of pCHOS to varying conditions of measured vibration data availability, the 4 additional data scenarios (DS1-DS4) described in Table 2 were also examined.

### Table 2 Description of additional data scenarios

<table>
<thead>
<tr>
<th>Scenario(s)</th>
<th>Abbreviation</th>
<th>Accelerometers</th>
<th>Missing Data Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DS1</td>
<td>123</td>
<td>Bearing 4</td>
</tr>
<tr>
<td>2</td>
<td>DS2</td>
<td>234</td>
<td>Bearing 1</td>
</tr>
<tr>
<td>3</td>
<td>DS3</td>
<td>124</td>
<td>Bearing 3</td>
</tr>
<tr>
<td>4</td>
<td>DS4</td>
<td>134</td>
<td>Bearing 2</td>
</tr>
</tbody>
</table>

In all scenarios (DS1-DS4), only data from 3 VCM sensors were used to compute the pCCB and pCCT components (assuming that the 4th VCM sensor was damaged). Based on the current experimental rig and cases simulated, the omission of measured vibration data from certain measurement locations did not have any significant effect on the classification patterns for C1-C5. In fact, a comparison between Figures 4 and 5 shows that the clusters corresponding to each case under ideal scenario (IS) as well as the 4 additional data scenarios (DS1-DS4) were relatively consistent. For all scenarios, the C2 cluster consistently occupied the highest position owing to its possession of significantly greater B11 pCCB and T111 pCCT components amplitudes. Although C1, C4 and C5 cases for all scenarios had relatively similar T111 pCCT components amplitudes, the difference in their B11 pCCB components amplitudes still enabled tangible separations which further highlight the benefits of combining pCCB and pCCT components. Similarly, the C3 cluster was always located at the bottom left hand side of the plots for all scenarios due to its lower B11 pCCB and T111 pCCT components amplitudes.

![Figure 5](image_url)
6. CONCLUSION

The objective of the generic vibration-based faults identification (GVFI) technique discussed in this paper is to reduce the rigour and complexities that accompanies the practise of conducting separate vibration analysis for identically configured rotating machines with different foundations. In the study, several rotating machine conditions (healthy and faulty) were experimentally simulated on 2 identical experimental rigs with different foundations. Vibration data sets were then acquired from both rigs under each machine condition at various machine speeds. The measured vibration data under each machine condition and speed were used to independently compute poly coherent composite higher order spectra (pCCHOS) components that later formed the features of a principal components analysis (PCA) based algorithm, so as to develop a multiple sensor multiple speeds and multiple machine (MSMSMM) faults classification approach. The integrated GVFI approach discussed in this paper immensely emphasizes the importance of data combination approaches when trying to reduce the levels of human judgements associated with commonly used vibration-based faults identification (VFI) techniques such as amplitude spectrum analysis. Additionally, the paper examined and affirms the possibility of conducting VFI on rotating machines despite the unavailability of vibration data from some measurement locations. Overall, the discussed GVFI approach is versatile, robust, non-intrusive and computationally efficient, which therefore enhances its potential for usage in industries.

REFERENCE


