Development of a degradation index for machinery condition monitoring using the fictitious frequency response function and its application to a centrifugal compressor

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ABSTRACT

Recently, many sophisticated machinery diagnosis techniques have been developed and incorporated to the condition-based maintenance (CBM) method for cost effective and reliable operation of machinery. However, many companies are still reluctant to change their maintenance strategy completely from the traditional time-based maintenance (TBM) method due to their conservative approach. Instead, they often want to reduce the maintenance cost by increasing the time between overhaul (TBO) provided that a machine under inspection has not been degraded too much. In order to meet this need, in this paper, a degradation index is suggested as a measure to evaluate how much a machine has been degraded since its last overhaul service. The proposed degradation index is based on the fictitious frequency response function method. It is simple to interpret, and has a clear physical meaning. It is applied to an integrally geared centrifugal compressor and validated its usefulness. The results show that the suggested degradation index can be used as a good complement to both the TBM and CBM methods.

Keywords: Machinery condition monitoring, Condition-based maintenance (CBM), Time-based maintenance (TBM), Degradation index, Fictitious frequency response function, Vibration signal

1. Introduction

Machinery diagnosis techniques have been greatly advanced in recent years, and this has brought about the increasing number of adoption of the condition-based maintenance (CBM) method in many industries due to its cost effective and reliable operation of machinery. Several review papers introduce the details of the CBM method with regard to implementation, and emphasize its importance in maintenance strategy: Jardine et al. summarized various data processing methods and maintenance decision-making approaches [1]. Jayaswal et al. discussed many conventional and recent techniques for machine fault signature analysis with particular regard to rolling contact bearing fault diagnosis through vibration analysis [2]. Peng et al. categorized various techniques and algorithms for prognostic models and summarized their advantages and disadvantages [3]. In particular, Ahmad et al. presented an overview of the TBM and CBM techniques and discussed the challenges in implementing each technique from a practical point of view [4].

The CBM method becomes more intelligent and sophisticated in these days. For example, artificial neural network (ANN) is used to optimize for predicting the remaining useful life [5], fault classification rules are updated adaptively and online condition monitoring schemes are developed [6-7], Hong et al. proposed a feature extraction method by combining the wavelet packet transform, the empirical mode decomposition, and the neural network [8].

Despite of these recent advances in machinery condition monitoring techniques and the CBM method, many companies are still reluctant to change their maintenance strategy completely from the traditional time-based maintenance (TBM) method to the CBM method due to their conservative approach. This is partly due to that such sophisticated CBM strategies require sufficient expertise for data interpretation and sufficient pre-knowledge about the machines and their components [7], and partly due to that further research on CBM is still necessary in order to make it more realistic for making maintenance decisions [4]. Thus, many companies may remain in using the TBM method until sufficient number of proven data on the CBM method is provided. In most TBM strategies, however, it is likely to encounter planned shutdowns of systems for predetermined overhaul or repair services on still well-functioning equipments, and the TBM tends to be too conservative that results in very high maintenance costs [3]. As a result, while not adopting the CBM method fully, a company often wants to reduce the maintenance costs by setting up the overhaul period more flexible provided that a machine under inspection has not been deteriorated too much.

In order to meet this need, in this paper, a degradation index is suggested as a measure to evaluate how much a machine has been degraded since its last overhaul service. The suggested degradation index is not intended for detecting a fault symptom, but for giving a general guideline to examine overall machine degradation and to decide whether an overhaul service is needed earlier or later than the predetermined schedule. The degradation index is developed...
The concept of the fictitious FRF was first introduced by Shin et al. for a source localization problem [9], and then the fictitious FRF has been applied to a machinery fault detection problem [10] and used as an alternative measure of similarity between two deterministic signals [11]. In particular, Shin et al. verified that the fictitious FRF based fault detection method is especially useful for detecting an incipient fault in a rotating machine [10]. In this paper, the fictitious FRF based fault detection method is modified to represent the overall degradation of a machine, and the degradation index is suggested as a criterion of degradation. An example of using the degradation index is then presented by applying it to a centrifugal compressor. The results validate its usefulness by showing distinctive changes in values of the degradation index between the beginning and last phases of the time between overhaul (TBO) of the investigated compressor.

2. Degradation index based on the fictitious FRF

2.1. A brief review of the fictitious FRF based fault detection method

In this section, a brief description of the principle of the fictitious FRF based fault detection method is given. Suppose \( X(f) \) and \( Y(f) \) are measured signals in the frequency domain acquired at two well-separated points in healthy operating condition. If the distance between two measurement points is sufficiently large such that two signals are nearly uncorrelated (but not perfectly uncorrelated) within the frequency range of interest, the cross-spectral density function between two signals can be written as

\[
S_{X,Y}(f) \approx 0
\]  
(1)

Later, if a new fault arises in the machine that produces a new excitation force signal, \( S(f) \) within the frequency range of interest, and let \( Y_1(f) \) and \( Y_2(f) \) be newly measured signals at the same points as depicted in Figure 1, then the cross-spectral density function between two signals at this particular frequency component becomes

\[
S_{Y_1,Y_2}(f) \approx H_1^*(f)H_2(f)S_{ss}(f)
\]  
(2)

Figure 1. Single input - two outputs model

Equation (2) shows that the cross-spectrum contains the fault power. However, in some cases, the fault power may be too small to detect properly due to a poor signal-to-noise ratio. This problem can be overcome by constructing a fictitious input-output relationship between two cross-spectral density functions as shown in Figure 2.

\[
S_{H(f)} = \frac{S_{Y_1,Y_2}(f)}{S_{X,X_2}(f)} = \frac{H_1^*(f)H_2(f)S_{ss}(f)}{S_{X,X_2}(f)}
\]  
(3)

The fictitious FRF, \( H_{\text{fic}}(f) \), describes the relationship between the current machine condition and the healthy initial machine condition, and can be written as

\[
H_{\text{fic}}(f) = \frac{S_{Y_1,Y_2}(f)}{S_{X,X_2}(f)} = \frac{H_1^*(f)H_2(f)S_{ss}(f)}{S_{X,X_2}(f)}
\]  
(4)

Equation (3) shows that the magnitude of the fictitious FRF has the ability to amplify the fault source power greatly because the denominator. \( S_{X,X_2}(f) \), is very small in the frequency range of interest. This illustrates that the use of fictitious FRF can be very helpful to detect any new fault symptoms whose frequency components are not correlated with those in healthy condition.

2.2. Fictitious FRF for the correlated frequency region

In the previous section, the excitation source, \( S(f) \) is assumed to be not present at initial state and thus is not correlated with the initially measured signals \( X(f) \) and \( X_2(f) \). In other words, the fictitious FRF based fault detection method is focused on the frequency regions where no excitation components are found in healthy operating condition. However, in general, many excitation frequency components are already exist even in healthy operating condition such as residual unbalance, dynamic eccentricity and blade passing frequency components. The amplitudes of vibration associated with these correlated excitation components may increase relative to the initial state as the machine operating time increases. Based on this perception, the fictitious FRF based fault detection method is modified to represent the overall degradation of machine condition relative to its healthy initial condition.

Suppose the excitation source \( S(f) \) is present at initial state. As is often the case, there may be changes in amplitude and phase of the excitation source after some time of operation. Then the excitation source may be written as \( A(f)S(f)e^{j\phi(f)} \), where \( A(f) \) and \( \phi(f) \) denote amplitude and phase changes in a specific frequency component, respectively. In such a case, cross-spectral density functions in equations (1) and (2) changes as below

\[
S_{X,X_2}(f) = \left| H_{\text{fic}}(f) \right| S_{ss}(f)
\]

And, the corresponding fictitious FRF becomes

\[
H_{\text{fic}}(f) = \frac{S_{Y_1,Y_2}(f)}{S_{X,X_2}(f)} = \frac{A^2(f)H_1^*(f)H_2(f)S_{ss}(f)e^{j2\phi(f)}}{S_{X,X_2}(f)}
\]  
(5)

It is noted that the magnitude spectrum of the fictitious FRF is a simple gain to illustrate how much the machine condition is degraded relative to its initial condition at a particular frequency component. Thus, equation (5) may be utilized to construct the degradation index as described in the next section.

2.3. Degradation index

As can be seen from equations (1) - (4), cross-spectral density functions, \( S_{X,X_2}(f) \) and \( S_{Y_1,Y_2}(f) \) consist of both correlated and uncorrelated frequency components. The amplitudes of the uncorrelated frequency components in \( S_{X,X_2}(f) \) are very small as...
shown in equation (1), whereas peaks in $S_{X_iX_j}(f)$ and $S_{YY}(f)$ are the correlated components. Suppose that $S_{X_iX_j}(f)$ is obtained at the beginning of the time between overhaul (TBO), and $S_{YY}(f)$ is obtained at later time. If we assume that the condition of a machine deteriorates gradually with time without a new notable defect, it is expected that the magnitudes of peaks in $S_{YY}(f)$ are greater than those in $S_{X_iX_j}(f)$, and may increase further until the last phase of the TBO. That is, as mentioned earlier, the correlated frequency components are related to the gradual machine degradation while a new fault symptom can be detected by observing the uncorrelated frequency components. Thus, only the correlated components are needed to account for the degradation index. The initial cross-spectral density function, $S_{X_iX_j}(f)$ in equation (5) is replaced with the envelope of $S_{X_iX_j}(f)$ for this purpose. The envelope can be constructed by connecting peaks in the magnitude spectrum of cross-spectral density function. Then, assuming that the symptom of machine degradation is mostly reflected to the frequency component having the largest amplitude in the fictitious FRF, the degradation index is defined as below.

$$DL_{i,j} = \operatorname{Max} \left( \frac{|S_{YY}(f)|}{|S_{X_iX_j}(f)|} - 1 \right)$$  \hspace{1cm} (6)

where $i$ and $j$ are the $i$-th and $j$-th measurement points, and $|S_{X_iX_j}(f)|$ is the enveloped magnitude spectrum of the cross-spectral density function. An example of the enveloped spectrum is shown in the next section.

If the degradation index, $DL_{i,j}$ is zero, the peaks in the newly obtained cross-spectral density functions, $S_{YY}(f)$ are equal to or less than those in the initial cross-spectral density function. This implies that the machine under inspection is as healthy as initial condition. On the other hand, the value of $DL_{i,j}$ may increase as the condition of machine deteriorates. Thus, it may be possible to evaluate whether the machine needs a further special inspection or an overhaul service by observing the degradation index regularly. If multiple degradation indexes are desirable, for example when applying to a large rotating machine having many bearings, the following weighted average of degradation indexes may be suggested to represent the overall condition of the machine, i.e., the overall degradation index is defined as

$$\bar{DL} = \frac{1}{N} \sum_{k=1}^{N} w_k DL_{i,j} \left( \sum_{k=1}^{N} w_k = N \right)$$  \hspace{1cm} (7)

where $DL_{i,j}$ is the $k$-th degradation index, $w_k$ is the corresponding weighting factor, and $N$ is the number of degradation indexes.

3. An application to a centrifugal compressor

In this section, the use of the degradation index is demonstrated by applying it to an integrally geared centrifugal compressor having three compression stages supported by four bearings as illustrated in Figure 3.

As is emphasized in [2], the most important and effective locations for measurement sensors are near bearings. Thus, four accelerometers are attached on bearing housings as depicted in Figure 3, and vibration signals are acquired with 4 kHz sampling rate. Two cases of compressor conditions are considered in this example: Case A is the condition when an overhaul service is recently performed, and Case B is the condition at the last phase of the manufacturer’s recommended TBO. While no particular fault symptom is observed for both cases, the feasibility of using the degradation index is examined by comparing the values of degradation indexes for two cases. Also, two pairs of measurement sensors are considered for calculating degradation indexes, sensors #1 and #2 for $DL_{1,2}$ and sensors #3 and #4 for $DL_{3,4}$, respectively.

Vibration signals are measured for 600 seconds for each case, and each signal is divided into 12 equal data blocks. Cross-spectral density functions are then calculated for each data block with a frequency resolution of 1Hz using the segment averaging method, where each segment is 1 second long and the Hann window with 50% overlap is used. A typical example of the measured time signal is shown in Figure 4(a), and the magnitude spectrum of the cross-spectral density function and its envelope are shown in Figure 4(b), where the envelope is constructed by interpolation after finding the peak values in the cross-spectral density function.
The individual degradation indexes, $DI_{1,2}$ and $DI_{3,4}$, are calculated using equation (6) for each data block of two cases A and B. As shown in Figure 5, the degradation indexes of Case A are relatively very small whereas those of Case B show great increases in their values. That is, the degradation indexes at the last phase of TBO are significantly greater than those at the beginning of TBO.

From Figures 5(a) and 5(b), it is observed that the degradation indexes of Case B are notably fluctuating across data blocks while those of Case A are not varying greatly. This indicates that non-stationarity may also be built up as the operating time of the machine reaches the last phase of TBO.

The individual degradation indexes averaged over all data blocks are summarized in Table 1, together with the overall degradation indexes calculated by equation (7) with equal weighting factors. It is noted that the degradation index, $DI_{1,2}$ of Case B is approximately nine times greater than that of Case A, and is nearly twice the $DI_{3,4}$ of Case B. This may imply that the first and second compression stages of the compressor are worn out more than the third compression stage. The overall degradation index, $\overline{DI}$ of Case B is more than seven times greater than that of Case A. This considerable changes in values of the degradation indexes between the beginning and last phases of the TBO demonstrate that the suggested degradation index can be used as an informative measure to decide whether an overhaul service is necessary or not. That is, a more flexible overhaul schedule can be allowed, and thus efficient and cost effective maintenance of machines can be performed by monitoring the degradation indexes.

![Cross-spectrum and its envelope](image)

**Figure 4.** Example of measured vibration signal: (a) time history and (b) cross-spectrum and its envelope

![Degradation index comparison](image)

**Figure 5.** Degradation indexes calculated for each data block: (a) Case A and (b) Case B

<table>
<thead>
<tr>
<th>Case</th>
<th>$DI_{1,2}$</th>
<th>$DI_{3,4}$</th>
<th>$\overline{DI}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.57</td>
<td>0.49</td>
<td>0.53</td>
</tr>
<tr>
<td>B</td>
<td>4.95</td>
<td>2.75</td>
<td>3.85</td>
</tr>
</tbody>
</table>

**Table 1.** Degradation indexes ($DI_{i,j}$) averaged over all data blocks and Overall degradation indexes ($\overline{DI}$) with equal weighting values

4. **Conclusions**

In this paper, the degradation index is introduced as a measure of overall degradation of a machine. The suggested index can be used to evaluate how much a machine has been degraded since its last overhaul service. This is verified by applying it to two cases of an integrally geared centrifugal compressor: Case A is the condition at the beginning phase of the TBO, and Case B at the last phase of the TBO. It is seen that the degradation indexes of Case B are significantly larger than those of Case A. This verifies that the suggested degradation index can be used as a guideline to determine whether an overhaul service is necessary or not. Consequently, without adopting a sophisticated CBM method, an efficient and cost effective maintenance scheme may be achieved by monitoring the degradation indexes regularly. That is, the traditional TBM method can be modified to perform overhaul services more flexibly by setting up a reference value of the degradation index after accumulating many relevant data for a specific type of machine.
Because the proposed degradation index is based on the fictitious FRF method that has been used for detecting an incipient fault in a rotating machine [14], both the incipient fault and the overall machine degradation can be monitored simultaneously by examining the correlated components and uncorrelated components of the fictitious FRF separately. Thus, the use of the degradation index in conjunction with the fictitious FRF based fault detection method may well be incorporated into many CBM strategies.

Acknowledgments

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References