INTELLIGENT CONDITION INDICES IN FAULT DIAGNOSIS

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ABSTRACT

Automatic fault detection enables reliable condition monitoring even when long periods of continuous operation are required. Dimensionless indices provide useful information on different faults, and even more sensitive solutions can be obtained by selecting suitable features. These indices combine two or more features, e.g. root-mean-square values and peak values. Additional features can be introduced by analysing signal distributions, for example. The features are generated directly from the higher order derivatives of the acceleration signals, and the models can be based on data or expertise. Generalised moments and norms introduce efficient new features which even alone can provide good solutions with automation systems, but combining several easily calculated features is an efficient approach for intelligent sensors. The nonlinear scaling used in the linguistic equation approach extends the idea of dimensionless indices to nonlinear systems. Indices are obtained from these scaled values by means of linear equations. Indices detect differences between normal and faulty conditions and provide an indication of the severity of the faults. They can even classify different faults in case-based reasoning (CBR) type applications. Additional model complexity, e.g. response surface methods or neural networks, does not provide any practical improvements in these examples. The indices are calculated with problem-specific sample times, and variation with time is handled as uncertainty by presenting the indices as time-varying fuzzy numbers. The classification limits can also be considered fuzzy. Condition indices can be obtained from the degrees of membership which are produced by the reasoning system. Practical long-term tests have been performed e.g. for diagnosing faults in bearings, in supporting rolls of lime kilns and for the cavitation of water turbines. The indices obtained from short samples are aimed for use in the same way as the process measurements in process control. The new indices are consistent with the measurement index MIT and the health index SOL developed for condition monitoring.

1. INTRODUCTION

Attempts to detect different types of machine faults reliably at an early stage requires improved signal processing methods and intelligent fault diagnosis. Vibration measurements provide a good basis for condition monitoring. Dimensionless indices are obtained by comparing each feature value with the corresponding value in normal operation. These indices provide useful information on different faults, and even more sensitive solutions can be obtained by selecting suitable features. Generalised moments
and norms include many well-known statistical features as special cases and provide compact new features capable of detecting faulty situations \(^{(2)}\).

Intelligent models extend the idea of dimensionless indices to nonlinear systems. Operating conditions can be detected by means of a Case-Based Reasoning (CBR) type application with linguistic equation (LE) models and Fuzzy Logic \(^{(3,4,5)}\). The basic idea is nonlinear scaling, which was developed to extract the meanings of variables from measurement signals \(^{(6)}\). The LE models are linear equations

\[
\sum_{j=1}^{m} A_{ij} X_j + B_i = 0 \tag{1}
\]

where \(X_j\) is a linguistic level for the variable \(j, j=1...m\). Each equation \(i\) has its own set of interaction coefficients \(A_{ij}, j = 1...m\). The bias term \(B_i\) was introduced for fault diagnosis systems. Various fuzzy models can be represented by means of LE models, and neural networks and evolutionary computing can be used in tuning. The first LE application in condition monitoring was presented in \(^{(7)}\). The condition monitoring applications are similar to the applications intended for detecting operating conditions in the process industry \(^{(8)}\).

This paper deals with condition indices and fault models with special emphasis on nonlinear scaling and linguistic equations.

2. FEATURE EXTRACTION

Feature extraction is based on velocity \(x^{(1)}\), acceleration \(x^{(2)}\) and higher derivatives, \(x^{(3)}\) and \(x^{(4)}\). The other signals have been obtained from acceleration through analogue \(^{(9)}\) or numerical integration and derivation \(^{(10)}\).

2.1 Statistical features

Signals \(x^{(a)}\) can be analysed with standard deviation,

\[
\sigma_{a} = \left( \frac{1}{N} \sum_{i=1}^{N} \left( x^{(a)}_i - \bar{x}^{(a)} \right)^2 \right)^{1/2}, \tag{2}
\]

and kurtosis,

\[
\beta_{a2} = \frac{1}{N\sigma_{a}^4} \sum_{i=1}^{N} \left( x^{(a)}_i - \bar{x}^{(a)} \right)^4, \tag{3}
\]

where \(\bar{x}^{(a)}\) is the arithmetic mean of the signal values \(x^{(a)}_i, i = 1,..,N\), and \(a\) is a real number. Root-mean-square of \(x^{(a)}\), i.e. \(x^{(a)}_{rms}\) is \(\sigma_{a}\) when \(\bar{x}^{(a)} = 0\).

These features have been used for fault diagnosis in a test rig which consists of an electric motor and a transmission between two axes with roller bearings \(^{(7)}\). The rig was to simulate different fault modes. Independent fault modes were rotor unbalance at two levels, three coupling misalignment cases between the motor and input shaft, bent shaft, and three bearings faults. One fault at time was simulated at five rotation speeds, and vibration data were collected using seven acceleration sensors. The offset was removed from the signals before calculating the features: rms and kurtosis of the acceleration \(x^{(2)}\), the average of the highest three values of the jerk \(x^{(3)}\), and rms velocities \(x^{(1)}_{rms}\) in two frequency ranges, 10-1000 Hz and 20-85 Hz.
The cavitation analysis for a Kaplan water turbine in (9) was based on two features: the mean peak \( x_{mpx}^{(a)} \) and the fraction \( F_h^{(a)} \) of the peaks exceeding the normal range \([-3\sigma_a, 3\sigma_a]\) obtained from the signal \( x^{(a)} \), \( a = 1, 3 \) and \( 4 \). The feature values for \( x^{(3)} \) and \( x^{(4)} \) are quite similar and give an indication of cavitation points. The velocity incorrectly shows a high indication of cavitation in some cases. The power range, which is free of cavitation, was taken as a basis for detecting an increase in the signal levels. The fractions \( F_h^{(a)} \) have low values in the low power range where the spikes are less frequent. The values rise with increasing power as the number of small spikes grows. This can be heard as an increasing noise.

The velocity \( x^{(1)} \) was replaced by the acceleration \( x^{(2)} \) in (10,11). The numerical derivation and integration of the acceleration signals were performed with LabVIEW, and all the signals were filtered by means of a sixth order Butterworth bandpass filter. The frequency ranges were 10-1000 Hz, 10-2000 Hz, 10-3000 Hz and 10-4000 Hz. Signals \( x^{(a)} \), \( a = 2, 3 \) and \( 4 \), were analysed in each frequency range by means of rms values, kurtosis and peak values. As the peak values are based on the highest three peaks in the discretised values, the three values may also originate from a single peak. The kurtosis is a useful feature in the low power range but for the cavitation-free area and the high power range, the kurtosis is close to value 3, which corresponds to a Gaussian signal, i.e. kurtosis does not give an indication of cavitation in the high power range. An alternative feature for kurtosis is peak value, which has fairly similar changes in the low power range and small changes in the high power range.

Detecting bearing faults and imbalance in fast rotating bearings (12) was based on standard deviations calculated for the signal \( x^{(4)} \) on three frequency ranges: 10-1000 Hz, 10-10000 Hz and 10-50000 Hz. Unbalance was clearly detected on the basis of the standard deviations obtained from the lowest frequency range. Several signals had to be combined for detecting the other faults. In this case the rotation frequency was in the range 65-525 Hz.

2.2 Signal distribution

The distributions of the signals \( x^{(1)} \), \( x^{(3)} \) and \( x^{(4)} \) have been used in monitoring the condition of the supporting rolls of a lime kiln (13,14). Fault situations were detected as a large number of strong impacts. The bins \( F_k^{(a)} \) of the histograms are based on the standard deviation \( \sigma_a \) of the corresponding signal \( x^{(a)} \) in the following way: (k=1) \( x^{(a)} \leq 2\sigma_a \), (k=2) \( 2\sigma_a \leq x^{(a)} < 3\sigma_a \), (k=3) \( 3\sigma_a \leq x^{(a)} < 4\sigma_a \), (k=4) \( 4\sigma_a \leq x^{(a)} < 5\sigma_a \), and (k=5) \( x^{(a)} \geq 5\sigma_a \), where \( a \) is the order of derivative. The velocity signal only shows very small differences between a serious surface problem and an excellent condition. For signals \( x^{(3)} \) and \( x^{(4)} \), large values for the features \( \sigma_a \) and the fractions \( F_k^{(a)} \), \( k=4 \) and \( 5 \) are related to faulty situations, and large values for the fractions \( F_k^{(a)} \), \( k=1\ldots3 \) are obtained in normal conditions. Similar results can be obtained with bins defined by the absolute average of the signals, and the resulting easier calculation is useful for developing intelligent sensors.

2.3 Generalised moments and norms

The generalised central moment can be normalised by means of the standard deviation \( \sigma_a \) of the signal \( x^{(a)} \):
\[
\tau \sigma M^p = \frac{1}{N(\sigma^2)} \sum_{i=1}^{N} |x_i^{(\alpha)} - \overline{x}^{(\alpha)}|^p. \quad \text{.......................... (4)}
\]

which was presented in \textsuperscript{(15)}. The order of derivation ranges from 1 corresponding to velocity to 4, which corresponds to the signal \(x^{(4)}\). The moment \(\tau \sigma M^2 = 1\), and the moment \(\tau \sigma M^4\) correspond to the kurtosis of the signal. The norm defined by means of

\[
\|\tau \sigma M^p\|_p = \left( \frac{1}{N} \sum_{i=1}^{N} |x_i^{(\alpha)}|^p \right)^{1/p}, \quad \text{.......................... (5)}
\]

was taken into use in \textsuperscript{(2)}.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Relative max(\(\|\tau \sigma M^p\|_p\)) when \(\alpha = 1, 3\) and 4, \(\tau = 3\) s and \(p = 8, 3\) and 2.75, and the knowledge-based cavitation index \(I^*_C\).}
\end{figure}

The knowledge-based cavitation index \(I^*_C\) (Figure 1) provides an indication of both clear cavitation and clearly good operation. Values -2 and -1 indicate good operating conditions. Value 1 corresponds to clear signs of cavitation, and value 2 means a very strong indication of cavitation.

The relative max(\(\|\tau \sigma M^{2.75}\|_p\)) provides a good indication for cavitation as explained in \textsuperscript{(2)}. The relative max(\(\|\tau \sigma M^{p}\|_p\)) is obtained by comparing max(\(\|\tau \sigma M^{\alpha}\|_p\)) at each power to the max(\(\|\tau \sigma M^{2.75}\|_p\)) at 15 MW. A slightly higher order of moment is needed for the signal \(x^{(3)}\) than for \(x^{(4)}\): The cavitation-free area and the cavitation cases at 2 and 10 MW are clearly detected. However, the values of the relative max(\(\|\tau \sigma M^{\alpha}\|_p\)) at 2 MW are slightly higher than for the relative max(\(\|\tau \sigma M^{2.75}\|_p\)). A much higher order of moment is needed for the signal \(x^{(1)}\): the strongest cavitation at 2 MW is detected with the relative max(\(\|\tau \sigma M^{\alpha}\|_p\)), and also the cavitation-free area is recognised. However, all the other cavitation cases would be classified as cases of short periods of cavitation.
2.4 Nonlinear scaling

The features described above are informative, some of them are dimensionless and normalized. However, the analysis can be further improved by taking into account nonlinear effects \(^{(7,9,12,13)}\). Operating conditions can be detected with a Case-Based Reasoning (CBR) application with linguistic equation (LE) models and Fuzzy Logic. The basic idea of the linguistic equation (LE) methodology is the nonlinear scaling developed to extract the meanings of variables from measurement signals. The scaling function scales the real values of variables to the range of \([-2, +2]\) which combines normal operation \([-1, +1]\) with the handling of warnings and alarms. The scaling function contains two monotonously increasing functions: one for the values between -2 and 0, and one for the values between 0 and 2. Both expertise and data can be used in developing the mapping functions (membership definitions) \(^{(5)}\).

The membership definition \(f\) consists of two second-order polynomials, i.e. the scaled values, which are called linguistic levels \(X_j\), are obtained by means of the inverse function \(f^{-1}\):

\[
X_j = \begin{cases} 
2 \text{ with } x_j \geq \max(x_j) \\
\frac{-b_j + \sqrt{b_j^2 - 4a_j(c_j - x_j)}}{2a_j} \text{ with } c_j \leq x_j \leq \max(x_j) \\
-2 \text{ with } x_j \leq \min(x_j) \\
-\frac{b_j + \sqrt{b_j^2 - 4a_j(c_j - x_j)}}{2a_j} \text{ with } \min(x_j) \leq x_j \leq c_j \\
-2 \text{ with } x_j \leq \min(x_j)
\end{cases} 
\] ................................. (6)

where \(a_j\), \(b_j\), \(a_j^*\) and \(b_j^*\) are coefficients of the corresponding polynomials, \(c_j\) is a real value corresponding to the linguistic value 0 and \(x_j\) is the actual measured value. Parameters \(\min(x_j)\) and \(\max(x_j)\) are minimum and maximum values corresponding to the linguistic values -2 and 2. \(^{(5)}\)

Nonlinear scaling has been used in previous studies for statistical features \(^{(7,9)}\), and features based on the signal distribution \(^{(13,14)}\). The scaling functions shown in Figure 2 were obtained with a data-driven approach from the features obtained at ten power levels: 2, 3, 5, 8, 12, 25, 45, 57.5, 58.1 and 59.4 MW. For each feature, the level 0 was obtained as a median of the values in the training set, and the levels -1 and 1 as medians of the lower and higher halves of the values, respectively. A cavitation index can be obtained by scaling the norm \((5)\) with the function \((6)\):

\[
I_C^\alpha = f^{-1}_\alpha(\text{relative max}(\|M_\alpha^\|)). 
\] ................................. (7)

Figure 2. Scaling functions of the relative \(\text{max}(\|M_\alpha^\|)\), \(\alpha = 1, 3 \text{ and } 4\), in a Kaplan water turbine.
3. Model-based fault diagnosis

Operating conditions can be detected by combining several features in case-specific models. Model-based cavitation indices are needed for a detailed analysis (10, 11).

3.1 Fault models

The machine condition monitoring application presented in (7) was based on models developed for normal operation and nine fault cases. One fault at a time was simulated at five rotation speeds. In each case the model consists of seven LE models developed for a sensor-specific variable group including the rotation speed and five features obtained from the measurements of the sensor. The sequence of the LE models is case-specific, and each equation has a weight factor \( w_{ij} \). The error \( \epsilon_i \), also called fuzziness, is calculated for each LE model by means of

\[
\epsilon_i = \sum_{j=1}^{m} A_{ij} X_j + B_i \]

Figure 3. Cavitation indices \( I_{C}^{(\alpha)} \) based on the scaled features, \( \alpha = 1, 3 \) and 4, in a Kaplan water turbine.

The nonlinear scaling is based on functions shown in Figure 2. The indices \( I_{C}^{(\alpha)} \), \( \alpha = 1, 3 \) and 4, were compared to the knowledge-based cavitation index \( I_{C}^{*} \) at 29 power levels varying from 1.5 to 59.4 MW (Figure 3). The coefficients of determination \( R^2 \), calculated as the square of the correlation coefficient are high for all the signals \( x^{(1)}, x^{(3)} \) and \( x^{(4)} \) (Figure 3). The index \( I_{C}^{1} \) based on the velocity signal has the lowest \( R^2 \) value, and also the classification result is the worst of these three. The index \( I_{C}^{3} \) has the highest \( R^2 \) value but the index \( I_{C}^{4} \) has the best classification result.
The models of the normal case already provide useful information, as higher fuzziness is detected in the fault cases, and each model has its own sensitivity profile (Figure 4):

- The first four models detect very clearly the differences caused by the bearing faults (data points 4001-5500).
- Model 5 detects the stronger rotor unbalance (data points 1501-2000).
- The bent shaft (data points 2001-2500) is detected with models 3 and 4.
- The shaft misalignment (data points 2501-4000) is seen in the fuzziness of the models 6 and 7.

The degree of membership of each equation, denoted as $\mu_i$, is based on the distribution of error represented as a trapezoidal membership function developed on the basis of the train case, see Figure 4. Since the degree of membership of the case is evaluated as the weighted average of the degrees of membership of the individual equations, the condition index $C_k$ of each case $k$ can be represented by means of

$$C_k = 4 \sum_{i=1}^{7} \frac{w_{ki} \mu_i}{\sum_{i=1}^{7} w_{ki}} - 2.$$ ................................. (9)

For fast-rotating bearings, the condition index $Ind$ is a sum of the scaled standard deviations of the signal $x^{(4)}$ calculated for three frequency ranges.

$$Ind = f_{41}^{-1}(\sigma_{41}) + f_{42}^{-1}(\sigma_{42}) + f_{43}^{-1}(\sigma_{43})$$ ................................. (10)
where $f_{4i}^{-1}$ is the scaling function of the standard deviation $\sigma_{4i}$ in three frequency ranges 10 –1000 Hz, 10 –10000 Hz, and 10 –50000 Hz. The faults are correctly detected by means of the algorithm (12):

- Calculating the condition index.  
- The condition is normal if $\text{Ind} < -5$…-4.  
- There is an outer race fault in the bearings if $\text{Ind} < 0$.  
- The condition is unbalance if the index for the low frequency range is very high,  
- Otherwise the condition is inner race fault in the bearings.

The minimum of the index $\text{Ind}$ is -6 which is achieved when all the features are at the lowest level.

The ranges of the $\text{Ind}$ values in the cases, $k = 1, 2, 3$ and 4, as shown in Figure 5, can also be represented as trapezoidal membership functions, and then the condition index of an individual case is calculated from the corresponding degree of membership:

$$C_k = 4 \mu_k - 2.$$  

Unbalance is efficiently detected with the lowest frequency range $f_{41}^{-1}(\sigma_{41})$ and inner race fault with the features $f_{42}^{-1}(\sigma_{42})$ and $f_{43}^{-1}(\sigma_{43})$ (12). However, the complete index $\text{Ind}$ is needed for detecting the outer race fault.

![Figure 5. Condition index for fast-rotating bearings, the rotation frequencies were from 65 to 525 Hz](image)

**3.2 Case-based reasoning**

A CBR type approach was used for the test rig (7): the degree of membership was calculated as explained above for all nine cases, and the case with the highest degree of membership was chosen. The classification results were very good. There are some faulty classified measurements but the mistakes are very logical, e.g. small unbalance and normal state. Misalignment increases when moving from class 5 to class 7. A small misalignment and the normal state are also close to each other. In all the ten cases, mistakes only occur between very similar classes. The system placed practically all the bearing faults into the right classes. The fault models and the CBR system are necessary since the five features obtained from the signals and the rotation speed need to be combined (Section 2.1). Since the difference between the bearing faults was more prominent than the difference between misalignment cases, there is more confusion in the misalignment categories.

**4. CONDITION INDICES**

The purpose with condition indices is to extract indirect measurements from the signal samples. Possibility to use short samples is beneficial for automatic fault detection.
4.1 Cavitation index

The intelligent cavitation indicator developed in (9) for a Kaplan water turbine is based on the nonlinear scaling of two features: peak height and the fraction of the peaks exceeding the normal limit. The classification results obtained from the experimental cases involving the water turbine were very good and logical. Different cavitation types, some causing low frequency vibration on structure and some only leading to fast impacts, can be identified. The indicators detect the normal operating conditions, which are free of cavitation, and also provide a clear indication of cavitation already at an early stage. The index obtained from the signal \( x^{(4)} \) is the best alternative but also the index obtained from the signal \( x^{(3)} \) provides good results throughout the power range. The cavitation indicator also provides warnings of a possible risk on short periods of cavitation. Uncertainties can be taken into account by extending the feature calculations and classification rules to fuzzy set systems.

Features of velocity \( x^{(1)} \), acceleration \( x^{(2)} \) and higher derivatives, \( x^{(3)} \) and \( x^{(4)} \) were compared in (10,11). The features of velocity had a very low correlation with the knowledge-based cavitation index. Strong cavitation can be detected with the features of other signals in the low frequency range, even in the range 10-1000 Hz. Kurtosis combined with rms values was the best combination in the low frequency range, but widening the frequency range makes the peak values better than kurtosis. Several model-based indicators based on nonlinear scaling and linear equations provide a good fit to the cavitation index. In this example, only higher derivatives can be used in the practical classification for cavitation, short-term cavitation and cavitation-free operating conditions. The indices obtained from \( x^{(4)} \) are the best alternatives.

Generalised moments and norms can also be used in the model-based cavitation indices. The generalised moment (4) indicates possible cavitation but one moment value is not enough for a detailed analysis (15): the moments should be combined with other features, e.g. rms values used in (10). The norm (5) introduced in (2) can be used alone, see (7), if the order \( p \) is chosen correctly. Combined indices, where several orders \( \alpha \) are used, require tuning of the scaling functions.

The health index SOL can be calculated from the cavitation index by means of

\[
SOL = 1 - \frac{I_C^* + 2}{4}(1 - \delta), \quad \text{............................................................... (11)}
\]

where \( \delta \) is the value of SOL index when the cavitation index \( I_C^* = 2 \). The measurement index MIT (2) is an inverse of the index SOL. If the parameter \( \delta = 0.2 \), the highest values of the index MIT are 5 (Figure 6).

![Figure 6. SOL and MIT indices obtained from the knowledge-based cavitation index in a Kaplan water turbine.](image-url)
4.2 Condition index

In the lime kiln application, the features were combined with a linguistic equation, i.e. \( i = 1 \) in (1). The condition index \( I_C \) is a number between -2 and 2, and the interaction coefficients \( A_j, j = 1...6 \), are based on expertise \( ^{13,14} \). \( A = [-2 1 1 1 -1 -1] \) includes the coefficients of the scaled features and the condition index. The same coefficients are used for both signals \( x^{(3)} \) and \( x^{(4)} \). Compared to (1), the index \( I_C \) corresponds to \( -B_i \):

\[
I_C = -2f_1^{-1}(\sigma_a) + f_2^{-1}(F_1^{(a)}) + f_3^{-1}(F_3^{(a)}) + f_4^{-1}(F_3^{(a)}) - f_5^{-1}(F_3^{(a)}) - f_6^{-1}(F_3^{(a)}) \ldots \ldots (12)
\]

The condition index developed for the supporting rolls of a lime kiln provides an efficient indication of faulty situations. Surface damage is clearly detected and friction increase is indicated at an early stage. The features are generated directly from the higher order derivates of the acceleration signals, and the model is based on expertise. All the supporting rolls can be analysed using the same system. The index \( I_C^{(4)} \) is very good and logical for all the measurement points, which makes it already suitable for practical applications. The index \( I_C^{(3)} \) requires further tuning. \(^{14}\)

The health index SOL and the measurement index MIT can be calculated from the condition index, the only difference to the cavitation case is that the condition index is a measure of good condition, i.e. value 2 corresponds to excellent condition. Figure 7 shows the results of 6 cases for two measurement points from a period of three years: fault situations include surface damage (case 1) and misalignment (cases 3 and 4).

![Figure 7. SOL and MIT indices obtained from the condition index of supporting rolls in a lime kiln.](image)

(b) Measurement point 2 B.

5. TUNING

The parameters of the scaling functions can be tuned by means of neural networks or genetic algorithms, for example: similar tuning approaches can be used for different LE models and condition indices \(^{5}\). For example, the cavitation indices \( I_C^{(a)} \) in Figure 3 can be improved in this way. Additional model complexity, e.g. response surface methods or neural networks, does not provide any practical improvements in these examples. Genetic algorithms have also been used for selecting sensors and features in the test rig study. Another possibility is to use artificial immune systems. The tuning and testing of the condition indices will be continued with measurements available in a large database.

6. CONCLUSIONS

Fault diagnosis can be carried out with several alternative approaches. Thus feature selection depends on the type of application: even a single feature can provide a good solution with automation systems, but combining several easily calculated features is an efficient approach for intelligent sensors. Nonlinear scaling and indices bring all the features and faults to comparable ranges in analysis. The indices obtained from short
samples are aimed for use in the same way as the process measurements in process control. The new indices are consistent with the measurement index MIT and the health index SOL developed for condition monitoring.

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