A strategy on selection of condition monitoring methods

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Abstract

High-maintenance or critical systems require a robust but affordable Condition Monitoring (CM) to be economical. Existing CM concepts can only be suitable for a limited number of applications and their real monitoring performance can only be estimated after intensive tests or while in actual operation. Due to the large number of methods available, it is difficult to decide for a specific one. Additionally, expert knowledge is required to select the most suitable technique for each case. This paper presents a strategy to select appropriate CM methods by showing example results from investigations on monitoring electro-mechanical actuators intended to be used as primary flight control servo drive systems. In detail, it presents how the proposed strategy works with vibration and motor current data of the main actuator bearing and subsequently discusses the implication for the actuator in its entirety. The strategy in this example consists in the application of different signal processing techniques on the performance metrics defined here, with a subsequent analysis of the techniques by means of a statistical evaluation of their performance. The suggested strategy quantifies the potential of a series of available CM techniques based on measurement data. Thus, it can be very useful to select the most suitable ones for the actual application when the variety of the CM techniques is available.

1. Introduction

Since machinery failures can cause serious consequences such as financial loss, environmental contamination or physical injury, there is a need for technologies and strategies that are desired to avoid those scenarios. No system is perfect, so it is necessary to determine the risk of failure and if this risk is too high, failure prevention techniques have to be implemented. Failure prevention strategies that end up in maintenance follow one or a combination of three categories: preventive, condition-based and predictive. Preventive strategy is the most basic one: it does not consider actual operation-related usage and is implemented by scheduled maintenance. Condition-based strategy considers detected initiating faulty states towards failure before conducting countermeasures. Predictive strategy is about the use of the estimated remaining useful life (RUL) for planning countermeasures.

To maximize efficiency in maintenance the condition-based strategies can be considered. This way, maintenance is only necessary if the part in question is actually likely to fail soon, which implies that real costs on unnecessary maintenance effort can be saved. The main issue here is to reach a balance between expenditures and the result. This balance relies on the accuracy of the condition-determination. Thus, reliability of condition-monitoring systems became the overall objective of many researches. Literature also shows significant potential for cost saving when condition-based and predictive failure prevention are combined (1). Forecasting of failures makes it easier to schedule maintenance activities, reducing downtime and, hence, contributing to cost saving.

Accurate fault detection is accomplishable for single components such as bearings and gears or simple machine systems such as induction motors; however, it is difficult to implement in systems with a more complex structure (2). Techniques and methods to monitor simple machine systems are available in a number of works, as explained in (3). Some sources deal with prognosis, compared to diagnosis, mainly containing approaches and references to forecast the remaining useful life (RUL). The accuracy of both diagnosis and prognosis outputs strongly depends on the specific application and the specific approach that can involve virtual models, expert knowledge, statistical information and representative data. When applying those approaches, good virtual models as well as expert knowledge are difficult to obtain. Firstly, models for complex machine systems are not simple to create (3). Secondly, expert knowledge can be achieved through experiences or extensive testing and analyzing data of a high number of machine samples. Statistical information is generally collected by the machine operator.

Mechanical components undergo a natural deterioration process, which can be modelled and, hence, is theoretically predictable. However, the failure of a dynamic system, as a consequence of deterioration, appears stochastically. Further unforeseeable failure-causes such as incorrect assembly or insertion of dirt also contribute to a random failure event. Since permanent monitoring is the basis for efficient failure prevention, measurement instrumentation has been used to make the internals of a system accessible. It is generally known that measurement data have been successfully analyzed to check for machine faulty conditions and to predict the remaining useful life.

CM methods include the type of measurement instrumentation as well as the processing and the analysis of measurement data. Oftentimes, one has to compare the variety of these methods for a certain purpose, for instance to aim at the minimized instrumentation effort or the maximized CM reliability. The strategy we present in section 2 leads to the selection of best methods based on measurement data with sole respect on the CM reliability. The objects of comparison are the fault indicators, quantities that carry abstract information about the machine condition. They are the result of the application of methods on measurement data. A fault indicator is also known as health parameter, which is needed to produce a diagnosis, or to form a condition trend that is used for prognosis. This establishes a foundation for reliable diagnosis and accurate prognosis. The proposed strategy helps ascertaining the most suitable fault indicators among a high number of others.

2. Strategy

This strategy was developed considering the two reliability aspects of CM methods defined here, which are robustness and performance certainty. Robustness means giving the correct diagnosis in any operation condition of a certain application, and performance certainty is the ability of a CM method to meet the constraints of that application. These same concepts can be applied directly on fault indicators to analyze CM methods, since fault indicators are results of applied CM methods.

The following subsections explain our strategy to manage evaluations on databases of fault indicators that have been extracted from measurement data by applying different CM methods. The strategy comprises two approaches named 1 and 2. In approach 1, we derive two equations to obtain valuable information from this kind of data using the basic understanding in diagnosis and prognosis. In approach 2, we introduce a procedure to visualize the evaluation results in order to restrict the scope of the search for the best fault indicators.

2.1 Approach 1

This approach is about the first essential reliability aspect of diagnosis and prognosis that is the performance certainty of the CM technique. Therefore, we introduce the term performance metric. Performance metric is a quantity to express the result of comparison between two condition states and is used to assess the performance certainty of a fault indicator. The overall performance certainty of a fault indicator increases with the increase of that metric.

A general problem with databases is the high volume of similar and redundant data that have to be compressed in a certain way for evaluation. A fault indicator database is a database obtained after applying different CM methods on a measurement database. For example, a measurement database originated from the investigation on bearing faults based on a series of testing (see section 3). These tests were executed under different conditions, and the test samples vary in their predefined degradation state. Additionally, each test also includes iterations. As a consequence, a fault indicator value varies slightly from test to test, and therefore, the very first challenge here is how to obtain a good representative value, e.g. for every tested bearing degradation state. This is conventionally done by averaging all correspondent sample values. However, outliers can be expected. To reduce the effect of outliers, we propose to apply the median instead of the mean.

In fault indicator domain, a certain difference between the value V_{nom} of the non-fault (nominal) case and those of fault cases V_{fault} is necessary to make a correct diagnosis. If this is always the case, the indicator can be considered a robust one. The difference between these two values can be defined as the deviation D which is the absolute difference of V_{fault} and V_{nom}.

$$\text{Deviation } D = |V_{\text{fault}} - V_{\text{nom}}| \tag{1}$$

This represents the diagnosis performance metric in this paper.

In prognosis, one needs health parameters with which it is possible to calculate a trend. The trend is considered ideal if it is monotonically increasing or decreasing. When considering fault indicators as parameters of machine health, several points along the deterioration scale are needed to generate such a trend. For example, each point represents a degradation state of a bearing. We introduce the prognosis performance metric in equation (2) as the gradient G of the linear fitting of all deviations D within the discrete degradation variable x (e.g. increasing fault size).

$$\text{Gradient } G = \text{Gradient } \{\text{linear fitting}\{D(x)\}\} \qquad (2)$$

2.2 Approach 2

In CM, signal processing techniques are used for preprocessing and for extracting of well-defined signal abstraction like descriptors and features, the most essential fault indicating information. The application of the sole extraction or the combination of both techniques creates fault indicators. Generally, application-specific preprocessing improves the reliability of fault indicators and a combination that reaches good fault indication is desired. A well selected fault indicator reduces uncertainty or increases fault detection performance, compared to a universal one. The challenge is to find that combination, from evaluating a high number of different combinations on measurement data. We propose the following evaluation procedure.

For $M \times N$ combinations (N is the number of preprocessing techniques and M is the number of the specific fault indicator), each combination of technique and description was given an identification.

A mapping method is needed to have an overview on the diversity of the results. We use an evaluation table. Table 1 shows the principle of that idea, which contains a column for the performance metrics introduced in Approach 1 (either "Deviation" or "Gradient") and a column for the "Combination identifier". Each column has $M \times N$ entries. In order to compare performance metrics and to obtain a good overview of the most valuable combinations, we recommend the three following steps.

In the first step, all performance metric values $V_{\min} \le V \le V_{\max}$ in the table should be normalized by their corresponding fault indicator value V_{nom} of the nominal case. Thus, equation (1) changes to

$$\text{normalized Deviation } D = \left| \frac{V_{fault}}{V_{nom}} - 1 \right| \; . \qquad (3)$$

In the second step, an overview can be reached by sorting the evaluation table based on the values in the performance metric column. We suggest a descending order with the greatest value on top of the table. To exclude very poor combinations beforehand, it makes more sense if there is a minimum threshold on the value of the performance metric. However, it is up to the experts of specific application to define a performance minimum that fulfils their diagnosis constraints. Combinations that have values under that minimum are discarded, thus, only those above remain for the third step of the evaluation. The new length L of the table is smaller than $M \times N$.

Table 1. Evaluation table principle

	Combination identifier	Performance metric
1	X_1	$V_{\max}$
$\vdots$	$\vdots$	$\vdots$
$M \times N$	X_{MxN}	$V_{\min}$

In addition to the performance metric, we also introduce the fault indicator probability as a second evaluation parameter that allows the consideration of robustness, as this is the second essential aspect that should be considered in diagnosis and prognosis. The probability calculated this way shows how often a combination appears throughout the database that has performance metric value higher than the predefined minimum threshold mentioned above. Now, one can count the appearance of every single combination, throughout all evaluation tables. There are as many evaluation tables as the number of tested operation conditions of the target application. The probability P_i of a combination X_i can be calculated based on the number of appearances and the total number of evaluation tables, obtained from a fault indicator database. While the tables of the type of Table 1 contain all intermediate results, the final evaluation result is mapped in one table of the type of Table 2. This table type differs from the type of Table 1 in the column "Probability".

Table 2. Evaluation table principle: probability included

	Combination identifier	Performance metric	Probability
1	X_1	$V_{\max}$	P_1
$\vdots$	$\vdots$	$\vdots$	$\vdots$
L	X_L	V_L	P_L

3. Example evaluation

This section explains an evaluation on a database of bearing fault indicators that has been created in order to investigate critical mechanical faults in primary flight control actuators. The investigation was motivated by the risk of jamming of mechanical parts of the actuators. The bearing is one of the main components that are directly affected by that risk, for example due to incorrect assembly, wear, etc. Once that jamming occurs, it can cause unexpected down time for an operative aircraft, since aeronautical regulations

[4] are very stringent. Down-time is very costly and this makes CM for aircraft components especially important.

The main idea behind the example evaluation is to obtain the best fault indicators from analyzing the effects on universal signal descriptors when using only a certain component of the measurement signal instead of the raw one. The measurement data originate from tests using a simple bearing test rig. The descriptors are well-known stochastic variables and the different signal components were obtained through a signal decomposition technique based on wavelet analysis. In the following paragraphs, we explain the test rig, the signal descriptors and the signal decomposition technique.

3.1 The test rig

The measurement signal database is the same that has been used in several related works, e.g. Pham gives a good overview on the database [5]. The present paper has a focus on the physical system and describes the test rig in detail. The test bench used to perform the bearing tests can use multiple test specimens and can load the bearings with axial forces while controlling the rotation speed. The bearing is isolated in the test bench, which prevents contamination of the results by mechanical defects of the test bench itself. The test rig is composed of a motor to which a belt transmission is coupled. The test specimen is made of two metal components that hold the bearing at center (see Figure 1). For general monitoring purpose: a thermocouple was measuring the temperature in the upper surface of the bearing, an encoder was used for measuring the speed, and the axial load was measured with a load cell. In particular, the bearing was monitored with a piezotronic accelerometer and the current consumed by the motor was monitored using two hall-effect sensors. The three-phase motor was star connected, so that measurements in two of the phases were sufficient.

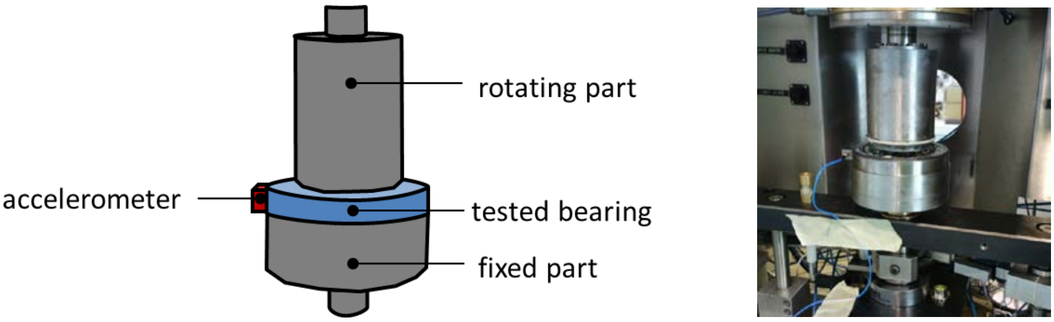

Figure 1. Bearing test rig: assembly principle (left), photography (right)

3.2 Mathematical description of the signals

Statistics is a powerful mathematical tool to describe time varying signals that are treated as random variables. The simplest form of statistics is the presentation in probability density parameters such as arithmetic mean and standard deviation. A well-known example in the praxis is the use of the root mean square (RMS), which is defined as the square root of mean square, as the name suggests. Further forms of statistics are also known as moments (e.g. variance) or higher order statistics (e.g. kurtosis). Machine fault diagnosis has used statistics as a method by solely applying those definitions or combining them with signal processing techniques such as the Fourier transform [2].

Statistical parameters are commonly used in vibration signal analysis, giving good results [6]. In the case of the motor current in the bearing example, they have been obtained from the processed signal, as there is evidence of their relation with the health state of the monitored rotating machinery elements[7].

3.3 Signal decomposition

As a pioneering attempt to overcome the limitations of windowed Fourier transform in the analysis of signals, i.e. fixed resolution in the time and frequency domains[8], Grossmann and Morlet proposed an analysis procedure based on the signal decomposition into a family of functions[9]. The evolution of this approach gave place to wavelet analysis, which expresses the signal as a linear combination of a particular set of functions, obtained by shifting and dilating one single function called mother wavelet [10]. The main advantage of the wavelet analysis is the variation of the time-frequency aspect ratio, giving good frequency localization at low frequencies, and good time location at high frequencies. It demands fewer processing resources than windowed Fourier transform for the analysis.

Wavelet analysis can mainly be applied in two ways. The first one is continuous wavelet transform and the second one is the discrete wavelets transform [11]. In the case of the discrete wavelet transform, the signal is decomposed in two frequency bands, the lower frequency band (approximate level) and the high level band (detail level). Multi-resolution analysis can be performed, decomposing the signal into a number of detail levels and an approximate level (Figure 2). The outputs $D1$, $D2$, ..., Dn of a so decomposed signal are called wavelet coefficients, where n is the maximal decomposition level. That signal can be reconstructed by a linear combination of the functions, weighted by the wavelet coefficients. An exact reconstruction of a signal can be achieved with the correct number of coefficients. The segmentation produced by this variation of the time frequency aspect ratio is particularly adequate for transient nature signals.

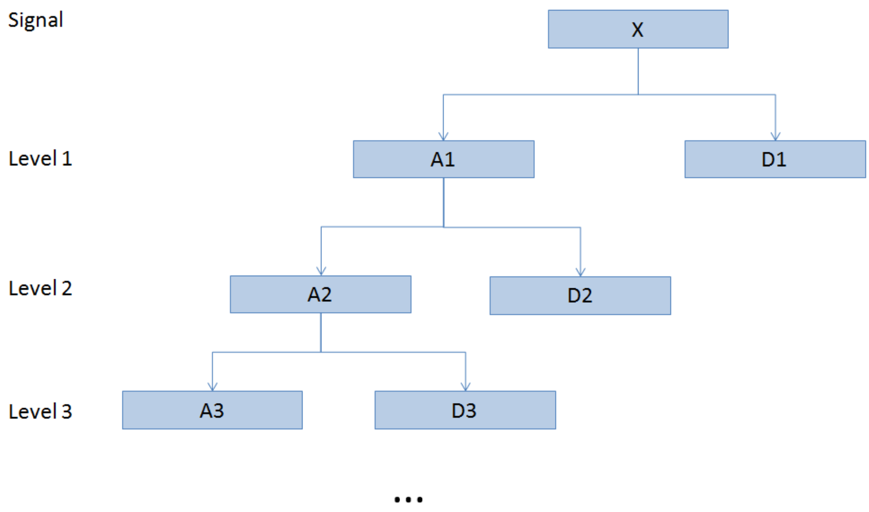

Figure 2. Discrete wavelet decomposition tree

We focused on the discrete decomposition wavelet, as it is more economical in computational resources. The equation for the discrete wavelet analysis is the following:

$$X_J(t) = \sum_{j=J0}^{J-1} \sum_k \gamma_{j,k} \Psi_{j,k}(t) + \sum_k \lambda_{J0,} \Phi_{J0,k}(t) \tag{4}$$

Where j and k are the level of data translation, $X_J(t)$ is the signal, both parts of the equation denote the details and the approximate levels respectively. The $\Psi(t)$ is the wavelet function, the $\Phi(t)$ is the scale function, and γ and λ are the coefficients of the functions. The number of decomposition levels is given by $J - J0$.

4. Result

We investigated monitoring methods for bearing, as a main mechanical component of drive servo actuators, based on vibration and current measurement data and created a database. That database was obtained through testing with the test rig described above. We tested in total one nominal bearing and three different bearings with three different sizes of artificial defect (simulated spall). Each bearing specimen was tested by eight different combinations of test conditions (constant speed and constant load) and each test was repeated three times. Detailed information about the test condition is described in [5].

In this paper, a database of fault indicators was created based on the database described above. This database includes analysis results of both current and vibration data from a set of 14 statistical descriptors (see below), 10 different signal components (8 detail levels including 1 approximation level and the raw signal) and 106 mother wavelets. We obtained 14840 combinations in total.

1. Median
2. RMS
3. Deviation
4. Average
5. Peak value
6. Crest factor
7. Skewness
8. Kurtosis
9. Minimum
10. Maximum
11. Variance
12. Clearance factor
13. Impulse factor
14. Shape factor

Instead of setting a specific performance constraint to shorten the evaluation tables (considering that the table is sorted in descending order of the performance metric, as explained in section 2.2), we selected a specific number of top rows of these tables. That number was obtained by finding a fault indicator with 100 percent probability (see Table 3). To realize that, a routine was created to compute the cell content for the probability column within a number of top rows L of the intermediate result in the tables of the type of Table 1. In other words, the routine checks how many times of the total number of evaluation tables a fault indicator appears in this part of an evaluation table. This routine was applied iteratively while increasing the number of top rows until one fault indicator X_i at row index i reaches a probability of 100. Once X_i is found, the bottom part of the evaluation table that is lower than L can be rejected.

Table 3. Example evaluation for bearing

	Combination identifier	Performance metric	Probability
1	X_1	$V_{\max}$	P_1
$\vdots$	$\vdots$	$\vdots$	$\vdots$
i	X_i	V_i	100
$\vdots$	$\vdots$	$\vdots$	$\vdots$
L	X_L	V_L	P_{L-1}
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$M \times N$	$X_{M \times N}$	$V_{\min}$	$P_{M \times N}$

rejected

In the bearing example, we attach high importance to the aspect robustness. Thus, the final evaluation table has to be sorted in the descending order of the contents in the probability column (instead of the performance metric column). This way, the most robust fault indicators can be simply found in the few very first rows.

The identifier of the fault indicator is coded using a combination of the wavelet mother nomenclature and a four digits code, where the first two digits are reserved for descriptor codes and the last two digits for the wavelet decomposition levels. For the evaluation, the most essential task is to watch for the highest probabilities as well as performance metrics.

The evaluation results for the bearing fault indicators are represented in Tables 4-5 (for bearing current data) and Tables 6-7 (for bearing accelerometer data), where only a few best are explicitly shown to have a clear overview. Through rejection of rows as explained above, Tables 4-5 are limited to the first 315 and 335 rows respectively and Tables 6-7 to the first 1389 and 1457 rows respectively from the total number of rows 14840. In Tables 4-5, the best result was found for the fault indicator with the identifier sym8_1006, which stands for the statistic descriptor number 10 (maximum) of wavelet decomposition detail level 6 where the wavelet mother with the acronym sym8 was used. In Tables 6-7, the best result was found for the identifier rbio3.1_0804, which signifies that the descriptor number 8 (Kurtosis) was applied to the signal detail of wavelet rbio3.1 decomposition level four.

The evaluation for bearing current data excludes more fault indicators of lower reliability then the one for bearing accelerometer data. Additionally, one can say that good results are reached for current at high decomposition level while for vibration at the middle decomposition level, when analyzing the identifiers. Interesting is that the best sorted results of both tables with deviation and gradient are similar. This indicates that similar adequate technique options are for both prognosis and diagnosis.

Table 4-5. Evaluation for bearing current data

No	identifier	deviation	prob
1	sym8_1006	1.103	100
2	sym10_1006	1.004	75
3	db34_1006	3.813	75
⋮			
315			

No	identifier	gradient	prob
1	sym8 _1006	18.293	100
2	sym10_1006	1.119	75
3	rbio2.8_1006	1.160	75
⋮			
335			

Table 6-7. Evaluation for bearing accelerometer data

No	identifier	deviation	prob
1	rbio3.1_0804	977887	100
2	rbio2.2_0804	613488	75
3	rbio3.3_0804	578257	50
⋮			
1389			

No	identifier	gradient	prob
1	rbio3.1_0804	106	100
2	rbio2.2_0804	24	75
3	rbio3.3_0804	23	75
⋮			
1457			

The proposed strategy filtered out many fault indicators of lower reliability and maps only the more reliable ones. Additionally, the most reliable fault indicators are presented in the way they can be simply recognized such as on the top of a table.

5. Discussion

When CM methods are not applied to monitor single machine components but to monitor the superordinate machine system, the sufficiency of CM methods has to be investigated. As an extended objective of improving/developing CM, we discuss in this section on the basis of bearing and actuator whether the methods mentioned here can be applied without further ado. Since the proposed strategy can be applied at any machine level, evaluation results of different levels can help finding out the limitation of CM methods.

The measurement data obtained from the test rig operation are a good indicator for effects taking place in an isolated bearing, however the situation changes once a whole actuator is considered. There are several aspects that might heavily influence the characteristics of motor currents and vibration signals. They can be loosely grouped into four categories: bearing attachment, component interactions, environmental factors, operation and fault shape, and are discussed in this section.

On the test rig shown in figure 1, the accelerometer is placed directly on the outer ring (OR) of the bearing; radial guidance of the OR is achieved by friction force to the fixed part and the rotating part. In the actuator, the OR will be radially guided by a tight fit to the surrounding structure. As a consequence, the sensor could not be placed on the same spot as in the test rig but needs to be attached to the structure. This changes the propagation path of the signal and by that some characteristics of the measurement signal. For example, the eigenfrequencies excited by the force impulses resulting from over rolling a spall are not any longer determined by contact stiffness of the bearing and the rigid outer ring but by the combination of these and the structural dynamics of the housing. These frequencies are determined by material, geometric and fixation properties of the housing. This would lead to a shift of the frequency bands with useful information for CM, when vibration is considered. On the other hand, the housing of a real actuator usually consists of several different parts connected by bolts and, for tightness reasons, gaskets. This will introduce damping into the propagation path and by that reduce the information content of the signal. In case the energy content of the force impulse is not sufficient or the shape of the impulse is not sharp enough to excite the new and possibly highly damped eigenfrequencies, the information necessary for CM might be completely lost.

When measuring the acceleration of the housing, not only one bearing acts as an excitation source but also other components such as a ball screw, gears, other bearings and even the electrical motor itself, have an impact on the measurement result. This kind of composition could be interpreted as a multiple input single output problem, where the dynamics from each input to the output are governed by the different structural dynamics of the housing. Due to similar dimensions and rotational speeds of bearings and ball screws, also the excitation characteristics of the inputs are similar making the isolation of a damaged component in the CM even more challenging.

When considering the working environment of a flight control actuator, obviously the broad temperature range has an impact on electrical properties such as phase resistance. Also tribological parameters as viscosity of the lubricant are affected by temperature changes. This has a direct impact on the damping and frictional characteristics of the bearings and by that also on the vibration and current measurement signal.

During flight operation, the loads and speeds for the actuator are far from being constant. The actuator is operated in a position control mode. During takeoff and landing the position demand signals coming from the flight control computer or the pilot might be highly dynamic resulting in high acceleration rates for the rotational speed of the bearing. On one hand this means that the acceleration and current spectrum will become smeared, on the other hand this might also lead to slippage of the rolling elements which would change the characteristic fault frequencies used for CM. In the cruise phase of the flight, the control surface deflection is kept more or less in neutral position and only slight corrections are made. As a consequence, the bearing is also just rotated by several degrees or some turns and only very few force impulses are created. These few impulses are probably not enough for spectral analysis. The loads for the actuator are governed by the aerodynamic loads on the control surface that are dependent on the flight condition of the airplane and the surface deflection and will change accordingly.

6. Conclusion

In this paper, we present a procedure that contributes to the process of selecting valuable CM techniques. We demonstrate how it works in an example that deals with the evaluation of bearing fault indicators, obtained by applying combinations of signal descriptors and signal components. This evaluation comprises of results for two signal types: current and vibration. For this example, we can make a clear statement about which combinations are best for each signal type, after studying the results. Additionally, we can confidently compare the results of these two signal types. At the last point, we briefly discuss the effect of system (vs. single component) on content of measurement signal based on the structure of a typical primary flight control actuator. From this, we postulate that the results vary when applying the same fault indicators on both component level and system level, dependent on the difference in physical structure and position of sensor. Thus, we recommend an implementation of the proposed strategy not only on component level but also on system level to reduce result uncertainty.

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