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New Approaches for Supervision of Systems with Sliding Wear: Fundamental Problems and Experimental Results Using Different Approaches

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Abstract: Reliability and availability of technically complex and safety-critical systems are of increasing importance. Besides the degree of wear, the quality of mechanical systems is significant for the system reliability. The focus of this contribution is the development and application of readily applicable and easily interpretable algorithms for industrial data obtained from technical systems during operation. The methods are within the focus of the production-oriented automation programs (Industrial Internet, Automation 4.0, China 2025). In this contribution as example a hydraulically driven machine in which parts slide over each other is chosen as sliding wear example. Monitoring is applied to distinguish normal and abnormal operation as well as to define end of useful lifetime. In this contribution four different methods will be introduced and experimentally compared without the availability of objective information about the wear state. The approaches differ with respect to the used measurements and data preparation. As measurements Acoustic Emission and the hydraulic pressure of the driving machine are used. For processing the accumulation of damage related values, a machine learning algorithm, and a sensitivity matrix are used. For comparison the experimental validation is based on identical data sets. Different operational states of the system denoted as actual system state are defined and classified. The comparison shows that the four introduced methods provide similar classification results although the underlying measurements are based on different physical principles. The newly introduced approaches allow online evaluation of the actual system state and can serve within improved maintenance strategies.

Keywords: condition monitoring; diagnosis; wear classification

1. Introduction

State-Of-Health evaluations and assessments of the actual wear state are important advanced features of modern condition monitoring systems [1–9]. Evaluations of the hazard rate/probability of failure (load-dependent) and the actual remaining lifetime are goals in the development of advanced methods and implementations [6,10]. In [11] a new approach is developed to define the useful lifetime of components and systems using only operation data in combination with the information of the end of lifetime (of systems failed used for training of the model used for test). This approach works only for stationary operation conditions assuming stochastically wear behavior. Approaches for ensuring the functionality of systems throughout their lifetime are related to Fault Detection and Isolation and/or maintenance-related aspects, such as Condition-Based Maintenance, machine monitoring, Structural Health Monitoring, or related paradigms. These approaches have been developed during the last two decades mainly by combining signal- or model-based diagnostic approaches that detect and partially evaluate changes during operation. Most of these approaches, e.g., [1,12,13], aim to detect changes in systems occurring caused by operation, aging, or both, which lead to changes in measurements. The focus is given to fault detection in the sense of the detection of changes, to fault isolation meaning the establishment of detected changes to system parts or components as well as diagnosis as the method to conclude to underlying physical causes or effects. The goal of these methods is the integration of automatic supervision and maintenance planning in operating systems. Practical requirements such as the transferability to different systems are of increasing interest. Three key issues that need to be addressed are: (i) processing the data measurements, which are typically problem-specific and acquired in real-time; (ii) interpreting the measurement data in terms of the machine's condition (filtering); and (iii) extracting task- and/or application-related knowledge from measurements and data (for classification).

In this contribution, different assessment approaches are introduced, which are partially combined and compared [14–16]. This survey introduces wear analysis and classification methods. For the first time in this contribution a detailed comparison considering different properties of the approaches is added.

Specific effects related to wear include changes in the tribological condition of surface (denoted as surface condition in the sequel) due to the movements of surfaces with material contacts. The wear mechanisms as described in [17] are defined in this context as adhesion, abrasion, surface fatigue, and tribochemical reaction. Depending on the type of tribological load, different wear mechanisms occur. Several mechanisms exist for sliding wear, so describing the wear process may become more difficult due to various wear mechanisms occurring simultaneously. Typical phenomena include wear debris and the transfer of material attributable to cold welding (adhesion), scratches due to hard particles and cutting processes (abrasion), cracks resulting from fatigue and loss of robustness because of cyclic loading (surface fatigue), and existing reaction particles generated by chemical reactions between the materials and lubricants (tribochemical reaction).

To measure wear effects directly, geometric dimensions such as changes in the length, surface, or volume are often considered, which are described in [18] for measuring the wear of brake friction materials as an illustrative example. The aim is to find indirect characteristics for describing the wear process. Another problem is related to the dependency of the wear process on different properties and interactions with the material used.

Several signal-based methods may be used to identify connections between variables measured during the process and the wear process itself. Common signal-based condition monitoring approaches include filtering and classification techniques. Filtering methods can be applied in the time-, frequency-, and time-frequency domains. Wavelet analysis is used often as filtering method, which is time-frequency domain-based, particularly when vibration signals are examined for condition monitoring. In [2], this technique was used for drill wear feature extraction using force signals, and in [19], for condition monitoring of rotating machinery. Gearbox condition monitoring using wavelet filtering based on vibration signals was described in [3]. In [4], wavelet filtering was used to extract features for classifying the wear level of mining tools based on the mining power. Statistical features are used for feature extraction, e.g., root mean square, skewness, kurtosis, and standard deviation. In previous publications, statistical features were also used for condition monitoring of tool wear [2,5] or of diesel engines [13]. More than one filtering method may also be used, as described in [6], where 25 features from the time and frequency domains were classified with a machine learning classification model. A review of sensor technologies, signal processing, and decision-making strategies was provided in [7], including filtering techniques such as principal component analysis (which is also used in [20]), the fast Fourier transform (FFT), and wavelet transform. After filtering (including feature extraction), the features must be evaluated and can be used for classification. In [7], classification methods (decision-making) such as neural networks (see also [3]), fuzzy-based methods, and hierarchical algorithms were described. Fuzzy-based methods often combine fuzzy logic with other common methods, such as fuzzy neural networks (used in [4]) or fuzzy c-means (used in [2]). The c-means algorithm is a clustering technique. Clustering is an unsupervised classification method for defining and distinguishing features before applying subsequent classification approaches, as discussed in [20]. The Support Vector Machine (SVM) is another common method and its use in condition monitoring and fault diagnosis was reviewed in [21], where it was concluded that SVM is developing from machine learning toward problem-oriented domains. For example, a SVM is used in [8] for wear degree classification of slurry pumps. Another method for monitoring slurry pumps was proposed in [9], where a moving-average wear degradation index is classified.

Threshold monitoring using statistical features is a common classification approach, but the difficulty of defining the threshold setting has to be solved and implemented, therefore expert knowledge is often necessary. In [22], the problem of automatic threshold calculation was discussed. Probability distributions were used in [23,24] to separate normal and abnormal behavior. In this approach, a threshold is defined based on the individual machine- and task-/load operating conditions. An optimal threshold can be found using the receiver operating characteristic (ROC) curve, as explained in [10].

The main problem when applying condition monitoring systems based on filtering and classification methods is identifying suitable task-related features for filtering as well as for classification approaches describing the application without knowledge of the real system state. Thus, the goal is to optimize the complete chain of measurement, filtering, and classification to obtain a reliable state classification based on measurements. Machine elements/parts are often designed for given lifetime for loads expected. To achieve realistic operation conditions and to match the identical wear conditions, it is necessary to control the mechanical and thermal conditions as well as the lubrication, and thus wear test runs are used for experiments.

In this contribution, different approaches are compared based on their application to the common experimental system used. A brief sketch of the test rig is explained in detail in [15,16] and is shown in Figure 1. The wear-related specimens (see Figure 2) were stressed tangentially, thus, the normal load was applied to shorten the runtime and tangential forces were applied as working forces. Measurements were obtained from the hydraulic system (proportional to the friction forces) and from the specimen via Acoustic Emission (AE) signals.

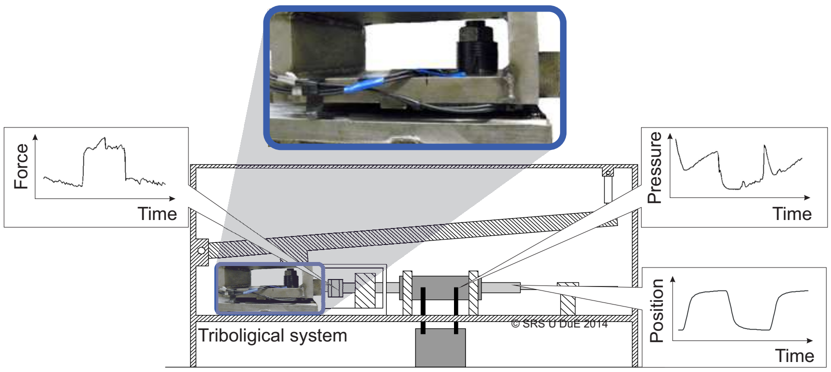

Figure 1. Wear test rig, Chair of Dynamics and Control, U Duisburg-Essen, Germany.

The measured values were used to monitor the system and to evaluate the state of the system, including the state of wear-related effects based on load patterns or stress-equivalent collectives, thereby deriving representative forces. As a consequence of the system's operation (friction velocity, cycle times (ratio of stress to break time), temperature behavior of the surface, lubricant distribution, etc.) and the materials used, abrasive sliding wear appeared. During the operating period, the system has an increasing probability of losing its functionality. The following sequence of effects is observed: (1) surface changes caused by crack initiation (2) and growth, (3) lacerated material, and (4) material losses. The surface quality and the degree of wear of the friction partners greatly affect the system's functionality and therefore finally the reliability. The stress (surface damage and degree of wear) of the friction partners can be represented as a probabilistic process, which depends on the stress history and the current operating parameters.

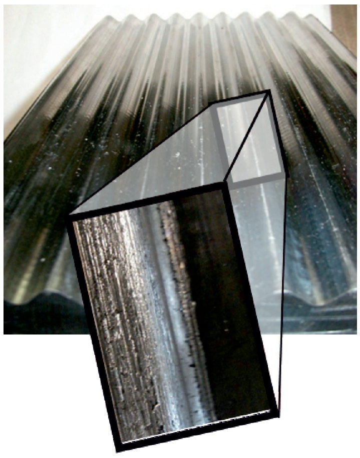

Figure 2. Material surface of wear-related specimens used for experiments.

In [14] three approaches (Acoustic Emission analysis, diagnosis-oriented data filtering and data-based classification approach) are already introduced.

Using the diagnosis-oriented data filtering with threshold-based classification approach results are obtained stating four different data sets with two different operating conditions [15].

The approach denoted as condition evaluation based on a sensitivity matrix was briefly introduced and described in [16]. A method for classifying the machine state is based on the filtering technique introduced in [15]. Two data sets based on the same machine operating conditions were analyzed. In this publication the comparison of the three approaches introduced in [14] is revised, detailed, and extended with the fourth approach introduced in [15]. With this contribution the previous publication of the author/s are detailed, finalized, and summarized to round up this research work and to establish resulting conclusions. Therefore, if necessary results are repeated.

The organization of this paper is as follows.

In Section 1, filtering and classification methods related to condition monitoring and wear diagnosis are reviewed, the test rig employed in this contribution is described. In Section 2, the four approaches employed for evaluations and comparison are introduced. In Section 3, the experimental results obtained using these four approaches are presented. The proposed approaches are compared in Section 4. In Section 5 the contribution is summarized, further work is suggested.

2. Four New Signal-Based Approaches to Be Compared

2.1. Acoustic Emission Analysis (Approach A)

Acoustic Emission (AE) is defined as "the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material" [25]. The advantage of AE is that the application of this method is usually achieved during loading. In addition, the frequency range of AE signals is much higher than that of vibration and environmental noise [26]. Advanced modern signal processing techniques are required to analyze AE signals. In this contribution, time-frequency analysis is used to extract features related to damage. The coupling between the surface of the sensor and the material was permanent and it was assumed to be very stiff. The measured voltage was converted by a high-speed AD-converter on an Field Programmable Gate Array (FPGA) board with a suitable sampling rate, so a wide frequency range up to 1 MHz can be covered by the measurement chain.

The aim is to detect characteristic frequencies that are strongly related to stochastic effects and to establish a unique assignment for the related wear mechanism. The Short Time Fourier Transform (STFT) is used to extract relevant frequencies that indicate transient events. The signal is multiplied by a window function in STFT algorithms. The FFT is then obtained and a sliding window is moved along the time axis to calculate the repeated chain continuously until the end of the signal. A criterion must be defined for distinguishing normal and abnormal operation. Therefore, the signals are recorded under normal operation during different operating phases. After correlating the STFT signals with the process signals, recurrent phase-specific patterns can be identified and only the frequency contents of the residual STFT pattern are used to examine the AE signals calculated over time. It is assumed that the result represents the damaging energy. It is generally conducted that a change in the AE energy indicates that there has been a significant effect on the lifetime of the system under consideration [27].

Transient events and the characteristic frequencies in these stochastically appearing effects are analyzed to detect correlations between the transient emissions (measured as piezoelectric voltage) and physical effects (material changes). Thus, changes in the AE signals indicate related changes in the process and surface condition. The severity of the change (wear process) may be indicated by typical transient events, amplitudes, etc., in the STFT results.

Related to a physical-oriented view evaluating the system state, the cumulative AE energy distribution obviously allows the distinction of the three main characteristic phases of system state development up to system failure [28].

2.2. Diagnosis-Oriented Data Filtering and Threshold-Based Classification (Approach B)

Due to the motion of the wear surfaces friction appears. The friction can be represented by the force required for movement. The hydraulic pressure applied to move the surfaces is proportional to the force, and thus to the friction between the wear surfaces (for details, see [29,30]). The following approach briefly introduced in [15] will be detailed in the sequel. The wear behavior is determined on a different time scale by measured signals. The successful compression of so-called macro-data introduced in [15] is employed in this contribution. The complete time behavior and history of the pressure measurements has to be taken during a load-cycle and is filtered to achieve an improved evaluation. The generation of characteristic values is calculated from the pressure behavior. The considered data are taken from the last 20 s of a load-cycle, so the results are not influenced by transient heating effects. For one load-cycle, the measured signal (20 s) is considered using a sliding window technique. Each window contains $n = 100$ data points, which equate to a time span of one second. The sliding effect is used to consider different data windows. The window step size is one data point, so for one load cycle, $N = 2000$ windows are considered. For one window j, the arithmetic mean $\overline{x}_j$ is calculated by

$$\overline{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_i. \tag{1}$$

If all means are calculated, the arithmetic mean of all windows

$$\overline{x}_c = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{2}$$

is determined. The arithmetic mean of all mean values from each window $\overline{x}_c$ is the characteristic value for this specific load-cycle c.

To illustrate the procedure in detail, the time-behavior of the pressure equivalent characteristic value for one measurement (here denoted as set-up Z15) is shown in Figure 3 (first row).

To generate further characteristics, the cycle-wise gradient of the pressure equivalent value denoted as damage increments is calculated by

$$S_c = \frac{|\overline{x}_c - \overline{x}_{c-1}|}{|t_c - t_{c-1}|} \tag{3}$$

using the absolute values of the difference in the individual characteristic values divided by the time-difference between two cycles. The individual cycle-based damage increments S_c can be computed during operation. After each load-cycle c, all previous calculated damage increments are accumulated to obtain the accumulated damage increments

$$AS_c = \sum_{k=1}^{c} S_k \tag{4}$$

and plotted as a function of time corresponding to the load cycle c (see Figure 3 (second row)).

The development of the AS-time behavior from $c = 1$ to M, with M denoting the last realizable load cycle, exhibits changes in the gradient with an increasing number of cycles.

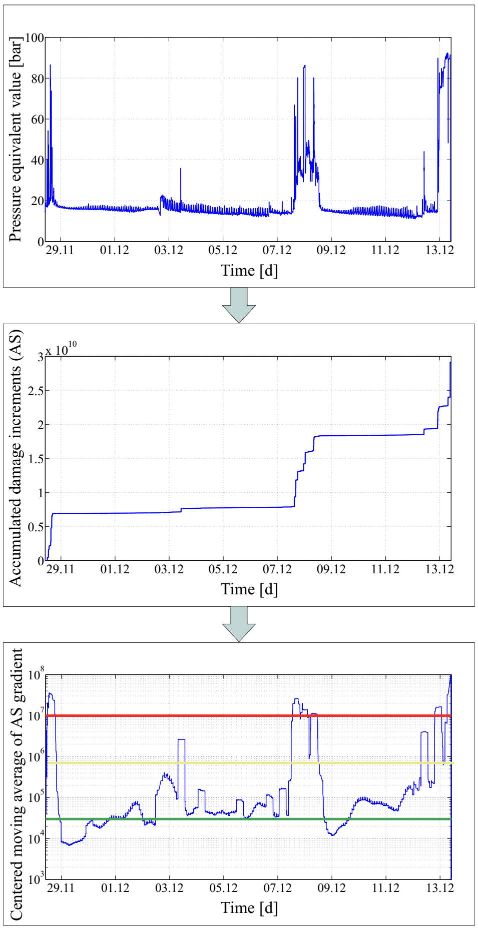

Figure 3. Procedure of the diagnosis-based data-filtering (approach B and C); first row: time behavior of pressure equivalent value for a complete test-run; second row: time behavior of accumulated damage increments (AS); last row: time behavior of smoothed AS gradient.

Finally, the gradient of the AS-curve is smoothed using centered moving average. Specific numbers of values $W = 100$ before and after the actual value are used to calculate the mean value, e.g., for the load cycle c, $AS_{c,smooth}$ is calculated as

$$\begin{aligned} AS_{c,smooth} = & \frac{1}{W}(AS_{c-\frac{W}{2}} + AS_{c-\frac{W}{2}+1} + \ldots \\ & + AS_c + \ldots + AS_{c+\frac{W}{2}-1} + AS_{c+\frac{W}{2}}). \end{aligned} \tag{5}$$

In Figure 3 (third row) the centered moving average of the AS gradient is plotted on a logarithmic scale.

The amplitude of gradient of the curve can be used to representing the different states of the wear surface. From the time behavior shown in Figure 3 (third row), it can be concluded that the surface condition temporarily generates very high friction. In this contribution, it is assumed that four distinguishable states exist to be used for classification of the surface condition as follows:

- State 1: Stable and error-free operation (below the green line).
- State 2: Stable with small changes in the surface condition (between the yellow and green lines).
- State 3: Acceptable changes in the surface condition (between the red and yellow lines).
- State 4: Significant changes in the surface condition (above the red line).

If no measurement data are available (e.g., during stop of the experiment), the corresponding state is denoted as state 0. The threshold values are selected experimentally based on previous measurements. In [31] the threshold values are optimized according to the minimization of the difference between results generated using approach B and C.

2.3. Condition Evaluation Based on a Sensitivity Matrix (Approach C)

The approach uses data generated by diagnosis-oriented data filtering (see Section 2.2) to further reduce the complexity by compressing the signal information into three states according to an operation-related judgment of the system state.

This approach differs from those described previously due to the advanced evaluation goal. Thus, instead of using thresholds to classify the states here the relationship between the actual value of a characteristic and the previous ones is employed to determine whether the actual value is greater, less, or about the same as previous values.

Thus, a strong state-related evaluation is possible using the diagnosis-based data filtering approach. From Figure 3 (last row), it can be concluded, that two main aspects become important when assessing the real state of the system related to wear: (I) the absolute level of wear (due to operation) defined by the absolute level of integrated *AS* and (II) the observation of actual changes. By combining both aspects, a sensitivity matrix can be built. The procedure was firstly introduced in [16] and is explained in detail in the following.

To consider the history of the absolute level of wear the left-sided mean (LM) of a specific number of the last load-cycles is calculated (shown in black in Figure 4 (first row)). This value considers specific numbers of load-cycles before the actual load-cycle to calculate the mean value of the previous characteristic values. The actual value of the centered moving average is compared to the LM-value: (I) if the actual value is less than LM-value, the trend is denoted as -1; (II) the trend is 0 if the actual value is in the same range as LM-value; and (III) the trend is 1 if the actual value is greater than LM-value. A short section of the time behavior (Figure 4 first row, dashed box) is used to show the calculation of the trend in Figure 4 (second row). The comparison shows that the actual load-cycle is related to the history of the wear level. The actual changes in the wear level are shown by the steps in the trend behavior. The algorithm employed is as follows: (I) if the last step is ± 2, the changes are more significant than those with ± 1; and (II) the last step is denoted as 0 if no step occurred during the last 50 load-cycles.

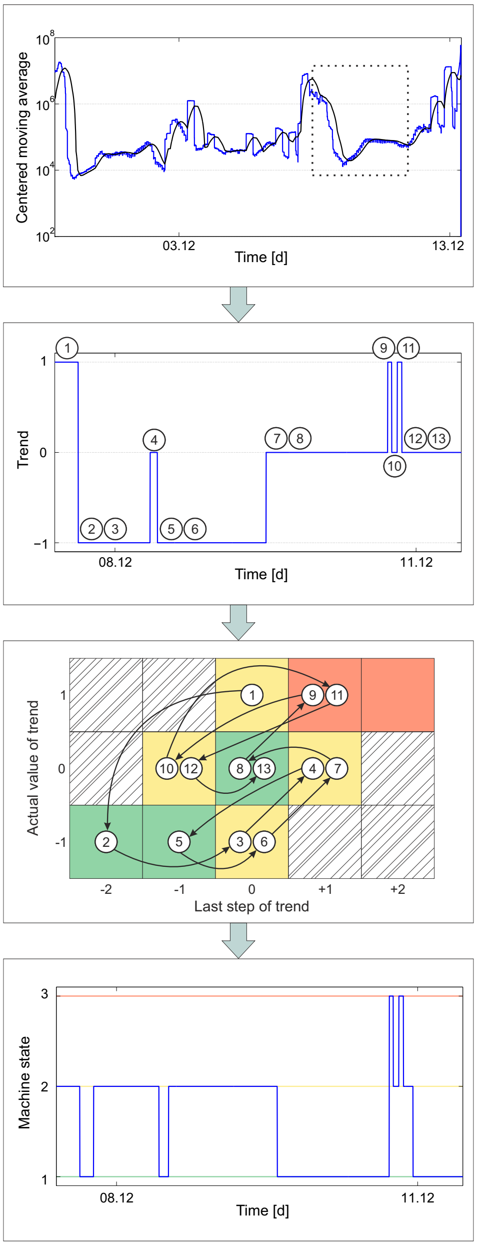

Figure 4. Sequence developing the process of state transition and classification using sensitivity matrix (approach C); first row: time-behavior of smoothed *AS* gradient (blue) and left-sided mean (LM)-value (black); second row: short section of trend value showing 13 states of this trend; third row: sensitivity matrix showing the above mentioned 13 states with state transition; last row: evaluated machine state.

By combining the last step of the trend (x-axis) and the actual value of the trend (y-axis), the sensitivity matrix shown in Figure 5 can be built and detailed based on the experimental data. Depending on the actual value and the last step of trend value, nine different combinations can be distinguished, as shown in Figure 5. A short section of the trend value is depicted in Figure 4 (second row). The calculating steps are numbered from 1 to 13. A transition connects two steps. Assuming that there are connections between the actual changes (last step) and the actual integrated damage increment, nine combinations can be combined as three states (denoted by green, yellow, and red) based on heuristic experience.

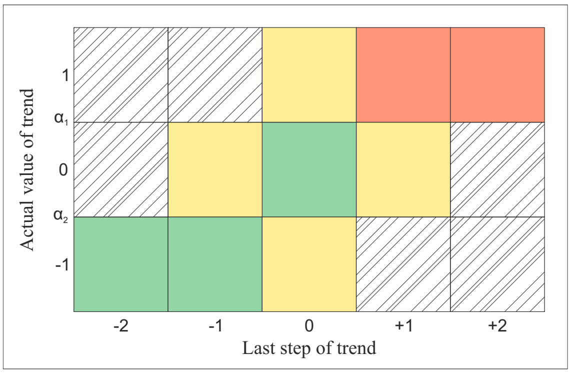

Figure 5. Sensitivity matrix (approach C); green: noncritical; yellow: alarming; red: critical.

2.4. Data-Based Classification Approach (Approach D)

The central idea of this approach is based on the assumption that algorithms should easily, rapidly, and reliably determine suitable features, like statistical or other features or other types of features to describe a data set, or allow the distinction between data sets. On this basis, it is assumed that data sets and data set elements are first classified by human experts into a small and strongly limited number of states (3–4), which can be distinguished for practical purposes (training). In the next step, algorithms are used for automated analysis to determine the best classification parameters that distinguish the given sets of classes. In this contribution, automated calculation of statistical characteristics of the analyzed data sets yields parameters and similar models. The sum of these structured parameters and their distribution is defined as a fuzzy-based model. Using suitable internal algorithms, any contradictions and ambiguities in the fuzzy-based model can be minimized, and a revised description to describe the different states of the system is used.

This classification approach is used as an example directly serving as a supervised classification approach. Other methods such as SVM, Artificial Neural Networks, or k-nearest-neighbor can also be used [32–34].

For the results firstly published in [14], 34 statistical features were used as descriptive variables. According to previous published results [14], the trained fuzzy model was generated based on five membership functions according to five characteristics. These features were used to distinguish the five states considered are described as follows (description and colored notation).

- Regular behavior 1:
  Stable and error-free operation: Green.
- Regular behavior 2:
  Stable with small changes: Blue.
- Regular behavior 3:
  Stable operation with changes: Cyan.
- Abnormal behavior 1:
  Acceptable changes in the surface condition due to minor surface condition changes: Yellow.
- Abnormal behavior 2:
  Significant changes in the surface condition due to major changes in the surface condition, ranging up to the destruction of the surface with partial loss of functionality: Red.

3. Application Results

The real training and test data were obtained from experiments realized at the Chair of Dynamics and Control, University of Duisburg-Essen, Germany.

3.1. Acoustic Emission Analysis (Approach A)

In Figure 6 the lead zirconate titanate (PZT) voltage for a load-cycle and the corresponding STFT result for the run-in phase are shown. Compared with Figure 7, where the PZT voltage and the STFT results obtained from a load cycle during the permanent wear phase is given, it can be seen that the STFT results differ in terms of their amplitude behavior.

The STFT results in Figure 8 were obtained from a load-cycle at the end of the experiment. The different frequencies have higher amplitudes than those in the other phases. Thus, the different phases could be distinguished using the STFT results. Measuring the AE energy during the test run (Figure 9 (right)) the cumulative AE energy (Figure 9 (left)) is an effective parameter for estimating the evaluation accumulated damage. The progress of the AE activity allows to distinguish the three phases.

First, a significant gradient due to the rapid increase in the AE activity is shown. The end of the run-in phase is clearly indicated by a reduction in the AE events, which remain constant. The last phase is characterized by an important gradient, which indicates an increase in the AE activity.

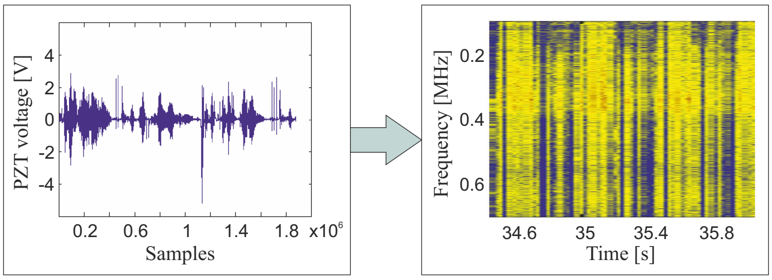

Figure 6. Establishing Short Time Fourier Transform (STFT) filtering technique based on Acoustic Emission measurement during run-in phase (**left**) showing time-frequency behavior (**right**) (approach A).

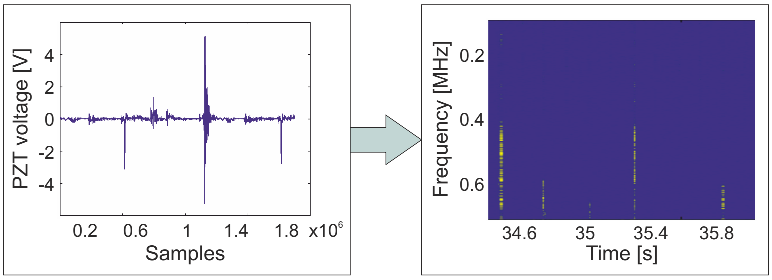

Figure 7. Establishing STFT filtering technique based on Acoustic Emission measurement during permanent wear phase (**left**) showing time-frequency behavior (**right**) (approach A).

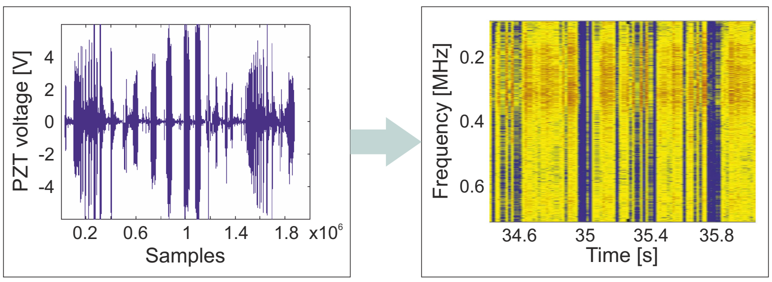

Figure 8. Establishing STFT filtering technique based on Acoustic Emission measurement during wear-out phase (**left**) showing time-frequency behavior (**right**) (approach A).

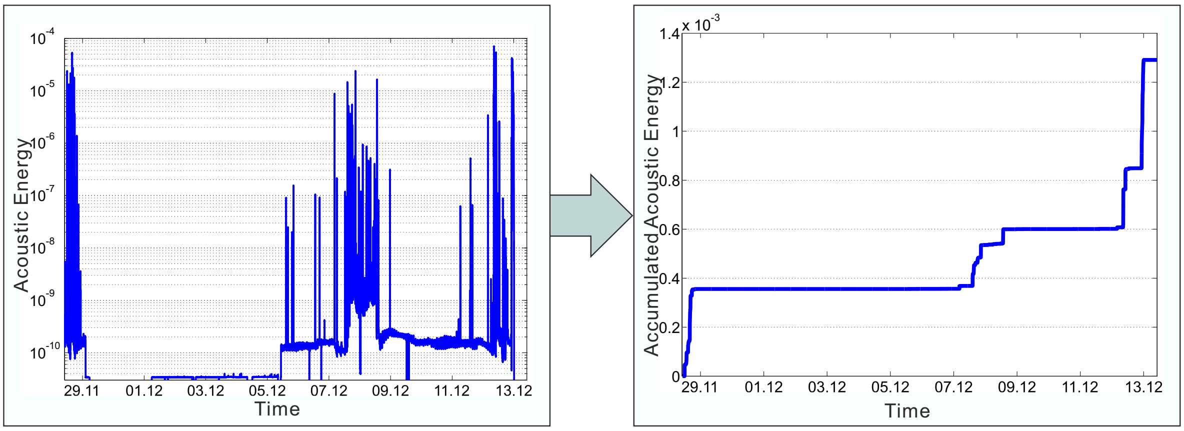

Figure 9. Establishing cumulative AE energy based on Acoustic Emission measurement during the measurement Z15 (**left**) showing damage accumulation (**right**) (approach A).

3.2. Diagnosis-Oriented Data Filtering and Threshold-Based Classification (Approach B)

In Figure 10 measurements obtained from two set-ups (Z15 and Z20) are shown, where the same operating conditions were applied. The filtering steps from the pressure equivalent value (Figure 10 (first row)) to the time behavior of smoothed AS gradient (Figure 10 (third row)) are shown. The same threshold values were used to classify the wear state, because the values of the centered moving average of the AS gradient are in the same range for both measurements after filtering. In principle, the classified machine states (Figure 10 (last row)) have similar structures, which comprise the run-in phase (at the beginning of the measurements), interim phase of permanent wear, and the final destruction phase. Phases with constant wear progression classify time periods with steady state behavior. Some phases were present that includes significant changes in the surface condition (State 4), but the system returned to stable and error-free operation (State 1). Based on the experimental results, it can be concluded that in spite of the different time behavior of wear processes, they can be compared from a structural point of view by distinguishing different phases, which are obviously identical to the development of the wear processes.

This approach based on the use of easy to measure operating data is simple to implement. The measurements can be readily taken from operation.

The modules can be implemented in the decision logic modules to allow condition assessment. The complexity of the application for users is also low. This approach has a high real-time capability, but the method might not yield directly identifiable information. Based on the classification of the machine state, operating conditions such as the lubrication interval can be changed according to the state, thereby reducing the changes in the surface conditions.

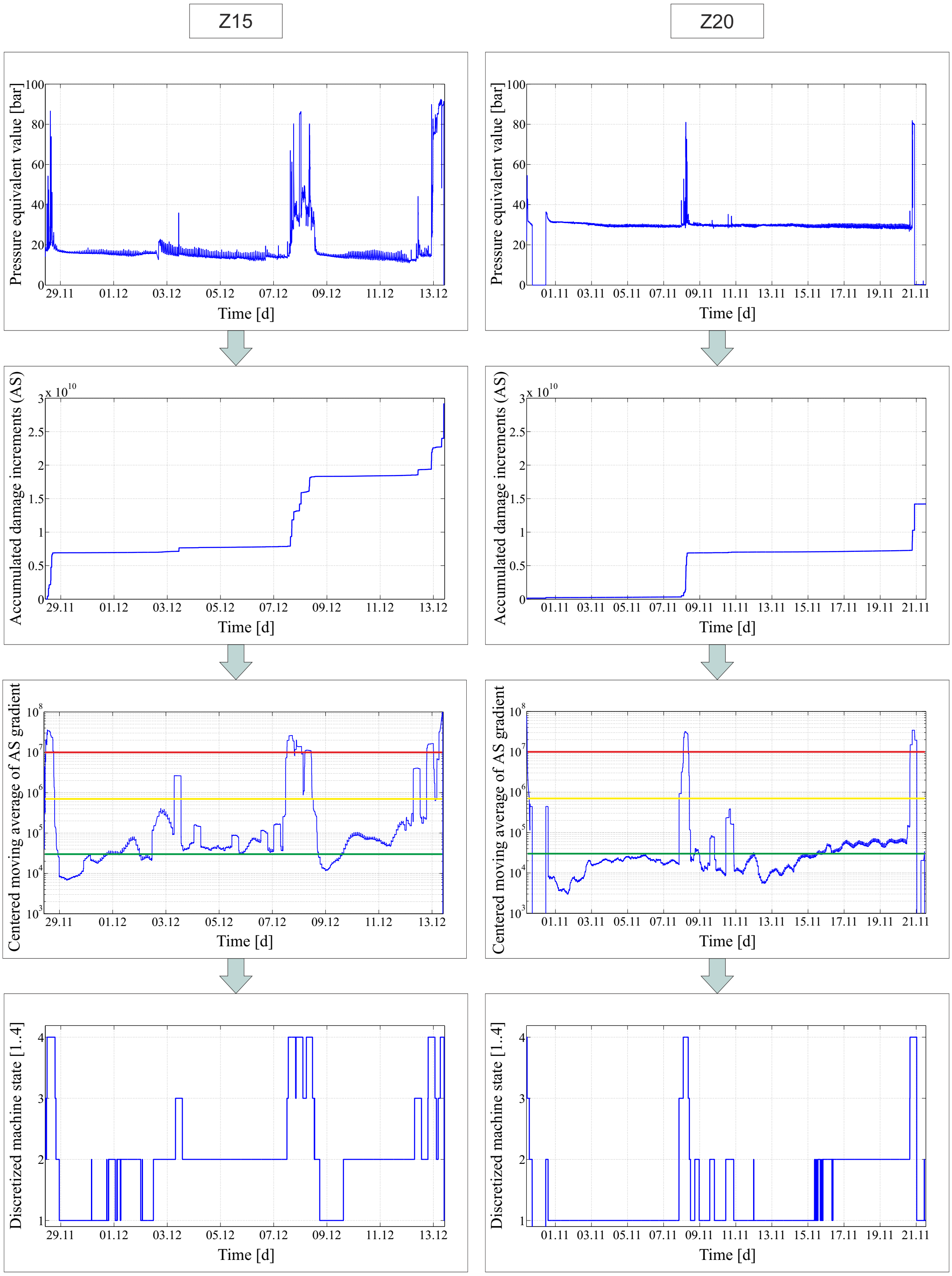

Figure 10. Establishing diagnosis-oriented data filtering and threshold-based classification based on two different test runs (Z15 and Z20); first row: time behavior of pressure equivalent value for a complete test run; second row: time behavior of accumulated damage increments (*AS*); third row: time behavior of smoothed *AS* gradient and, thresholds,last row: classified machine state (approach B).

3.3. Condition Evaluation Based on a Sensitivity Matrix (Approach C)

The experimental results for Z15 and Z20 are shown in Figure 11. These set-ups are obtained using the same operating conditions (hardness, normal force, lubricant, and lubrication interval).

The filtering methods described above are used to determine the centered moving average (Figure 11 (first row)). Comparing this value to the LM-value (black line), the trend value (Figure 11 (second row)) is calculated. Using the introduced sensitivity matrix, the machine state can be classified (Figure 11 (last row)).

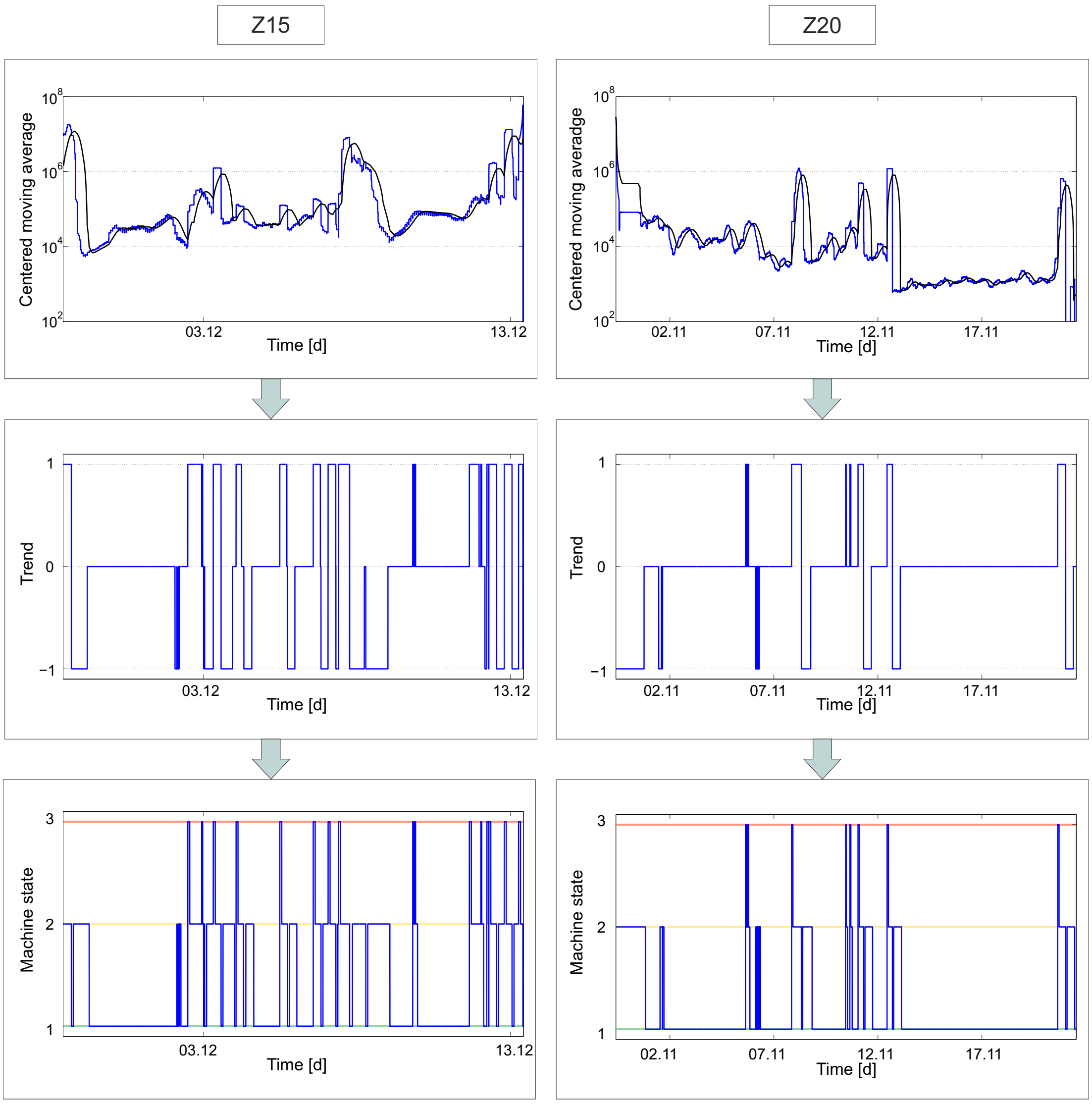

Figure 11. Establishing diagnosis-oriented data filtering and condition evaluation using sensitivity matrix based on two different test runs (Z15 and Z20); first row: time-behavior of smoothed *AS* gradient (blue) and LM-value (black); second row: time behavior of trend value for the complete test run; last row: evaluated machine state (approach C).

In principle, the time behavior of the machine states indicates the same structural behavior, with a run-in phase (at the beginning of the measurement), an interim phase of permanent wear, and a final destruction phase. Constant wear progression phases were used to divide (and therefore to classify) the time periods with steady state behavior. Based on the experiments, the following can be observed:

- The probability of sudden changes increases as the system is used longer.
- Sudden changes are often connected to other sudden changes.
- The periods of reliable use alternate with periods where strong changes in operation occur.
- After some periods with changes, the system is not capable of stable problem-free usage.

3.4. Data-Based Classification Approach (Approach D)

The results of the evaluation using the raw pressure data set are shown in Figure 12 (left). The five rows in Figure 12 (left) show the gradual changes in the regular states for different characteristic values. Obviously the rate of erosion increases (color changes from blue to red). These results also agree with human classification of the condition changes in this data set. Thus, based on a predetermined set of test data (derived from the real data set), any streamed data can be efficiently evaluated online. The results are summarized in Figure 12 (right), thereby demonstrating the progression of the states and thus increasing wear. Based on the detailed analysis, it can be concluded that the surface friction condition can recover in short time, and damage was already very significant at the beginning. According to practical experience, it is known that the surface conditions change constantly, layers are removed, new layers are established by internal processes, and a short-time stable state arises again. However, the material is ultimately exhausted, the entire surface is destroyed, and the formation of a wear-resistant surface is not possible. During the test run, the data were evaluated using the fuzzy-based model.

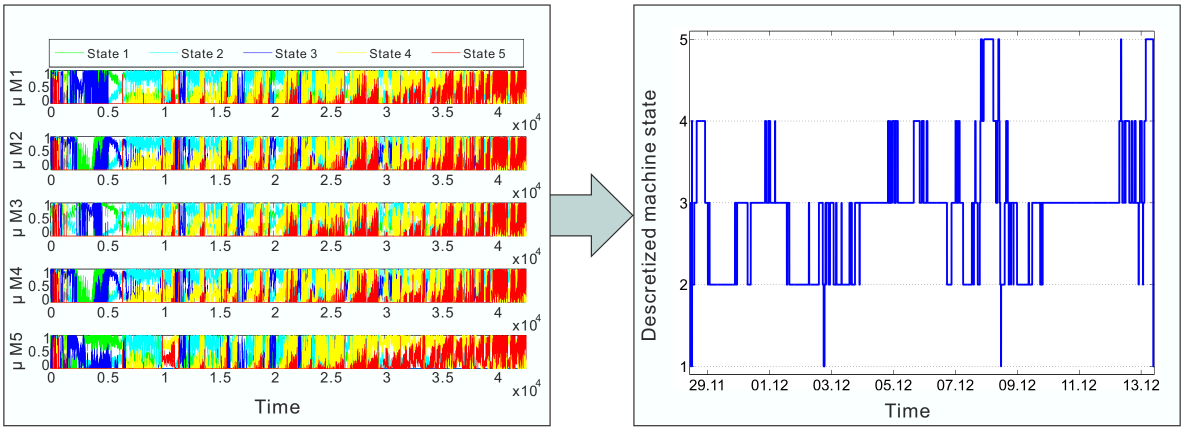

Figure 12. Establishing data-based classification approach based on the measurement Z15; (**left**): time-behavior of state distribution for different characteristics, (**right**): classified machine state (approach D).

4. Discussion

The four methods developed and introduced by the authors differ in several aspects when applied to wear monitoring. Due to the fact that from a principal point of view no objective information about the wear state is available (due to missing theory for real practical systems) the contribution offers four options to evaluate wear states. Unlike the method introduced in [11] the methods in this contributions allows adapting the approaches to individual systems and requirements. This appears as the main new advantage of the approaches introduced. Criteria for the different methods and the related results are given in Table 1. In this contribution, main features considered for practical applications are: implementation and technical effort, capacity for real-time evaluation, complexity, practical aspects related to the validity and reliability of the results obtained, and the capability of reliable fault detection and diagnosis.

The AE-based approach (approach A) provides deep physical insights into the wear processes via a strong filtering effort, whereas methods based on the use of easy to obtain macro-data (approaches B–D), such as data acquired from hydraulic systems, are simpler from various perspectives, e.g., simple integration into operations management and simple implementation in the decision logic modules used for condition assessment. However, these mechanisms will not directly lead to identifiable information, although the capacity for the automatic classification of training and test data using the fuzzy-based approach (approach D) should facilitate significant applications in practice. In particular, the use of combined approaches should allow significant further progress. Summarizing all approaches the following can be stated:

- More detailed sensor information can yield a more complex diagnosis. Here detailed information with respect to the frequency content was provided by the AE-sensor providing more frequency-based information.
- The implementation becomes more difficult when the underlying physics behind and related mathematical background are more complex.
- Surprisingly, the simplest methods (approaches B and C) can yield similar quality of evaluation results with respect to the general goal of Structural Health Monitoring (SHM)-systems (qualitative evaluation of health based on the system's state).
- The implementation and use of suitable filtering algorithms is important, especially for methods based on operational data. Thus, knowledge and experience are required for tuning, similar to experienced previous signal analysis methods.

Table 1. Comparison of the Four Methods Evaluating the Performance of Different Criteria; - - : very low, - : low, 0 : neutral, + : high, ++ : very high.

Criteria / Method	Acoustic Emission analysis (approach A)	Diagnosis-oriented data filtering and threshold-based classification (approach B)	Condition evaluation based on a sensitivity matrix (approach C)	Data-based classification approach (approach D)
Effort for sensor application	-	- -	- -	- -
Effort for filtering	+	0	0	0
Costs and complexity of technical equipment	+	- -	- -	- -
Real-time capability	- -	+	+	+
Usage complexity (users)	+	0	-	- -
Usage complexity (developers)	0	- -	- -	+ +
Capability for reliable fault detection	0	+	+	+
Capability for reliable diagnosis	+ +	0	0	0

5. Summary and Conclusions

Supervision, monitoring, and diagnosis of technical systems are essential features of SHM-systems and assumed as key components of new automation systems (for production machines and equipment).

For practical realization often approaches easy to implement but also providing qualitative or quantitative meaningful statements are required. Applied online realizable approaches are often related to threshold monitoring or to the detection of features representing damages, etc.

This contribution presents four approaches providing continuous information about the system status based on measurements. In addition, the problem of missing objective (or analytical) statements about the end of useful lifetime is not solved (due to missing theory), but new ideas for continuous evaluation of the health status are provided, which can be easily adapt to arbitrary given systems for which individual thresholds have to be defined.

In this contribution, we propose four new methods for signal-based data evaluation to be applied to health monitoring. Designed properties are compared with respect to monitoring wear state. The first method (AE analysis) uses specific wear characteristics based on AE signals using piezoelectric ceramics. The wear phases can be distinguished using STFT and the accumulation of the emitted acoustic energy. This deep insight into the physical nature of the AE facilitates a complex diagnosis. The second method (diagnosis-based data filtering) is used to generate characteristic values (the arithmetic mean from the hydraulic pressure) to evaluate the surface state. The accumulated damage increments and the slope of the related curve allow conclusions to be made about the wear stages and the actual level of damage. An evaluation of the machine state can be made using threshold-based classification. The same filtering technique (diagnosis-oriented data filtering) is used in the third approach (condition evaluation based on a sensitivity matrix). A sensitivity matrix is constructed to consider the absolute level of wear and the actual changes in this level. Using this sensitivity matrix, the machine state can be evaluated as noncritical, alarming, or critical. Using the fourth method (data-based classification approach), a fuzzy-based classification algorithm analyzes the expertly classified data and generates a fuzzy-based model. The states are classified automatically. The first three methods allow a simple integration and implementation into the operation level, while the fourth method is characterized by the capacity to classify different states automatically after training and therefore represents the class of supervised (machine learning approaches) to be applied for monitoring. Based on these methods, the relationship can be determined between the physical failure modes and the calculated characteristics. Thus, the automatic classification of the changes that occur stochastically during wear processes is possible. Based on a feature-based evaluation of the available signals, the actual machine state can be determined continuously. All introduced methods are developed to address the issue of problem-specific real-time capture and the influence of wear in systems with sliding wear. All methods introduced are applied to experimental measured data obtained from the same test rig. All approaches show similar and comparable results. Based on these approaches, further maintenance strategies can be implemented, e.g., the control of failure rates or modeling of lifetime.

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