Adaptive Features in Condition Monitoring Systems

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Abstract

This paper presents some aspects concerning the problems of adaptive monitoring systems. Each automatic monitoring system has to be adapted if it is installed in a new environment. Characteristic of solving the monitoring task, the number of fault classes and free parameters in the internal classifier are potential switchers to adjust the system. We discuss general problems in the field, such as fault simulation, provide the necessary definitions of different levels of adaptivity, describe the state of the art and give some hints about how the implementation of intelligent data pre-processing can improve the transfer of data from an existing system to a new one. As an application we use the detection of fault in a roller bearing using the derivative $x^{(4)}$ to obtain a higher sensitivity in the monitoring system.

Keywords: Condition monitoring, roller bearing diagnostics, adaptivity, fractional derivative

1. Introduction

The use of advanced pattern recognition systems in assuming an objective perspective in statements concerning the state of technical systems has gained increasing importance. Thus the economy of highly automated and cost-intensive machines can only be guaranteed upon the high availability of these machines. The use of advanced, high-performance monitoring and diagnosis systems can make a significant contribution to this. Certain processes can be carried out safely for man and the environment only by means of reliably operating machines, particularly in fields where safety and environmental aspects play an important role. In the automatic control of technical systems, supervisory functions serve to indicate undesired or non-permitted machine or process states and to take appropriate actions in order to maintain operation and to avoid damage or accident. The following basic functions can be distinguished: 

(23,24)
1. Monitoring
   Measurable variables are checked with regard to tolerances, and alarms are generated for the operator.
2. Automatic protection
   In the case of a dangerous process state, the monitoring system automatically initiates an appropriate counteraction.
3. Monitoring with fault diagnosis
   Based on measured variables, features are determined and a fault diagnosis is performed; in advanced systems, decisions are made for counteractions.

The advantage with the classical level-based monitoring (1. and 2.) is simplicity, but it is only capable of reacting to a relatively large-scale change in a given feature. If the early detection of small faults and a fault diagnosis are desired, advanced methods based on Fuzzy Technology, Neural Networks or their combinations could be used\(^{(23)}\). A general problem which is very often cited as an argument against the application of adaptive methods in monitoring is the risk that the system may gradually and unnoticeably adapt to undetected changes. As a result, the system may fail to detect real faults, if these faults likewise develop slowly. Problems could occur if the transition from state A to C proceed over a long time (Fig. 1), because the classifier adaptation could follow the transition in small steps. Consequently, adaptive monitoring systems have hardly become established in fields which are especially critical, such as safety-relevant applications\(^{(24)}\).

![Figure 1. Transition of machinery condition from a healthy state A to a fault state C \((24)\).](image)

The second limitation arises from problems to generate a learning data set for the classifier design. In most cases only few or sometimes even no real measurement data are available to represent information about all possible machine or process states. Consequently the simulation of fault classes becomes more important. This paper will empha-
sise the main aspects regarding the integration of simulation results to improve the adaptive behaviour of monitoring systems.

2. Smart Adaptive Monitoring Systems

The concept of “smart, adaptive monitoring system” must first be defined. Furthermore, if a system is to be considered “smart” and “adaptive”, the requirements imposed on such a system must be specified.

2.1 General Properties of Smart Monitoring Systems

In the present section, the following four properties are employed as necessary criteria for a smart system\(^{(1, 24)}\):

1. Adapting
   Ability to modify the system behaviour to fit the environment, new locations and process changes. The aspect is identified as the most important feature for smart adaptive monitoring systems.

2. Sensing
   Ability to acquire information from the surrounding world and respond to it with consistent behavior. Chemical and nuclear power plant monitoring are large scale sensing systems. They accept input from hundreds of sensors to regulate temperature, pressure and power throughout the plant. In spite of the fact that different sensors exist, more and better sensors are continuously required. Along with a proliferation of sensors comes a greatly increased need to combine, or fuse data from multiple sensors for more effective monitoring. The required range extends from the processing of multiple data streams from a simple array of identical sensors to data from sensors based on entirely different physical phenomena operating asynchronously at vastly different rates.

3. Inferring
   Ability to solve problems using embedded knowledge and draw conclusions. This expert knowledge is in general a combination of theoretical understanding and a collection of heuristic problem solving rules that experience has shown to be effective. A smart monitoring system should be able to detect sensor faults to prevent the use of nonsensical input values for a classification.

4. Learning
   Ability to learn from experience to improve the system performance. Learning and adaptive behaviour are closely combined and without the implementation of learning strategies adapting will not work.

2.2 Adapting Monitoring Systems

The property of "adapting" is of special interest here and is therefore considered in greater detail. At this point, it may be helpful to provide an example of monitoring in which no adaptive capability exists. The roller bearings of a rotating industrial centrifuge must be monitored for possible damage. For this purpose, the vibration signals are
frequently recorded by means of an acceleration sensor. If the value exceeds a limit that has been manually preset on the basis of experience or as specified in standards and guidelines, an alarm is triggered. The alarm threshold can be adjusted, of course, but its value then remains constant for the monitoring phase. A system of this kind, which is still employed for most monitoring applications in industry today, is not adaptive and certainly not smart. Which prerequisite for this designation is lacking in such a system? A change in vibratory behaviour can be due to a wide variety of factors that do not result from a fault in the machine itself. Minor conversion work may have been performed on the machine, for instance, in the course of maintenance and servicing; such measures can cause a change in behaviour without resulting in a malfunction. The following levels of adaptability are conceivable in conjunction with monitoring systems\(^{(24)}\): 

1. **Level 1**
   An adaptive monitoring system is capable of recognising variations in the surroundings and process conditions. Modifications, such as the adaptation of limiting values, can be performed automatically by the system itself. The previously mentioned monitoring system for roller bearings remains unaltered on a machine.

2. **Level 2**
   An adaptive monitoring system can be transferred from one machine to another without the need of readjustment by an expert. Any necessary adjustment work should be reducible to an absolute minimum. However, the monitoring task itself should not be altered in this connection. That is, monitoring of a roller bearing is still the specified task, although the type of roller bearing and the parameters are different.

3. **Level 3**
   An adaptive monitoring system can be employed for other monitoring tasks without the need of altering the basic structure. The necessary limiting values or control parameters of the classification algorithm are, to a large extent, specified independently. At this third level, the monitored object itself can also be varied. The system that had previously been employed for detecting damage to roller bearings should now be employed for recognising imbalance in the rotor or for monitoring the process. For allowing the system to function at this level, learning strategies are implemented, rather than pre-programmed algorithms for calculating problem-specific features, such as the effective value of the acceleration.

In its present status, the technology usually does not even attain the first of the levels just defined. This situation may at first be surprising, and perhaps also somewhat disappointing, but is easy to understand from an engineering standpoint. The decisive external parameters causing variations in the monitoring parameters are highly diversified, and the mutual interactions among them are often unknown, consequently, a consideration of these parameters in a diagnostic model is difficult or impossible\(^{(24)}\). Once trained, a system is capable of performing a monitoring task as long as the prerequisites for the training status are satisfied. If these conditions change, however, problems will occur in the monitoring system, and the system must be retrained. For example, a defective roller bearing generates a typical fault signal. The results of experimental investigations indicate that the level of vibration generated by a bearing with identical damage can vary by a factor as high as 100 with different machines. Thus, they cannot be applied for attaining level 2, that is, transferability to other machines. However, methods
of this kind are typical of industrial monitoring to the present day and are applied in a wide variety of fields. Slight variations in vibration results from one survey to the next are assumed to be due to "process conditions", and regarded as not significant. If we were able to collect relevant quantitative data regarding the "process conditions" existing at the time that the vibration data were collected, and correct the vibration data for these conditions, then our diagnostic capability would become far more accurate and adaptive(2). The aforementioned level 3 currently exists only as a vision in the minds of researchers.

2.3 Requirements and Acceptance of Adaptive Monitoring Systems

If monitoring problems are already being solved sufficiently well today without adaptive behaviour, a logical question is why there is a demand for smart systems at all and whether this demand can be justified? For this purpose, the type of monitoring currently applied in industry must first be considered. From a methodical standpoint, this kind of monitoring no longer satisfies all of the requirements that must be imposed on a modern monitoring system. The concept of preventive maintenance implies the application of techniques for the early detection of faults and thus the implementation of appropriate maintenance measures in due time. As far as the monitoring of machines in industry is concerned, however, a change of this kind has hardly taken place at all in practice. Changes in the process or in the machine, of the kind not resulting from a fault, must be distinguished from ones that do result from a fault. Precisely this adaptivity at level 1 still presents serious problems for many systems, however. If a given system functions correctly, weeks or even months are often necessary for transferring this property to similar machines. Support for the expert in charge by the system itself is severely limited or completely absent. The requirement for human experts and the associated labour costs still severely restrict the acceptance of monitoring systems. On the other hand, precisely this situation offers a special opportunity for those who develop and supply monitoring systems, since an adaptive system becomes independent of particular applications and can thus provide specialised solutions at acceptable prices(24).

3. Learning Procedures for Smart Adaptive Monitoring Systems

Besides adaptivity, the learning ability is a decisive factor for a smart technical system. To a certain extent, these two properties are inseparably related, since the previously mentioned concepts of learning anew or relearning for achieving adaptive behaviour are not possible without the implementation of learning algorithms. The two fundamentally distinct approaches of "supervised" and "unsupervised" learning also apply to monitoring systems. The following three learning objectives are essential for a monitoring system(24):

1. Number of fault classes and quality states
   Especially in the case of machine monitoring, faults are often the result of a gradual transition from a good to a poor condition, rather than instantaneous occurrence. Consequently, the number of status classes to be selected is not clearly evident. For classical monitoring with limiting values, only two classes are employed. The transition
then occurs very quickly, and the operator's indicating lamp suddenly changes from green to red. However, one would expect an entirely different kind of information behaviour from a smart system. A possible solution is the introduction of additional, intermediate states. Thus, an alternation class can improve the transition between "good" and "poor". Another possibility is the use of fuzzy classifiers, which allow the appraisal of a condition not only for a status class, but also for gradual differentiations. In this case too, however, the number of fuzzy classes to be defined must first be specified. If one prefers to apply an algorithm for controlling the performance of this task, rather than doing it oneself, the use of "Kohonen feature maps" or Artificial Immune Systems are advisable. The appropriate number of class parameters can be determined automatically and a change in the number of classes is also conceivable, if new error classes occur.

2. Limiting values and classification parameters

For dealing with these parameters, training is certainly the most important task for monitoring systems. Manual entry and management of several hundred limiting values is not practicable; however, the need for such a large number of values is quite normal with the use of many features. Of course, a system capable of learning and which has recognised that new classes are necessary for the monitoring task can also be trained to employ the associated classifiers in a second step.

3. Features

An adaptive system should recognise the condition that the previously applied features no longer suffice for solving a monitoring problem with sufficient reliability. Hence, a further learning objective is the calculation - or at least a new selection - of new features which are better suited for the purpose. For achieving this objective, the application of automatic selection methods is necessary. The selection has to consider constraints of the classification algorithm. In this sense only so called wrapper approaches for the feature selection process will find suitable feature combinations.

![Trendline showing manually set alarm levels and adaptive levels (bold lines) and the overall vibration measurement data of rotating machine](image)

Figure 2. Trendline showing manually set alarm levels and adaptive levels (bold lines) and the overall vibration measurement data of rotating machine

One of the major problems is the manual setting of alarm levels. As two identical machines will not run or wear out in the same time the levels need to be adjusted during the
machine lifetime. There are several approaches to calculate the levels automatically based on historical data concerning outlier elimination. Even the use of a moving average with adjustable window length and different methods of the exponential weighting of data in the window will provide very sufficient results. Comparing the two bold printed solid lines in Figure 2, it can be seen that the levels set by the algorithm are approximately the same as those set manually. Events where the vibration level was higher than the current alarm level are identified in both cases. The markers indicate measurement points where the vibration is below or above the level.

3.1 Signal Processing Techniques for Adaptive Monitoring Systems

The measurement parameters traditionally used in condition monitoring are displacement, velocity and acceleration, i.e. \( x \equiv x^{(0)} \), \( \dot{x} \equiv x^{(1)} \) and \( \ddot{x} \equiv x^{(2)} \). The first time derivative of acceleration, i.e. the jerk \( \dddot{x} \equiv x^{(3)} \), is commonly used to examine the comfort of travelling in vehicles. The parameters \( x^{(3)} \) and \( x^{(4)} \) are very suitable for the condition monitoring of slowly rotating bearings. This is due to the fact that although the acceleration pulses are weak and occur at long intervals, the changes in acceleration are rapid and become emphasised upon differentiation of the signal \( x^{(2)} \). The use of fractional derivative \( x^{(\alpha)} \) allows stepless differentiation. The general suitability of this technique even in practical real world applications is without any controversy. An advantage of this method is the ability to obtain integer, real or complex order derivatives, which all can be used for machine diagnosis.

High frequency vibrations are excited in roller bearings as the rolling element passes a damaged area. Figure 3a shows the raw acceleration time signal \( x^{(2)} \) gained by an accelerometer with a length of 0.5 s, which is in accordance to a number of 65536 digital data and a sampling rate of 131072 Hz. From the original and non-filtered time domain signal, it is not possible to detect a high frequency vibration. But after zooming in neighbourhood of 0.04 s, one can see how the signal structure changes at about 0.041 s (Figure 3b). Another way to make this change noticeable is calculation of the amplitude spectra of the signal with data sets before and after the excitement. Two sets (each 1024 data points) were taken out from \( x^{(2)} \). Both have the same length. The first data set ends at 0.04 s and the second one starts at 0.04 s. The comparison of amplitude spectra in Figure 3e shows that the high frequency vibration generated by the rolling contact between ball and the damaged surface is not present before the excitement. The spectrum on the right shows the high frequency vibration in 40 – 60 kHz range shortly after the excitement. High frequency vibration can be shown also via filtering. In Figure 3c and 3d filtered signal is shown by two different band pass settings (1-40 kHz and 10-40kHz). The first band pass filtered signal in Figure 3c (1-40 kHz) does not significantly differ from the raw signal in Figure 3a. A significant change can be seen in Figure 3d, in which the second band pass filtered signal (10-40kHz) is shown, at about 0.041 s. The similar effect can be obtained via second derivative of the acceleration signal. The advantage is that it is not necessary to filter the raw signal (Figure 3f). This method can be very helpful in searching small faults in roller bearings, hence high frequency vibrations are excited via small damages.
Figure 3. Example for demonstrating the usefulness of higher derivatives.\(^{(25)}\)
4. Application - Roller Bearing Diagnostics

The idea suggested here is to use only parts of the time signal which stand in close relation to possible bearing faults. For that purpose a peak in the time signal is defined as a local extremum in the measured acceleration signal \( x^{(2)} \). All peaks in the time signal which fulfill the requirements of the peak definition are detected and for each all significant information like position and amplitude, and adjacent data points are stored. This data are used as an input for the calculation of features. The calculation of the fourth derivative \( x^{(4)} \) was carried out by using a fourth-order centered difference formula on uniform grid \( \text{adj} \). Therefore a set of adjacent data points on the left and right side of each peak have to be considered. Now the calculation of different features on the basis of this set of peak information containing position and amplitude of peak, and adjacent data points is possible.

A feature vector is defined as a set of parameters extracted from the considered signal, which gives indications about the current state of the operating system. In condition monitoring statistical methods have been widely used for investigation, where measured data are time series. Extensive literature is available on diagnostic techniques using RMS, Kurtosis, Crest Factor and histograms and other statistical moments \(^{10,11,12,13}\).

The method suggested here uses peaks as a source of information corresponding to bearing faults. Possible features may be calculated from the ratio of local maxima of measured \( x^{(2)} \) and \( x^{(4)} \). Also the distance variation between local maxima on adjacent or non-adjacent locations over a predefined offset value can be considered. Further features can be obtained by the number of local maxima with absolute values, which are over some predefined threshold values. The histogram of peak amplitude and peak distance distribution are additional features which could be considered. Taking the norm of signal values - for instance with root mean square - may be useful to eliminate the influence of signal energy of the measured impact sound. A selection of features from a total of 32 is listed in Table 1 in Section 4.1.

4.1 Detection of small bearing fault in simple demonstrator

For the investigation of the method described in Section 4 a simple bearing test rig was used. In Figure 4, on the left the very simple test assembly is shown. The components are the outer race of a roller bearing and a cage, in which the outer ring is mounted. Only one ball driven by compressed air is rotating and the inner ring is replaced by a whole shaft with eight nozzles around it. The vibration signal is measured by an accelerometer mounted at the outer ring. This assembly allows the measurement of the isolated vibration generated by the rotating ball and all other sources of excitation are omitted. The pathway from the source of vibration and the sensor is well defined and the number of join patches is minimized. Figure 4, right side, shows the fault in the outer race, which was induced by creating a small groove using electric spark erosion.
Figure 4. (left) Test rig is air driven and consists of outer race of a deep groove ball bearing type 6310, cage and accelerometer. (right) Outer race of the ball bearing. A point fault (diameter 510 µm) was introduced using electric spark erosion.

The comparison of the signals in Figures 5 (bearing without a fault) and 6 (faulty bearing) indicates that a separation of the signal from a bearing without a fault and the outer race groove is possible in the time and frequency domain without any problems. The overall vibration level differs significantly. To eliminate the influence of the vibration level signals are normalised. The impulse of the ball in contact with the groove excites natural frequencies of the bearing and the surrounding elements (assembly parts).

Figure 5. Time signals and the amplitude spectra of intact outer race. Above measured signal, below signal was normalised by its rms value. 
The amplitude spectra in Figures 5 and 6 have amplitudes in a frequency range up to 30 kHz, which is typical for a small damage size but also for a random excitation of an intact bearing. One has to consider that the duration of contact between the damage and the ball is very short in comparison to the complete measurement time. In consequence the normalised spectra in Figure 5 (lower right) and 6 (lower right) do not show significant differences between the two states.

![Image of time signals and spectra](image)

**Figure 6. Time signals and the spectra of faulty outer race. Above measured signal, below signal was normalised by its rms value**

All feature combinations in Figure 7 are calculated after the normalisation of \( x^{(2)} \), and are well suited to separate the both classes. The distances between the class centres are much higher than the variation of the feature within a single class. In Table 1 a description of the selected features used in the figures and the corresponding dimensions are listed. The numbering indicates that these features are only a subset of the complete feature pool. All feature combinations could be used to design an automatic classification algorithm, but it is not the objective of this investigation to test such a classifier.

The two combinations of features in Figure 7 are selected to demonstrate the potential of the peak features. Comparing the scatter-plots of various feature combinations from different surfaces, one can observe the separation of data points which belong to different surfaces. This property can be used to monitor bearing health state and to perform damage detection. When using the combination 5 \( \mid 8 \) and 9 \( \mid 10 \) an 100% classification is possible. In general the selection of feature combinations could be executed by a soft-
ware algorithm, see \((14,15,16)\). In addition a couple of algorithms are available for a broad range of classification tasks.

Table 1. Description of features, which are used for roller bearing tests.

<table>
<thead>
<tr>
<th>No.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Mean value of the peak amplitudes from (x^{(2)}) at local maxima (peak) after normalisation. (x^{(2)}) is the normalised form of (x^{(2)}). Dim: -</td>
</tr>
<tr>
<td>7</td>
<td>RMS of (x^{(4)}). (x^{(4)}) was built, using local maxima (peak) in (x^{(2)}). Derivation method was named in Section 4. (x^{(2)}) is the normalised form of (x^{(2)}) and (x^{(4)}) is the normalised form of (x^{(4)}). Dim: ((1/s^2))</td>
</tr>
<tr>
<td>8</td>
<td>Mean amplitude value of (x^{(4)}). (x^{(4)}) was built as described in Feature 7. Dim: ((1/s^2))</td>
</tr>
<tr>
<td>9</td>
<td>Standard deviation of (x^{(4)}). (x^{(4)}) was built as described in Feature 7. Dim: ((1/s^2))</td>
</tr>
</tbody>
</table>
| 10  | Mean value of the ratios, which are obtained using the amplitude of the local maxima (peak) in \(x^{(2)}\) and \(x^{(4)}\) at the corresponding position. Dim: \((1/s^2)\)  

\[
F_{10} = \frac{1}{n_p} \sum_{i=1}^{n_p} \frac{x_i^{(4)}}{x_i^{(2)}}  
\]

\(n_p = \text{Number of peaks}\)

Figure 7. Scatter-plots of good and faulty outer races in air driven test rig\(^{(9)}\). Each measured time signal was normalised by its RMS value before feature extraction.
4.2 Hybrid Systems for Monitoring

An approach of this kind can be useful especially in applications where hybrid monitoring systems utilise various trial solutions for intelligent data processing in a parallel structure. The following components have already been implemented for improving the adaptivity of monitoring systems(24):

1. Neural networks (NN)
   Neural networks are certainly suited for applications in machine monitoring. Numerous reports on successful applications have been published. Because of their capability of operating with noisy signals and of representing the non-linear relationships between sources of error and the resulting signal, neural networks are predesigned for this field of application. A further advantage is the high potential for generalisation, that is, the capability of reaching a sensible decision even with input data that have not been learned.

2. Rule-based fuzzy systems
   Despite the general reservations with respect to expert systems, the application of rule-based systems for machine monitoring still makes sense. Especially the possibility of expanding an initially rudimentary system speaks in favour of this approach. During the initial stage of installation, such a system is very well suited for representing expert knowledge by means of simple rules in the form of 'if-then' relationships. The rule base is frequently very broad and applicable to a wide variety of machines and plants. The degree of adaptivity is therefore relatively high. A general disadvantage in such a system is the fact that it cannot operate more efficiently than the rules that are introduced by the human expert. The loss of information resulting from the conversion of knowledge for deriving the rule base must be taken into consideration here. Thus, it can be concluded that the diagnostic reliability of such control systems is no better than that of a human expert with average experience. However, advantages result from the fact that the expert can define or establish rules even for classes and states for which no data are available.

3. Neuro-fuzzy diagnostic systems
   Neuro-fuzzy systems are one key to the implementation of learning capability in intrinsically static rule bases. Many possible methods are available for the automatic generation of rules. For instance, the NEFCLASS(17) software is capable of performing this function. The rule bases thus derived are often considerably better than those resulting from a purely linguistic description of expert knowledge. Furthermore, the dependence of process parameters can be modelled in this form even if it is not possible for the experts to express it in such a form. Vibration signals can frequently be recognised and represented by a neuro-fuzzy system if the process parameters are recorded together with the vibration signals as a learning set. With the application of a neuro-fuzzy system, a high priority also results for the simulation, since the generally valid fuzzy rules thus derived are of special interest here, rather than the exact numerical values, for instance, of an individual natural frequency of a machine. For this purpose, an error of a few percent in the result of a numerical simulation is not important. The decisive features are the variation of the value in modelling a fault and the conclusions that can be reached from this result.
4. Artificial Immune Systems (AIS)

They are a relatively new area of research in Condition monitoring\(^{(18,19)}\). There has been an increasing interest to development algorithms and engineering tools inspired by natural and human immune system. The classical self/non-self model for the immune system as the classical approach dominating research activities over more than 40 years. There are many publications that discuss artificial immune systems applications in robotics, optimization, control, computer science and other areas. Various mechanisms or processes in the human immune system are investigated in the development of AIS. In a system of high complexity (because of its many connections and diversity of equipment) it is difficult to make a complete catalog of all the possible, and probable, anomalous situations. With its ability to detect and react to novel situations, the immune system seems to be an adequate source of inspiration to develop algorithms for early detection of anomalous behavior in mechanical and electrical systems.

5. Best Practice

Best practices. These two words represent benchmarking standards- nothing is better or exceeds a best practice\(^{(20,24)}\). The area of monitoring is much too broad to give a general best practice guideline.

But the questions in the following list should be answered before the selection of a method or combination of various methods, in order to ensure that the methods considered are really suited for the problem involved. That will not assure the best practice but the use of suitable methods that represent the state-of-the-art.

1. Are enough data available for all (as many) conditions or qualities (as possible)?
   
   This question must be answered in order to decide, for instance, whether the automatic learning of the classifiers can be accomplished with neural networks. For a neural network employed as a monitoring system, the situation is more favourable than for one employed as a process controller. With a monitoring system, an unlearned condition results either in no indication at all or, in the worst case, in a false indication, but the process itself is not affected. If only data for a "good" condition are available, these data can still be employed as starting material for a monitoring operation. All significant deviations from this condition are then detected. The adaptive system then evolves in the course of the operation with the continuing occurrence of new events.

2. How many features are available?

   Features should be closely related to the monitored object. How many features of this kind can be provided? It is necessary to determine the number of the features from that on a feature selection, and this can only be decided by considering the current monitoring task. As a provisional value you can take a number of 10 features. If more features are available, a selection should be carried out. Notice the existence of the close relationship between the number of features and the number of necessary random samples for a lot of classifiers. If it is necessary to reduce dimensionality, prefer feature selection if possible. The interpretability of new features, for instance,
calculated by a principal component analysis is difficult for both an expert in the field and most of all for an operator.

3. Can every set of process or machine data be unambiguously correlated with a class attribute (quality or damage)?
   If this is possible, methods of "supervised learning" should be applied. If this is not possible, or if class information is only available for portions of the data sets, cluster methods, such as Kohonen networks, should be employed. The problem is especially difficult if the task involves a very large number of available features, and the associated databases cannot be classified by an expert. In such cases two questions must be considered in parallel: the question of feature selection and that of clustering. Nearly all methods for the selection of features utilise the classification efficiency of the learning or test data set as a selection criterion. However, if no class designation is available, the classification efficiency is not calculable, and so-called filter methods must then be employed. As a rule, these methods yield features that are decidedly less efficient.

4. Do I have enough theoretical background, system information and suitable software to carry out a precise simulation, which should include fault simulation?
   The development of a model-based prognostic and diagnostic model requires a proven methodology to create and validate physical models that capture the dynamic response of the system under normal and faulted conditions\(^{(21)}\). There are a couple of model update algorithms that could improve the accuracy of a FEM-Model but you should never underestimate the work load and expert knowledge which is necessary for the implementation of the corresponding experiments and program usage.

5. What is of better quality or more reliable? The system model or the response of your sensors indicating changes in the machine or process?
   Having both would be the best situation because you are free to decide on the use of a forward model, which calculates a prognosis of the system response, and compares the estimation with the actual sensor signal. This procedure allows an estimation of the time to failure of the system. Additionally the difference between the sensor and the model will give you useful information about possible faults. For the inverse problem, the quality of the model is less important because the describing features and all condition information are extracted from the sensor signal independently from the model. For the diagnostics of roller bearings we have a rough model about the signal structure but in most cases not enough information for the prediction.

6. Do I have a safety relevant application?
   Until now there are a couple of problems concerning self-adaptive monitoring systems in safety relevant applications. These limitations result from problems that could occur during the evaluation and testing phase of such systems in all conceivable situations. The behaviour today and in future after system adjustment could differ significantly. This will encounter legal aspects because national and international testing institutions might have problems to certificate a system. In nuclear power plants, advanced self-learning and adaptive systems are today additional information sources but in general not the trigger for an automatic shut-down.
7. The cost factor. Do I have sensor technique and communication infrastructure for on-line monitoring?

Current commonly used sensor technology only permits the most rudimentary form of signal processing and analysis within the sensor. The use of advanced data analysis techniques will need more signal data. This means that large quantities of data must be transmitted from the sensor to a separate data collector for subsequent processing and analysis. If permanent on-line vibration monitoring is required - and for adaptive techniques it is absolutely necessary - then at present, for anything other than an overall vibration alarm, the cost of providing the required communications infrastructure and the data collection and analysis equipment far outweighs the benefits to be obtained\(^{(22)}\).

6. Conclusions

In analysing the current status the gap between new research developments in monitoring ideas, methods and algorithms and real-world applications in use in industry cannot not be neglected. New hybrid diagnostic systems using combinations of expert knowledge, data-driven modelling and advanced soft computing algorithms for classification and prediction proved their performance in the past. The combination of different techniques is the key to implementing learning ability and in consequence-adaptive behaviour. No expert in this field will argue the predominance of these techniques in comparison to standard methods that use simple threshold monitoring or a fixed classification algorithm. But there are still many problems to solve. The automatic determination, extraction and selection of features that are best suited for a given process is a challenging field of research in general and also in condition monitoring. Even future research activities will not lead to an exclusive monitoring strategy because the field of application for the various monitoring applications is too broad. But the permanent improvement of the simulation techniques will offer new possibilities by replacing the experimental learning part with computer-based fault simulation. Then we will also find adaptive techniques in areas where safety-relevant aspects nowadays prevent a real fault simulation and therefore possible broader applications of adaptive monitoring systems.

References

