Smart Adaptive Monitoring and Diagnostic Systems

Prof. Jens Strackeljan (*), Prof. Sulo Lahdelma (**),
(*) Otto-von-Guericke-University of Magdeburg, Institute of Applied Mechanics, Germany
(**) University of Oulu, Mechatronics and Machine Diagnostics Laboratory, Finland

Abstract: In this paper we present some aspects concerning the problems of smart 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 fractional derivatives 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 [17]:

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. 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.

![Diagram of machinery condition transition](image)

**Fig. 1** Transition of machinery condition from a healthy state A to a fault state C

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 emphasise 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 [19]:

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 behaviour. 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 required continuously. 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 adaptivity are conceivable in conjunction with monitoring systems.

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 the 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 vibratory 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. 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. The main reason for this variation is the difference in conditions of installation and paths for structure-borne sound with various machines. Consequently, all approaches that depend on limiting values must be excluded, since these limits likewise fluctuate by a factor as high as 100. 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. For controlling the quality of products during flexible manufacturing, the systems for monitoring the machines and products must also be flexible. In this case, flexibility can be equated to adaptivity.
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:

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" is advisable. The appropriate number of class parameters can be determined automatically with the use of these maps. A change in the number of classes is also conceivable, if new error classes occur. An adaptive system must allow such an extension.

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.

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 3. 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

Without going into details it has to be pointed out that the classical technique to represent time signals in the frequency domain by calculating a normal Fourier transformation (FFT) is an inadequate technique if adaptive behaviour is to be considered. The main disadvantage of the FFT is the lack to distinguish time variant effects. Transient malfunctions or the analysis of non-stationary effects requires other transformations than the ordinary FFT. One approach to improve the resolution in time is the Short Time Fourier Transformation (STFT). But with shortening the time window for each FFT, the time resolution could be improved but that implies a lower accuracy in the frequency domain (Fig. 3). While the FFT has no temporal resolution in STFT the resolution is fixed for the whole time-frequency plane. The Wavelet analysis (WA) is now able to adapt both the time and frequency resolution. WA can provide a high-frequency resolution at low-frequencies and maintain good time localization at high-frequency end.

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

Fig. 3  Comparison of FFT, STFT and WA in time-frequency plane [3]
This, coupled with the incapacity of FFT to detect non-stationary signals, makes WA analysis an alternative for machine fault diagnosis. WA provides multi-resolution in time-frequency distribution for the easier detection of abnormal vibration signals. Recently WA has been applied extensively in the analysis of mechanical vibration signals. A good summary about the effectiveness of WA for rolling element bearing diagnosis can be found in [4] and the authors in [5] have used WA in processing non-stationary signals for fault diagnosis in industrial machines.

4 Applications

A number of research papers describing new developments in the field of condition monitoring using advanced techniques can be found in the literature. These applications were selected because the authors were involved in the design of the monitoring concept and its implementation.

4.1 Roller Bearing Diagnostics

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 [6], [7]. 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 [6], [8], which means that it will be possible to move from the acceleration signal $x^{(2)}$, for example, to the signal $x^{(4)}$ via a number of intermediate stages [9], [10], [11].

Functions of the form

$$\bar{x}(t) = Xe^{(a + \varphi)}$$  \hspace{1cm} (1)

occupy a prominent position in vibration mechanics. Let us define the derivative $\bar{x}^{(\alpha)}$ of function (1) as

$$\bar{x}^{(\alpha)} = \omega^\alpha Xe^{i(\omega t + \varphi + \frac{\varphi}{2})}$$  \hspace{1cm} (2)

where $\alpha \in \mathbb{R}$ is the order of derivative, $\omega$ is the angular frequency, $X$ is the amplitude, $e$ is the Napierian number, $i = \sqrt{-1}$, $t$ is the real variable and $\varphi$ is the phase angle. The derivative $x^{(\alpha)}$ contains as special cases the derivatives where the order is an integer or a rational number. It can be seen from the definition (2) that differentiation involves the multiplication of $X$ by $\omega^\alpha$ and the change of the phase angle by $\frac{\varphi}{2\alpha}$ in a linear manner as a function of $\alpha$.

In this analysis, the sensitivity of detecting bearing faults means the ratio between the features of damaged and undamaged bearing. The fault was caused by two transversal grooves situated at approximately 90-degree intervals on the same side of the inner race (Fig. 4). Sensitivity increases first with increasing the order of the derivative. Later feature-specific threshold sensitivity starts to decrease [10]. High sensitivity is beneficial for the early detection of faults. In an example shown in Figure 5, the best results by using the peak value were obtained when $\alpha$ was 4.75 and in the case
of the kurtosis $\alpha$ was 4.5. The measurements were performed in the frequency range 3-2000 Hz, with a shaft rotation speed of 120 rpm. The $x^{(2)}$ and $x^{(4,5)}$ signals are presented in Figure 6.

Fig. 4 The testing equipment used is on the left and one of the grooves on the bearing’s inner race on the right.

Fig. 5 Sensitivity of detecting an inner race fault by using the peak value $x_p^{(\alpha)}$ and the kurtosis [10]
The $x^{(2)}$ and $x^{(4.5)}$ signals were measured from a faulty roller bearing in the frequency range 3-2000 Hz. The fault was on the bearing’s inner race and the rotation frequency was 2 Hz [10].
5 Introduction of Simulation Results into Monitoring Concepts

5.1 Status of Simulation Technology with the Application of FEM

A general problem in designing classifiers on the basis of learning data is the need to provide a sufficiently large learning set. In the ideal case, the learning set should include all the states that will occur during later operation, as far as possible. This requirement also includes all fault situations. For machine monitoring and process control tasks, this demand can hardly be fulfilled in practice. Consequently, the generation of fault classes by alternative methods has been the subject of intensive research work for several years. One of the largest research projects on this topic was VISION [12], which was supported by the EU. The project was conducted by an international consortium over a period of 6 years, and comprehensive publications have resulted from these investigations. The objective of the project was the integration of computer simulations and measurements on test rigs into the process of accepting data from real measurements for improving the reliability of automatic monitoring systems (Fig. 7). The data from the fault simulation were compared with data from very simple test rigs, for which the specific implementation of defective machine components is feasible, in contrast to real industrial plants. The basic idea of this approach is not new in itself, but the objective of the project was to achieve a new dimension in the quality of the simulation. From a conceptual standpoint, promising trial solutions have certainly resulted from this project, but these are concerned essentially with integration strategies for the different data sets to yield a standardised learning set. However, the overall result can never be better than the simulation, which is taken as the basis. Precisely this weakness limits the applicability of FEM in the field of machine monitoring at present. Modelling of the extremely complex, frequently non-linear processes of contact between machine components in motion is feasible in simple cases only. As an example, consider the contact of a roller bearing with pitting in the track. Hence, simulations by FEM have not yet been developed to the extent necessary for direct application with neural networks as a part of learning sets for individual faults. Are there any fields of application in which this approach can still be useful?

Fig. 7 Diagnosis integration overview [1]
5.2 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:

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 predestined 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 [13] 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. Vibratory signals can frequently be analysed only as functions of process situations. These relationships can be recognised and represented by a neuro-fuzzy system if the process parameters are recorded together with the vibratory 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.

A criticism of neural network architecture is their susceptibility to the so-called catastrophic interference, which should be understood as the ability to forget previously learned data when presented with new patterns. To avoid this some authors have described neural network architectures with a kind of memory. In general, two different concepts are promising: either the network possesses a context unit which can store pattern for a later recall, or the network combining high levels of recurrence coupled with some form of back-propagation [14].
6 Best Practice

Best practices. These two words represent benchmarking standards - nothing is better or exceeds a best practice [15]. 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 [16]. 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 the 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 [2].

7 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 [18]. 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


