Technical Design of Condition Based Maintenance System
-A Case Study using Sound Analysis and Case-Based Reasoning

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Abstract
Productivity is a key weapon for manufacturing companies to stay competitive in a continuous growing global market. Increased productivity can be achieved through increased availability. This has directed focus on different maintenance types and maintenance strategies. Increased availability through efficient maintenance can be achieved through less corrective maintenance actions and more accurate preventive maintenance intervals. Condition Based Maintenance (CBM) is a technology that strives to identify incipient faults before they become critical which enables more accurate planning of the preventive maintenance. CBM can be achieved by utilizing complex technical systems or by humans manually monitoring the condition by using their experience, normally a mixture of both is used. Although CBM holds a lot of benefits compared to other maintenance types it is not yet commonly utilized in industry. One reason for this might be that the maturity level in complex technical CBM system is too low. This paper will acknowledge this possible reason, although not trying to resolve it, but focusing on system technology with component strategy and an open approach to condition parameters as the objective is fulfilled. This paper will theoretically discuss the technical components of a complete CBM system approach and by a case study illustrate how a CBM system for industrial robot fault detection/diagnosis can be designed using the Artificial Intelligence method Case-Based Reasoning and sound analysis.

Introduction
Industrial competition today is truly global with fragmented markets and customers expecting to get the best product at the best price with immediate availability. Success in manufacturing, and indeed survival, is increasingly more difficult to ensure and it requires continuous development and improvement of the way products are produced. Meeting customer demands require a high degree of flexibility, low-cost/low-volume manufacturing skills, and short delivery times. These demands make manufacturing performance a strategic weapon for competition and future success. This view is supported by Rolstadås who state that many managers believe that the greatest potential for improvement of competitiveness lies in better production management (Rolstadås, 1995).

One important weapon in securing the productivity is to have a well functioning maintenance organization. The maintenance organization in a company probably has one of the most important functions, looking after assets and keeping track of equipment in order to secure productivity. With no or a poor maintenance organization a company will loose a lot of money due to lost production capacity, cost of keeping spare parts, quality deficiencies, damages for absent or late deliveries etc.

Today, most maintenance actions are carried out by either the predetermined preventive- or the corrective approach. The predetermined preventive approach has fixed maintenance intervals in order to prevent components, sub-systems or systems to degrade. Corrective maintenance is performed after an obvious fault or breakdown has occurred. Both approaches have shown to be costly in many applications due to e.g. lost production, cost of keeping spare parts, quality deficiencies etc. Since a few decades some industries have started to perform maintenance action in a predictive manner, where the assets condition is the key parameter to set the maintenance intervals and appropriate maintenance tasks. The condition can be assessed through different levels of automation, from human visual inspection, to condition monitoring of e.g. vibration-levels (with human diagnosis and prognosis) all the way to completely automated Condition Based Maintenance (CBM) systems.

On-line, semi- or fully automated CBM systems has not been widely accepted within Swedish industry. The reason for this can come from many different sources. The maturity level within complex technical systems might be too low. The fear of investing a lot of money without knowing exactly what will come out of it might be yet another reason. The methods and techniques to diagnose faults might also be on a too abstract level. This paper will not try to resolve the issue of what reason might be the biggest, although taking the aspect of condition parameters and system architecture into context as the objective is fulfilled. The objective of this paper is to describe and (by a case study) illustrate the necessary technical components of a CBM system. The paper contains a short theoretical frame of reference (covering maintenance and Condition Based Maintenance in particular); a theoretical discussion of technical components within a CBM system; a case study illustrating the technical design and components of a CBM system for industrial robot fault detection, using Case-Based Reasoning and sound analysis; and conclusions.

Theoretical frame of reference

Maintenance is traditionally performed in either time based (or distance based) fixed intervals, so called preventive maintenance, or by corrective maintenance. With the preventive approach, maintenance is performed in order to prevent equipment breakdown and do this by performing repair, service or components exchange. With the corrective approach, maintenance is performed after a breakdown or when an obvious fault has occurred, for some equipment the maintenance action must be performed immediately, for others the maintenance action can be deferred in time, all depending on the equipments function. In the Swedish standard SS-EN 13306 (2001) one can see that also the preventive maintenance have been divided into two categories (see Fig. 1), Condition Based Maintenance and predetermined maintenance. The predetermined is scheduled in time were as the condition based can have dynamic or on request intervals. The Condition Based Maintenance is sometimes referred to as predictive maintenance, see figure 2 for strengths and weaknesses of the different maintenance types.

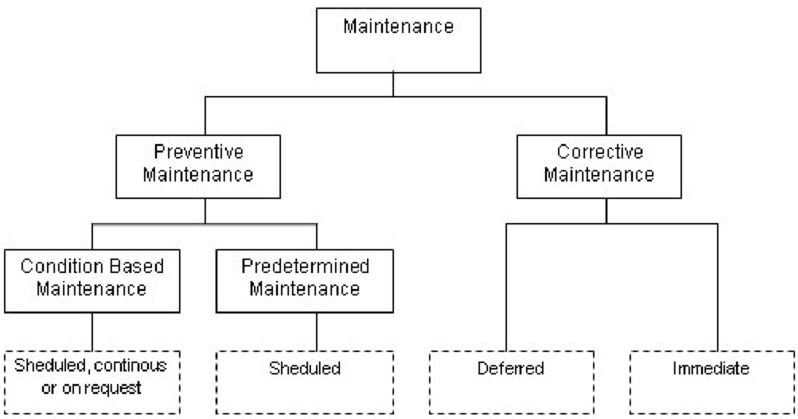

Figure 1. Overview of the different maintenance types (SS-EN 13306, 2001).

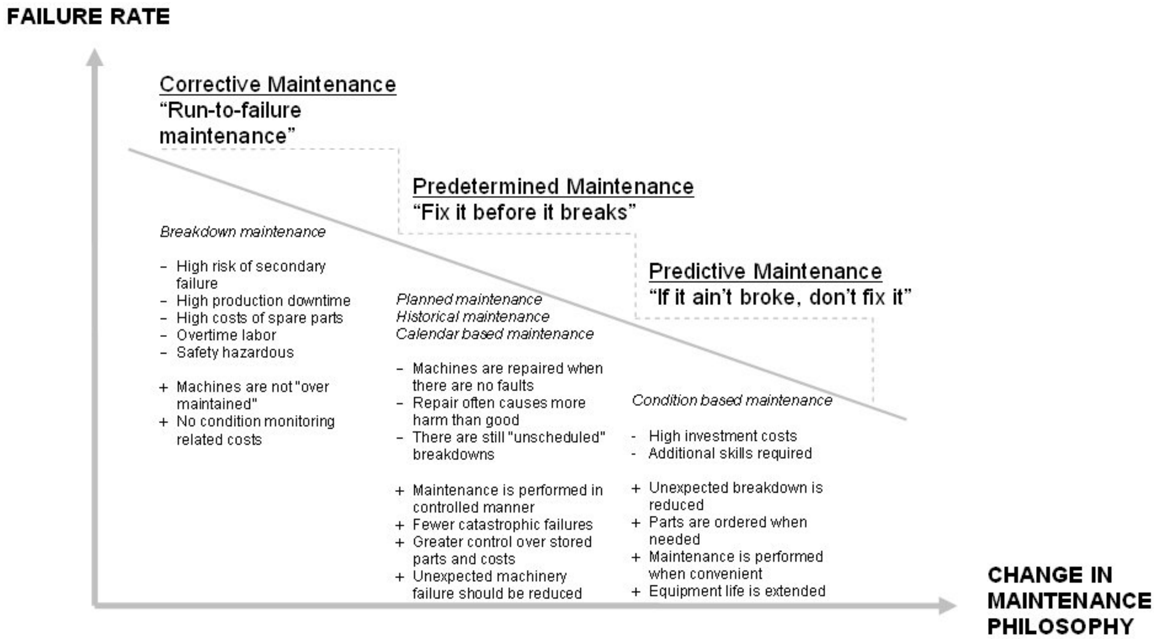

Figure 2. Strengths and weaknesses of different maintenance types.

As early as 1978, Nowlan and Heap (1978) presented a study of conditional-probability curves of United Airlines aircraft components. The study showed that the conditional-probability curves fell into six different patterns (see Fig. 3) were only 4% of the components fell into the commonly known bathtub curve. Further, it showed that only a total of 6% of the components showed a well-defined wear out region, another 5% had no well-defined wear out region but it was visible that the probability of failure was higher as age increased. This means that 89% of the tested components had no wear out region; therefore the performance of the components can not be improved by introduction of an age limit. Nowlan and Heap also concludes that the failure rate of a component is not a very important characteristic within maintenance programs; although a good figure for setting up maintenance intervals it tells nothing of "…what tasks are appropriate or the consequences that dictate their objective." (p 48). Corresponding conditional-probability curves for the manufacturing industry is presented by (www.wmeng.co.uk) and it is estimated that 30% of all components have well-defined wear out regions, consequently 70% does not. Evidently, the ageing feature of a component is not the best approach of deciding appropriate maintenance tasks, introducing Condition Based Maintenance is one solution to the issue.

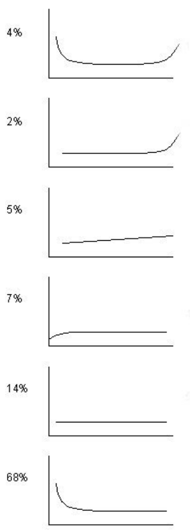

Figure 3. The six different conditional-probability curves generated by the United Airlines aircraft study.

Condition Based Maintenance (CBM) has been defined as “Maintenance actions based on actual condition (objective evidence of need) obtained from in-situ, non-invasive tests, operating and condition measurement.” (Mitchell, 1998). Butcher (2000), defines the maintenance technology as “CBM is a set of maintenance actions based on real-time or near-real time assessment of equipment condition which is obtained from embedded sensors and/or external tests & measurements taken by portable equipment.”. Moya and Vera (2003) defines that the purpose of a CBM Program is to “…improve system reliability and availability, product quality, security, best programming of maintenance actions, reduction of direct maintenance costs, reduction of energy consumption, facilitates certification and ensures the verification of the requisites of the standard ISO 9000.”. The Swedish maintenance terminology standard SS-EN 13306 (2001) defines CBM as “Preventive maintenance based on performance and/or parameter monitoring and the subsequent actions.”. More similar quotes can be found in literature and on the internet, the common point being that maintenance actions are not considered until there is an obvious need, which will increase the availability of an asset as well as lower maintenance cost (labour and spare parts). CBM systems (programs) will also increase quality and improve environmental aspects.

Condition Based Maintenance System Architecture

In order for a system to achieve full potential as a Condition Based Maintenance system, it needs to be constructed of a number of different functional capabilities. The Open System Architecture for Condition Based Maintenance organization (OSA-CBM) has specified an open standard proposal how a CBM system should be designed technically. The OSA-CBM is an industry consortium that includes industrial, commercial, and military participants, the Applied Research Laboratory at Penn State, and the MIMOSA (Machinery Information Management Open System Alliances) are two of the team participants. The open, non-proprietary, standard proposal was developed in order to create a free market for CBM components, where users of CBM technology will be able to choose CBM components from different manufactures. The organization has divided a CBM system into seven different technical modules (Thurston, 2001) (see Fig. 4). The standard proposal covers more than the technical design of CBM systems, e.g. means of communication within the system etc., this paper though, will solely focus on the architecture design.

Layer 1 Sensor Module: The sensor module provides the CBM system with digitized sensor or transducer data.

Layer 2 Signal Processing: The signal processing module receives signals and data from the sensor module or other signal processing modules. The output from the signal processing module includes digitally filtered sensor data, frequency spectra, virtual sensor signals and other CBM features.

Layer 3 Condition Monitor: The condition monitor receives data from the sensor modules, the signal processing modules and other condition monitors. Its primary focus is to compare data with expected values. The condition monitor should also be able to generate alerts based on preset operational limits.

Layer 4 Health Assessment: The health assessment module receives data from different condition monitors or from other health assessment modules. The primary focus of the health assessment module is to prescribe if the health of the monitored component, sub-system or system has degraded. The health assessment module should be able to generate diagnostic records and propose fault possibilities. The diagnosing should be based upon trends in the health history, operational status and loading and maintenance history.

Layer 5 Prognostics: The prognostic module should have the possibility to take account data from all the prior layers. The primary focus of the prognostic module is to calculate the future health of an asset, with account taken to the future usage profiles. The module should report the future health status of a specified time or the remaining useful life (RUL).

Layer 6 Decision Support: The decision support module receives data from the health assessment module and the prognostic module. Its primary focus is to generate recommended actions and alternatives. The actions can be related to maintenance or how to run the asset until the current mission is completed without occurrence of breakdown.

Layer 7 Presentation: The presentation module should present data from all previous modules. The most important layers to present would be the data from the health assessment, prognostic and decision support modules as well as alerts generated from the condition monitors. The ability to look even further down in the layer should be a possibility. The presentation module could be built into a regular machine interface.

When studying scientific reports and papers one can see that several developments within CBM systems more or less have followed the OSA-CBM architecture, giving the proposal positive feedback. Garga et.al (2001) has used a CBM system approach with sensors, data processing, fault classification techniques, and for some features prognostic models. Discenzo et.al (1999) presents a nine step hierarchy of intelligent machines with data acquisition, monitor, detect, diagnose, prognosis, prognostics & control, system-level prognosis & control, dynamic optimization/multi-objective control, and adaptive/reconfigurable.

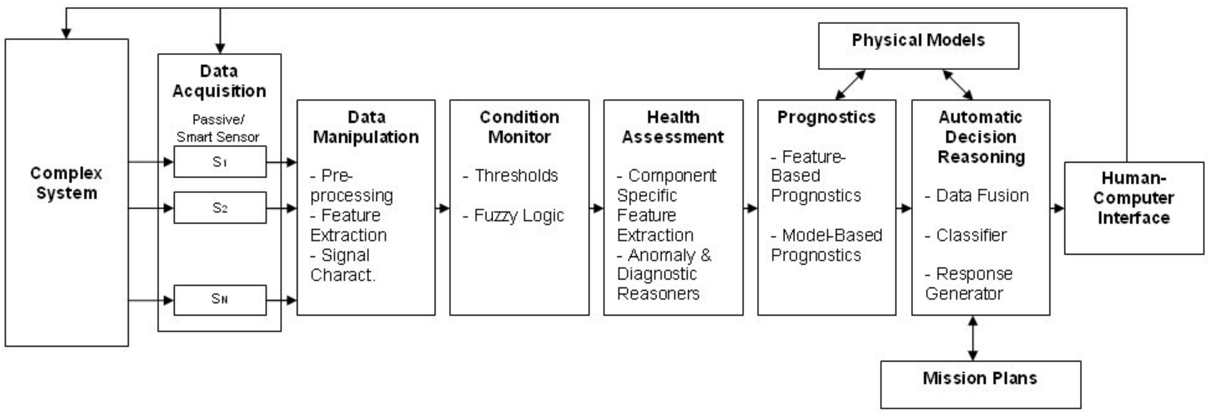

Figure 4. The seven modules in the OSA-CBM architecture standard proposal as presented in Lebold et.al (2003).

Sensors

Sensors have been defined as a "device that receives and responds to a signal or stimulus." (Fraden, 1996, p. 2). The definition is according to Fraden (1996) broad, and that it could contain everything from the human eye to the trigger of a gun. He, instead, would like to use the definition "a sensor is a device that receives a signal and responds with an electrical signal."(p. 3). A sensor or other technical measurement devices have some advantages to human inspection: they are reliable and precise, they can measure in unhealthy and hazardous conditions, they work fast, they work continuously, and they can perform measurements to a relatively low cost.

A sensor never functions on its own but is a part of a larger system with other tools, such as signal processors. Those tools are in its turn a part of an even bigger system, such as a condition monitor. When an engineer chose an appropriate sensor for monitoring she/he needs to ask what the simplest way of discovering the stimuli is without constitute any degradation of the comprehensive function of the system (Fraden, 1996).

The rapid technology developments within the sensor industry have pressured both the prices and sizes of sensors. MEMS (micro electromechanical systems) and smart sensors have made it into the market of CBM as the lowest level of system health management (Lewis and Edwards, 1997). Sensors that have decreased in size can perform more tasks than conventional sensors. Takeda (2001) classifies industrial inspections in four categories:

- Inspection of infrastructure or facility,
- Inspection of equipment,
- Monitoring of products, and
- Monitoring of the environment

Lewis and Edwards (1997) means that MEMS devices are more reliable and produce more accurate sensor data than conventional sensors due to:

- Sensor redundancy,
- Low drift and increased temperature stability,
- Sensor self-test,
- Multi-parameter output,
- Operation in harsh environment, and
- All-optical versions for operation in hazardous environments

Signal Processing

The purpose of signal processing in diagnostic applications and CBM is: (1) remove distortions and restore the signal to its original shape, (2) remove sensor data that is not relevant for diagnostics or predictions, and (3) transform the signal to make relevant features more explicit (may be hidden in the signal, FFT analysis is an example of such a transformation). Distortions in sensor data may be caused by an imperfect:

- Sensor,
- Media (metal, water, air etc.) in which the signal travels before reaching the sensor, and
- Media from the sensor to an analogue/digital converter

Signal processing may also manipulate the signal that some characteristics enabling prognosis are more visible (for an analysis program or a human). Creating a feature vector from a signal is an abstraction of the signal, preserving the features used in diagnosis and prognosis.

Condition Monitoring

Condition monitoring has been defined as “A means to prevent catastrophic failure of critical rotating machinery.” and as “A maintenance scheduling tool that uses vibration, infrared or lubricating oil analysis data to determine the need for corrective maintenance actions.” (Davies, 1998). The parameters to monitor should be characteristics that will indicate an assets condition. The parameters to monitor should be selected by the ones that in normal mode remain stable but in abnormal or unhealthy mode will indicate some sort of a trend, e.g. increased vibration levels, increased noise, or decreased pressure etc. (Yam et.al, 2001).

According to Johansson (1993), condition monitoring has been divided into two separate techniques:

a) Subjective condition monitoring:
    - Sight,
    - Hearing,
    - Sense, and
    - Smell

b) Objective condition monitoring:
    - Sensors and other measuring equipment give data for either immediate condition assessment or as basis for trend analysis.

The subjective parameters can of course be used objectively if collected through sensors or other measuring equipment. Tsang (1995) divides condition monitoring techniques into six categories:

- Dynamic effects, such as vibrations and noise levels,
- Particles released into the environment,
- Chemicals released into the environment,
- Physical effects, such as cracks, fractures, wear and deformation,
- Temperature rise in the equipment, and
- Electrical effects, such as resistance, conductivity, dielectric strength etc.

Tsang (1995) also shortly presents a few different common condition monitoring techniques such as vibration monitoring, process-parameter monitoring, thermography, tribology, and the subjective technique visual inspection.

Diagnosis

Diagnosis has been defined as "…fault recognition and identification" (Lewis and Edwards, 1997, p. 8.5-5), i.e. a means to find out where something will go wrong and possibly even why. According to Yam et.al (2001) condition based fault diagnosis can be divided into three categories:

- Rule-based diagnostic systems,
- Case-based diagnostic systems, and
- Model-based diagnostic systems

Rule-based diagnostic systems comprise of a knowledge-base and a set of rules the system use to diagnose or predict a fault. These rules may be derived from experts in their field, and are then compiled into a set of rules. Extracting, validating, and verifying the rule base is essential in such systems since one faulty rule may wreck the complete result and make the system unreliable. This problem is often referred to as the "brittleness" of rule-based systems. The expert becomes the so called "knowledge acquisition bottleneck" and the rule-base needs maintenance, updates and extensions once circumstances change or new knowledge is developed. A set of rules in a rule-based diagnostic system may be translated to a decision tree traversed to determine the fault. This is only possible if the rules meet a number of criteria's (e.g. being deterministic). In some applications the rules may be induced automatically. For many applications rule-based diagnostics systems is the most appropriate solution. If statistics and fuzzy logic are used, these systems become powerful diagnostic tools for industry.

Case-based diagnostic systems are based on Case-Based Reasoning (CBR), a method from artificial intelligence, based in a cognitive model of learning from experience. Cases capture both a specific situation/problem and the solution to the problem. When a new problem occurs, it is compared with the case library and similar cases are retrieved. These cases are adapted, using domain knowledge, to fit the current problem. The solution in the case is reused after validation/verification and if necessary revised (performed by a human or by the system). The problem and the new solution is added to the case library as a new case. Case-based diagnostic is used in situations where the task to create a large and consistent rule base is too difficult or where model based diagnosis is inappropriate (example of these is given in the following section). If statistics and feedback (automatic, semi automatic or manually) is included in the cases, the system will not only improve performance with the addition of new cases, but also with experience derived from feedback.

Model-based diagnostic system is a powerful solution if a complete model of the equipment to monitor can be created. The model is used to detect any deviations and if a deviation is detected the model is used to identify what the problem is. The abstraction level of the model is the limiting factor for what faults are detectable. If it is possible to build a model based diagnostic systems, this is the most desirable diagnostic system. Unfortunately it is a manual process to build a model and it is difficult to build a model detailed enough for a majority of industrial applications where diagnostic systems are desirable. If a model can be built, real-time simulation is to computationally costly or impossible with available computers.

To build intelligent diagnostic systems, combination of the above mentioned methods is often necessary. Also other techniques and methods from artificial intelligence are needed, e.g. reinforcement learning to learn and adapt to normal conditions, reducing diagnostic mistakes. Genetic algorithms may be used to find the cause of multiple faults, avoiding the "state space explosion" when using traditional search strategies.

Prognosis

Prognosis has been defined as "…prediction of when a failure may occur" (Lewis and Edwards, 1997, p. 8.5-5), i.e. a means to calculate remaining useful life of an asset. In order to make a good (reliable) prognosis it must be followed after a good (reliable) diagnosis has been made.

Some diagnostic systems are able to make predictions when a fault may occur and with what probability. This information may be used as input by a prognostic system to predict a future health profile and calculate remaining useful life of some asset, given a required reliability level and safety limits. Further on this calculations may be used to produce a prognosis of the overall reliability of a large system. The weakest links in a system may be identified and counter measurements taken to stay within some specified reliability and safety limits. These measurements may be different maintenance tasks, but also measurements to ensure that certain replacement parts are available or redundant production capacity is within access within a certain time frame.

Thurston and Lebold (2001) present a proposal to a generic prognostic module where they present a standard set of input and output requirements for an OSA-CBM prognostic module. Input requirements cover historic data in form of e.g. prognostics, health, failure, mission, and maintenance history, as well as model information and spare assets capacity. Output requirements cover information about the current health along with remaining useful life with confidence levels of the prediction. The prognostic algorithms can be generic and can range from simple historical failure rate models to physical models.

Decision support

Decision support systems are computer systems aiding in the decision making process. A human expert is needed to make the final decision and the system provides the necessary information for making the decision. It may also be legal reasons for using decision support systems instead of fully automated systems, e.g. if decision making is not time critical, but the consequences of a faulty decision is large. Computer systems can be reliable up to certain level, but are often so complex that it is known that there are faults in them. The price of finding and removing all faults in a system may be too expensive, and even software sold in very large quantities contain large number of faults, e.g. Windows based systems.

A decision support system may have a number of diagnostic and prognostic tools, human experience and statistical data, all accessible by the human to aid in the decision making process. In intelligent human computer collaboration both humans and computers takes initiative and action. The computer system may notice, based on previous experience that a human operator tries to do something that may damage the equipment and intertwine. A dialogue between the system and the operator may result in a modified procedure, acceptable for both parts. Hence the step beyond decision support systems is human computer collaboration system.

Case Study

This chapter presents a case study of a Case-based fault diagnosis system implemented as a part of a master thesis in computer science at Mälardalen University (Olsson, 2003). The system was implemented to show how sound comparison and Case-Based Reasoning (CBR) can be used to detect faults in the gearboxes of industrial robots. In this paper it will serve as an illustration of how a technical CBM system can be designed.

Mechanical faults in industrial robots (and other machines) often show their presence as audible deviations compared to a normal sound profile. As a part of the end-test of industrial robots, a subjective condition monitoring based on hearing is used in order to detect audible deviations. Correct classification of those deviations is a critical part of the end-test. An incorrect classification of the sound can result in the delivery of a faulty robot to the customer. An operator needs long experience in order to make a correct classification. Artificial Intelligence (AI) methods, such as Case-Based Reasoning, have some advantages in this category of applications. The fundamental idea of CBR – applying old knowledge of problem solving to solve new problems is very feasible for this type of industrial applications. The method preserves experience that is often lost if personnel leave their employment.

The proposed fault diagnosis system uses a hybrid Case-Based Reasoning method using a nearest neighbour approach for a light weight solution of recognizing and diagnosing audible faults on industrial robots. Sound is recorded with a microphone and compared with previous recordings. Similar cases are then shown to the user corresponding diagnosis and actions based on previous experience. The system aids engineers in making a correct objective diagnosis of the industrial robot based on earlier classifications of similar sounds. The system is able to successfully diagnose faults in an industrial robot based on sound recordings (6 recordings from faulty robots and 30 recordings from normal robots are used in the evaluation).

The Case-based fault diagnosis system uses three different steps in its classification process; pre-processing, feature identification and classification. Sound is obtained from the robot to be diagnosed via a microphone as shown at the left in Fig. 5. The sound is recorded to a computer and the recording is taken as input to the pre-processing step. The pre-processing process is responsible for filtering and removal of unwanted noise. It also extracts period information from the sound. In the feature identification process, the system uses a two-pass model, first identifying features and then creating a vector with features. Once the features are identified, the system classifies the feature vector. The classification is based on previously classified measurements (case library). When a new sound has been classified, the new case is added to the case library.

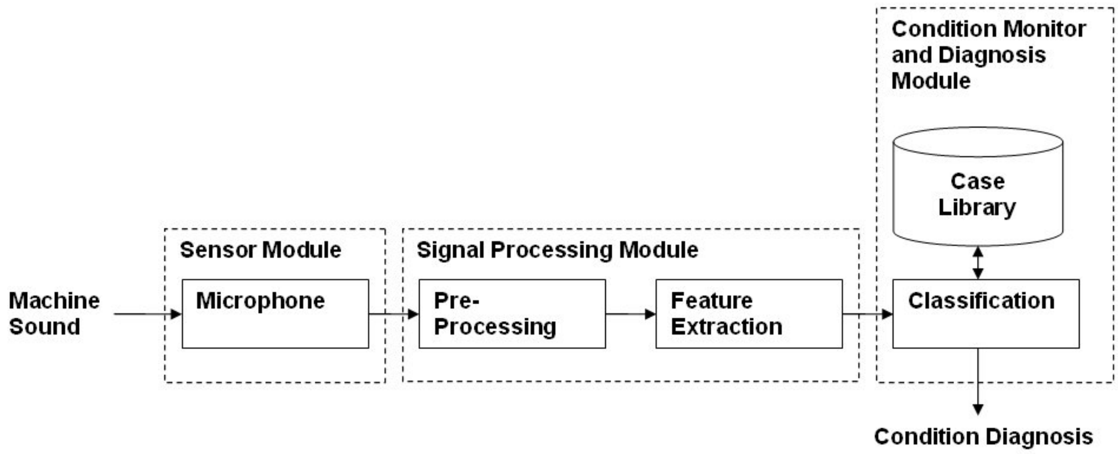

Figure 5. Schematic picture of the Case-based fault diagnosis system with its three steps to condition diagnosis.

Condition Monitor and Diagnostics

Sound from 24 healthy robots and 6 faulty robots were recorded during the case study. All recordings where made during the end-test of the robots. Among other tests, the end-test includes a separate axis test. In the separate axis test, all axes of the robot are individually tested. A microphone is mounted close to the axis of the industrial robot being measured (in this case axis 4). The robot is set to separate axis test and axis 4 is chosen. Two types of faults were recorded; fault 1 is caused by a notch on the big gear wheel in the gearbox of axis 4. The fault is hearable and it is characterized by a low frequency impulse sound in the middle of the rotation of the axis. Fault 2 is caused due to a slack between the gear wheels in the gearbox. The fault can be heard as bumps at the end of each rotation of the robot arm.

In the time/frequency plot in figure 4 the sound of the notch is seen as two repeating prominent peaks (see Fig. 6). The frequency of the plot is sound intensity for the frequency 180-220 Hz during 12 seconds. The normalised sound intensity level is a value indicating the peak intensity at a specific time. The plot shows four successive rotations of the robot arm. The peak is only visible in one direction of the rotation of the arm.

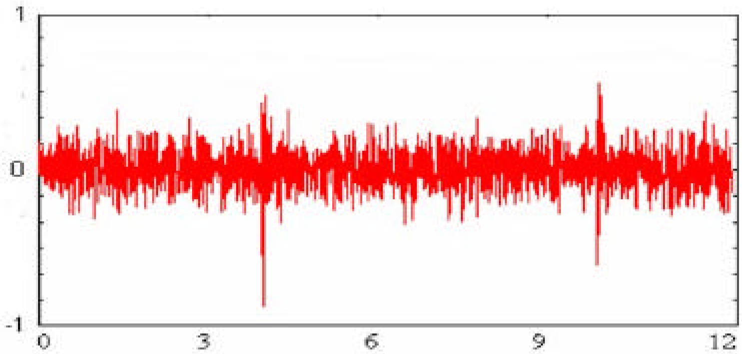

Figure 6. Illustration of X+1 recording sample with time/frequency plot from axis 4 on a faulty robot.

A feature vector is assembled from the sound and matched with the vectors in the case library. Table 1 displays a list with the five best matching cases in the case library ordered according to similarity in present. The similarity measurement is based on a straight forward nearest neighbour algorithm. The matching could be significantly improved using domain knowledge (Zhao et.al, 1991), but is already giving good results and classifying sound recordings correctly in 91% of all tests. As can be seen in table 1; a previously diagnosed notch faults is ranked close to a current recording verified to be a notch fault. The case ranked as second candidate (case #12) and third candidate (case #4) comes from normal recordings in the case library.

Case name	Similarity	Case ranking
Notch fault #2	98%	1.
Normal case #12	84%	2.
Normal case #4	83%	3.

Table 1. The three best-ranked classifications of cases in the case library

Case Study Results

CBR was found to be a feasible method to use to identify faults based on sound recordings in industrial robot fault diagnosis. Sound recordings where made under realistic industrial conditions. The CBR system has a number of benefits as an industrial diagnostic tool:

- New cases are easy to add to the library, one sound recording is sufficient,
- The method is easily accepted by engineers and is seen as a tool enabling them to perform better,
- It transfers experience; engineers are able to listen to different sounds and make manual comparisons,

- The system does not need to be "complete" from the start, a list of similar sounds and their classification are shown to the engineer, and
- Performance increases continuously, if a new "not normal" sound is recorded that cannot be classified, the engineer contributes to the systems experience by classifying the sound after the fault has been identified and corrected.

It has been shown in the validation that one recording is sufficient for identification of a similar sound in the case library. Also producing a straight forward feature vector from the original sound recording is sufficient for good results in the matching based on nearest neighbour. The feature vector and matching has potential for improvement. Potential users have been interviewed and their reaction to the research prototype tool is positive and they all judge it would improve their performance and productivity.

After analyzing the architecture of the developed Case-based fault diagnosis system, some similarities to the OSA-CBM standard proposal can be visualized. The microphone can be regarded as the sensor module. The pre-processing and the feature extraction process can be deduced to the signal processing module. The classification (with the case-library) performs both the condition monitoring and the diagnosis as it both detects deviations in the sound profiles and can classify different sound profiles to different fault modes.

Conclusions

This paper has presented a theoretical discussion of the components necessary for a complete CBM system approach and illustrated the first four of them through a case study. The OSA-CBM approach of seven modules has proven to be an appropriate way of developing CBM system technology. Although the development in the case study of this paper does not have complete modular design, the modules as they have been described has been a good template for development. The modules can also be seen as a template as technical aspects of CBM implementation. All of them are necessary to uphold a CBM strategy, level of automation can be seen as secondary importance. Although, for logistic reasons, the more complex, critical, and big sized processes to monitor the more automation will be necessary, but for smaller companies with less critical machines it might be enough just to have specified the way to think within the different modules. It might also be enough to take the level of automation to e.g. the condition monitor and leave the diagnosis, prognosis, and decision to the human intellect, thus making CBM a strategy not to complex for small companies to handle, but as a tool used by the maintenance personnel to plan more accurate maintenance intervals.

The case study did not only show that the modules specified by OSA-CBM were a good template for development, it also showed how a CBM system can be developed using maintenance personnel's tacit knowledge as condition parameters. End-testing of the industrial robots had previously been done manually by listening and recognizing audible deviations in the sound profile as the test program was launched, an experience taken long to acquire. With the development of the system the tacit knowledge of the testing personnel was recorded, secured to be used as a condition based quality assurance tool and possibly as a training tool for new employees. The system can also be further developed to involve condition diagnosis while the robots are used in actual production, as a tool to assess maintenance need, thus making it more necessary to include prognosis ability and possibly a more enhanced decision support function.

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