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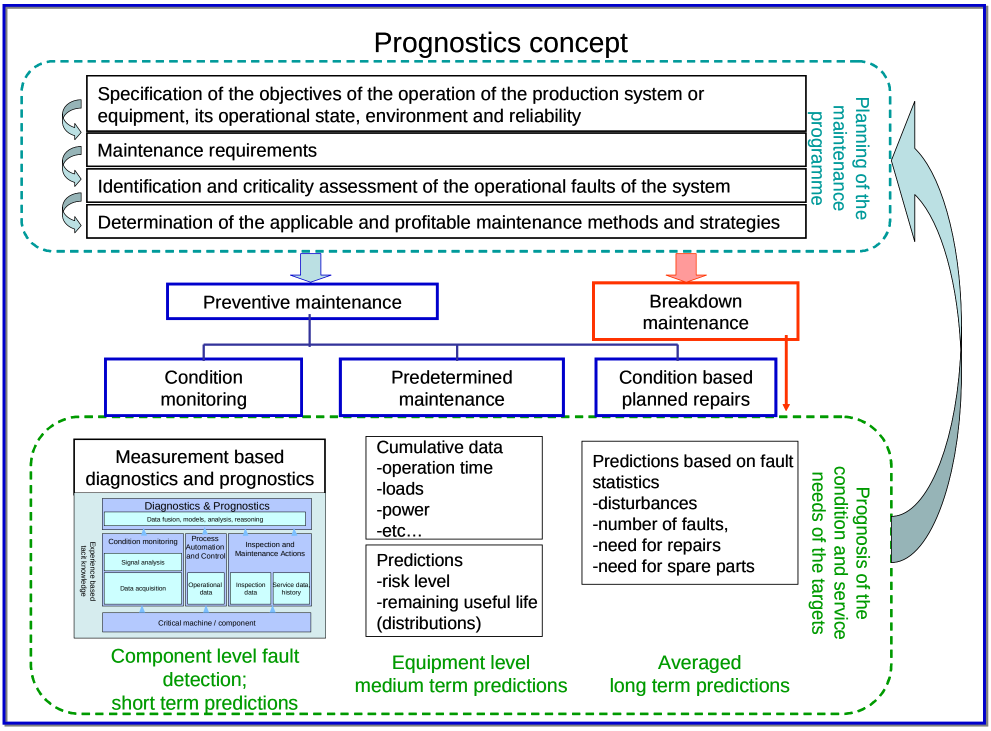


# Prognostics for industrial machinery availability

Prognos

Final seminar

VTT

VTT SYMPOSIUM 243

**Keywords:** Industrial machines, cranes, robots, electric motors, loaders, fans, paper machines, remote monitoring, condition monitoring, diagnostics, prognostics, operational reliability, control systems

# Prognostics for industrial machinery availability

## Final seminar

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Aino Helle

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# Preface

The three-year project Prognos – Prognosis for Industrial Machinery Availability started in October 2003 was a joint research effort of VTT Technical Research Centre of Finland, Lappeenranta University of Technology, Tampere University of Technology and University of Oulu. The objective of the project was to generate methods for improving and maintaining industrial machinery availability by developing tehniques which enable prognosis of the operational condition, failure probability, and remaining operating life of the machinery and production lines. Industrial cases selected on the basis of the strategic needs of the industrial partners formed the basis of the work carried out by the research organisations.

The results of the project have been reported in more than 90 publications, including 7 M.Sc. theses and one doctoral thesis. This final seminar is the third annual seminar held during the project to present the work and results both to the project partners as well as to other interested parties in Finland. This symposium publication summarises the main results of the project. In addition to oral and poster presentations, the final seminar also included workshop type discussions about ways of exploitation of the results, and identification of long term research needs and possibilities of future technologies within this field.

The editor, as the project coordinator, wishes to express her gratitude to the chairman of the project steering group Mr Seppo Tolonen of Pyhäsalmi Mine Oy, and to Mr Kari O. Nieminen from Metso Paper, as well as to Mr Mikko Ylhäisi from Tekes, the Finnish Funding Agency for Technology and Innovation for their presentations in the final seminar as representatives of Finnish industry and the main funding organisation. All the research organisations, other partners and individuals contributing to the seminars and the research work in the project are also gratefully acknowledged.

The research organisations would like to thank Tekes, VTT and all the 13 industrial companies participating in the project for financial support. Both Tekes and the industrial partners are also thanked for their interest and contribution to the active collaboration realised throughout the project.

# Contents

# Development of prognostic concepts and tools

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## Abstract

Diagnostic and prognostic tools have been developed in a three year project Prognos – Prognostics for Industrial Machinery Availability. Industrial cases selected on the basis of the strategic needs of the industrial partners in the Prognos-project formed the basis of the work carried out by the research organisations. A general schematic description of prognostic concepts made in the project assists in figuring out the different areas of existing methods, available data and possible further development needs in any specific cases considered. The results of the research and development in the Prognos project include methods, tools and knowledge covering many areas and technologies including tools from maintenance planning to component level monitoring, diagnostics and prognostics and 3D visualisation of respective data. A conceptual software tool was developed for prognostics, as well as tools for combining monitoring and process data, and for feature extraction. Vibration based method for adaptive grease lubrication was developed. The results also include methods and techniques required for remote diagnostics of electrical motors as well as diagnostics of quality control systems of paper machines. An on-line method for monitoring coating wear under erosive environment was also developed. The results have been published in a number of publications, the total number being in excess of 90. This includes 7 M.Sc. theses, one doctoral thesis, and 5 international journal articles, 31 international conference papers, 11 national journal articles, 24 national conference papers and a number of other publications. This article presents a short summary of the project, together with a general description of the prognostic concept, main results and industrial benefits.

# 1. Introduction and scope

Technological development has resulted in increased complexity both in industrial machinery and production systems, at the same time with the increasing demand in the society for improved control of economy, reliability, environmental risks and human safety. The economical consequences from an unexpected one-day stoppage in industry may become as high as up to 100 000–200 000 euros, see Figure 1 [1, 2]. Operational reliability of industrial machinery and production systems has a significant influence on the profitability and competitiveness of industrial companies. This emphasizes the increasing importance of on-line monitoring, diagnostics and prognostics of machinery, production processes and systems in industry.

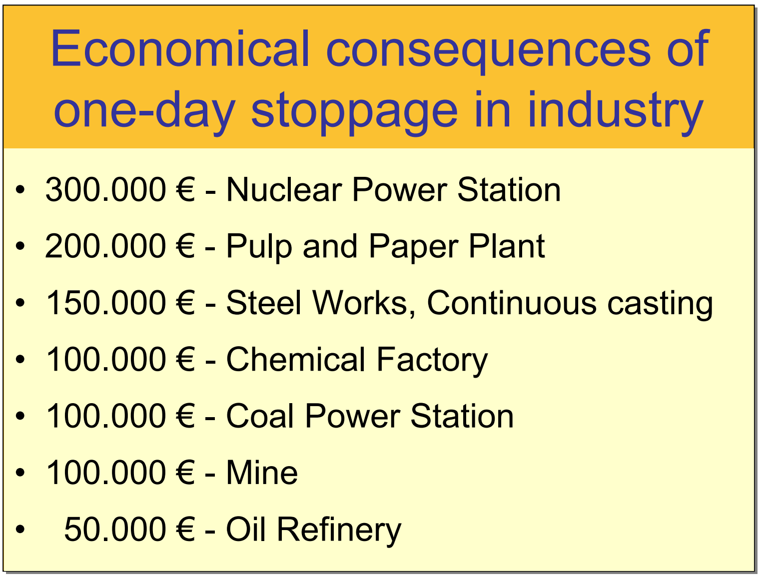


*Figure 1. The economical consequences of a one-day stoppage in industry based on ref. [1] and on estimates made by the industrial project partners.*

Research and development work focusing on improved reliability was successfully carried out in a national Technology Program Competitive Reliability during the years 1996–2000 by several research organisations and a large number of industrial companies [3]. Besides direct results, the program increased the awareness and understanding of the importance of reliability within industry and formed a good basis for further R&D efforts. A trend towards increasing maintenance service business has been evident as well as a trend towards predictive maintenance and condition based maintenance in order to identify service needs, optimise maintenance actions and to avoid unexpected production stoppages.

Research in this field was seen as strategically important by Tekes – Finnish Funding Agency for Technology and Innovation. This resulted in the preparation and start-up of the Prognos-project, Prognostics for Industrial Machinery Availability in 2003 as a joint research effort by VTT Technical Research Centre of Finland, Lappeenranta University of Technology, University of Oulu and Tampere University of Technology. Several companies took part in the preparation stage, and thirteen industrial companies joined the three year project as partners. Some facts and figures as well as a list of project partners are given in Appendix A.

The objective of the project was to generate methods for improving and maintaining industrial machinery availability by developing techniques which enable prognosis of the operational condition, failure probability, and remaining operating life of the machinery and production lines. The challenge was to combine and analyse data from measurements, history data and models by applying and developing novel ICT solutions and thereby to be able to give a prognosis, i.e. to predict the forthcoming condition and state of the machinery in order to be able to determine the right and rightly timed operation and maintenance actions.

# 2. Methods

Industrial cases selected on the basis of the strategic needs of the industrial partners in the Prognos-project formed the basis of the work carried out by the research organisations. The research and development work was partly generic and partly case specific in nature. Work plans were made for each case, taking into account possible synergies between the cases so that at least part of the work could serve several cases or result in widely adaptable generic solutions. For each case there was one research organisation nominated as responsible of the R&D work. The cases and the responsible parties are listed in Appendix A.

All cases involved a more or less thorough study of the current status of the case. In several of the cases this involved risk analysis and Failure Modes, Effects and Criticality Analysis (FMECA) in order to identify the most critical targets and components to be considered, taking into account the potential achievements that could be obtainable from impending improvements. The status with respect to the level of consideration, i.e. component or system level, as well as the technological methods available already, e.g. for monitoring and diagnostics, differed quite much from case to case.

A common objective in several cases was to develop methods with which failures and needs for maintenance actions could be predicted by combining and analysing data from different sources such as condition monitoring or other measurements, process data and history data, for example. Though in some cases a lot of data was available right from the beginning and some diagnostic methods were already in use, proper methods for selecting the essential data, combining and further processing it into more reliable and useful diagnosis and predictions was needed. The number of different features which can be extracted from measurement data by signal processing methods is nearly endless, and in order to be able to identify and select the best features and feature combinations in any specific case, tools for evaluating features were developed. In some cases no monitoring methods were currently in use or even available, and in such cases the work was focussed on selecting and developing on-line monitoring and diagnostics methods to enable identification and prediction of failures or faulty conditions.

System level considerations were required in cases where the maintenance strategies were not quite clear, e.g. due to new type of production lines or machinery involving new technology, and hence there was lack of experience or new and more demanding requirements about their maintenance. In addition to making new maintenance plans, tools for dynamic and cost effective planning and decision support for maintenance management were also developed.

Due to the different statuses and requirements of the cases, the project involved research and development on a variety of methods and technologies which can be regarded as the steps towards prognostics and identifying maintenance needs, to support decision making and manage operational reliability, see Figure 2. Concurrent with the Prognos-project some of the industrial companies ran their own industrially driven development projects in order to obtain a business oriented prognostic software, supported by the work and results of the Prognos project but beyond its scope.

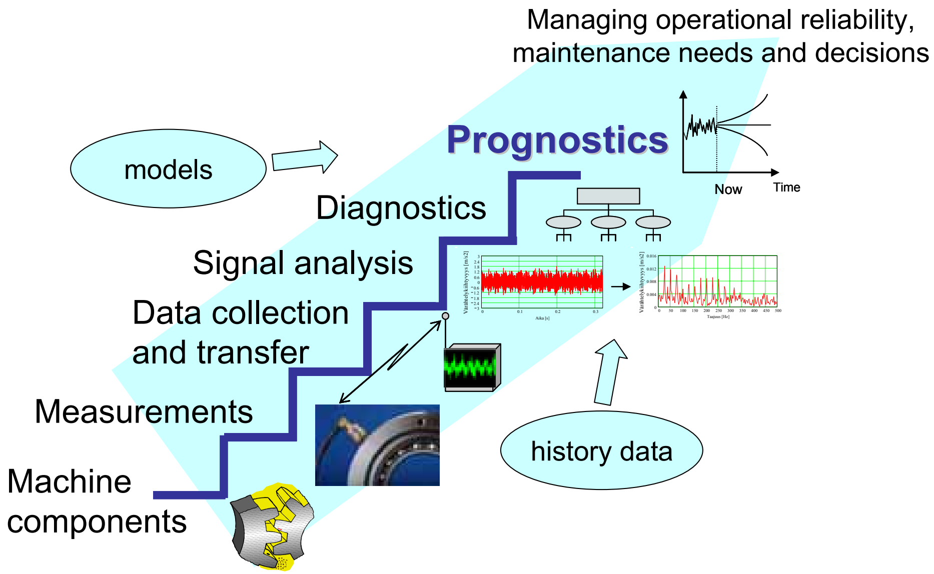


*Figure 2. Technological steps and knowledge required to form the basis for prognostics and reliability management.*

# 3. Results

## 3.1 Concepts of prognostics

Diagnostics and prognostics is very much case dependent. Prognosis may be made at different levels, e.g. at system level for predicting economical, technical, environmental or safety related risks to support long term planning of operations and maintenance, investments, refurbishment etc. or at machine or component level for faulty conditions, failures and disturbances, and the remaining useful lifetime and service needs. Depending on the case there are large differences in machine construction, components, materials and other factors influencing the onset and progress of a failure such as the operational conditions, temperature, dynamic or static loading, environmental effects, possibility for misuse or human errors etc. Also the consequences and the rate of the failure progress are different, as are the available data and methods for making a prognosis. Hence, instead of a generic prognostic architecture, a general schematic description of prognostic concepts was compiled as a collaborative effort, see Figure 3. It assists in figuring out the different areas of existing methods, available data and possible further development needs in any specific cases considered. It also points out that there is always a feedback loop in the system, cumulating service history and other historical data, which can then be used to update the knowledge and evaluations of critical parts, best maintenance practices etc. based on possible new operational and economical possibilities, constraints and demands.

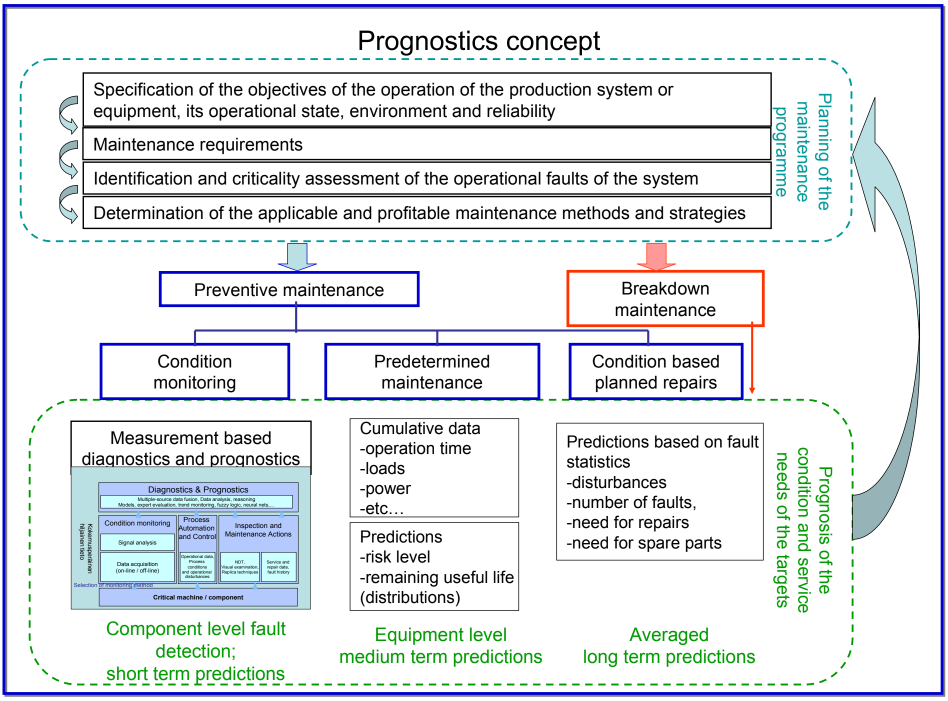


*Figure 3. Schematic presentation of prognostic concepts relating the prognostic methods to the maintenance strategies and the specific target in question.*

On the basis of the higher level or system level analysis decisions are made about the maintenance strategies applied to each machine and machine component. The most critical ones, for which it is technically, economically or due to safety related reasons justifiable, measurement based diagnostics and prognostics could and should be applied. On the basis of measurements it is possible to monitor the exact, specific component and to detect a fault developing in it. Short term predictions can be made as to whether this specific component is going to fail in near future, or can it be used until the next scheduled stoppage. Figure 4 gives a more detailed insight into the various data sources and technologies involved in measurement based diagnostics and prognostics, indicating also the important role of experience based tacit knowledge. Reliable predictions about the remaining lifetime require good understanding of the phenomena behind the deterioration or failure process, as well as good knowledge about the expectable future operational conditions, utilization rate and loading of the component. When making a prognosis, it is important also to indicate the conditions and assumptions for which the prognosis is valid.

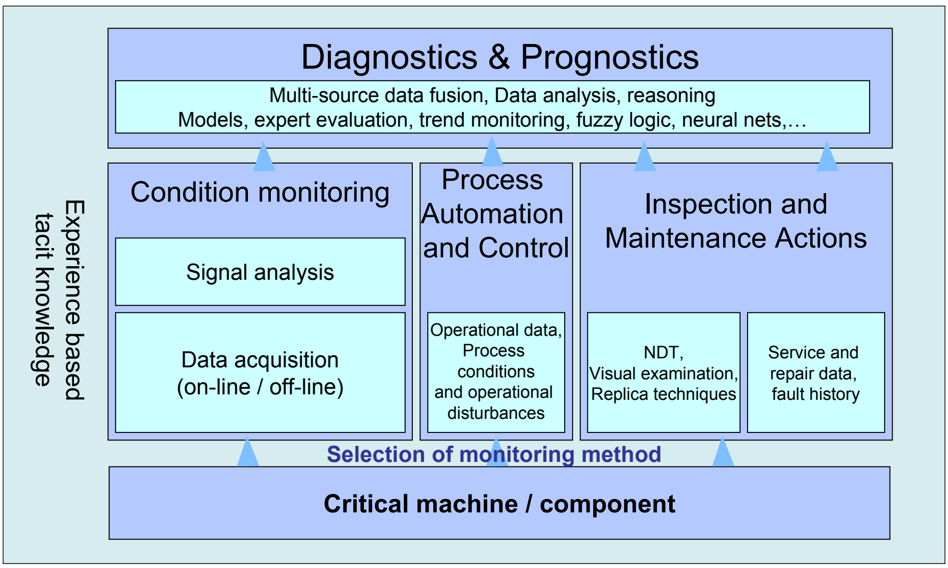


*Figure 4. Schematic presentation of the data sources and various techniques or methods involved in measurement based diagnostics and prognostics with multi-source data.*

In some other cases there is no possibility or need for online condition monitoring of the component but medium term predictions on the condition and damage or failure progress can be made based on cumulative information about the operational time, loads, temperature, power etc. together with some stress distributions and historical, design or expert knowledge of the specific or similar components. This also applies to those critical components for which more data is available through continuous monitoring, but in their case the monitoring data enables, in addition to the medium term predictions, to refine the estimates and thus achieve better accuracy also for short term predictions.

Statistical data about failure occurrences and history of similar components can be used for making average long term predictions, also in cases where monitoring is not possible or justified and no information about cumulative stresses etc. is available. For example, based on statistical failure data it is possible to make predictions about the number of failures of certain type of components during a certain time period, and hence also to predict the need for spare parts and repairs.

## 3.2 Main results

In diagnostics and prognostics, different methods and technologies are applicable in different cases depending on the objectives, maintenance requirements and the machinery in question. The results of the research and development in the Prognos project include methods, tools and knowledge covering many of the areas and technologies in Figures 3 and 4. The main results are summarised in the following. For the list of the industrial cases, responsible research organisations and the industrial partners in them, see Appendix A.

The maintenance planning tools include tools for comprehensive developing and updating of maintenance programme and for comparing the cost-effectiveness of different maintenance tasks. These were developed in Case Baling Line and also utilised in Case Underground Loader.

A 3D visualisation system for easy access to diagnostic and prognostic data as well as service data was developed in Cases Charging Crane and Underground Loader. Both cases also involved development work related to wireless sensors and data transfer, as well as monitoring and diagnostic methods utilising vibration measurements and oil analyses.

In Cases Ventilation Air Fan and Primary Air Fan the initial basis of the development work was to identify the most critical failure modes and to select the proper measurements to focus on. The major results in these cases include a flexible diagnostic or prognostic reasoning hierarchy, and tools for feature selection and evaluation. A prognostic software was also developed for the Ventilation Air Fan in an industrially driven product development project running concurrently with the Prognos project, in cooperation with the work in this industrial case.

A conceptual software tool for prognostics was developed in Case Servo Motor and Industrial Robots, utilising also data from Cases Charging Crane and Ventilation Air Fan as basis for the work. In the Servo Case remote monitoring system was also demonstrated and some means for monitoring and diagnostics of servo motors and planetary gears of industrial robots were developed.

The prognostic tools developed in the project include also a method for lubrication control in grease lubricated bearings based on existing vibration measurements. The method developed in Case Grease Lubrication can be used for adaptive lubrication and for making predictions of failure risk based on cumulative data of lubrication problems.

In Case Electric Motor Control, tools for combining data from electric motor control system and process data were deloped.

Several condition monitoring and diagnostic tools were developed in Case Paper and Cardboard Industry. These include a tool for phase spectrum retrieval from impedance amplitude spectrum utilising maximum entropy model fitting, wireless data transmission from the shaft of an electric machine, inductive power supply for wireless sensors attached to an electric motor, a tool for data collection and stationarity detection in a frequency converter, as well as tools for automated data collection from remote sites. Also a method for communicating between a motor and e.g. motor protection relay by using motor cable as a communication channel was developed. In addition, tools for diagnosing quality control systems on paper and board machines have been developed.

In Case Screen Cylinder, an on-line monitoring method for detecting coating failure under erosive conditions was developed and demonstrated. The method is based on the use of fibre optical sensors or resistance measurements.

Diagnostics and prognostics, on a more general perspective, have been discussed in two conference paper during the project [5, 6]. Besides those and this final seminar, the results obtained during the Prognos-project have been reported in two annual Prognos-symposia [2, 4], as well as in numerous conference papers, journal articles and other publications listed in Appendix B. Excluding internal or confidential project reports, the total number of publications is 92. This includes 7 M.Sc. Theses, one doctoral thesis, and 5 international journal articles, 31 international conference papers, 11 national journal articles and 24 national conference papers and a number of other publications.

# 4. Industrial benefits

The industrial benefits include direct benefits already during the Project both through the interaction, discussions and sharing of experiences and knowledge between the participants during the very active participation in project meetings and seminar throughout the three years. This has been realised as an increased knowledge both within the industry and the research organisations in all areas related to monitoring, diagnostics and prognostics, and in maintenance planning. Direct benefits for the industrial partners also include the risk analysis results obtained in several cases, as they have helped the companies to focus the maintenance efforts in a more efficient way.

In case of the end user companies, the economical benefits from the project arise from the reduced costs of production losses and disturbances, lower maintenance costs and from the increase in product quality. The economic value can be estimated e.g. from Figure 1.

For equipment manufacturers the results give possibilities to widen their business towards service business, which is an increasing trend in today's world. Smart solutions with embedded monitoring systems give added value to the equipment. The project results can be utilised as better tools and methods for the service provides, increasing their competitiveness and ability to provide added value to their customers. A large economic benefit arises e.g. from a satisfied customer buying also the next equipment from the same manufacturer which also provides after sales service.

The ways of exploiting the results within a short term as well as needs for further research will be discussed in the work shops during the final seminar. The work shop results will be discussed in the final project meeting and plans for exploitation and further R&D actions will be made accordingly.

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# Tools for the remote monitoring, diagnostics and prognostics of the operational state and condition of a charging crane

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## Abstract

The aim was to develop an on-line monitoring system for the main hoisting machinery of a charging crane used in a continuous casting process at Ruukki Production Raahe Steel Works. This was due to be done during the renewal of the crane condition monitoring system. In addition, a wireless system was required for transferring condition monitoring data from the crane to the network of the factory for expert use.

The monitored objects were four electric motors of which two were always in series. Additionally the drive and driven gears of multiple-gear trains were monitored. The signals measured were transferred from the crane to the factory network via a WLAN connection. This made it possible for the members of research facilities outside the factory to obtain data freely through a firewall.

## 1. Background and scope

The charging crane moves a ladle to the lifting and turning table of the continuous casting machine. It also brings the empty ladle for re-fill. The charging crane has to be extremely reliable, because it forms an important part of a continuous process. Stoppage of the crane causes delays in the whole casting process. Any catastrophic failure of the crane leads to an interruption of the production of the casting machine, thus causing large financial losses. The reliability of the crane also has to be excellent from the safety viewpoint in order to prevent accidents to people working close to it.

The charging crane at Ruukki Production Raahe Steel Works formed one case project in the Prognos project and was called the case charging crane. The case project included both signal analysis for diagnosing condition and different driving states of the crane and also wireless signal transfer. The aim was to develop an on-line monitoring system for the crane and a wireless system for transferring condition monitoring data from the crane to the network of the factory. Because of the special requirements caused by the working environment, such as dust and large temperature variations, wireless condition monitoring is almost the only possible solution for the crane when safety and reliability issues are taken into consideration.

The monitored objects were four electric motors of which two were always in series. The drive and driven gears of multiple-gear trains were also monitored. The importance of the targets was determined using risk analysis for the hoisting equipment. The developed system includes measurement and analysis methods, which describe the normal and failure states of the hoisting machinery as well as possible. The final result of the operational state of the machine is indicated visually with the help of a graphical interface. The results of the diagnosis will be used to carry out a prognosis and to conclude a decision. The final aim was to provide a procedure to recognize the operational states of the crane and a prognosis for decision making in order to control maintenance actions.

# 2. Methods

The performance of the target machine is monitored in predictive maintenance, with the aim of predicting machine failure and the remaining lifetime of the target. Predictive maintenance is based on different measurement techniques which are used to monitor and analyze losses of performance in the studied machine.

## 2.1 On vibration measurements

Vibration measurements are very useful in predictive maintenance. Their usability is based on the following facts [1]:

- All machines vibrate as a result of faults of different severities.
- Excessive vibration indicates that the faults have developed into mechanical problems.
- Different faults cause vibrations in different ways.

Vibration measurements are usually carried out using a piezoelectric accelerometer whose functioning principle is the formation of an electric charge between the surfaces of the piezoelectric material under the influence of mechanical loading. The measurement parameters traditionally used in vibration measurements are displacement (μm), velocity (mm/s) and acceleration ($m/s^2$) [4]. Choice between these parameters depends on the used frequency range, measured machine and studied faults. Displacement measurements can be applied at low frequencies. These are usually carried out at a frequency range from zero to couple of hundreds of hertz. Relative displacement measurements are especially suitable for turbines and machines with sleeve bearings. Vibration velocity is typically used at the frequency range of 10–1000 Hz. Norms are based on the basic assumption that the rms values of velocity at that frequency range can be thought to be equal when discussing the severity of faults. Acceleration is used at a very wide frequency range, even to 20 kHz. Impact-like phenomena, such as bearing and gear faults, friction and insufficient lubrication, can be studied by means of acceleration measurements more effectively than using velocity measurements.

The derivatives of displacement, which are of a higher order than acceleration, such as $\dddot{x}$ and $x^{(4)}$, can be used especially for studying impact-like phenomena. This way more sensitivity can be gained. An example of this are the experiments [3] in which very slowly rotating bearings were studied using the peak value of $x^{(4)}$ signal as a measurement parameter with the upper limit frequency of 2000 Hz. Sensitivity can be increased even more if the order of differentiation is a real or complex number, which can be used to develop even better measurement techniques that react to a beginning failure at an earlier stage than before. [2]

## 2.2 On oil analysis

Efficient lubrication is important in order for machines to work reliably. This can be ensured by regular condition monitoring of the lubricant used. The analysis of lubricating oils provides information on the wear of machine elements, functioning of the process, efficiency of lubrication and condition of the oil itself. Different kinds of laboratory analyses may be carried out variably depending on the studied machine. The oil analyses often applied are e.g. wear metal and additive analysis of oils, qualitative and quantitative analysis of solid debris in oils and determination of the physical parameters describing the lubrication efficiency of oils. Certain oil properties can also be determined through on-line measurements, which naturally enhance the possibilities to detect faults at an early stage. [7–8, 10]

Certain faults, such as imbalance and misalignment, cannot be detected using oil analysis unless they are so severe that they cause wear of machine elements. On the other hand, certain faults, such as gear and hydraulics faults, can be detected at a very early stage using oil analysis. For the condition monitoring of a specified target, the best available analysis techniques should always be selected. Combining fault data obtained either by means of an oil analysis or vibration analysis makes very efficient predictive condition monitoring possible in many cases. One study [9] indicated that 40% of the bearing faults of a nuclear power plant were detected using oil analysis, 33% using vibration analysis and 27% by means of both techniques. Combining oil analysis and vibration measurements has also produced good results in more difficult cases, such as in the condition monitoring of worm gears [11–12].

# 3. Charging crane

The charging crane of the continuous casting machine is a bridge crane consisting of two bridges, main and secondary hoisting cars on the bridges, car and bridge transfer machinery and steel structures. The charging crane is mainly used to lift the ladle and move it to the lifting and turning table of the continuous casting machine. The main car consists of two separate main hoisting machineries whose functioning parts are two electric motors in series, a multiple-gear train and a winding drum (Figure 1). The winding drums are connected to each other by a gear without cover, and the gear ensures that the ladle is set down in a controlled manner even if the hoisting machinery breaks down. The gear also synchronizes the rotating motion between the winding drums. In addition, the main hoisting machinery contains the brakes of electric motors, couplings and pulleys.

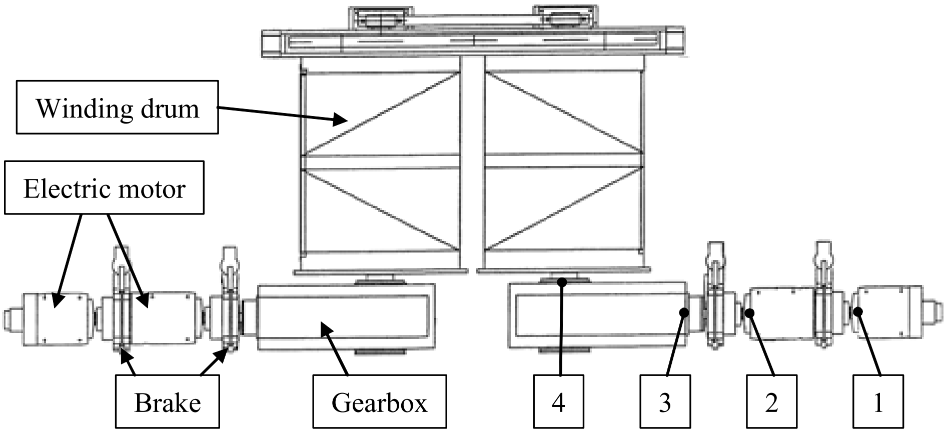


*Figure 1. Monitored targets and measurement points.*

The monitored targets were determined using the failure mode, effects and criticality analysis (FMECA). The existing condition monitoring system of the crane also affected the selection of the targets. FMECA showed that the most critical target was the main hoisting machinery.

The main hoisting machinery was measured using a portable vibration analysis system [6] before the installation of a continuous condition monitoring system. The aim was to study the behaviour of the main hoisting machinery using vibration measurements and to find out features that could be used to identify and distinguish between different operational states.

In addition, the fault frequencies of the crane's machine elements were calculated and a measurement plan including measurement points, features and frequency range selections was drawn up. Vibration measurements were carried out in six different operational states when the crane was working in normal use. The measurement parameters were velocity, acceleration and jerk, and the features were the rms, peak and kurtosis values of these signals. The vibration behaviour in the normal condition of the crane was determined by analysing the results of these measurements. Different operational states were also identified using the selected features.

## 3.1 Condition monitoring system

The vibration signals detected by the accelerometers are processed using a measurement system mainly consisting of National Instruments' hardware and software applications. Data acquisition sensors were connected via a power supply to a modular SCXI signal conditioning system. After that the data are transferred to a DAQ card at the measurement station and finally from the DAQ card to the store memory of a computer (Figure 2). The SCXI system makes it possible to collect even thousands of measurement channels to a single measurement card in a computer. It can also be used e.g. to isolate and amplify the measured signals.

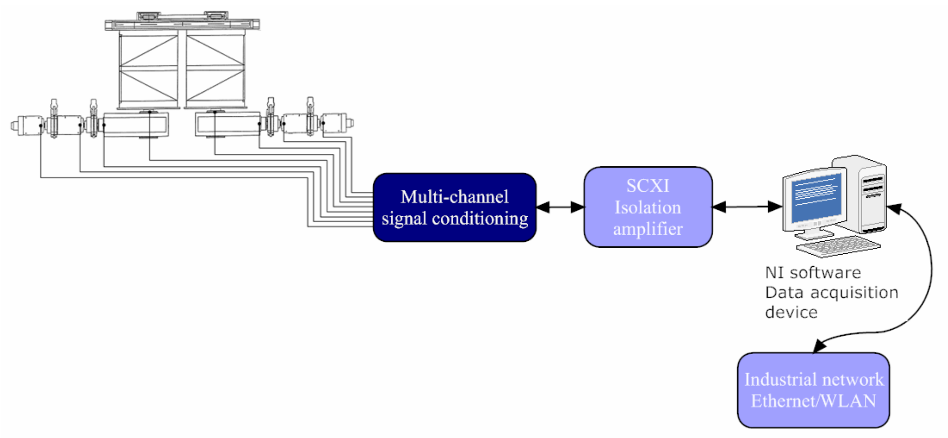


*Figure 2. Crane data acquisition system.*

When the data have been stored into a hard disk, a specific transfer program transfers the file flawlessly to the file server via a WLAN connection. The file server is used to store the required number of measurements in archives. The measurements have been filed in different folders on the file server, and measurement data from every channel have been placed in specific folders of their own, equipped with a time stamp (Figure 3).

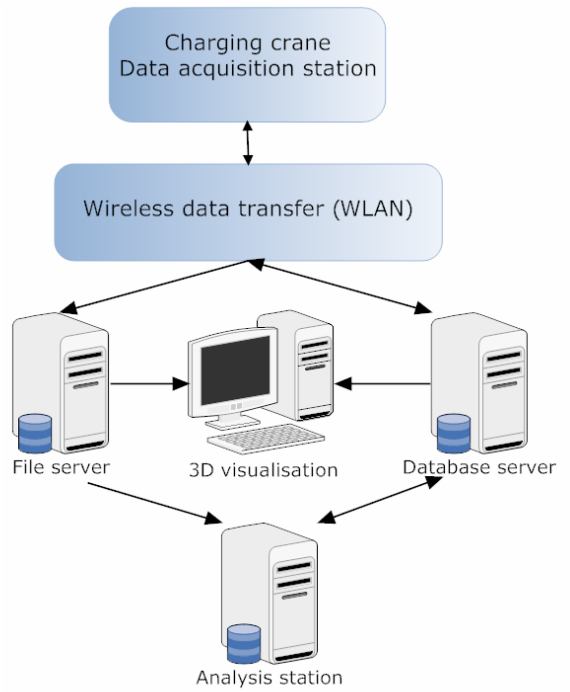


*Figure 3. Crane data flow chart.*

The analysis station searches the produced measurement file from the file server, carries out the required calculations, for instance the features, and stores the feature equipped with the measurement position, event data and time stamp. A trend curve may also be drawn easily from the calculated features. A quality factor is calculated per each feature and stored in the database. The last required feature and quality factor are available, e.g. to be used in the 3D modelling program, in the database using only a simple enquiry. The analysis application can be performed at regular intervals or continuously in a free work station (Figure 4). The real time situation with the crane can be seen visually with the help of the developed 3D program. Machine parts with developing failures are shown in different colours, and service instructions for these parts can be searched conveniently from the system.

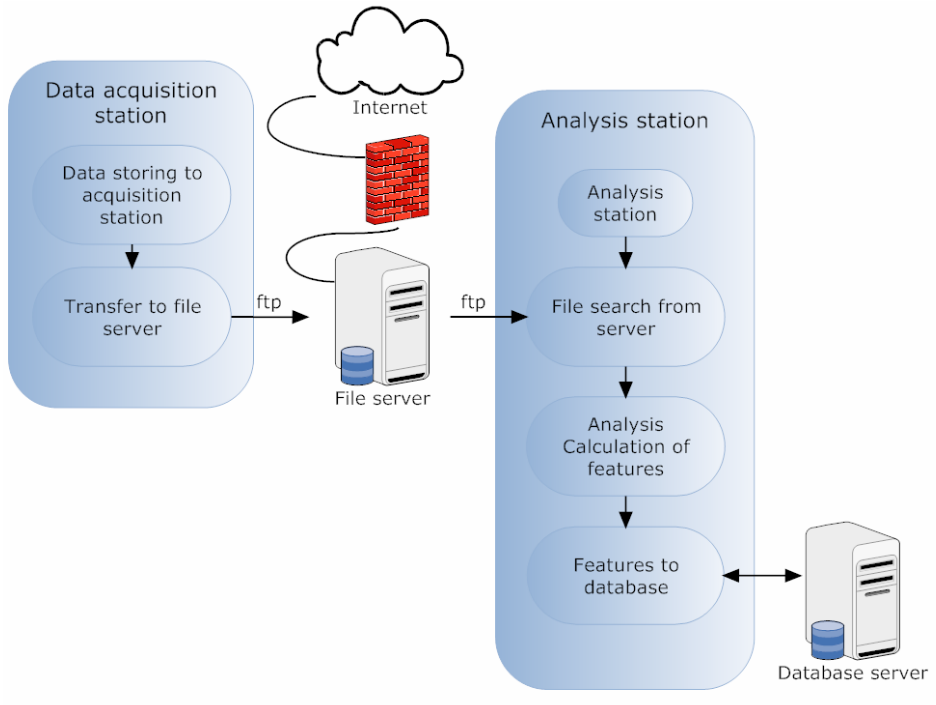


*Figure 4. Data acquisition station and analysis station.*

All the parameters used in the measurements, as well as measurement and analysis guidelines, have been stored in the database. In addition, the file server can be reached through a firewall that makes it possible to distribute data e.g. as raw signals to experts.

# 4. Results

When the results of the portable measurement system were analyzed, abnormal behaviour was observed at certain measurement points. This behaviour was examined thoroughly in the frequency domain analysis, which revealed that a certain machine element had misalignment so maintenance actions were required. The different loading states of the crane could be separated clearly from each other, depending on the features used. In addition, features not sensitive to crane's loading variations could be found and can be used in detecting certain faults at an early stage. Features applicable to distinguishing between different process states were also found.

The antenna tests revealed that reliable data transfer requires one omni-directional receiver antenna if it is correctly positioned. A similar type of antenna can be used to transmit data if it is positioned underneath the structures of the crane. Visual connection to the receiver antenna must also remain throughout the working range of the crane.

Every channel of the measurement chain from a sensor to the measurement station was calibrated. The levels of different channels deviated from each other by less than one percent. Wireless data transfer worked flawlessly and the shape of the signal remained unchanged. Signal distortions were also not observed when a remote connection to the remote diagnostics facility at the University of Oulu was used through the firewall. When the sensors were compared with each other based on calibration, their sensitivities were observed to be within the error margin of 10%.

# 5. Industrial benefits

The use of wireless data transfer for condition monitoring even in the industrial environment has already been studied at the University of Oulu in an earlier project [5]. This project takes studies and applications to the next level in a demanding steel mill environment. Information has been gained on the positions of antennas and measurement devices in order to transfer data flawlessly at sufficiently long distances. This information can also be applied to other similar targets. The elimination of sources of error, such as electrical interference and iron dust, was also been investigated during the project.

Features to describe the condition of the crane have been developed and they can be followed-up in the predictive maintenance facilities by means of wireless data transfer. This facilitates crane condition monitoring significantly and improves its reliability.

Cranes are critical machines in production. Knowledge of their functioning and fault diagnosis increased significantly in the target enterprise, and the staff is also better familiar with measurement and calibration methods.

Cranes are used in different industrial plants in Finland, such as the pulp and paper industry, manufacturing industry, steel industry, power plants, harbours and dockyards. The information generated in this project can be applied in all these industrial fields. Wireless data transfer and remote diagnostics solutions can be transferred easily to other types of machines as well.

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# Operational reliability of remotely operated underground loaders – prognostic needs and possibilities

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## Abstract

Operational reliability of autonomous loaders might be problematic, because the operator has weak touch of the loader. Stresses of the machine are bigger and need for sensors are higher. Failures can be unobserved for a long time. In comparing with normal loaders the maintenance has been reviewed at the autonomous usage perspective. As a result understanding of costs and risks has increased. For better prognostics, new informative measurements have been tested.

# 1. Background and scope

A mine is demanding environment for human and machine. The excavation in rock, including loading, hauling and dumping, is noisy, dusty, and vibrational work, which can cause work-related disability and has also sudden concrete risks as mountain slides and fire. Therefore, new techniques are developed, like autonomous loaders (LHD-machines, load-haul-dump), to diminish the physical stress and accident possibilities at the dangerous places. Then, in the future, it might be possible that all the equipments of the mine are operated from a control room, which locates in a safe place, and one person could be operator of many autonomous loaders. Naturally, that depends on target and degree of autonomy of the machines. However, machine autonomy might be also problematic, because at the remote control the operator is losing touch of the loader and the stresses of the machine are even bigger. Also, without sufficient amount of sensors the faults can be unobserved for a long time, which can lead to more harmful failures.

Moving from the old system to more autonomous system requires new perspective of maintenance and measurements developing, so that the reliability of the machines is at least same as earlier. Because the operators are not driving loaders continuously the missing information needs to be collected some other way. But new measurements is just a base for information, the raw data should be transmissed, collected, analyzed and combined with early knowledge. The target is that failures can be prognosticated so that the usability of loaders doesn't drop and main components are repaired and their life times are known. Also the safety issues demands systematic approach for adequate maintenance practices and a process for information transfer to prevent the possibility of injuries.

# 2. Methods

Noticing the basis for a study, where changeover is going on at the perspective of loaders maintenance, the progression was performed systematically and iteratively towards new system, which could guarantee the good performance of the loaders with high reliability. At first an assessment of the situation was made, which led to following development areas: fault modes, effects and criticality analysis, maintenance programme updating at the autonomous usage perspective, 3D visualization, and new measurement considerations. Naturally these all parts got support of generic literature like research of prognostics and fault diagnostics.

During the study one of the main ideas has been that the maintenance system should be prognostic, so it has been natural to review the prognostic systems based on literature and standards. As described, *prognosis is an estimation of time to failure and risk for one or more existing and future failure modes.* The task is normally intuitive and based on experience. Prognosis is usually effective for faults and failure modes with known, age-related, or progressive deterioration characteristics, the simplest of which is linear. Prognostics are most difficult for random failure modes. There are four basic targets to define for prognosis: the end point, current severity, parameter behaviour and deteriation, and time to failure. *[ISO13381]*

Prognostics is focused on the future and the following need to be considered. The basis is the knowledge of existing fault modes and their deteriation. Then there needs to be conception of future failure modes and how they initiate. After that it is possible to consider the interactions and the influences between the existing and future failures. One key part of the system is to consider how the failure modes can be observed, their sensitivity and monitoring in practice. Based on these issues the monitoring strategy should be matched. Naturally, just like in all the systems, the valid area should be defined. *[ISO13381]* Shortly, the above mentioned development areas of the study are selected so that the prognostics perspective of standards is met.

## 2.1 Fault modes, effects and criticality analysis (FMECA)

The profound knowledge of the system is necessary for developing systems. That is the motivation for Failure Mode and Effects Analysis (FMEA). When this analysis is added with economical, financial or safety components in purpose to assist in maintenance management decisions it is called Failure Modes, Effects and Criticality Analysis (FMECA). FMECA is used to analyse all the fault modes of the equipment item for their effects on other components and the system *[IEC-60300-3-9]*. The approach at this study included workshops, which started by FMEA sessions with industrial participants. After FMEA sessions were performed criticality analysis sessions, which were followed by Reliability Centered Maintenance analysis (RCM). At the RCM-analysis are scanned actual maintenance records to objectively determine which components are critical to machinery reliability, safety, and repair costs *[Danks et al. 1999]. [Ahonen et al. 2006]*

## 2.2 Fault diagnosis

At the prognostics is important to consider how the failure modes can be observed, their sensitivity and monitoring in practice. This section was performed by literature review, which included main components of the loaders as combustion engines, hydraulics, power transmission, steel construction, and bearings with lubrication.

## 2.3 Data transmission

Important part of the mobile systems is the data transmission, which has gone through literature review. Most of the equipments in mines are mobile and they are not connected to any systems hard-wired. Therefore, it is natural that implemented data systems in mines are developed at the wireless perspective. Continuous data transmission is needed only in certain places, and thus the systems need data storage possibility at the machines, so the data can be transferred at the best possible time. There are many suitable data transfer protocols available, and it appears that it might be simplest to use only one protocol for transfer. However, if we consider new mobile phone developing, which can have more than five standards in use at the same mobile, it can be stated that parallel usage of standards is possible if the undisturbed data transfer is guaranteed. General criteria for wireless data transfer are signal carrying, signal strength, possibility for positioning, versatility, data transfer capacity, power need, roaming ability, and environmental strength.

## 2.4 Maintenance development

Autonomous system requires new perspective of maintenance developing, so that the reliability of the machines is at least same as earlier. Therefore, the maintenance development was performed by taking into consideration the characteristics of the system and the experiences gathered. This process included several steps and content of steps depends on the phase of life cycle of the target system. According to *[IEC-60300-3-11]*, maintenance programmes are composed of an initial programme and an on-going, dynamic programme. So, at this case the development was based on maintenance manual of the loader manufacturer and practiced maintenance programme of the user. The experiences of the current system from databases and tacit knowledge were combined with future demands for updated maintenance programme. More about this is presented at the section "Cost-effectiveness as an important factor in developing a dynamic maintenance programme" of this report.

## 2.5 3D visualization

Visualization is an important part of complicated system control. Although it is not necessary in developing maintenance or prognostics, the usage of 3D visualization can offer a scene of equipment to fast piece together its general state and estimate the need for maintenance. When the 3D model includes advisable current and prognostics state based colours, only one look can give enough information of possible failures. More about this is presented at the section "3D visualisation as a tool for managing diagnostic and prognostic information of industrial machinery" of this report.

## 2.6 Oil analysis

Oil analysis can give important information of equipment condition. Especially if the analyses are made regularly it is possible to follow stabile and variable values statistically. Oil analysis can include different kind of parts as basic properties, impurity particle analyses, and abrasive metal analyses. Statistical methods can be used to predict wear and abrupt level changes and exceptional component contents are marks of failures, leaks, or failed sampling. More about oil analysis is described in section "Towards adaptive grease lubrication" of this report and in the first Prognos-seminar publication *[Parikka 2005]*.

## 2.7 New measurements

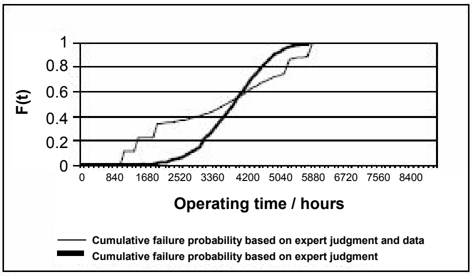
Loaders are powerful and robust machines, which are made to work at the very demanding environments and also at the undeveloped areas of world. That is why loaders have typically made based on durable, sometimes simple, but practical measurements, which can give the needed information for the normal user. Current measurements were examined from autonomous usage perspective, which are important to store, which operator needs to see all the time, and what is the additional information needed to guarantee the good performance of loaders. The operator of the loader sits in the control room and may get information by television monitors and loudspeakers, and digital measurements can also be transmitted, but analog measurements and response of the machine are hard to arrange. Typical loader might be outfitted with as many as 150 sensors of one type or another. These include sensors to measure hydraulic or engine pressure, air pressure sensors on tires, and accelerometers to sense rocks lying in the vehicle's path *[DeGaspari 2003]*. Also it is possible to use sensors which are commonly used in maintenance like vibration transducers, strain gages, and acoustic emission. However, every measurement might cause also false alarms, which is more probable at the demanding environment, and therefore there should be used only necessary sensors.

# 3. Results

Operational reliability of machines requires that all the parts of maintenance programme works well. It has been said that a system is as reliable as its weakest part is. So, developing reliability has gone through process were all parts of the system have been considered to focus the actions on the right areas. Because the main target is prognostic system the task includes developing utilisation of event data, current system focusing, and new measurements, which are important for the prognosis. The results of this section include only the maintenance development and new measurements, because other methods described above are presented in their own chapters.

## 3.1 The maintenance development

At this case the situation in developing the maintenance was updating the model of loaders with remote control effects i.e. autonomic usage features. Shortly, the results of developing process includes the criticality assessments to focus the maintenance, the quantitative analysis for background information about component lifetimes, and decision making model and procedures to help maintainers use and collect new data. An example of the results of the work is in Figure 1 which shows the reliability functions for two transmission components. Example of criticality assessment of components and subsystems based on event data is presented in Figure 2. The maintenance developing is described in details in reference *[Ahonen et al. 2006]*.



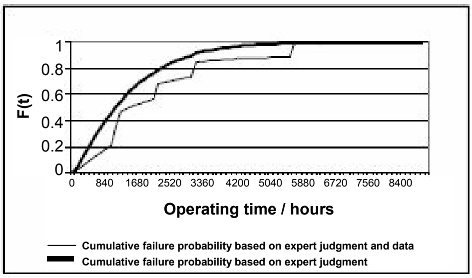




*Figure 1. The cumulative failure probability functions of two transmission components [Ahonen et al. 2006].*

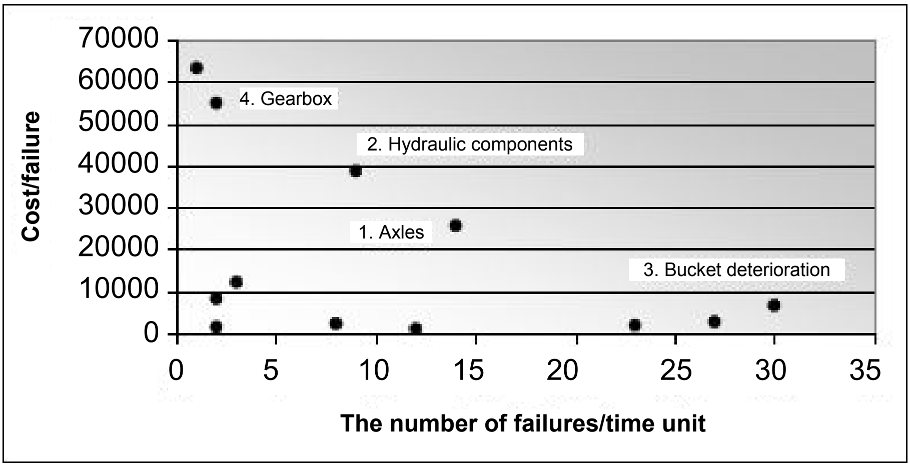



*Figure 2. Criticality assessment of components and subsystems based on event data [Ahonen et al. 2006].*

## 3.2 New measurements

In the assessment of the situation was noticed that the present measurements are not able to produce that kind of data which can be utilized in making reliable prognostics. Main purposes of these measurements are to improve following the loader status and enhance the reliability of maintenance operations and thus be probable sources of the prognoses. Naturally, that reliability can be also enhanced if there are the needed measurements and their accuracy could be improved or the data could be decoded and followed automatically. There were many interesting targets, which needed the screening of the candidates, so that they are among the most valuable measurement, but also challenging.

It is important to recognize that wear is typically dependent on operating time, but in many cases that is too rough expression for reliable predictions, because the life-time of many parts depend more on total load. E.g. when considering the motor condition, the operation time is important, but also how it is used. If motor is used all the time at very variable situations, lots of accelerations, driving at maximum power, short distances and lots of braking, it certainly breaks faster than the motor at the steady use. One good index might be the fuel consumption and another could be tachometer. If they are conflated with operating hours, that could make wear predictions more reliable. However, those can be used as better estimates for motor wear, but other parts of the machines might need another index. Failures in hydraulics and in frameworks are depended on operating times, but also the amount of loads and road conditions have their effects. Loads can be weighed, but determining the road conditions demands accelerometers, strain gauges or some other measurement.

Vibration measurements by accelerometers were tested in normal loaders for to clarify their possibility to be used as driving situation identification and thus follow the stresses of the loaders and operator. These were typical vibration measurements which were frequency filtered by standard ISO 2631-1 (1997) before RMS-values are calculated. Example of vibration measurements in Figure 3 looks quite messy, and for the practical use it is much better to follow the total vibrations within driving time and use these indexes in prognostic calculations. Also, different tasks can be separated based on vibrations *[Järviluoma 2006]* and count the used times for them like empty driving forward or backwards, hauling, dumping and loading, which is probably the task causing most wear during the loaders usage.

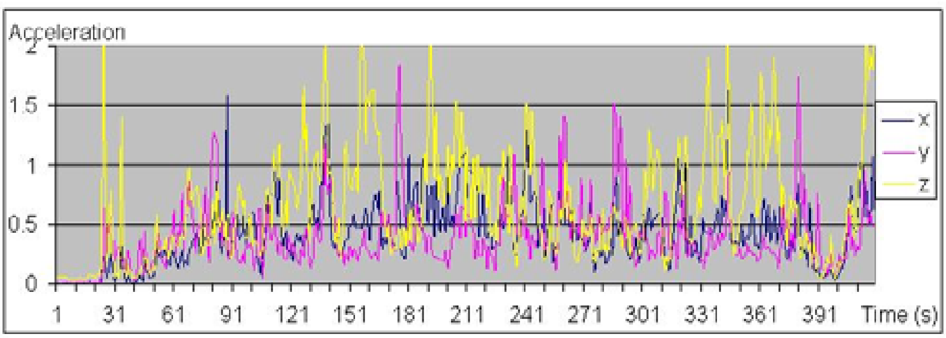



*Figure 3. Part of the vibration measurements of loaders.*

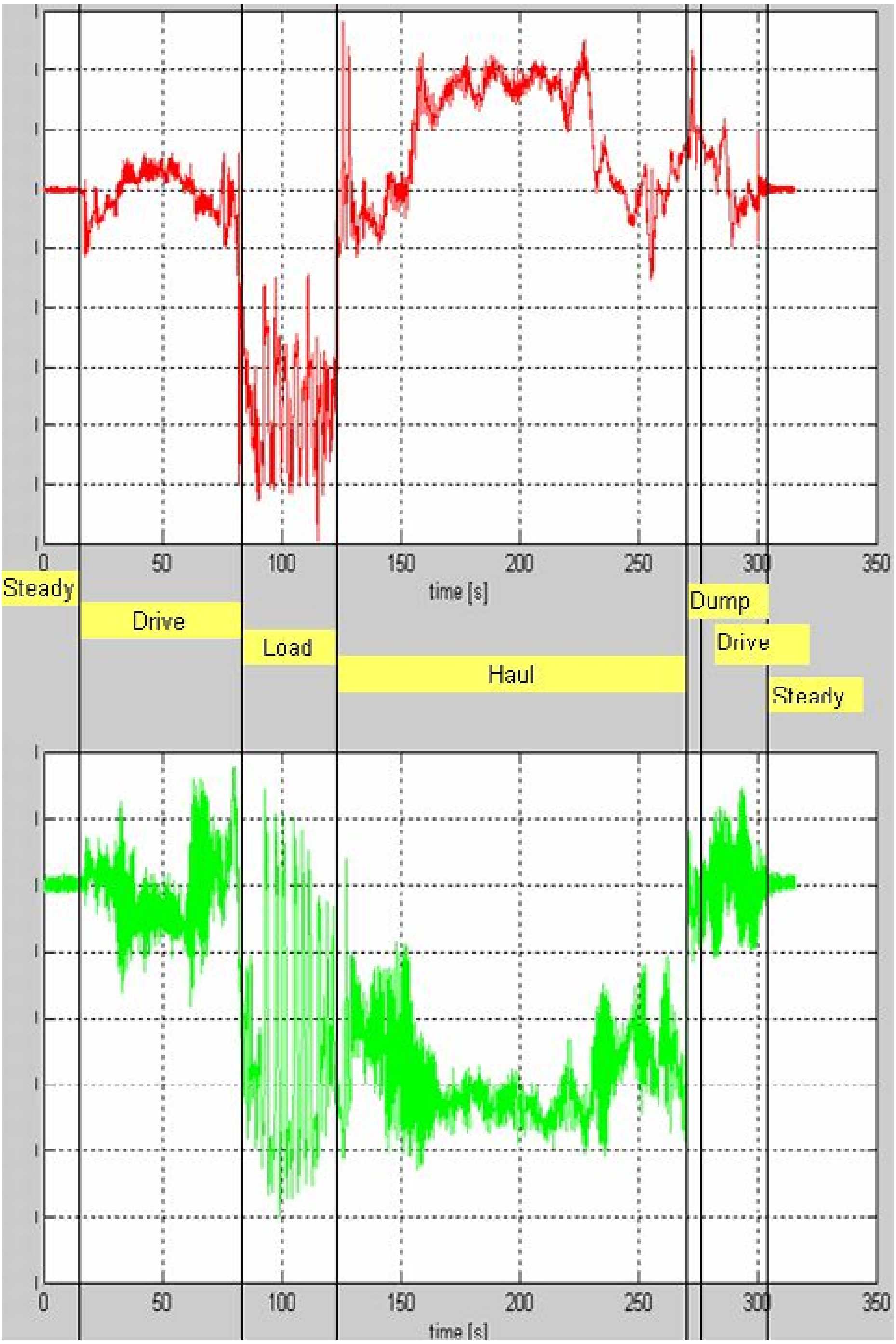



*Figure 4. Trends of strain gauge measurements of loader cardan and upper turning link plate.*

Strain gauge measurements were performed to monitor different forces in the loaders. Selected targets were cardan and upper turning link plate, which were monitored using new wireless technique, see Figure 4. These measurement points and methods were demanding, but supposedly, able to give new important information. At the cardan the stresses have been gauged and they seem to be useful in mapping power transmission, but as well as in following driving events, traction control, terrain type, forces needed in loading, and loads. The upper turning link plate gauging seems to give information of the stresses in frame, elapsed loading time and difficulty, the needed forces, load weight, and road inequalities. If these measurement and driving situations is combined and classified we can talk about context aware machine. When enough data has been collected the synthesis of these measurements, working hours and failure statistics gives much better view of real stresses and the maintenance operations can be prognosticated more reliably.

# 4. Industrial benefits

As a result of FMECA, understanding of costs and risks has increased. Based on analysis and developing work with failure estimation have led to new maintenance program. If the actions are right both reliability and maintenance cost should decrease, however at the current situation there are not enough statistics for to verify that. New measurements with system development has made possible to predict failures and wear of the machine at the more reliable manner. Despite of the fact that the measurement system is not in daily use and there is not enough historical perspective for prognostication, the promising steps have been taken towards prognostic maintenance system. Anyway, the presented methods and measurements offers useful base for the further development work. The performed study in Prognos-project within prognostic calculation methods and concept of prognostics might be a great help at this.

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# 3D visualisation as a tool for managing diagnostic and prognostic information of industrial machinery

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## Abstract

This article presents the results of the Prognosis 3D project. A 3D user interface is presented, which combines the results of the prognosis computation with the factory model, producing an intuitive 3D interface, where the failing / failed components can be located easily. Both the 3D user interface principles and an example application demonstrating these principles are presented.

There were two cases: The loading machine in the Pyhäsalmi mine and the crane in the Rautaruukki works. In both cases a commercial software package has been recently installed for operational use, which contains a 3D component that fulfils the principles presented here. The example application is more limited in scope, and it uses simulated data.

The data transfer protocol between the status / failure data producing system and the 3D interface is OPC XML-DA. So the status / failure data producing system is an OPC XML-DA Server, while the 3D interface is an OPC XML-DA Client.

The 3D interface has the following features: The real-time state of the machinery is shown; the user can navigate in the model; soon-to-fail or failed devices are shown in colour; and clicking a component with the mouse opens the service instructions relevant to that particular component.

# 1. Background and scope

There were two cases in the 3D visualisation of the Prognosis project: The loading machine of the Pyhäsalmi mine and the crane of the Rautaruukki works (Ruukki Production Raahe Works).

In both cases a commercial software package has been installed for operational use during the Prognosis project, which contains a 3D component that fulfils the principles presented here. However, this article presents an example application that is more limited in scope; the example application has the following features: Real-time orientation/position of the machinery is shown; the user can navigate in the model (i.e. watch the component under inspection from various angles and distances); colouring of the components that are in risk to fail or have already failed; and by clicking a component in the 3D model, the service instructions of that component are shown.

The example application presented here used simulated data, which is as similar to the real data (measured by the factory information systems) as possible.

## 1.1 General principles of a 3D user interface

The prognosis system should supply the plant operators with relevant information so that they can make correct decision as easily as possible. The results of the analysis should be presented in an intuitive manner so that the failing component and its location are clearly shown. A 3D user interface fulfils these requirements [1].

The 3D user interface must provide some basic capabilities [2]: presenting the 3D models of the plant and the components to the operators, navigation in the model, different views to the model, and displaying fault data and service instructions of the selected failure. In addition, the current positions of moving components in the model should also be presented. Typically the position data is not produced by the prognosis system, but is directly measured.

This article describes one possible implementation for the 3D interface of the prognosis system.

## 1.2 The architecture of the Prognos system

The 3D visualisation must provide clear interfaces for the prognosis data and the position data. A modular architecture is presented fulfilling this requirement. Figure 1 presents the architecture of the whole prognosis system.

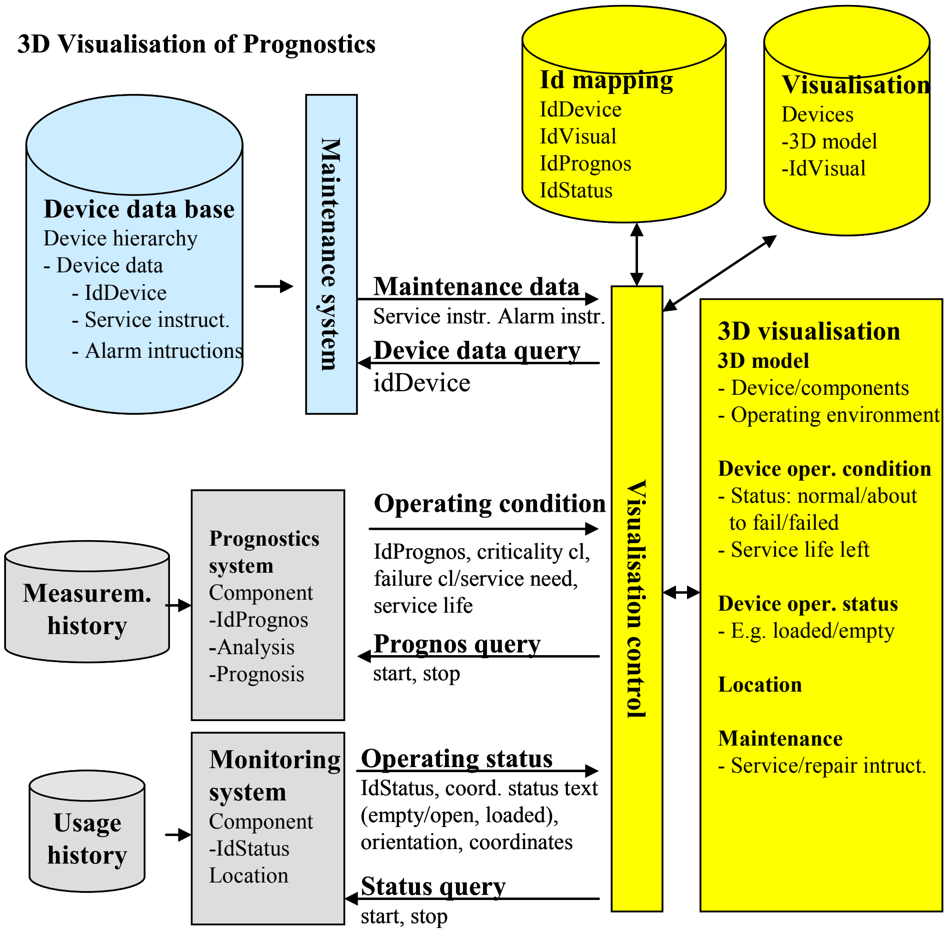


*Figure 1. Architecture of the Prognos system.*

The system consists of components that can be distributed to different computers. The 3D visualisation is presented in yellow. The device data base contains the service instructions, accessible by device ID. The prognostics system produces prognosis data for the visualisation, while the monitoring system produces position data.

When the 3D visualisation is started messages are sent both to the prognosis system and to the control system, which start the data transfer. The systems send messages about the device health, service need, operating status and position every time there is a change. The visualisation control updates the user interface accordingly. When there is a fault, the maintenance system is accessed to fetch the corresponding instructions.

The data and the analysis of the prognosis system are based on measurement history data base, which contains the measurement data of all devices. The position data sent by the control system are obtained from the plant information system. The operating and service instructions are stored in the device data base; an auxiliary table is needed to connect the identifications of the components with the corresponding 3D models.

# 2. Methods

There were two cases in the 3D visualisation of the Prognosis project: The loading machine of the Pyhäsalmi mine and the crane of the Rautaruukki works.

In both cases a commercial software package has been taken into operational use, which contains a 3D component implementing the required functionality. The operational system was programmed by WA Technologies [3]. However, this article presents a more limited example implementation, which was not connected to the plant information systems, but used simulated data.

## 2.1 OPC XML-DA

Because it was not necessary to connect the example application presented here to the plant information systems, the data transfer protocol could be chosen freely. OPC XML-DA was selected as the data transfer protocol between the status / fault data system and the 3D user interface. OPC XML-DA is an updated version of OPC protocol, which is widely used especially in process industry [4]. It is a part of the larger specification being defined known as OPC Universal Architecture (OPC UA). Thus the status / fault data producing system is an OPC XML-DA Server and the 3D user interface is an OPC XML-DA Client.

The earlier definition OPC (OLE for Process Control) was based on Microsoft COM definition and it was limited to Windows operating system. Besides, Microsoft has stated that COM is “legacy technology”, which has been replaced by the Web Services definition. Therefore OPC has been updated to use this definition (and even OPC now stands for “Openness, Productivity, Connectivity”), and the new definition is called OPC UA, and a part of that is OPC XML-DA. An additional benefit is that the new Web Services base addresses better the aspects related to networking, security, firewalls etc.; fetching data from Internet is similar as fetching data from intranet.

OPC XML-DA has Servers and Clients; Servers are usually connected to measurement devices, so they provide measurement values; the Clients needing those values connect to the relevant Server and read the values.

OPC Foundation provides a public and free demo server application (programmed in MS Visual C#) as well as a demo client application (also C#). Besides, there are several continuously operating demo servers, which provide random data; anybody can connect to them and test his/her own Client code.

The parameters of OPC XML-DA (i.e. the values measured by the Server) form a hierarchy that the Client can browse. Each parameter has (besides value and type) e.g. a timestamp and quality. The Client can request the current value of a parameter, but often the Client creates a Subscription to the Server, where it states which parameters it is interested in and at which frequency it will request data updates from the server.

There is a figure on the next page (Figure 2) demonstrating the operation of the OPC Foundation demo client connected to a public demo server. The various dialogs show different phases when creating a Subscription (a part of the parameters available at the Server are selected with a 1 second update interval); the window below shows the Subscription in operation: values are updated.

## 2.2 The programming tools

Both the OPC XML-DA Server and the Client have been programmed using the Microsoft Visual C++ programming language (version Visual Studio 2005).

3D-graphics has been programmed using the OpenSceneGraph program library [5], which has been programmed on top of OpenGL definition.

The 3D models that were used were either provided by the industry partners (Pyhäsalmi mine) or else have been modeled with the 3D modeling tool 3ds Max. The models were converted to the format (*.ive), which is directly supported by OpenSceneGraph.

OPC XML-DA data transfer is programmed using an OPC library developed at VTT.

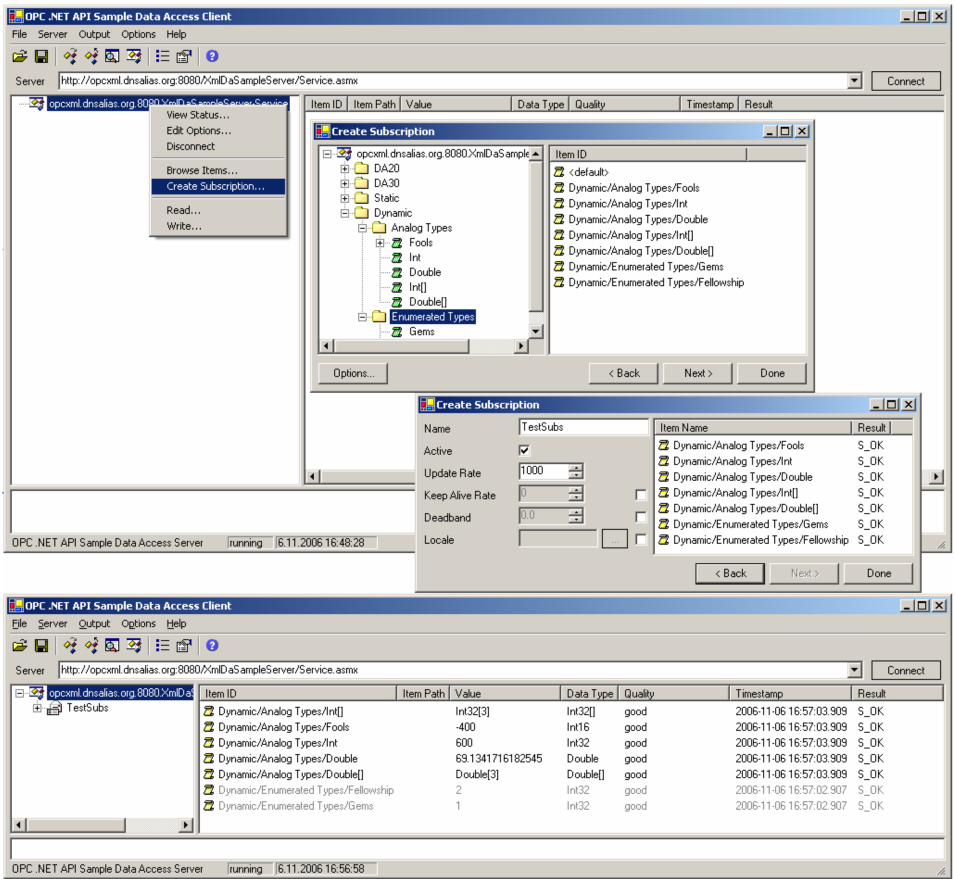


*Figure 2. OPC Client in operation (creating a Subscription).*

## 2.3 Visualisation principles

In the beginning the operator is presented with the 3D model of the device and its surroundings. The device is in default state and position. After that the 3D visualisation is updated with health/status (prognostic system) and position (control system) messages. Based on the *health/status messages* the fault status and the need for service are updated; the manner of visualisation is selected based on the criticality of the component and the severity of the fault message. The *position messages* are used to update the device position, orientation, operation mode etc.

The operator can select more or less detailed views of the visualisation: *general view*, *device view*, or *component view*. Each view displays the device faults and need for service. The operator can use a menu to move to a more detailed view of the failing device.

In *general view* the operator is presented a large-scale view of the plant and of the locations of various devices within the plant. Faults are reported using colour codes: if the potential fault is severe or it has already occurred, the device is coloured red; if the device fails later, it is coloured yellow. A dynamic menu contains the names of the failing / failed devices.

In *device view* a flag is attached to the failing / failed device, which reports the estimated time of the failure in text. If there are sensors in the individual components of the device, the operator can navigate from the device view to the *component view*, so he/she can see which component is failing.

It is possible to navigate in the different hierarchy levels (general view, device view, component view) using context-sensitive menus. Besides, spatial navigation in the model is also possible using a space mouse or keyboard and ordinary mouse.

However, the example implementation is more limited in scope: There are no hierarchy levels, but the operator must navigate and zoom to the interesting device him-/herself. There are no menus, but some functions have direct keyboard commands, and service instructions can be accessed by clicking the desired device with the mouse.

## 2.4 Pyhäsalmi case

The loading machine transports the ore along underground tunnels to surface for further delivery. If this machine is broken, the ore cannot be delivered.

For demonstration a hierarchy of parameters was defined: 7 position parameters (3 for position, 4 for orientation) and 7 status parameters (each reporting a failure or anomaly in a subsystem).

## 2.5 Rautaruukki case

The crane lifts the ladle, which contains steel melt, and moves it to the continuous casting machine. If the crane is broken, it delays the whole casting process.

For demonstration a hierarchy of parameters was defined: 5 position parameters (different components, each in its own direction) and 8 status parameters (each reporting a failure or anomaly in a subcomponent).

# 3. Results

## 3.1 Pyhäsalmi case

Figure 3 below displays the 3D user interface: The whole Pyhäsalmi mine tunnel network. In the figure there is also the loading machine, which is displayed 10 times too large, so it would be easier to detect.

Figure 4 shows a user interface view in which a component of the loading machine is failing, and the loading machine is displayed semi-transparent, while the failing component is colored.


*Figure 3. The loading machine in the Pyhäsalmi mine.*

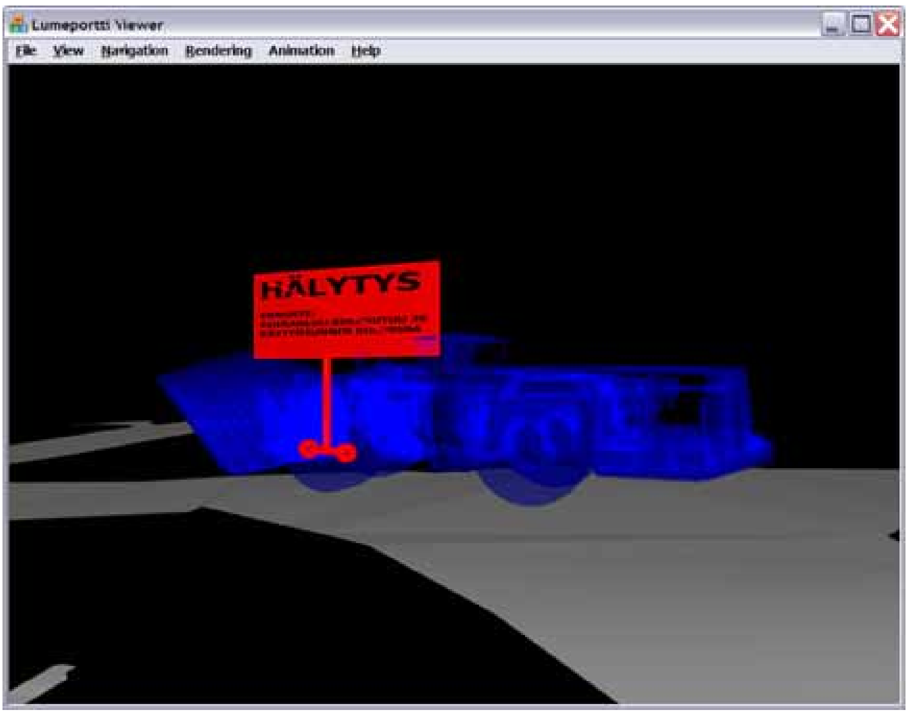


*Figure 4. The loading machine in the Pyhäsalmi mine: alarm in one part.*

## 3.2 Rautaruukki case

There is another example of the 3D user interface in Figure 5 below: Rautaruukki crane operating. In this figure all components with a sensor are warning except one, which is alarming. The main rails of the crane are much longer in reality, but they are displayed shortened. However, the relative position of the crane on the rails is shown.

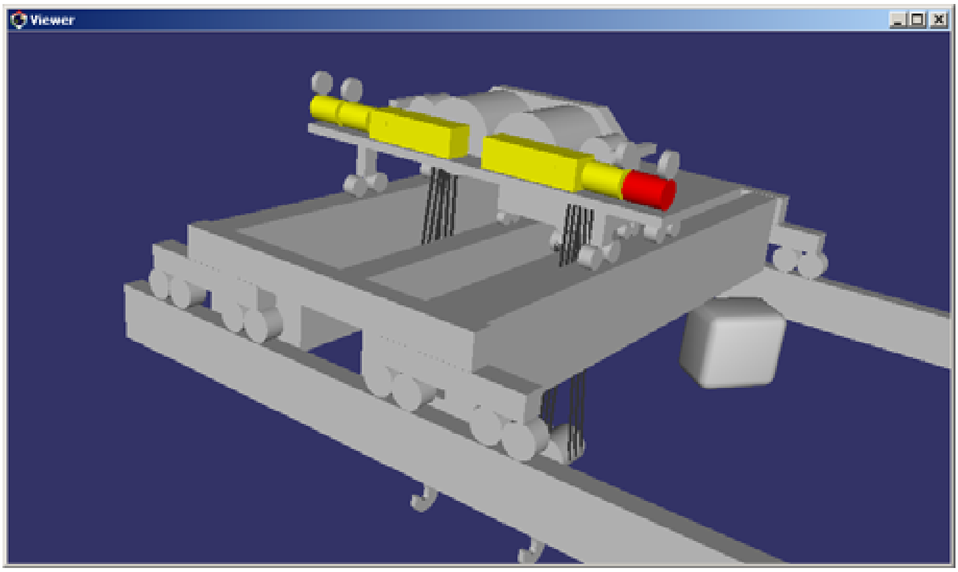


*Figure 5. The crane in operation: alarm in one part, warning in all other parts.*

# 4. Industrial benefits

A well-implemented 3D user interface of the plant prognostic system displays the operator an intuitive understanding of the fault status of the plant. Besides, the soon-to-fail and failed components are easy to locate. The main requirements and functionalities of the 3D user interface were presented, as well as one possible implementation. A 3-level hierarchy to manage the visualization was presented, which consists of a general view, device view, and component view. However, in the simpler example application this hierarchy has been replaced with free navigation in the model. Especially in the component level the operator can easily access the service instructions. A well-implemented 3D user interface can be an integrating element between various data stores in the complex environment of an industrial plant. It is advantageous to apply the 3D interface to present the prognosis results also, so the conclusions of the prognosis analysis, data on the device location, factory model, and the service instructions are integrated under a single interface.

The main benefits of the 3D user interface for the operator are thus the following:

- The real-time operation of the device can be seen, a 3D image is easy to understand.
- Anomalies and early hints of a failure can be seen easily.
- The service documents relevant to the component are easily found.

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# Towards adaptive grease lubrication

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## Abstract

Currently used rolling bearings are in most cases grease lubricated. The annual grease consumption at a paper mill or a steel works, for example, is typically between 3000 and 8000 kg, the majority of which is used for lubricating rolling bearings [1]. Large amounts of grease are also used to lubricate sliding bearings, guides, and other tribologically stressed components. However, the distinctive characteristics of grease lubrication are generally less well known than those of oil lubrication. Film formation on the lubricated surfaces of a grease-lubricated bearing is determined by many factors other than just base oil viscosity, which need to be considered when selecting a lubricant [2]. One way to improve grease lubrication control is by learning to identify poor lubrication conditions and lubrication system problems and thereby to be able to better predict damage development in lubricated components.

This article presents a measurement-based method for identifying poor lubrication conditions in grease-lubricated rolling bearings. The study showed that poor lubrication conditions ("dry run") can be detected using acceleration sensors. The use of acceleration measurement for this purpose seems to work efficiently when there is a high natural frequency of either the bearing structure or the sensor present in the measuring chain. Quite possibly the clearest indication is obtained when the above mentioned natural frequencies are close to each other. In such a case the small impulses from metal to metal contact excite the measuring system and a clear response can be seen in acceleration spectrum. One way to make the diagnosis more reliable is to combine temperature measurement with acceleration, i.e. when the temperature decreases and acceleration increases at high frequencies, the most likely cause in grease lubricated bearings is lack of proper lubrication. Acceleration measurement, together with temperature measurement, enables active lubrication adjustment. Automatic lubrication can be controlled by means of diagnostic software. The software developed by VTT monitors bearing temperature and both high- and

low-frequency vibrations in two frequency bands. At industrial sites, the use of this method is complicated by changes in operating parameters.

# 1. Background and scope

## 1.1 Mechanism of grease lubrication

In grease lubrication, the mechanism of film formation is somewhat different from what classical lubrication theories suggest [2]. In an oil-lubricated rolling bearing, lubrication film is formed based on laws of elastohydrodynamic (EHD) lubrication theory [3]. EHD theory is a factor to be considered in grease lubrication and selection of the correct grease as well, but grease lubrication also involves a number of distinctive features that limit the applicability of the theory. Lubricant film thickness in full film lubrication conditions is generally greater in grease lubrication than it is, according to EHD theory, in an oil-lubricated bearing of the same type. This is because the base oil contains thickener fibers that may appear to increase oil viscosity and can add to the thickness of lubricant film formed on lubricated surfaces. In practice, grease lubrication rarely works as described above, except at start-up or immediately after re-greasing when the bearing is full of grease [4]. Grease soon starts to come out of the bearing raceways, and if there is no external mechanism for supplying more grease, lubricated contacts will start to suffer from oil starvation, leading to reductions in lubricant film thickness. Under conditions of starved grease lubrication, the impact of increasing base oil viscosity and/or thickener content may be completely different from what was expected.

According to measurement results presented in the literature, full film lubrication is a condition that in some cases only lasts a few minutes after start-up [4]. The duration of full film lubrication conditions is naturally dependent on bearing type as well as operating conditions and parameters. In general, it can be said that the less readily the oil component separates from the thickener, the more the lubricated contact starves for oil. Lubrication conditions are further determined by movements and vibrations taking place inside the bearing housing. These, together with the qualities of the lubricating grease used, have a major impact on how the grease moves around in the housing and how base oil is reapplied to surfaces that come into rolling contact. Moreover, the geometry and surface properties of the bearing holder also play a significant role in grease lubrication of rolling bearings.

## 1.2 Problems of centralized lubrication systems

The most fundamental problems relating to centralized lubrication are changes in the composition of the lubricating grease and separation of oil from grease. The oil starts to separate whilst the grease is still in storage, and in the lubrication system the process is enhanced by variations in pressure and temperature, as well as long retention times. As a result, the grease loses some of its lubricating qualities before it even reaches the bearings. In a paper mill or a steel works, for example, there may be dozens of centralized lubrication systems, each lubricating hundreds of bearings. The distance between the lubrication unit and the most remote of the parts to be lubricated may be hundreds and the difference in height dozens of meters. Moreover, the operating temperature, rotation speed and vibration may vary from one bearing to the next, even within the same lubrication system, which places high demands on the grease and lubrication techniques used [1, 5].

## 1.3 Re-greasing instructions

There are a number of different instructions issued for the purpose of determining re-greasing intervals and amounts of grease to be used – these have been compared in [5] and [6], among others. The instructions provided by bearing manufacturers typically apply to situations where grease is added using a grease gun or pump, and what calculation software for automatic lubrication usually does is to take the re-greasing volume required in manual lubrication and divide it over shorter re-greasing intervals. There are generally significant differences between re-greasing intervals and volumes obtained using different methods. Exceptional conditions, such as high rotation speed, high or low temperature, high load, severe vibration or exposure to dirt, can be accounted for by reducing the re-greasing interval by a certain factor. Since industrial environments usually involve a large number of different variables affecting lubrication, any re-greasing intervals or volumes stated in different instructions can often be treated as a guideline and starting point only, and should be further refined based on on-line monitoring.

## 1.4 Survey of industrial sites

To identify the most important development needs, the companies participating in the Prognos project were surveyed for problems relating to grease lubrication of rolling bearings. The survey was conducted as part of a project-related Master's Thesis [5] carried out at UPM Kymmene Kaukas. The main causes of damage to grease-lubricated rolling bearings appeared to be insufficient lubrication or lack of lubricant, see Figure 1 [1]. This category included damages due to dispenser breakage or malfunction, failure to re-grease, insufficient lubricant quantity or overly extended lubrication intervals. All these cause gradual lubricant starvation in lubricated contacts, which may lead to bearing damage or premature end of bearing life.

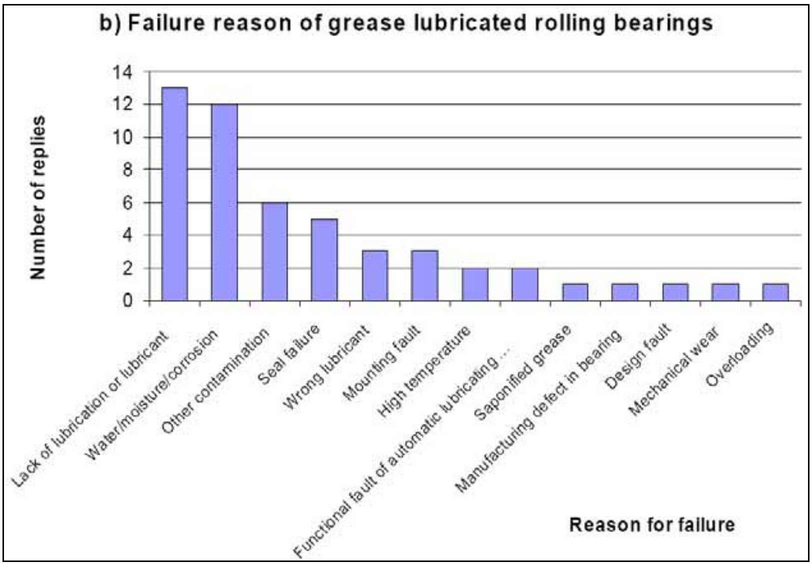


*Figure 1. Causes of damage to grease-lubricated rolling bearings according to the survey [1].*

# 2. Methods

## 2.1 Condition monitoring of lubricating greases

Today, the condition monitoring of lubricating greases is based not only on visual inspections but also on laboratory analyses. A grease sample can be subjected to a number of different analyses providing information on the condition of the grease itself and that of the equipment it is lubricating. There are also numerous test methods available, many of them standardized, that can be used to determine basic grease properties [2].

The methods of grease condition monitoring can be divided into direct methods and solvent-based methods. Using a direct method means analyzing a grease sample for a certain property in the condition it was in when it was extracted [2]. Since the sample does not change in any way during the analysis, further analyses can be performed on the same sample. The accuracy of direct methods is in many cases lower than that of methods where the grease sample is first converted into liquid form using a solvent. Since lubricating greases have a two-phase structure (base oil – thickener), selecting the correct solvent is a demanding task that requires knowledge of physical chemistry. It is quite easy to find combinations that can dissolve conventional greases, whereas silicone greases and polyurea greases, for example, are much less soluble.

The reports [2, 7] provide an overview of a comprehensive study summarized in the Prognos research report BTUO43-041258 [6]. The methods presented in the report and their applicability to monitoring different aspects are summarised in Table 1 below.

*Table 1. Methods of grease condition monitoring and their applicability to the monitoring of different grease properties [2, 6].*

| Analysis method | | Detected property | | | | |
|---|---|---|---|---|---|---|
| | | Solid contaminants | Water | Oxidation | Additive degradation | Other |
| Direct methods | Microscopy | x | | | | |
| | Mechanical filtering | x | | | | |
| | Scratching test | x | | | | |
| | X-ray fluorescence (XRF) | x | | | x | |
| | Electromagnetic detection | x | | | | |
| Solvent-based methods | Particle counting | x | | | | |
| | Ferrography | x | x | | | |
| | Micro filtration | x | | | | |
| | Atomic-emission spectrometry (ACP-AES | x | | | x | |
| | Atomic absorption spectrometry (AAS) | x | | | | |
| | X-ray diffraction (XRD) | x | | | x | |
| | Energy dispersive spectrometry (EDS) | x | | | | |
| | Karl Fisher-titration | | x | | | |
| | Distillation test | | x | | | |
| | FTIR analysis | | x | x | x | x |
| | Total acid number (TAN) | | | x | | |
| | Four-ball test | | | | x | |
| | Penetration test | | | | | x |
| | Oil separation test | | | | | x |

The possibilities of using laboratory analyses for on-line monitoring are very limited. The next step forward are methods of rapid on-site analysis providing at least some indicative information on the condition of the grease and that of the equipment it is lubricating. There are a large number of different basic methods that could be used as a basis for developing methods and equipment suitable for in-field analysis.

## 2.2 Vibration-based monitoring of lubrication condition

Grease starvation in lubricated contacts within a rolling bearing can be detected using measurement methods based on high-frequency vibration [4]. The problem with vibration-based methods is how to filter out noise and identify the excitation caused by insufficient lubrication, especially in the case of industrial systems that may contain a large number of possible sources of deviating vibration components. Another factor complicating the interpretation of measured signals is the fact that the mechanism of film formation in grease lubrication differs from conventional lubrication theories. High-frequency methods are based on the phenomenon that as the thickness of lubricant film decreases, more metal-to-metal contact occurs between rolling elements and raceways, exciting natural frequencies in bearings and adjacent structures. Sound and ultrasonic technologies are also used for grease condition monitoring, but these methods are not discussed in detail here because of their susceptibility to interference and the limited amount of experimental data on their use.

Vibration-based methods have been used at industrial sites, but not in a very systematic manner. In some cases, the poor lubrication conditions detected by vibration have been corrected by adding grease with a grease gun. At some power plants, for example, optimized lubrication has been achieved using the shock pulse method (SPM) [9]. Other viable methods include, among others, measurement of frequency band specific root-mean-square values of high-frequency vibration, SEE, PeakVue, envelope method, use of higher derivatives, and different methods of measuring and analyzing acoustic emission. [8, 14]

Most methods are based on the presence of a natural frequency within a frequency band with increased amplitude, highly responsive to changes in lubrication conditions. Conventional measurements are usually not enough to determine whether it is the natural frequency of a bearing, its housing or a component of adjacent structures, or that of a sensor or its mounting [10]. This means that the measurement results obtained using a certain type of bearing or system and any conclusions drawn may not necessarily be generalised and directly applicable to other bearings and measurement systems.

Lubricant film thickness is more difficult to monitor in grease-lubricated bearings than it is in oil-lubricated bearings. There is a general recognition that viscosity ratio, or κ value [11], is not enough to allow reliable assessment of film thickness in grease lubrication [5]. In the case of an oil-lubricated rolling bearing, the measurement of acoustic emission is one of the methods suitable for determining the critical rotation speed, that is, the speed below which contact between the peaks of surface asperities becomes more frequent and the lubrication regime becomes one of boundary lubrication. In a grease-lubricated bearing, the lubrication conditions may remain good even if the rotation speed falls far below this critical level, or they may vary between fully functional and boundary lubrication [4, 15]. Inside the bearing housing, lubricating grease also dampens vibration. On the other hand, if there is not enough grease in the raceways and hence not enough pressure for EHD lubrication, a theoretically good condition of fluid film lubrication may turn into a situation where lubricated contacts suffer from grease starvation (see above). These situations call for vibration-based monitoring, since they cannot be explained by conventional lubrication theories and are extremely difficult to predict at the stage of planning the system of bearings and their lubrication. The method is applicable to industrial fans, pumps, electric motors, etc.

# 3. Results

## 3.1 Industrial measurements

In industry, the need for grease lubrication research (Figure 2) has emerged because of a striking number of cases of bearing damage and lack of clarity about the reason. A long-term research aim is to minimize unplanned downtime and unexpected damage to be able to achieve reductions in maintenance costs and production losses. Centralized lubrication systems and related problems are discussed in a Master's Thesis prepared in conjunction with the Prognos project at UPM Kymmene Kaukas [5].

*Figure 2. Grease-lubricated bearings at an industrial site (UPM-Kymmene Oyj).*

Industrial fans are a typical example of grease-lubricated equipment prone to lubrication problems. Vibration measurements have revealed damage and increased vibration levels within certain frequency bands, most probably due to starved lubrication conditions ("dry run"). These situations have been temporarily corrected by adding more grease to the bearing using a grease gun. Figure 3 shows a typical pair of vibration spectra obtained from an industrial fan. What can be seen is the acceleration spectrum before and after lubrication.

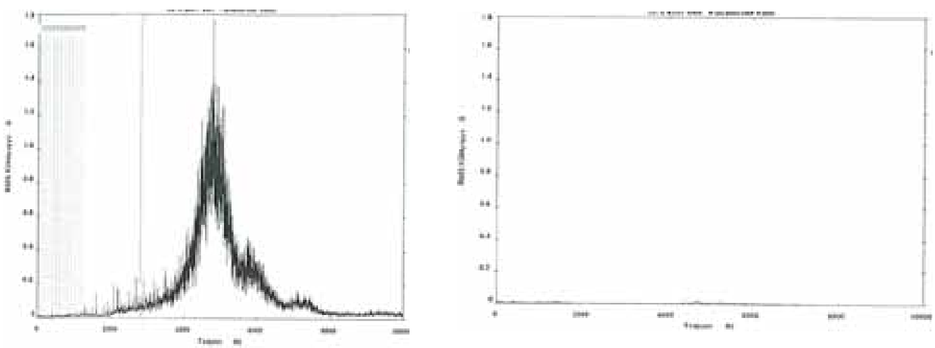

*Figure 3. Acceleration spectrum results for an industrial fan before and after re-greasing [5].*

The situation presented in Figure 3 is one where increased vibration in a frequency band has caused the occurrence of a wide local rise in the vibration spectrum, sometimes referred to as a haystack effect [12]. In terms of physical laws, this phenomenon is most likely due to excitation of components at their natural frequency as a result of metal surfaces coming into impulse-like rolling contact. This phenomenon – its emergence, causes and usefulness in monitoring lubrication conditions in bearings – was investigated by means of laboratory tests as part of the Prognos project [1].

## 3.2 Laboratory tests

### 3.2.1 Testing arrangements

The tests were conducted using equipment specially designed for the purpose of testing rolling bearings (see Figure 4). The same equipment have previously been used to perform loaded tests on ball bearings with circulating oil lubrication. For grease lubrication tests, the equipment was fitted with a replaceable bearing housing provided with a grease feed mechanism and a number of sensors monitoring different variables. Grease can be supplied either from the side or through the hole in the outer ring of the bearing. The bearing tested was a spherical roller bearing 22207 EK with outer ring outside diameter D = 72 mm and inner ring inside diameter d = 35 mm.

*Figure 4. Rolling bearing test equipment with sensors and grease feed mechanism (right). Bearing housing opened after pre-filling (left).*

The bearing was subjected to radial stress supplied via a hydraulic power unit and cylinder. The equipment allows the load to be increased or decreased up to 15 kN, and rotation speed can be adjusted up to 2500 rpm with an AC drive. For this test, the equipment was fitted with an SKF MultiPoint lubricator LAGD 400 [13]. The test load was 6.7 kN, and the bearing was rotated at a speed of 1200 rpm. The bearing was not externally heated during testing.

### 3.2.2 Test results

The measurements revealed that a significant change in lubrication conditions took regularly place far before re-greasing was calculated to be due. The bearing housing was first filled with grease as instructed, and then the equipment was run with standard parameters until a poor lubrication condition was detected. As regards acceleration measurements, the clearest indication of changes was an increase in the level of high-frequency vibration, and the total level reached in the frequency band 0–12 kHz also showed clear evidence of change. The fact that, at the same time, the bearing temperature decreased and the findings made after opening the housing all indicated that the lubricating grease fed into the bearing had largely flown out into the empty space on the “secondary side” (facing the electric motor). In other words, the rolling resistance offered by the grease had decreased, leading to a temperature drop. The measurements backed up the assumption that a calculated pre-greasing volume and re-greasing interval do not necessarily provide a sufficiently sound basis for the preparation of re-greasing schedules.

When grease was added to the bearing after a poor lubrication condition had been detected, the level of vibration soon returned to normal (see Figure 5), and the bearing temperature rose close to the level where it was when the test was started.

Examination of the vibration spectrum from a wider frequency band (0–20 kHz) showed that the haystack effect causing an increase in the RMS value, i.e. the situation where poor lubrication conditions increase the spectrum level, always occurred in the region of 10–15 kHz. This means that, during the test described above, there was a natural frequency present in this region that was highly responsive to changes in lubrication conditions.

The test was terminated after about a month because damage was suspected due to increases in temperature and vibration levels. Damage caused by failure of the taper sleeve supporting the bearing resulted in changes that could be most clearly seen in the frequency band 2–6 kHz.

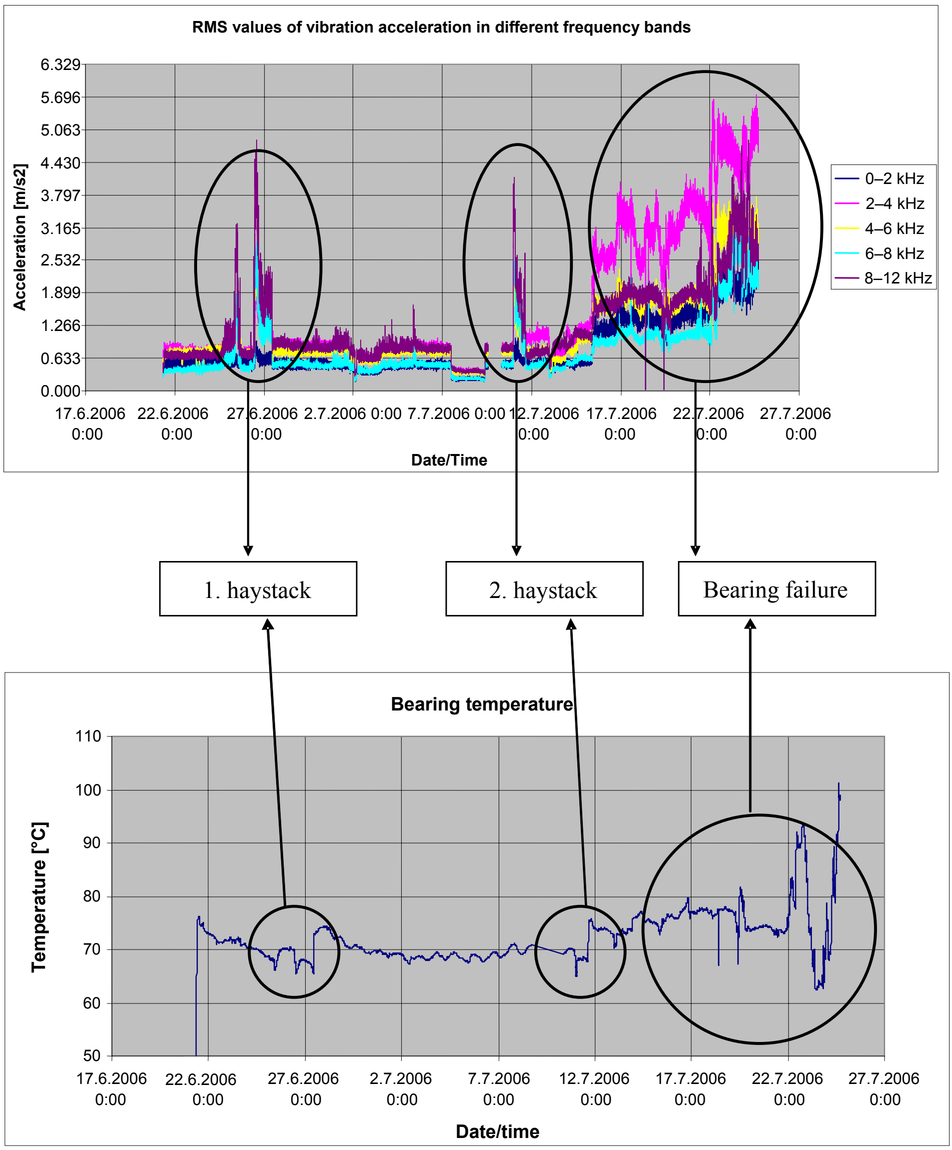


*Figure 5. The root-mean-square values of acceleration in different frequency bands and the bearing temperature trends during a single test run.*

The SPM value trends measured with a hand-held instrument also provided clear evidence of poor lubrication conditions. The interpretation of the results was, however, complicated by the presence of some measurement uncertainty due to the small number of measurement points (one measurement per day) and variation in the values obtained, even if they were from successive measurements. To compensate for this variation, efforts were made to perform measurements at the exact same point, and calculations were based on the results of 2–3 successive measurements.

### 3.2.3 Conclusions

The measurement method presented here is based on resonance effect. On the basis of spectrum analysis, it seems likely that the increase in the level of high-frequency vibration was triggered by resonance of a sensor fastened with a glued washer. One of the facts leading to this conclusion is that the resonating structure had a different level of stiffness in different directions, which appeared as a difference in the frequency band indicating the resonance (see Figure 6), and that the sensor fastened by means of a magnet was not affected by the phenomenon.

It is a known fact that sensor resonance increases the amplitudes that are subject to its amplifying effect. The reason why this property has not been widely utilized in condition monitoring is due to the fact that the mounting method may cause variation in the amplifying effect from one measurement to the next [10]. Exceptions are methods that rely on this sensor resonance effect. One of these methods is SPM, where vibrations are measured within the sensor resonance range (32 kHz) only. In this case, spurious low frequencies are filtered out, and broadband excitation increases vibration.

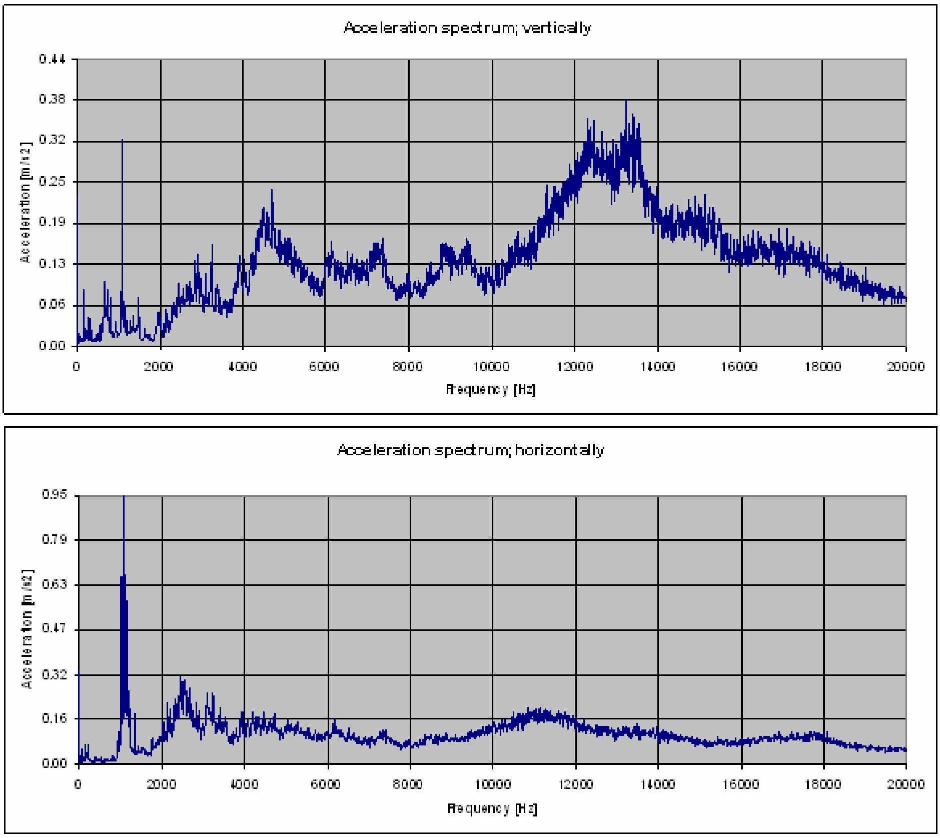


*Figure 6. Acceleration spectra in the vertical and horizontal directions. The spectrum of horizontal vibrations shows only a slight increase in vibration levels, a "haystack" being evident in a lower frequency band.*

# 4. Industrial benefits

The study showed that lubricant film failure or, in the case of grease-lubricated bearings, starved lubrication conditions ("dry run") can be detected using acceleration sensors. The use of acceleration measurement for detecting poor lubrication conditions seems to work efficiently when there is a high natural frequency of either the bearing structure or the sensor present in the measuring chain. Quite possibly the clearest indication is obtained when the above mentioned natural frequencies are close to each other. In such a case the small impulses from metal to metal contact excite the measuring system and a clear response can be seen in acceleration spectrum. It could be expected that the optimal frequency range is a function of bearing size (bigger bearing lower natural frequency) and consequently, the optimal natural frequency of the sensor and its mounting is a function of these. Hence the best way to connect the sensor to the surface varies, i.e. it might be advantageous to use magnet attachment with bigger bearings, or glue the sensor in case of a smaller bearing. The natural frequency of the sensor also has an influence to this choice. One drawback in the proposed method is that natural frequencies of this kind are also excited by other short impulses like noise or defects in the bearing. One way to make the diagnosis more reliable is to combine temperature measurement with the acceleration, i.e. when the temperature decreases and acceleration increases at high frequencies, the most likely cause in grease lubricated bearings is lack of proper lubrication.

The benefit of this method, compared to the SPM for example, is that it allows analysis with existing vibration measurement equipment. Acceleration measurement, together with temperature measurements, enables active lubrication adjustment. One possible drawback of the proposed approach is that while making the sensor very sensitive at high frequencies, and using its natural frequency for this, the sensor becomes somewhat less suitable for detecting small changes at lower frequencies. Hence some consideration is needed regarding which fault modes are the most important ones and how well the sensor performs at those frequencies which indicate them.

Automatic lubrication can be controlled by means of diagnostic software. The software developed by VTT monitors bearing temperature and both high- and low-frequency vibrations in two adjustable frequency bands. Re-greasing can be done automatically, either when acceleration readings indicate poor lubrication conditions or, at an even earlier stage, when the temperature falls below a critical level. Moreover, with this kind of software it could be possible to optimize the amount of grease used for re-greasing, helping to eliminate the problem of over greasing.

The software can be provided with a counter that collects data on in-operation occurrences of lubrication failure, recording both the number and the duration of these occurrences. The software is a helpful tool for long-term monitoring and for assessing overall bearing performance and the effects of different lubrication conditions on bearing life. It also makes it possible to recognize damage at an early stage and to separate it from changes in lubricating or operating conditions affecting the bearing.

The user interface of the software used with the VTT test equipment for rolling bearings is shown in Figure 7. The algorithms are simple and easy to integrate, as software components, with different monitoring software. At industrial sites, the applicability of the method may be limited by challenges posed by frequent changes in operating parameters, such as rotation speed and load.

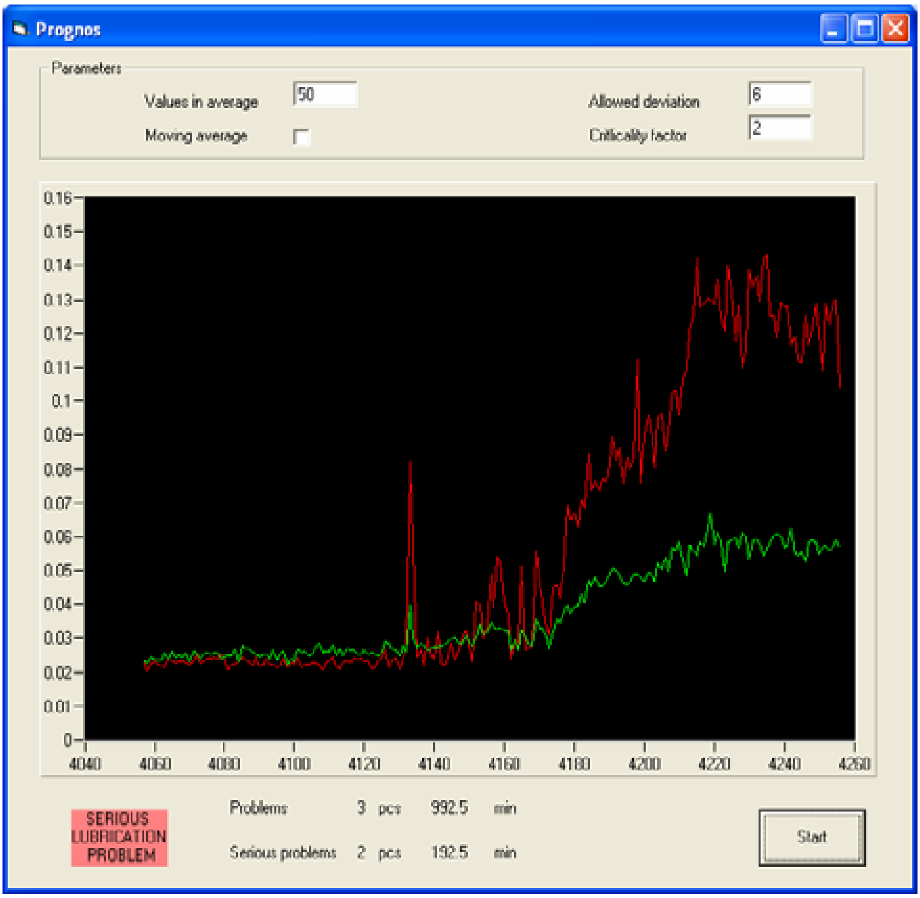


*Figure 7. The user interface of the software used with the VTT test equipment.*

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# Condition monitoring of industrial robots and concept for prognostics

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## Abstract

In this paper the basics of robotics and its condition monitoring as well as general, conceptual level prognostics is discussed. The focus of prognostics is on statistical methods without direct connection to robotics. The operational state at the robots is typically non-constant since in practice there are no constant states available. For non-constant time series, like this, the usage of data segmentation and overlapping method grabs better the part of the data that should be analysed. The process performance itself can be monitored with enveloped vibration based resemblance of the process path. The prognostic concept is based on statistical review of available maintenance data. The future reliability of a component can be estimated with the demonstrated concept. The concept was done on a Windows Excel spreadsheet.

# 1. Background and scope

Basis of the paper is on the Servo-case of the Prognos project in which condition monitoring and prognostic methods were studied on a material handling industrial robot used at a production site owned by Foxconn. However, during the project the company rearranged its production and the participating site was run down. As a consequence of this decision the scope of the case was reoriented as well, from the robot specific prognostics to more general, conceptual level prognostics.

In this paper, this division is handled in such a way that the basics of robotics and its condition monitoring is shown and discussed first, but very shortly mainly because it is already well reported. Then as a natural causal step, the prognostic phase and chapters follow. Hence, the focus of prognostics is on statistical methods without direct connection to robotics.

# 2. Methods for condition monitoring of robot and prognostics

## 2.1 Condition monitoring of industrial robot

### 2.1.1 Measurements

One of the most essential functions of a robot is to follow its path accurately and precisely. From the maintenance point of view the most precious components are servomotors and joint gears. Failure in these cause deviation and may lead to a total failure and, in the worst case, it may cause a long stoppage in production. To be able to study interdependences related to condition monitoring of a robot, an industrial robot was instrumented with a data acquisition system measuring signals from externally attached vibration acceleration, acoustic emission and sound sensors. The very difficulty in robotics is that characteristically they do not involve any constant load or steady rotational state at any point during the handling process whereas most of the condition monitoring techniques are preferably applied for a steady state. For the evaluation of the condition of the robot a measurement based twofold monitoring approach was adapted, namely the path and process sequence accuracy assessment approach and the condition monitoring of the most valuable components. The former approach is suitable for detecting deficiencies (such as ineffective brakes, excessive clearances) affecting timing and dynamic properties in focused sequences between different process cycles. For the latter approach appropriate methods for monitoring condition of the robot gears under the invariant state are discussed.

### 2.1.2 Signal processing and feature extraction

Typical methods applied to vibration based condition monitoring promote signals sampled from equal or at least controlled rotation and loading conditions. The lack of stationary states in robotics makes the detection of vibration excitation sources and vibration analysis challenging. One possibility to detect the deviation such as positioning error due to wear or uneven braking in robot performance is to compare different vibration responses with the reference case measured from the same production process but at different time. If necessary, cross-correlation can be used to assist the positioning of signals to be compared in time domain. It might be favourable to band-pass filter and envelope the signals to be compared since the original signals contain stochastic features which are by nature not directly correlated with the robot performance [Halme 2005a, Halme 2006].

From the point of view of the most critical components of the robot, condition monitoring is challenging. The robot movements interfere the dynamical analysis as well as does the continuous change in speed and load. Maximum allowable rotational speed at the most critical joint 2 is according to the definitions 1/3 Hz [Halme 2006]. Maximum rotational speed (53.3 Hz) at the gear input side can be calculated from the defined maximum rotational speed of the joint (gear output speed) and the gear transmission rate (160). At these maximum rotational speeds and the applied gear tooth numbers, the gear mesh frequencies are 640 Hz and 533 Hz at the input and output side, respectively. Analysis carried out in the frequency domain can be used to detect and evaluate different frequency components. Most commonly used frequency domain analyses are based on FFT (Fast Fourier Transformation). It is, of course an asset if the signals to be analysed are as stationary as possible.

## 2.2 Prognostic methods

### 2.2.1 Prediction of condition monitoring data

Prognostics is the process of predicting the future state of a system. Key challenge is to extract relevant information from the condition monitoring and operational experience to produce reliable diagnostics and prognostics about the state and remaining useful life.

There are several reasons, which can cause degradation of a system. They may be related to time (e.g. aging), operation time (e.g. fatigue breakdown), distant driven, cycles done, fuel or power consumed, work produced (e.g. elevators) or any of numerous other factors [Greitzer & Ferryman 2001] not to forget maintenance and operation neglects or misuse. Recognition of these application specific degradation factors, which features are implicating, facilitates the formulation of the prognostics models.

Relevant, failure sensitive features are extracted from the available data. The data itself can be from several sources such as condition monitoring (e.g. vibration acceleration, oil contamination and oxidation), operation and process control data (e.g. operation time, motor current, control signal of a servo-valve). The most important is that the selected feature (parameter) has as positive (or negative) correlation to the failure as possible. It is also outmost important from the cost point of view that the failures monitored are the most critical ones. If planned right this hopefully leads to economically justified operation as well.

Extracted parameters can be fitted to appropriate parameter models and equations. Parameter models are basically divided either to the models having physical connections and background or not. Models without physical connections are often called black box -models. If the main physical connections can be realised and formulated, these should be favoured simply because of their more or less known mutual dependencies are favouring intelligent solutions instead of pure data power. If the physical connections are too complicated or unknown then black box -type models can be tested. The basic in the latter case lies in that every time series can be regarded as the realisation of a stochastic process. Developed methods mimic adequately the behaviour of series without usually requiring very much parameters to be estimated [Gooijer & Hyndman 2006]. The methods are formulated to models such as autoregressive (AR) and moving average (MA) models with or without extra input signal part (X) and used for e.g. forecasting purposes. The outcomes of models are often represented as Box-Jenkins model (ARMA), ARMAX and ARX models, etc. An example of a simple, univariate model used for prognostic is an ARMA model of the form [Yan *et al.* 2004]:

$$y_t = \alpha_1 y_{t-1} + \ldots + \alpha_p y_{t-p} + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \ldots - \beta_q \varepsilon_{t-q}$$

where $p$ and $q$ are respectively orders of autoregressive and moving-average parts, $\alpha_1$, … , $\alpha_p$ and $\beta_1$, … $\beta_q$ are respectively autoregressive and moving-average parameters, while $y_t$ and $\varepsilon_t$ denotes series of independent variables and errors respectively. Model orders are first determined. This can be done by validating the model with different orders. When $p$ and $q$ are selected model parameters can be modelled by using normal regression fitting minimizing the mean square error. Model fitting can be either done offline or online by using recursive algorithms to minimise the quadric error. The built dynamic model, in this case ARMA, can then be used for predicting next values. It is also adviseable to play around with other time series models as well. The playing order is like any normal human being normally (or at least should) proceed: Try simple things first. ARX and ARMA models are simple enough for the beginning. If the validated results are not enough then more complicated models can be tested. Also nothing, except available resources, hinders to expand, if needed, the model from univariate to a multivariate model, which is operating with several independent variables.

In addition to time series models polynomial equations can be used as well to predict the future of data progress. One can think of these as a special case of the time series modes. While time series models output depends on the number of previous values of output and input variables (i.e. values at different phases), the polynomial equations operate only with all the values acting at the same time. This means also that time series involve frequency response and thus they are dependent on the frequency, while polynomial equations are immune to frequencies. Table 1 presents basic polynomial equations and their linear representatives in which either the dependent or independent variables, or both are transformed to achieve linearity.

*Table 1. Polynomial equations and their linearized representatives [Norusiss 1993].*

Polynomial equation types

| Type | Equation | Linear Equation |
|---|---|---|
| Linear | $y = b_0 + b_1 x$ | *same* |
| Logarithmic | $y = b_0 + b_1 \ln(x)$ | *same* |
| Inverse | $y = b_0 + (b_1 / x)$ | *same* |
| Quadratic | $y = b_0 + b_1 x + b_2 x^2$ | *same* |
| Cubic | $y = b_0 + b_1 x + b_2 x^2 + b_3 x^3$ | *same* |
| Compound | $y = b_0 (b_1)^x$ | $\ln(y) = \ln(b_0) + [\ln(b_1)] x$ |
| Power | $y = b_0 (x^{b_1})$ | $\ln(y) = \ln(b_0) + b_1 \ln(x)$ |
| S | $y = e^{b_0 + b_1 / x}$ | $\ln(y) = b_0 + b_1 / x$ |
| Growth | $y = e^{b_0 + b_1 x}$ | $\ln(y) = b_0 + b_1 x$ |
| Exponential | $y = b_0 (e^{b_1 x})$ | $\ln(y) = \ln(b_0) + b_1 x$ |
| Logistic | $y = 1/(1/u + b_0 (b_1^x))$ | $\ln(1/y - 1/u) = \ln(b_0) + [\ln(b_1)] x$ |

In the Table 1 $b_0$ is a constant, $b_n$ regression coefficient, $x$ value of an independent variable or a time value, *ln* natural *log* (base *e*), *e* natural *log* base and *u* upper bound value for the logistic model. If there are dependencies between several variables, it is possible and also recommendable to incorporate multiple independent variables as was the case with time series.

Regression analysis by using e.g. least squares method is carried out for the selected equations and their variables to find out the proper regression coefficient. The goodness of fit can be evaluated with $R^2$ coefficient [Norusiss 1993]:

$$R^2 = 1 - residual\ sum\ of\ squares / total\ sum\ of\ squares$$

The residual means in this case the distance between the observed and estimated value. If the fit is perfect i.e. no residuals (which is in the real life never true), $R^2$ is 1, and if $R^2$ is near 0, then there is no direct relationship. It is advisable to try different equations and both think of and utilise any known physical relationships between variables. In addition, also the prediction ability should be considered.

Different systems exhibit different condition related trends. For example, two types of wear processes can be distinguished: progressive and cumulative. A typical example of a progressive wear type is the wear volume of plain journal bearing operating with some metal-to-metal contacts while typical example of a cumulative wear type is ball-bearing [Roylance & Hunt 1999, Onsoyen 1991]. In progressive case, after an initial running-in phase there is a steady wear rate state prior to the final phase of bearing life with accelerating wear rate. In the cumulative case between the initial and the final phase there is a period, where the wear rate is almost zero for a long period of time, but the effects of loading are accumulated, leading finally to accelerating wear e.g. due to fatigue. How long the steady state lasts, depends heavily on the case. However, in the advent of the end of steady phase there is a clear change with an increase in the wear rate and volume. To reveal this change selected, case specific variables can be used. The change in the variables (independent) can either be positive or negative, the amount and sensitivity to the change depends on the case (dependent) and variable(s) in question as well. E.g. during a step from the steady to the final wear phase of a ball bearing, the most remarkable increasing indications of an accelerating wear process were detected with measured vibration acceleration responses and amount of particles in lubrication oil, while the measured oil visibility decreased only slightly [Halme 2002].

Modelling can be carried out for the whole data or only part of the data. However, if the response of a coming failure has a progressive nature, such as was in the bearing case, the ability to react promptly to the change prior to total collapse is essential. On the time series models this depends on the dynamic properties of the model. Frequency responses of time series models that are emphasising lower frequencies are by nature slower and more stable compared to models where there are more energies at the higher frequencies. What is the optimum frequency weighting, depends on the case, of course. With polynomial models this may be accomplished by varying the order of degree as well as emphasizing in the modelling phase the latest data values, although this may be done somewhat at the expense of model robustness. Different polynomial models such as linear (first degree), third degree and higher degree were tested against vibration acceleration RMS-values (dependent variable) measured from a ball bearing test rig to study model behaviour and prediction abilities [Jantunen 2003]. All the models operated as a function of time (independent variable). The higher order equation was partial $9^{th}$ degree polynomial equation and formed to mimic simplified wear development. The higher order equation and the third order equation were modelled by using all the RMS-values from healthy to faulty state. However, the higher order equation was modelled by emphasising the most recent values. Linear equation was modelled based on the last three measured RMS-values. Based on the tests, it was suggested, that the higher order model used seemed to follow the measured RMS-value in a reasonable way so that it can predict the near future trend of the RMS-value whereas the tested third order model seemed to be too slow and the linear model too unstable.

In the end of data prediction part it is good to remind the reader of different modelling options and strategies. In real life every model is only a resemblance of the reality and every model, independent of the type, has a limited optimum operation area, state and time. For this and other reasons it might be reasonable to utilised more than just one model for different sequences and phases [Ljung & Glad 1989]. It might also be good to have, at least for certain cases, models predicting and looking for both faster and slower responses. However, independent of these the data responses should be related to the component reliability as well.

### 2.2.2 Prediction of component condition

Irrespective of the condition monitoring technique, methods and variables, the available data and its progress needs to interpreted and appropriate actions taken. Generally, there is a stochastic relationship between the data, its derived variables and the unobserved true condition of the system [Wang & Zhang 2005]. However, most studies related to diagnostics and prognostics tend to concentrate on the prediction of data and its trend itself, not the prediction of future condition of the system. E.g. the prediction of the remaining life of a bearing is achieved by the prediction of the future of the vibration acceleration RMS-value. However, the decisions based only on the current data readings lack some practical justifications related to the reliability of the component and statistical studies of residual life.

The quality and usefulness of reliability models are once again directly proportional to the accuracy of the data they are based upon. To avoid unnecessary errors it is recommended first to identify the particular situation of a system [Vlok *et al.* 2004]. Have any preventive maintenance actions been performed, is the diagnostic maintenance data available and is the information covering the whole lifetime and the recorded effects of carried actions available from previous, respective systems. Current reliability and remaining lifetime can then be estimated based on the recent data, selected variables and statistically meaningful historical data.

Suitable origin of data and data derivative variables depend on the case. Condition monitoring data such as vibration accelerations and lubrication contaminations, operational data such as operation time, loadings etc. as well as operation and maintenance statistics may be used as long as they have a connection to the component reliability. This connection is in most cases stochastic. Wang and Zhang [2005] used oil monitoring information, time of operation and failure statistics of 30 aircraft engines to predict the residual life of engines. The oil monitoring consisted of the total metal concentration information monitored on an irregular basis. Due to the aircraft solution, the engines were, for the relief of the possible passengers, not allowed to run to an actual breakdown. As a failure time, the point of time was used, where replacement or overhaul cannot be delayed any further. Overhauled engines were therefore regarded as good as new. I a paper reeling system, loading information was deduced from the strain gauge measurements. A cumulative stress factor was calculated and the current reliability stage was estimated based on the prior given, designed fatigue strength distribution of the factor [Halme *et al.* 2006]. Remaining lifetime at each measurement point was assessed by using polynomial regression model for the cumulative factor data.

Reliability analyses are mostly based on life distribution data analysis of the components. Mathematically several different type of distributions can be formed, like a normal distribution (i.e. legendary Gaussian distribution), which can be defined as a function of the mean and standard deviation value of the data. However, in the reliability theory, the most widely used distribution type for the length of life is the Weibull distribution [Råde & Westergren 1990, Wang & Zhang 2005]. Equation for the Weibull cumulative distribution is (rank regression):

$$F(x) = 1 - e^{-(x/\beta)^{\alpha}}$$

where x is the data value (either time or value of an independent variable), α is shape (or slope) parameter and β is location parameter. Parameters can be estimated with maximum likelihood method [*Maximum* 2006, Wang & Zhang 2005], probability plotting [*Probability* 2006], rank regression [*Rank* 2006], etc. Taking the natural logarithm of both sides of the cumulative Weibull distribution equation yields:

$$\ln(-\ln(1-F(x)) = -\alpha\ln(\beta) + \alpha\ln(x)$$

which results in a linear equation of the form $y=a+bx$, where $y= ln(-ln(1-F(x))$, $a=-\alpha ln(\beta)$ and $b = \alpha$. These can be estimated with least squares estimation method (i.e. regression analysis). $F(x)$ is estimated from the median ranks. After regression analysis, appropriate Weibull parameters can be easily solved from $\alpha = b$ and $\beta = e^{-a/\alpha}$. Normal spreadsheet programs such as Excel offer functions to calculate Weibull as well as normal distribution for the given data and pre calculated distribution parameters.

Weibull distribution has been used to provide reasonable model for lifetime of equipments such as ball bearings, composite materials, aircraft engines [Wang & Zhang 2005], hot strip steel mill [Jardine *et al.* 2006], etc. In some cases just the operation time is compared to the recorded lifetime of component. However, this yields mainly a mean residual life estimate and thus it is somewhat unreliable in practice [Vlok 2001]. Practical, dynamic residual life estimates based on monitored effect i.e. condition related variables such as lubrication oil contamination level, vibration acceleration at certain, critical frequencies are required. Variables focusing the actual cause for a degradation process of a system, not just a response on an effect, should be favoured. E.g. cumulative loading [Halme *et al.* 2006], power consumed, etc. can be used if available with the historical life data. Modelling the historical life data with these cumulative variables e.g. by using Weibull distribution and calculating the model response with the respective variables, a better connection to the current reliability of the component can be achieved than just relying on the operation time. The real life difficulty of using cumulative parameters is that there are in most cases not statistically enough information available.

Any of the variables related to the component life can be modelled e.g with any of the polynomial models discussed previously. However, if cumulative variables are used, the dynamics of changes are not especially high. This leads to a natural conclusion that the standard linear modelling of last values can even give reliable enough base for predictions of progress of cumulative variables. Anyway, independent of the used variable and degree of polynomial model, the predicted future value of the variable can be forwarded back to the modelled reliability distribution. If there are not any major changes between modelled and current case, and if the prediction is within sufficient limits, then the future reliability can be predicted. Connection from the current reliability estimations and predictions back to the condition monitoring data models can be established. With reliability estimates indicating a good reliability state, condition data prediction models, which are not that aggressive can be favoured whereas during indications of decreased reliability faster and more aggressive condition data models might naturally lead to better judgements of the future true data progress and derived estimates of condition.

# 3. Results

## 3.1 Condition monitoring of industrial robot

### 3.1.1 Performance monitoring

In cases, where the product family and working sequences are changing frequently, the comparison to reference signals is not necessarily always possible. In those situations, it is possible to construct a successful test sequence, which is run every now and then. The monitoring of changes in robot performance can be parametrisized by calculating, either stepwisely or for the whole envelope curve, the time dependent trend of the specific square sum of the residuals. Values deviating from the normal distribution of responses can be used to indicate mechanical and electrical differences affecting the process and the robot positioning and timings. However, the method can not be considered to be very selective. Condition monitoring of the components of the robot and failure detection requires additional research.

### 3.1.2 Condition monitoring

If the vibration signal contains clear bursts originated e.g. from different process sequences, it is possible to average the spectrum piecewisely to be able to diminish the effect of stochastic noise. In a piecewisely averaged spectrum the original vibration acceleration time series signal was broken into overlapping segments, where each segment is a small subset of the original time series. 50 segments with 50% overlapping were used. Each of these segments is transformed by FFT and the coefficients of the transformed magnitudes are averaged. By this way, the gear mesh and its multiples, occurring at the maximum rotation speed become more clearly visible [Halme 2006]. From the gear condition point of view, important features to be monitored are vibration energy changes at the sidebands of the gear mesh and natural frequency [Randall 2004]. Sidebands are occurring at the shaft rotation speed. In addition, vibration energy at the harmonic components of gear mesh can be changed. However, it should be kept in mind that the gear mesh and its harmonics can even be seen from gears in good health due to small shaft eccentricities. As was discussed earlier in the performance analysis section of this chapter, it is, of course, possible to develop an additional test run, which is designed to produce a relatively long constant loading condition and rotational speed at least for the most critical joints. This would naturally help to detect the existence of the most critically assessed frequencies.

## 3.2 Prognostic concept

A prognostic concept was developed for the prognostic demonstrations of the condition progress of a component. The concept was tested with partly fictive data from a charging crane used in a steel mill. Focused component was a lifting rope, for which real maintenance replacements dates were recorded. In addition, an artificially made cumulative parameter was made to demonstrate the real degrading effect based in this case on cumulative consumed power, number of lifts and operation time. If the respective data had been available, of course, it would have been used instead of artificial data. However, in real life the degradation process is far more complex and depends on several other factors as well. Anyway, with the artificial parameter, the difference between just time based maintenance cycle and a parameter correlating better with the reasons causing repairing can be demonstrated, as will be done. The time spans and artificial parameter values for six individual maintenance occasions are shown in Figures 1 and 2. The construction and equation of the artificial parameter can be seen from Figure 2.

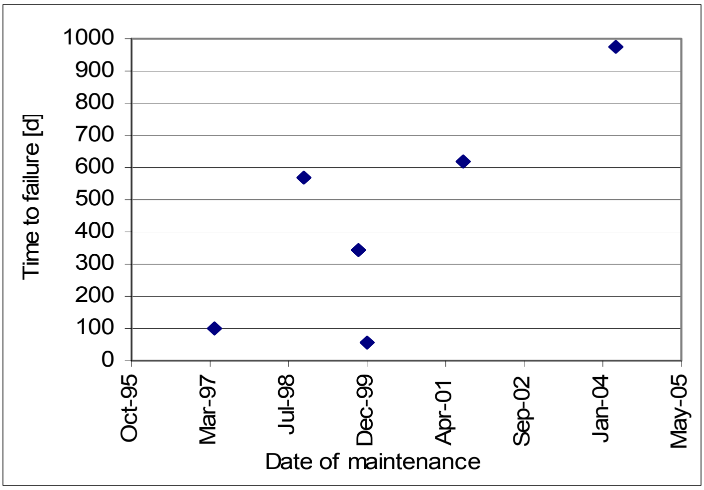


*Figure 1. Recorded time to failures for six individual maintenance occasions.*

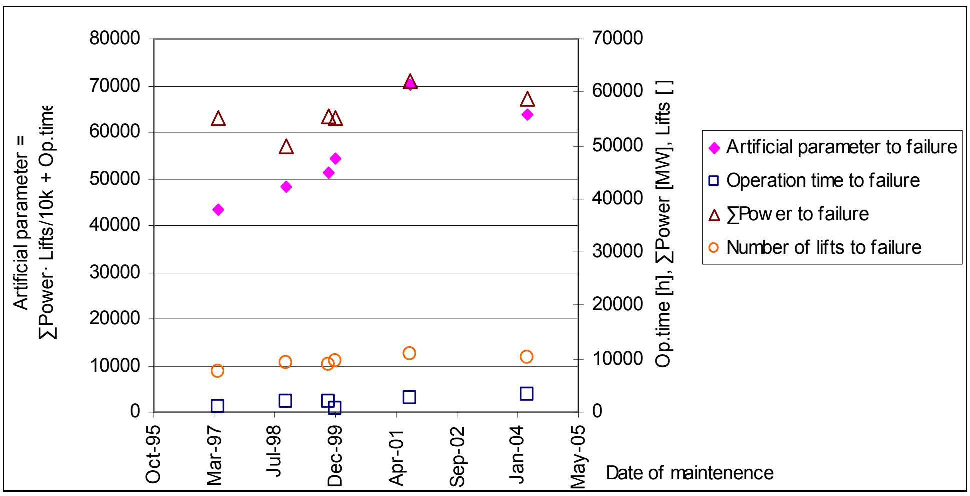


*Figure 2. Artificial parameter and auxiliary variables to failures for six individual maintenance occasions.*

In the demonstration of the concept, a Weibull distribution was used for the modelling of data. Shape and location parameters for the Weibull distribution were modelled with the rank regression mainly because of its simplicity. Both the time spans and the artificial parameters of maintenance occasions were modelled. Resulting Weibull density distributions are shown in Figure 3. It is evident from the Figure 3 that in this example the artificial distribution is grabbing better a closed form of a distribution and resembles more a traditional image of a Weibull density distribution.

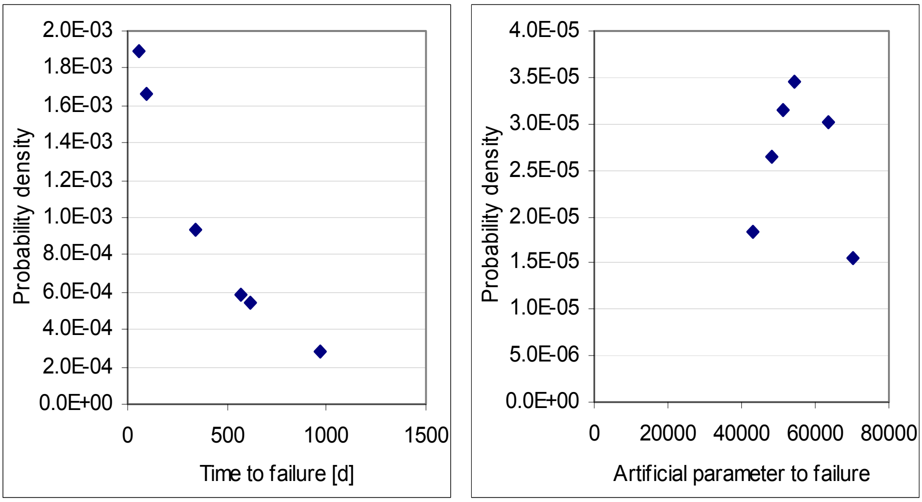


*Figure 3. Weibull probability density distributions of time span (on the left) and artificial parameter (on the right).*

The modelled distributions can be used for estimating the current reliability of the component. This is demonstrated with operation time from the last recorded replacement (6.4.2004) as well as with the coexistent artificial parameter. Although the days are passing linearly, the artificial parameter is here thought to deviate by a small amount each day so that it is not fully linear, which is also the the case in real life. The parameters representing the current situation are shown in Figure 4 and the respective current reliability values according to the modelled distributions are shown in Figure 5.

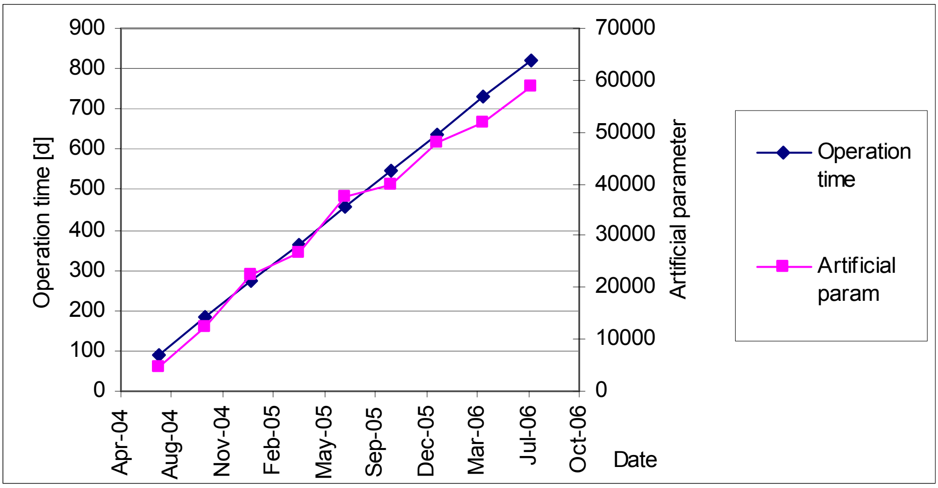


*Figure 4. Current operational time and coexistent artificial parameter.*

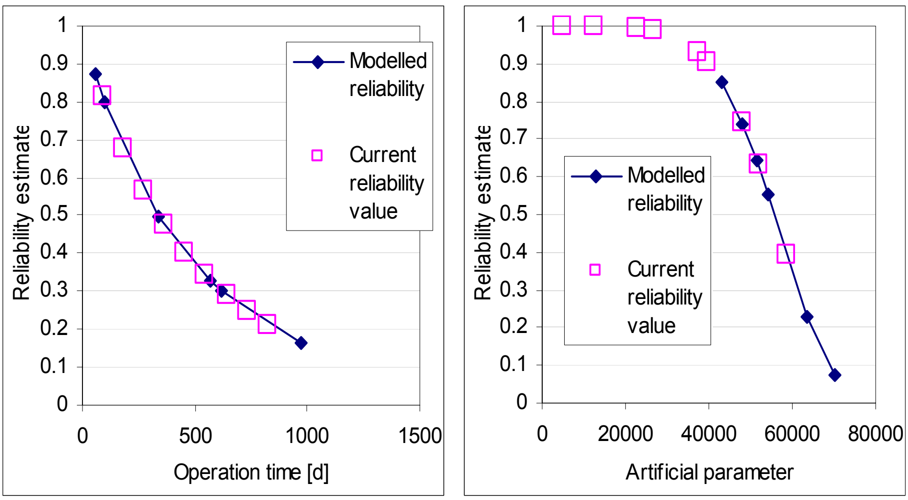


*Figure 5. Current reliability based on progress of current operational time (on the left) and artificial parameter (on the right).*

The progress of the current data was predicted with a polynomial regression model. Just as is the typical case with cumulative values, the data progress of the parameters is not complex and simple linear regression fitted for the five last values is now considered adequate enough. The fitted model is then used to give prognostics for two time steps ahead. Forwarding these prognostics estimates to the modelled reliability distributions, the future reliability of the component can be estimated. In Figure 6 both the current operation time progress, linear prediction of operation time and prediction of reliability are shown as a function of time. Respective values for the artificial parameter are shown in Figure 7.

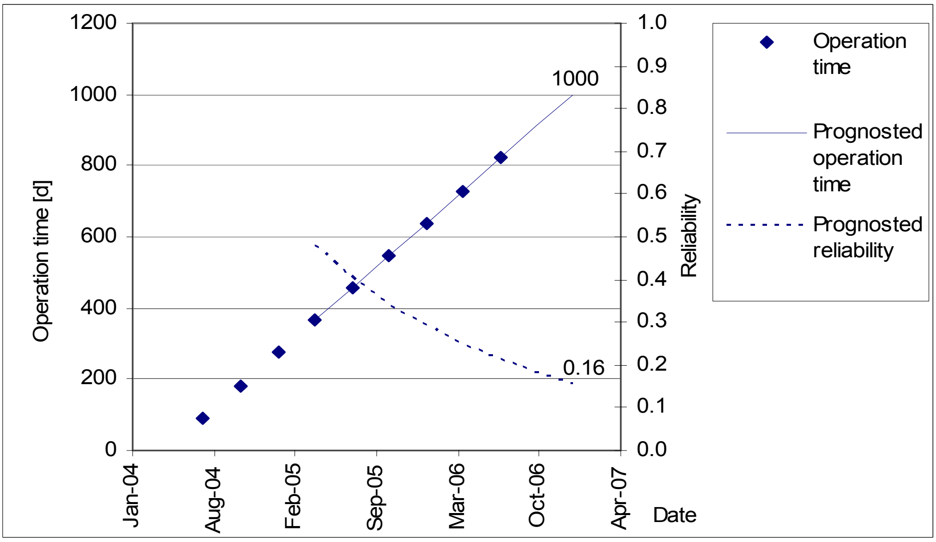


*Figure 6. Current operation time, linear prediction of time progress and prediction of reliability as a function of time.*

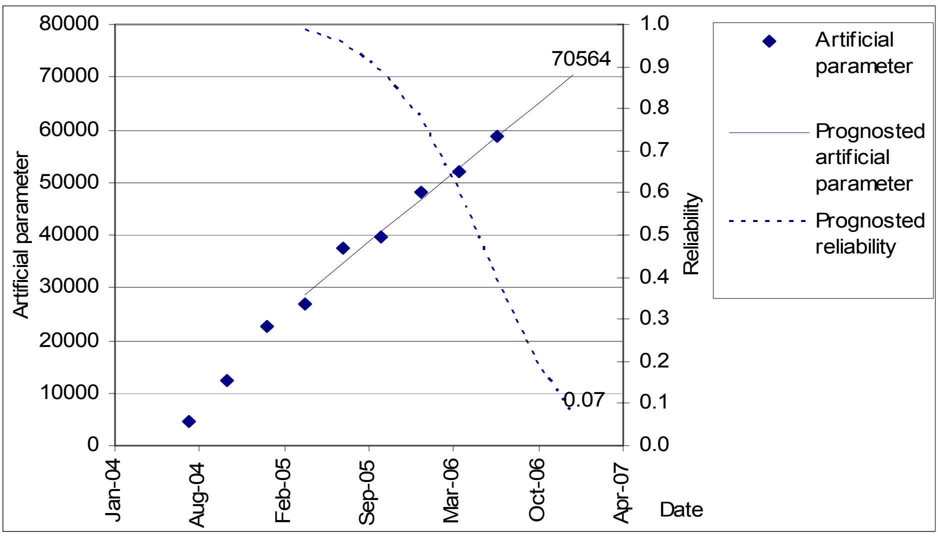


*Figure 7. Current artificial parameter, linear prediction of time progress and prediction of reliability as a function of time.*

It can be deduced from Figures 5, 6 and 7 that the time based reliability estimates are at the beginning giving lower reliability estimates than the artificial based estimates. This is considered to be due to the tendency of operation time studies to yield mean life estimates, although this case is just an artificial example. However, using operation time etc. is better than nothing and can be used with or without other operation related parameters of a component as one tool to adjust both the maintenance and monitoring intervals and the allocated resources as well as to change the sensitivity of data interpretations and predictions. Nevertheless, direct detection of a sudden breakdown should always be done based on responses from condition monitoring, automation, etc. systems.

# 4. Industrial benefits

Condition monitoring of small planetary gears were studied and the main results were shown and discussed in the previous chapters as well as in papers Halme [2005a, 2005b, 2006]. For example, important features to be monitored are vibration energy changes at the harmonic components of gear mesh and changes at the sidebands of the gear mesh and natural frequency. Sidebands are occurring at the shaft rotation speed. The results and published studies can be exploited in areas where condition monitoring of planetary gears is considered. This is far further than the scope of just this case.

The operational state at the robots is typically not constant and in practice there are no or only a few steady states available favoured by traditional condition monitoring techniques. This can be similar to other industrial applications such as handling manipulators, sequential packing and transport machines, etc. For the vibration analyses of these machines and their components, e.g. gears, the straightforward use of the FFT is often not the best approximation. For long time series, where only some data points represent dynamically the most relevant features, the usage of demonstrated data segmentation and overlapping method grabs better the part of the data that should be analysed. The component specific results of non constant state process can be exploited here and other industrial cases as well.

In addition to component specific results of non constant state process, the process performance can be monitored by band pass filtering and enveloping the vibration acceleration response from some selected repetitive process sequence. Derived vibration based resemblance of process path can then be compared later with respective responses in order to find out deviations outside acceptable levels. The ideas of demonstrated performance monitoring can be exploited widely, if necessary.

Besides gears, the most critical components in a robot are servomotors. The condition monitoring properties of these were briefly discussed in paper [Halme 2006] and in more detain in paper [Halme et al. 2005]. These results have supported LSK Electrics Company's awareness of different condition monitoring methods of electrical motors and further increased their know-how to plan more advanced maintenance of servo motors.

The demonstrated prognostic concept is based on statistical review of available maintenance data. The adaptation of the concept can give tools for statistical, fault based reliability estimation and for parameter based time dependent progress estimation and prognosis. The concept was done on a Windows Excel spreadsheet. The spreadsheet program contains a prognostic example anchored in to industrial maintenance data and it will be delivered to all participants as one result of this industrial case. The program can be utilised as an informative way of understanding a one possible way to promote industrial prognostics.

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# Prognostics through combining data from electric motor control system with process data

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## Abstract

Condition monitoring and process control data are typically observed separately. Also certain equipments like electric motors offer several measurements which are not followed at the process control. Within the Prognos-project combining data from electric motor control system with process data is studied by pilot scale tests and by industrial tests. A Labview based tool for data diagnosis is developed. Results of the study show that the motor current measurements can be used for process situation and equipment condition diagnosis and also with historical perspective for prognosis.

## 1. Background and scope

In industrial plants reliability of production should be kept as high as possible, naturally within economical constraints. Condition monitoring systems are made to increase reliability of the plant due to influencing working capability of equipments, when process control system is concentrated more on processes and system dynamics. There are both process control data and condition monitoring data in usage, but they are observed separately, mainly for historical and operational reasons, but also practical reasons for data differences presented in Table 1. [1]

Partly for the differences between control and maintenance data there are typically available lots of measured data which are not properly utilized, but there are many other reasons for that. For example increase of measurements, faster measurement frequencies, more complicated processes, and new equipments with embedded measurement systems. This kind of integration presents electric motor protection and control systems which offers vast amount of available data. Mainly the data is utilized only at the operational control and condition monitoring of the motor. But, in practice, the motors are planned to perform a certain task, which is monitored by target based requirements. If at the controlled system events happen, which diminish the possibilities to perform the task, the process control system compensates the situation so that the process continues production at the desired capacity to achieve desired quality, and if that is done successfully only small changes might be seen. At these kind of situations failures can proceed within a long time without warning sign.

*Table 1. Control and maintenance data differences [1].*

| **Feature** | **Control Data** | **Maintenance Data** |
|---|---|---|
| **Size** | Bytes | Kbytes/Mbytes |
| **Format** | Variables | Variables and samples |
| **Time reliability** | Time critical | Non time critical |
| **Frequency** | msec | On request |
| **Complexity** | Simple structure | Complicated structure |

At the industry, most of the constant speed motors are squirrel cage motors. These types of motors are durable and do not need DC power or slip-rings. They are the most common type of industrial AC electric motor, and especially low-voltage cage induction motors are the dominating motor-type in industrial applications, when cage induction motors controlled by speed variable drives are commonly used in production lines and electronic speed control is available [2, 3]. At this case Evoline is used, which is a motor control system for constant speed electric motors by ABB.

Our approach at this task was to search possibilities of combining data from constant speed electric motor control system with process data as presented in Figure 1. Both process data and motor control system data are diagnosed and analyzed, including history and online approach. This approach includes also clarification how the motor control system could be utilized in process phenomena analysis. The problems at combining process control data and condition management data can be seen at the table 1, but at this case the motor control data is not only for condition monitoring. Other problems are at the data collection and separate databases, but if the collection is performed coordinated these problems could be solved.

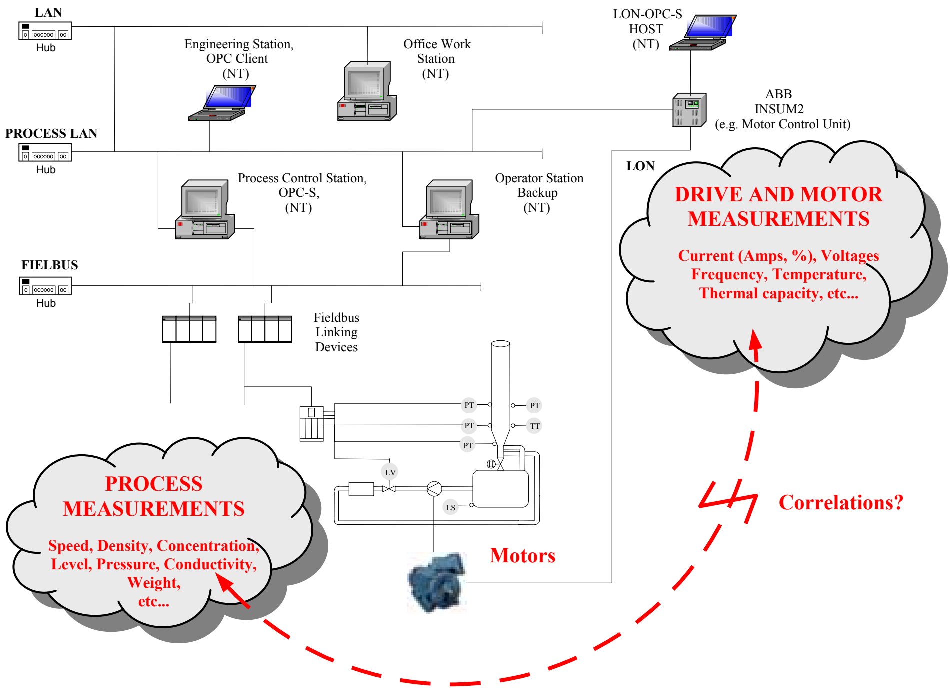


*Figure 1. The idea of the case approach.*

## 2. Methods

Because the used motor control system was available for usage at the beginning of the Prognos-project it was natural to start by searching a suitable test place. At first the system was installed in the pilot plant. After pilot testing and verifying that the system works was performed industrial scale tests. During both tests were performed calculations by Excel and developed calculations and tool for diagnosis using Labview.

## 2.1 Testing at the pilot scale

Pilot tests were performed at the stock preparation process, where a constant speed motor spins the stock storage tank mixer. At the stock storage tank water and stock flows are mixed. The purpose of the storage tank is to keep certain stock consistency and work as buffer for the process. The mixing keeps the stock homogeneous and prevents flocculation and accumulation.

The Evoline motor control system was installed so that it could collect data from the mixer motor and also one selected process variable: stock consistency percentage, INMA (%). Evoline data included following variables:

- *Phase current percentages of nominal current, I1, I2, I3 (%)*
- *Phase voltage percentages of nominal voltage, U1, U2, U3 (%)*
- *Power ratio, PF*
- *Earth fault current, I0 (mA)*
- *Active power, P (kW)*
- *Apparent power, S (kVA)*
- *Frequency, FN (Hz), inverse value of rotation speed*
- *Root-mean-square currents, I1_RMS, I2_RMS, I3_RMS (mA)*
- *Root-mean-square voltages, U1_RMS, U2_RMS, U3_RMS (mV)*
- *Thermal load, THERLOAD (%).*

At the stock preparation process there was Metso DNA process control system, which was used to collect selected process variables: consistency of high consistency pulp (%), temperature of stock storage tank (°C), stock level (%), and output flow (l/s).

At first the data was collected only by Evoline at the 0.2 s measurement frequency. The purpose was only to verify that the system works. After that also process data was included and data was collected using 1 h, 5 min and 10 min frequencies couple of months. The collected data was analyzed statistically.

## 2.2 Testing at the industrial scale

The industrial scale tests were performed in the paper mill. The test object was screening machines power unit, 160kW/500V constant speed electric motor, where Evoline was connected. Same variables were measured as in pilot tests, but this time INMA (%) was pressure difference of screening machine, one of the key variables of system. Collected variables from process control system linked up the screening process were:

- *reject (l/s)*
- *load (%)*
- *drawing roll speed (machine clothing) (m/min)*
- *inlet pressure (kPa)*
- *headbox pressure (kPa)*
- *outlet (accept) pressure (kPa).*

Both process control and Evoline data was collected and analysed. Data collection frequencies were 150 s and 300 s, and the whole data set included about 3 month data. Based on earlier performed pilot scale tests the data analysis could be performed more concentrated on important areas.

# 3. Results

## 3.1 Results of the pilot scale testing

All the pilot test data went through analysis by Excel and Labview. At the Excel correlation and statistical analysis was performed, which included all the typical functions for all variables as mean, standard deviation, variance, maximum, minimum, range, median, mode and sample amounts. Shortly, the results of statistical analysis show that only at the first trial section the pilot plant was in real test usage. Naturally, that reflected to correlation analysis with process variables, but the correlations between motor variables were as expected. Scatter diagrams and histograms were done by Labview, but they didn't give any more information as statistical analysis. Anyway the pilot test showed that the system was usable and the different kind of data sets can be combined. Problematic issues were time stamp integration, data storing reliability and the small number of events.

## 3.2 Results of the industrial scale testing

All the industrial test data went through analysis by Excel and Labview. Variables were studied statistically, by trends, by moving average trends, by trends of variations, by correlation analysis, by multivariable regression analysis, by scatter diagrams and by developing a Labview tool for combining data from electric motor control system and process data. At the Figure 2 is presented an example of trends. As a result it shows similarity of pressure difference and combined current and also their variations. Same types of trends were drawn of other variables. Main results were that certain motor variables are related to each others and all those selected process variables were related to each others but also to currents (I) and to apparent power, (S). Same results can be seen in Table 2, which presents correlations of variables.

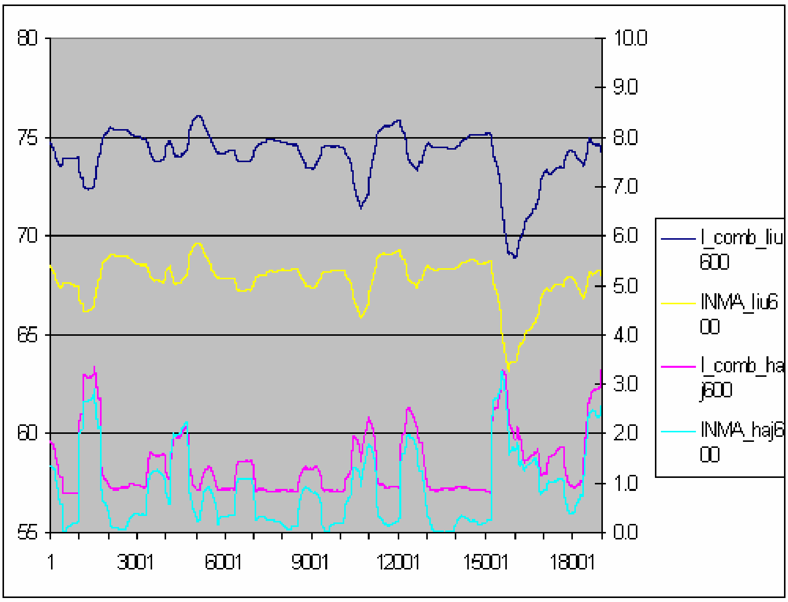


*Figure 2. Trends of combined moving average current, I_comb_liu (%), and moving average pressure difference INMA_liu (%) and their variation trends.*

According to Table 2, the dependences seem clear, but those numbers doesn't tell all about truth. More thorough analysis was performed using Labview and also with concentrated on different time periods. The statistical distribution of variables and dependences were studied also by Labview and some results are presented in Figure 3. The figure shows quite same things as presented of correlations: certain variables are very strongly related, when other groups seem to be totally uncorrelated. However at the time based analysis it was noticed that at the shorter reference periods the correlations were varying much more and in certain cases there were not any dependence.

*Table 2. Correlations of industrial scale test variables.*

| Variables | I1 | U1 | PF | RCT | P | S | FN | INMA | Reject | Load | Cloth |
|---|---|---|---|---|---|---|---|---|---|---|---|
| I1 (%) | 1.00 | | | | | | | | | | |
| I2 (%) | 0.98 | | | | | | | | | | |
| I3 (%) | 0.97 | | | | | | | | | | |
| U1 (%) | 0.29 | 1.00 | | | | | | | | | |
| U2 (%) | 0.29 | 0.86 | | | | | | | | | |
| U3 (%) | 0.31 | 0.86 | | | | | | | | | |
| PF | 0.04 | -0.01 | 1.00 | | | | | | | | |
| RCT (mA) | 0.17 | 0.17 | 0.03 | 1.00 | | | | | | | |
| P (kW) | 0.41 | 0.10 | -0.14 | 0.03 | 1.00 | | | | | | |
| S (kVA) | 0.98 | 0.43 | 0.03 | 0.19 | 0.42 | 1.00 | | | | | |
| FN (Hz) | 0.01 | 0.03 | 0.07 | 0.01 | -0.02 | 0.01 | 1.00 | | | | |
| I1_RMS (mA) | 0.99 | 0.29 | 0.04 | 0.17 | 0.41 | 0.98 | 0.01 | | | | |
| I2_RMS (mA) | 0.97 | 0.32 | 0.03 | 0.18 | 0.41 | 0.98 | -0.01 | | | | |
| I3_RMS (mA) | 0.97 | 0.31 | 0.02 | 0.17 | 0.43 | 0.98 | 0.00 | | | | |
| U1_RMS (mV) | 0.29 | 1.00 | -0.01 | 0.17 | 0.10 | 0.43 | 0.03 | | | | |
| U2_RMS (mV) | 0.29 | 0.86 | -0.03 | 0.19 | 0.16 | 0.43 | 0.03 | | | | |
| U3_RMS (mV) | 0.31 | 0.86 | -0.01 | 0.17 | 0.13 | 0.44 | 0.04 | | | | |
| INMA (%) | 0.83 | 0.26 | 0.03 | 0.19 | 0.41 | 0.82 | -0.01 | 1.00 | | | |
| Reject (l/s) | 0.66 | 0.22 | 0.01 | 0.08 | 0.47 | 0.66 | 0.02 | 0.76 | 1.00 | | |
| Load (%) | 0.84 | 0.35 | 0.02 | 0.20 | 0.45 | 0.85 | 0.00 | 0.96 | 0.77 | 1.00 | |
| Cloth speed (m/min) | 0.78 | 0.22 | 0.01 | 0.11 | 0.53 | 0.77 | -0.01 | 0.90 | 0.83 | 0.91 | 1.00 |
| Inlet pressure (kPa) | 0.83 | 0.26 | 0.02 | 0.16 | 0.48 | 0.83 | -0.02 | 0.96 | 0.79 | 0.98 | 0.96 |
| Accept pressure (kPa) | 0.83 | 0.26 | 0.02 | 0.16 | 0.48 | 0.83 | -0.02 | 0.95 | 0.79 | 0.97 | 0.96 |
| Headbox pressure (kPa) | 0.78 | 0.23 | 0.01 | 0.12 | 0.52 | 0.78 | -0.01 | 0.90 | 0.81 | 0.91 | 1.00 |
| Presure difference | 0.84 | 0.26 | 0.03 | 0.19 | 0.42 | 0.83 | -0.02 | 0.98 | 0.76 | 0.98 | 0.89 |
| Pressure ratio | 0.29 | 0.10 | -0.02 | -0.05 | 0.42 | 0.30 | 0.01 | 0.25 | 0.43 | 0.35 | 0.61 |

So it seemed that the correlations at the shorter period were bad as presented in Figure 4. However, there are logical explanations for that kind of situations, the current measurements might be more accurate than pressure difference or the measurement is noisy. However the measurement frequency was so slow that the first possibility might be the right one. Clear result is that pressure difference follows currents when the changes are big enough, but at the quite stable situation that is not happening.

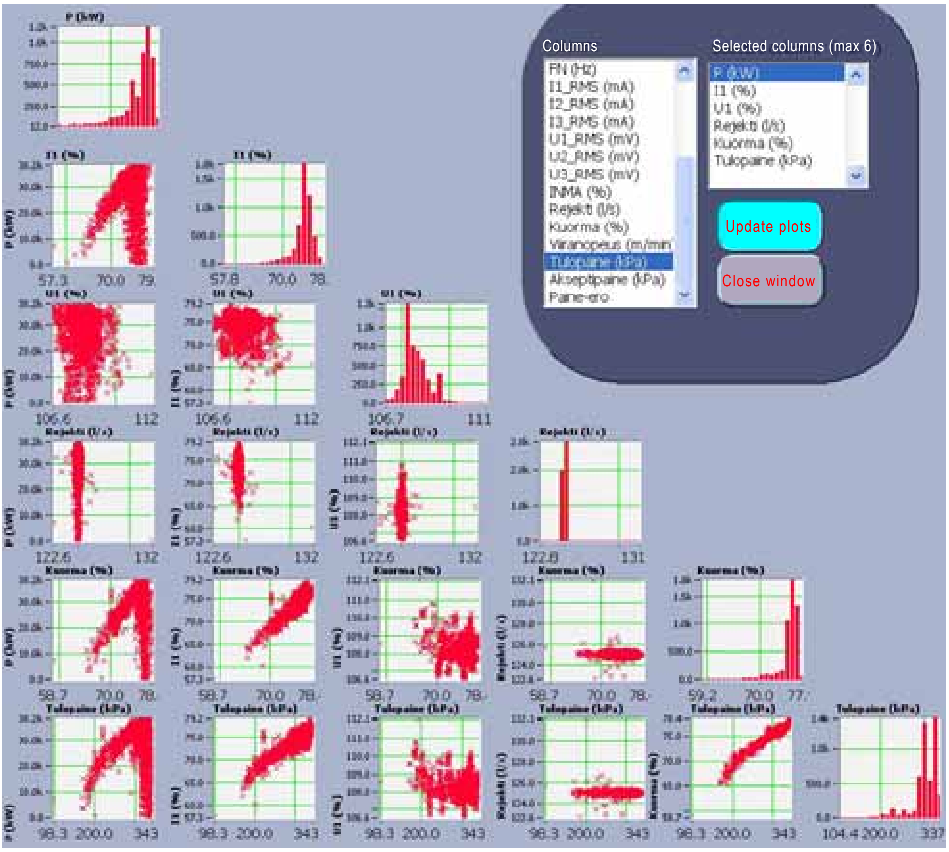


Figure 3. Example of Labview based analysis of variable dependences.

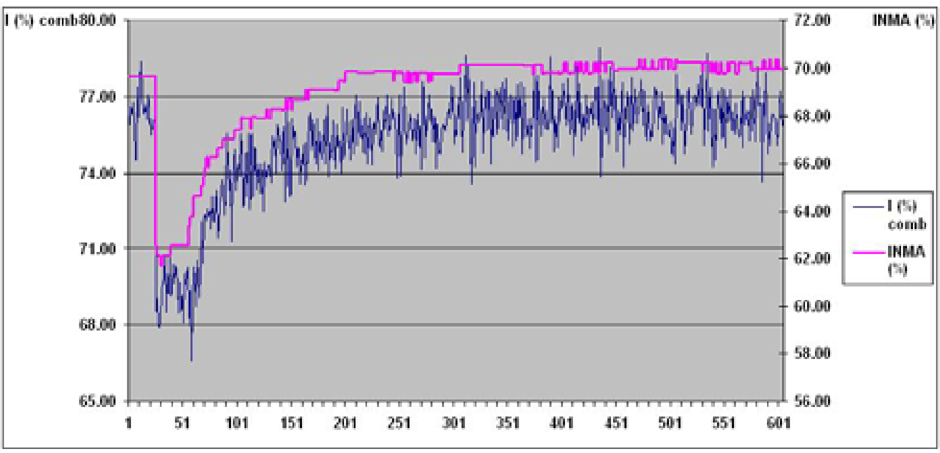


*Figure 4. Trends of combined current I_comb_(%), and pressure difference INMA (%) within one test day.*

## 3.3 Tool for data diagnosis

Labview based tool was developed for data diagnosis look-up. It is possible to follow-up selected trends at the same time. The tool includes XY-graph, where borders can be drawn based on statistical analysis and amount of confidence deviation (e.g. ±3σ, ±5σ) for borders can be selected [4]. The tool logs also alarms of every border crossings. (See Figure 5.)

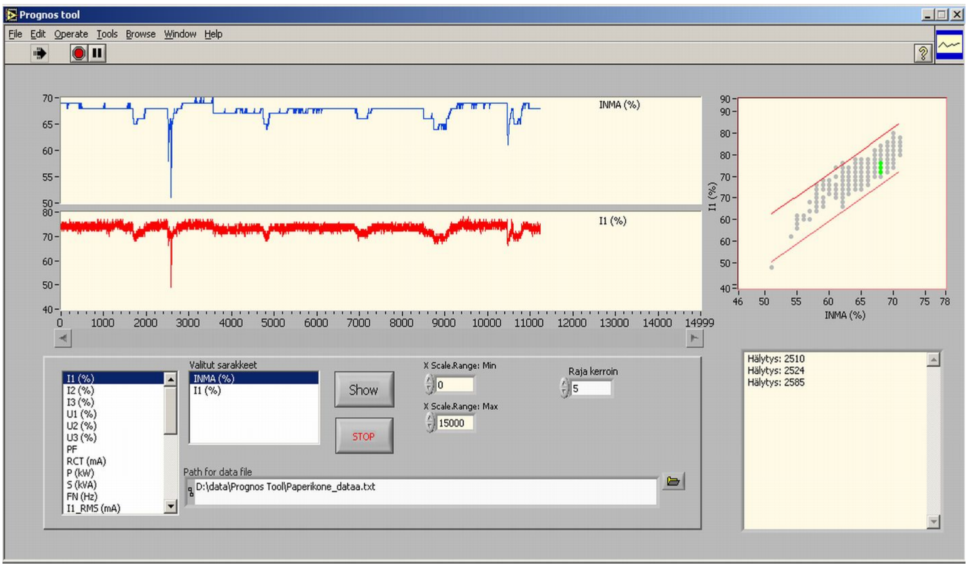


*Figure 5. Snapshot of developed tool for data diagnosis.*

Clear result of the measurement is that phase currents are possible to be used to follow the electric motor impact on process variables. The comparative analysis can be used for diagnosis and it seems that knowledge of the current effect might give the faster control of processes, so before the variations are seen in process measurements. Some situations of diagnosis are presented in Figure 6. Top left corner shows normal situation, which is selected to be shown as green. Other figures are some alarm situations. Grey points presents the history data and orange lines are statistical action limits. One crossing doesn't cause alarm and there needs to be enough exception of the statistics, naturally depending on used confidence level. Even the action limits are not exceed, exceptional deviation as presented in top right and down left part of Figure 6 is mark of something. At this system typical deviations are in the direction of current, which varies more than pressure difference. So the abnormal pressure deviation is a good reason for checking the situation.

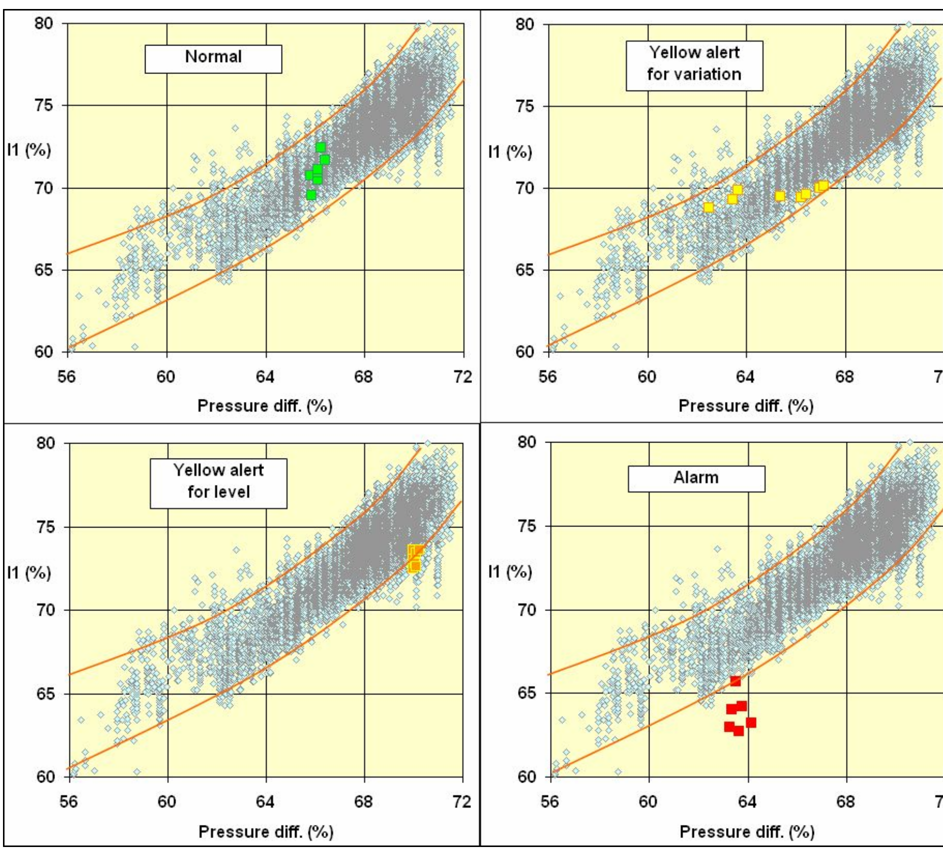


*Figure 6. Some possible situations according to qualification.*

This kind of examination requires longer follow-up of the target and more historical perspective of the variables and their normal deviation, if the data is used for the prognosis. There should also be knowledge of performed maintenance operations and failure rates of the system.

# 4. Industrial benefits

The results have shown that it is possible to combine data from electric motor control system with process data in practice. This is a benefit which can be practically utilized if the information of data can be displayed naturally. There are clear reasons for Evoline utilization, which enhance its exploitation. If the system is used at remote diagnosis the link to process measurements gives more reliable understanding of the situation. Equipment supplier can offer better service and even telemaintenance. However, there is only one input at the system for process measurements, which is a clear constraint, and needs very careful selection of the variable. Also some possible benefits are that in some cases system could be used to diminish process measurements or it can react for the abrupt changes. Finally, the knowledge of the project is transferable to future products.

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# Tools for diagnostics and prognostics of disturbances and faults in air fans

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## Abstract

This article is related to the monitoring task of fans, which are in critical position of the current processes, *i.e.* mining and power plant. Monitoring task is handled from point of diagnostic and prognostic views, taking into account both process and machine condition states simultaneously. Firstly the critical failure modes are selected for monitoring. Then the measurements were chosen to focus them to the critically classed failures. Diagnostic or prognostic reasoning hierarchy is described, being flexible and thus allowing inference chains with several degrees of complexities to propagate simultaneously. Measurements were analyzed by taking into account the current process state, which have a great influence to the operation monitoring methods. Feature analysis, especially the PCA and correlation analysis are in central role in reasoning chain, since they forms the basis to the decision process.

# 1. Background and scope

Process usually has some machines or their components which can be named as critical ones. In this article the critical machines are fans running in mining and power plants. The aim is to increase their lifetime and failure free operation time. This is done by evaluating the right measurements, then by selecting the suitable features and finally choosing the diagnostic and prognosis methods. This will increase the amount of information to the end user, thus helping the operator to make a decision about the optimal scheduling of condition and repair tasks.

Firstly the initial conditions were checked from viewpoints of surrounding process, available measurements, data transferring and data storages. This was reported in two documents made in the project for internal use, including a survey of diagnostic and prognostic methods and methods available especially for the machine parts or components, which were presented in different cases. In addition, the initial situation of measurements etc. was reported for each of the cases separately.

Starting point for a study was the use of expert based system for fault recognition and classification. Even though those fans as a research objects were quite a simple by means of their function and degree of mechanical complexity, it still is impossible to prefigure all the possible failure types which may concern them. Expert based system, on which the failure types are depicted in different forms of rules, are often criticized from that perspective. However, this is not a true problem since system can be focused to the critical failures only. Critical ones are found by analyzing the appeared failures with statistical or risk analysis methods by experts.

For focusing the resources only for critical failures, analyses for finding the crucial ones from the set of all the failures were made for both of the case fans. The fan in mining industry did not have real failures recorded. Thus experts established the imagined failure modes, causes and effects on it, their incidences and risks from viewpoints of safety and costs. The other fan in power plant (shown in Figure 1) had the information about real failures, produced downtimes and the reasons for failure. Since this analysis was different on its starting point, the statistical methods were introduced. Both failure analyses exposed the fan-specific failures which have the need for develop the diagnostic tools. Surprising was, that the critical failure types were quite dissimilar for those fans. The biggest risk for mining fan was found from its framework, otherwise than the power plant fan had the risk in bearings.

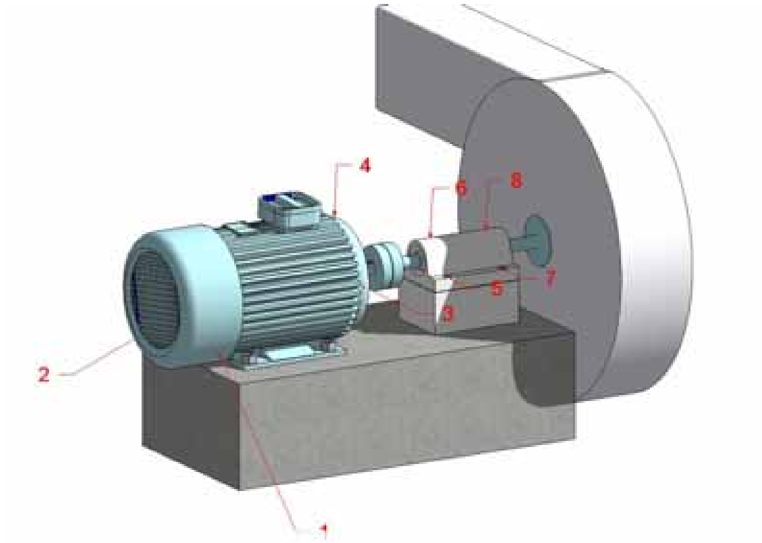


*Figure 1. One of the two target fans with the measurement points.*

## 2. Inference chain

In the article Järvinen et al. 2006 [2] the flexible hierarchy for making decisions is presented. The lowest level is focused to the machine parts, in where the main parts of decisions are made. The next level concerns machine which concludes the classification results from the component level, whereas the highest level, named as factory level, concludes the results from machine level. Concluding is done simple by using the logical rules. The lowest level is in the crucial role in reasoning chain, and it has own small scale reasoning chain. This chain propagates from measurement space through the feature space to the decision space. The main idea of the mentioned paper is to concentrate the expert knowledge to the feature space, in order to avoid the complexity in the decision.

In it's simply form, the decisions are made by wideband features verifying them to the vibration standards. The step to the more complex way is then to use some logical rules, which can be taken into account the process state. The propagating is based on small decisions, as the IF-THEN-ELSE commands. Again, step to the more complex way is to introduce the fuzzy rules, by which some descriptive information may be included to the reasoning. After that, the most complex way is to use so called machine learning methods.

Reasoning chain starts from measurement space, then propagating via feature space to the classification space.

## 2.1 Measurement space

### 2.1.1 Data acquisition

Based on analysis of degrees of criticality for fault types, the preliminary plan about the suitable measurement methods was done. In both fan cases, the physical phenomena behind the critical failures were though to be indicated mainly by acceleration measurements. Selection of the measurement domains is one of the key questions thus forming the guidelines for following feature analysis.

Acceleration measurements were performed in the power plant. The measurement system was kept at the place about one week. The data was collected from eight points (Figure 1). Five hundred separate records were done systematically by time interval of 15 minutes. Duration of each record was one second, and time series were recorded at 2500 Hz sampling frequency.

Afterward those 500 vibration measurements were synchronized with process data, which were collected at the same time instances. From the hundreds of available process variables, the set of 30 variables were chosen by experts, in order to get a good description over the process state.

### 2.1.2 Data validation

#### 2.1.2.1 Vibration data validation; selecting the best measurement points

In the current study the measurement points (shown in Figure 1) were selected from the closeness of the bearings of motor and fan, since it was found being a critical machine component. Measurements were done at each of the cross-sections in both vertical and horizontal directions. Clearly we can reduce some of those eight measurement points and still reach the target; increase the monitoring level for critical failures. Data reduction is performed later, but in this chapter one way to the coarse measurement point reduction is presented. Often the sensors are systematically placed to measure at horizontal direction based on the fact that the support stiffness generally is at minimum in this direction. However, the further observation shows that the support stiffness is not always a right ground to choose the measurement direction.

In Figure 2 one of the features is shown by means of its correlation over the different measurement channels. By referring to the vibration features by that way, we will find the specific measurement points, in which the features are unique. It helps us to choose the right measurement channels and the minimum amount of measuring points. Even though, the starting point was that each of the critically classed four bearings needs at least one measurement.

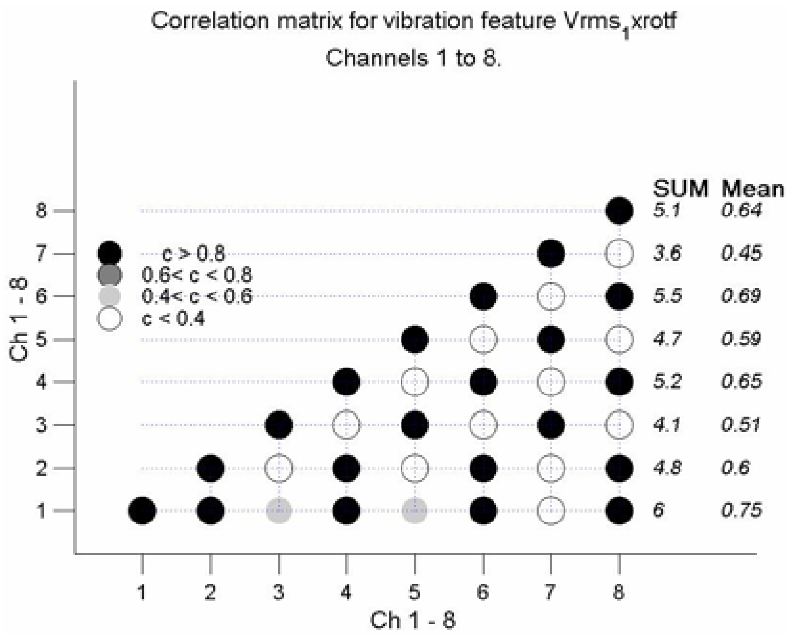


*Figure 2. Correlation matrix for RMS velocity from narrow band closed to the rotational frequency.*

The question is, does it need to measure both directions, and if not, which one should be selected? Figure 2 can help in this question, but the final solution is got after the features are weighted by expert taking into account also the process dependency, as viewed in Figure 5.

### 2.1.2.2 Process data validation; reducing the independent variables

As a pre-processing for a later presented PCA (Principal Component Analysis), the author is proposing to take an overview over the correlations. As is done in the following, the visual inspection over the correlations may show the grouped independent data sets immediately, and the use of PCA is not necessarily needed. At least the pre-calculated correlations gives some ideas about the variables to be chose to the PCA analysis.

The rough data reduction for process variables is done on following order: at first the experts chose the initial process variable set in order to describe the process state of fan. Furthermore, some variables from surrounding processes were chosen for taking into account its affect to the dynamical behaviour of fan. Surrounding process has thought to affect not only to the measurement levels but also to the durability of mechanical parts. This dataset was initially chosen from a group of several hundreds of variables. After that the correlation matrix was calculated for this dataset. This matrix is shown in Figure 3.

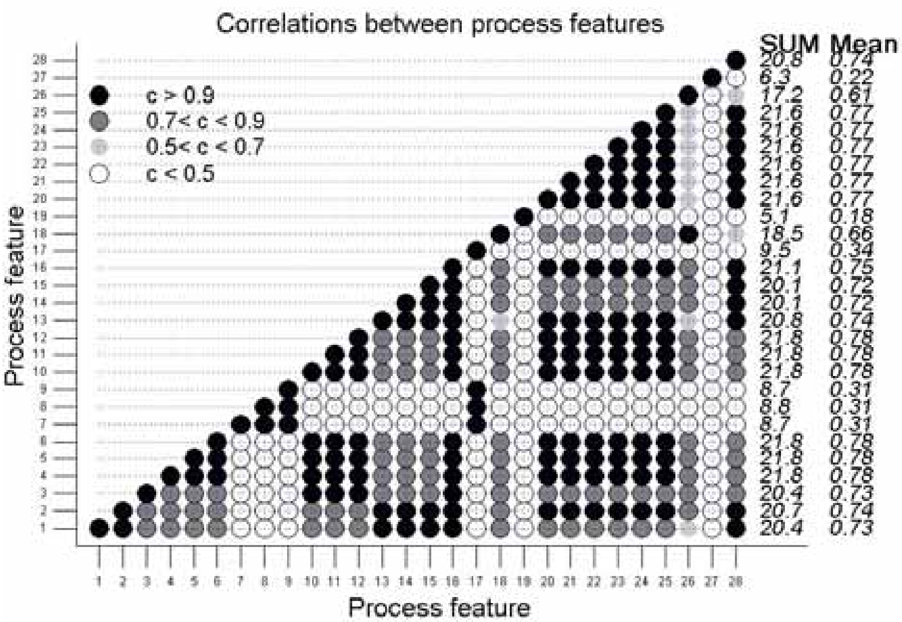


*Figure 3. Correlation matrix of the process variables.*

Correlation matrix is symmetric, thus only the second half on it is presented. In Figure 3 the black filled circle indicates the correlation (marked as c) is greater than 0.9. That level of correlation means that the verified data are close to identical, thus denoting the nearly same information. Surprising is, that fully correlated process variables may have a totally different physical meaning, *i.e.* pressure, current, flow, or rotational frequency. However their analytical connections are not linear. Circles filled with dark gray mean the correlation is $0.7 < c < 0.9$, light gray filled $0.5 < c$ $0.7$ and white filled circle is for correlation under 0.5, which may be interpreted so that the variables are linearly quite independent.

Again, from Figure 3 one may find the overall view that the variables either are or are not correlated with each other. Based on this one may conclude that in fact we only have two kinds of data in use. From process monitoring point of view we could ask, is there still too many variables to be measured? On the other hand, this matrix helps us to decide the variables, by which the process state can be determined.

## 2.2 Feature space

The function of feature space is to transform the measurements to the classification space. In this study we give a great weighting to the feature space, since the use of sophisticated feature analysis methods allows reducing the degree of complexity of deduction engine.

Authors have studied feature analysis in two published articles [1, 2], which concern especially feature extraction and compression tasks. The first one has 20 and latter one 21 references, by which the art of the feature analysis is determined.

The more complex is the classification algorithm, the less information about the classification is passed to the user. That is the main reason, why the authors have not introduced learning methods such as the genetic algorithms or artificial neural networks, but prefer that the research is concerned for right measurements and feature analysis.

### 2.2.1 Vibration guidelines

In order to get the overall view and feeling about the fans dynamical behaviour in its ‘normal’ state, the vibration measurements were presented as waterfall presentations. Those spectra are in the main role for factual and heuristic decisions and will work as a comparison material to the latter performed measurements. Factual knowledge is commonly accepted, has strong references and can be found in textbooks. In contrast to that, the heuristic one is more individualistic taking into account causes and effects according to the expert’s empirical knowledge. In Figure 4 one of the important sources for heuristic rules is presented: waterfall spectrum through the RPM values of 960…1160.

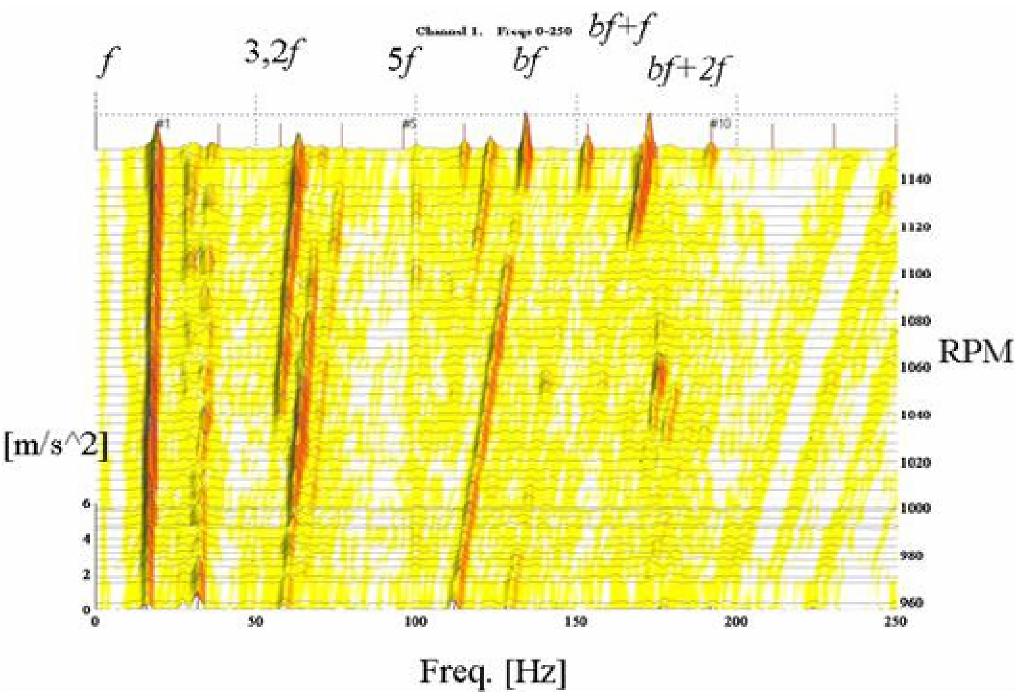


*Figure 4. Spectra sorted by RPM values from measuring point 1.*

From the Figure 4 one may pick up the typical spectral amplitudes for both the fan and motor parts, in function of RPM. RPM is the dominating process feature, but as well the sorting may be done using the PC:s, as explained later. Frequency lines related to the fundamental frequency (*f*) and blade passing frequency *bf* can be separately monitored, thus forming the reference values for motor and fan.

Add to this, via amplitude modulation some sidebands can be found in the closeness of blade passing or its higher order frequencies. Furthermore, unchanging frequencies as are the resonance or line frequencies can be discovered. From the figure, alarming is the appearing of 3.2 x *f* frequency line, if it does not originate from the other machine.

As Figure 4 shows, presenting all the measurement channels through the measured frequencies gives to the expert a starting point for feature extraction work. Expert will propose some frequencies or frequency bands to monitor. Add to this, an expert can give a verbal interpretation about the monitored frequencies and set the limits for its degree of dangerousness.

There are some standards available regarding wideband features, as vibration velocity RMS value in band 10…1000 Hz is handled at least in ISO 2372 and VDI 2376/1964. The standards are generic and thus cannot handle specifically narrow band features. Contrast to that, large number of common fault types as misalignment, unbalance, poor lubrication, loose bearings, faulty clutch etc. are tabulated. In the tables, the typical fault frequencies and amplitude relationships are listed as a heuristic knowledge.

### 2.2.2 Data reduction

Data reduction is the important stage in the feature space operations, because the amount of available data may become a problem in order to storage it or utilize it efficiently. That is why several methods are developed for reduce the amount of data by compressing its information. In chapter 'Data validation' the identical data sources were reduced, this chapter is focused prefer to the reducing dependent or misleading data.

Feature analysis methods can roughly be classified to the extraction, compression and data subset selection methods. In the compression part, correlation based statistical methods and PCA are mostly used, has the strong references, are conventional, simply and easy to explain, and they does not hide any information during the inference chain from the user. Based on those reasons they are chosen as key methods in this research. In fact, the PCA is the sophisticated form of correlation. Principles of PCA are explained in detail in references [3, 4].

PCA and correlation analysis are a part of multivariate statistics. They are suitable especially for linearly dependent data series, but can utilize also in the context of more complicated relationships.

PCA will not miss the connection to the original variables, because in the principal domain we have the eigenvalues and nominal modes by which the transformation to the original domain is possible. The aim is to choose some, which means two or three main components, which include about 90% from the process information. From the Figure 3 correlation matrix we visually choose some variables as 1, 8, 17, 18, 26, to the PCA. Visual inspection shows that those variables are not fully correlated which each others. Thus, afterwards we only have those five measurements to be recorded in order to explain the current process state.

Before the calculation procedure, the datasets has to be normalized. Normalization guarantees that the verified datasets get the similar weighting. The normalization is done by eliminating the offsets and then by dividing the data by their variance.

PCA gives the eigenvectors Ψ and nominal values λ for the selected process dataset in following matrix form:

$$\Psi = \begin{bmatrix} 0.4873 & 0.2350 & 0.8264 & -0.0784 & 0.1350 \\ -0.2853 & 0.6460 & 0.0806 & 0.6756 & -0.1961 \\ 0.2779 & -0.6501 & 0.1102 & 0.6825 & -0.1493 \\ 0.5617 & 0.2103 & -0.2847 & -0.1430 & -0.7340 \\ -0.5371 & -0.2463 & 0.4662 & -0.2264 & -0.6183 \end{bmatrix}$$

and

$$\lambda \quad = \quad diag\{2.7722 \quad 1.7677 \quad 0.3555 \quad 0.0726 \quad 0.0308\}$$

respectively and they make the connection between uncorrelated new variables and original datasets. New variables *i.e.* principal components are obtained by multiplying the original dataset by Ψ, and the nominal values λ are variances of PC's. Those variances correlate to the ability to explain the variability. In Figure 5 this property is visualized by means of percentage parts.

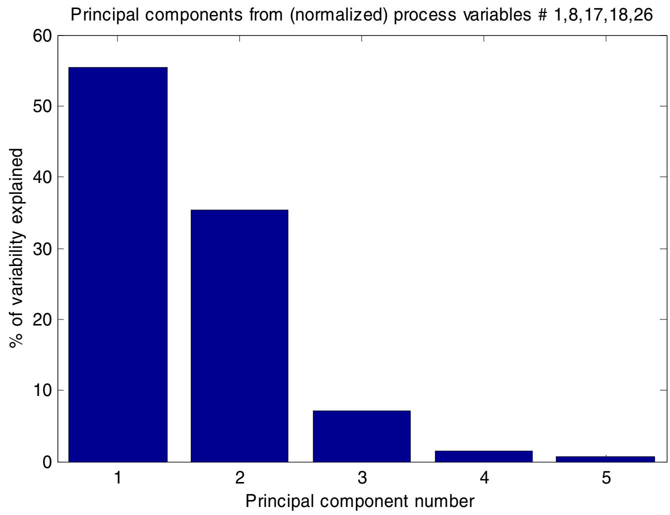


*Figure 5. Percentage parts of explainability of principal components.*

The cumulative sum over the first three λ -values results 55.5, 90.8, 97.9%. Thus the first two components are chosen to represent the current process state thus explaining about 91% of total process variability. The process state can now be taken into account in the monitoring work by different ways.

### 2.2.3 Process compensation

The fan in the mining plant had only few of process variables available, for that reason power plant fan was selected to the data source.

Not only the vibration state, but also the process state must be described, since they are correlating in many ways. Process variation often changes the signal levels of the condition monitoring measurements, as is the acceleration. For a chosen fault indicator, at the same level of amplitude the machine component or machine state may be classified as normal or abnormal, depending on the current process state. That is the point which should be taken into account, when the warning or alarm limits are outlined.

Often the process is classified to some, say to 10 categories by neural networks or other learning algorithm. That is a workable method. However it has to be said again, that the monitoring work must keep as simple as possible in order to get clear information to the end users. That is why the different way of approach is chosen in this study. Add to this, by avoiding the rough classification of the process state, it may be keep close to continuous one which increase the accuracy of process compensation operation.

The vibration features used in the following data handling procedure are presented in Table 1.

*Table 1. Features calculated from vibration measurements.*

| Feature | Domain | Function | Frequencies |
|---|---|---|---|
| 1 | Velocity | RMS | 0...$f_{max}$ |
| 2 | Acceleration | Skewness | 0...$f_{max}$ |
| 3 | Acceleration | Kurtosis | 0...$f_{max}$ |
| 4 | Acceleration | Max | 0...$f_{max}$ |
| 5 | Acceleration | Min | 0...$f_{max}$ |
| 6 | Velocity | RMS | 1 x $f_{rot}$ |
| 7 | Acceleration | RMS | (1 2 3 4)x $f_{rot}$ |
| 8 | Acceleration | RMS | 1 x $f_{blade}$ |
| 9 | Acceleration | RMS | 2 x $f_{blade}$ |
| 10 | Acceleration | RMS | 3 x $f_{blade}$ |
| 11 | Acceleration | RMS | 4 x $f_{blade}$ |
| 12 | Acceleration | RMS | 7 x $f_{blade}$ |
| 13 | Acceleration | RMS | 2 x 7 x $f_{blade}$ |
| 14 | Acceleration | RMS | 1 x $f_{rot}$ |
| 15 | Acceleration | RMS | 2 x $f_{rot}$ |
| 16 | Acceleration | RMS | 3 x $f_{rot}$ |
| 17 | Acceleration | RMS | 4 x $f_{rot}$ |
| 18 | Acceleration | RMS | [1 2 3 4] $f_{rot}$ |
| 19 | Velocity | RMS | 10...100 |

In the table, $f_{rot}$ is the fundamental rotational frequency, $f_{blade}$ is the blade passing frequency, $f_{max}$ is the maximum analyzed frequency 1000 Hz.

In the process compensation, firstly the correlation matrix is introduced. Matrix expose the vibration features which correlate or not with the process. This relationship is calculated for each of the channels, from which the channel no. 1 is selected to the Figure 6.

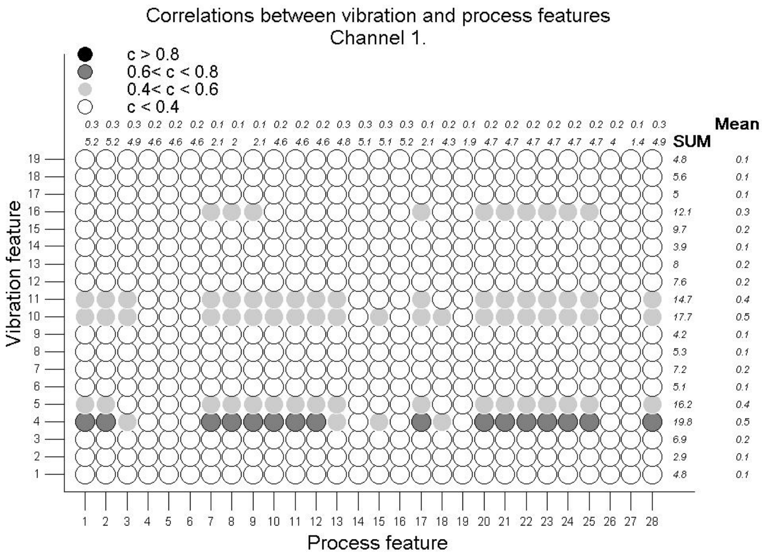


*Figure 6. Correlation matrix of vibration and process features.*

In Figure 6 one may find, that in the measurement channel 1 the vibration feature #4 is (acceleration max. value from the measured frequency band) strongly correlated with most of the process features. Add to this, vibration features #5, 10, 11 and 16 are clearly dependent on process.

Calculating the correlation matrices for each of the channels, we can ask what is the measurement channel being least depending on the process as a whole. This is valuable information, especially for the user who makes simple decisions based on the heuristic rules. The simplest way is to use process independent features, however this is not always possible. Then the process compensation must be done.

Following two figures are the practical examples of taking into account the process state. In Figure 7, one vibration feature is drawn against to the 1$^{st}$ PC. Add to this, 95% confidence limits has been drawn and theirs equations are solved. This way is not restricted to the linearly dependent cases, but is suitably also to the complicated relationships. The equations of the upper and over limit curves are in the main role and their parameters have to be saved. Monitoring is done by measuring the selected five original process variables, and then by PC transform the vibration feature is fitted to the figure.

Alternatively, if some dominant process parameter can be named, the same regression can be done for it. This is illustrated in Figure 8 with process variable RPM.

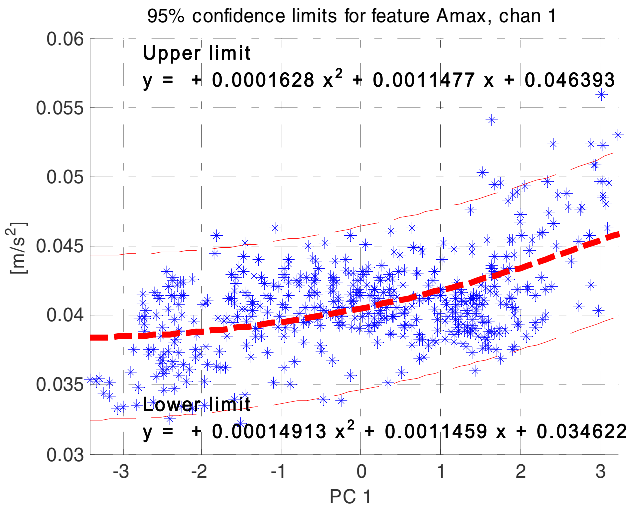


*Figure 7. Feature 'Acceleration max value from the measured freq. band' plotted against the PC 1.*

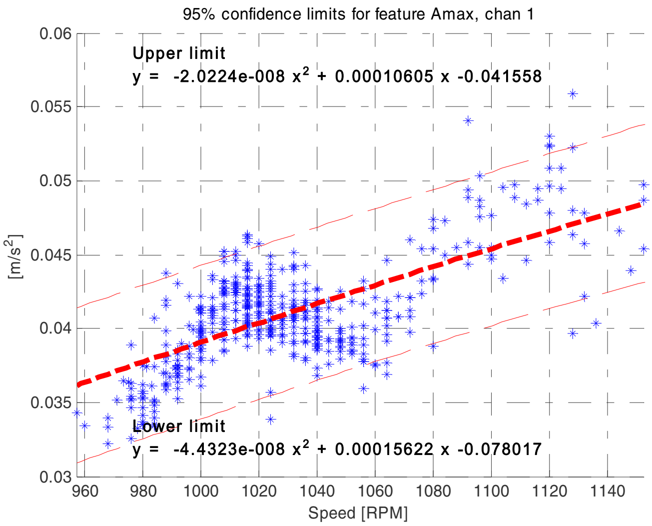


*Figure 8. Feature 'Acceleration max value from the measured freq. band' plotted against the RPM, which is one of the predominant process features.*

After the regression some corrective work is needed, due to the resonances or other local disturbances. For example in Figure 7, the correction to the upper limit might verbally be formed as "If the PC >1, allow the double value for upper limit".

## 2.3 Decision space

Learning methods as are the neural networks has been used as classifiers in many types of applications. As it was depicted earlier, the use of learning methods is the suitable way to make decisions. This study does not introduce them because of their complexity. Complex inference algorithm leads to the lack of information, on which the decision is based on. On the other hand, also the complex solution needs suitable initial values, which are just the features.

In order to support the process operator in decision-making, the following PC-application is presented. One way to handle PCs is to visualize them on the same figure, thus it is reasonable to choose two or three first PCs to be handled. Figure 9 below is drawn by two of first PCs.

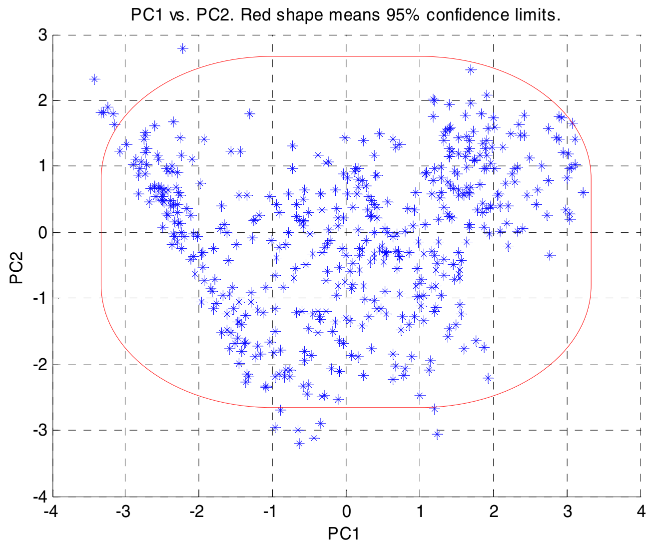


*Figure 9. Normal process region by means of two of the lowest PC:s.*

In Figure 9 the surrounding red line is covering the area, in which the process data by means of two PC is situated with 95% confidence limits, which means 95% of data is inside the limits. Thus it can be hold as a process window or control region, in where the combination of chosen process variables should be situated. Process is monitored by measuring the five original process variables and then fitting them via PC transform to the process window.

Some processes can be divided to the several distinct areas, which may produce some distinct areas to Figure 9, and could be named according the state in question. However, the processes of fans is so straight forward that this kind of division is not reasonable, but prefer the task can be handled as a continuous one over the measured speed range of the fan.

# 3. Methods

In the study, methods for data extraction, reduction and compensation were introduced for industrial cases.

Especially the PC and correlation analysis were found to be suitable methods.

One of the key problems, process effect to the condition monitoring measurements, has been solved by means of PC and regression analyses.

WA Technologies, as a commercial company, has formed algorithms, which are focused to predict failure propagating.

# 4. Results

In the study, the measurement systems were updated for the case fans. Measurements were handled by taking into account the critically classed failure modes. Furthermore, some ways to compensate the process effect to the measurements were introduced.

As a result from the current study, the increased level of monitoring is achieved.

Power plant fan (and other case targets) has got knowledge to choose suitable measurement methods, analysis techniques and monitoring ways.

Case power plant fan will realize the researched techniques immediately after the PROGNOS project.

PROGNOS system (commercial) is installed by WA Technologies to the mining fan.

Case ‘crane’ in steel factory has also realized the measurements and feature calculations, and the next step is to install the PROGNOS system.

# 5. Industrial benefits

This article describes the chain from measurements to the decisions, by which the monitoring work of industrial fans is developed. It starts from the definition of the initial monitoring methods, and then it classifies the typical and most critical failures related to the fans. After that, the suitable measurement methods and the ways to analyze them are presented.

This work is increasing the degree of monitoring level of the fans and the understanding the behaviour of the failure modes. Since both of the observed fans are situated at the central place in the surrounding process, the risk for non predictive failure is also reduced. This is eliminating unscheduled maintenance works and increasing the production time.

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# Diagnostics concepts for predictive maintenance of electrical drives

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## Abstract

Electrical drives are common systems in industrial plants. They are also typically on the top of the list when a criticality analysis is carried out for an industrial process. Due to number and importance, the research of on-line diagnostics of electrical drives may produce significant savings and competitive advantages to industry. This article briefly presents the main contributions of the research related to the diagnostics concepts of electrical drives. The research was carried out in this project during years 2003–2006.

# 1. Background and scope

An electrical drive is a system that converts electrical energy into mechanical energy. The energy conversion is in most cases carried out by an electric motor. Electrical drives can be e.g. divided into two classes: fixed and variable speed drives (Figure 1). In industrial applications, the number of variable speed drives is constantly increasing mainly due to controllability and energy saving requirements. According to [1], electric drives are responsible for 69% of the electricity usage in industry in EU. In addition, according to [1], there are three main applications for electrical drives: pumps (23%), compressors (21%) and blowers (16%), which together cover up to 60% of all applications of electrical drives. The number of electrical drives in industrial plants is also significant. For example, there are probably more than 3000 electric drives ($P_N$ > 15 kW) in a mid-size forest or metal integrate. In general, electric drives are also classified as most important devices when a criticality analysis is carried out to an industrial plant. The factors evaluated in the criticality analysis may be e.g. lost production, personnel safety, environmental damages or repairing costs.

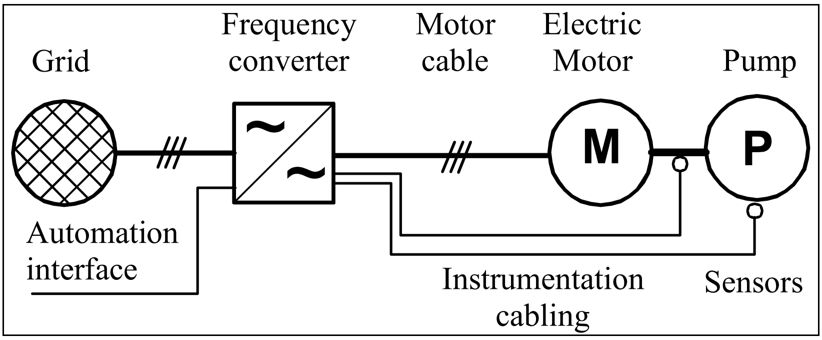


*Figure 1. The diagram of a variable speed drive.*

Due to the factors mentioned previously, the reduction of life-cycle costs of electrical drives is an important research topic. Reliable on-line diagnostics of an electrical drive condition is an essential tool for this. The condition diagnostics has the following objectives:

1) To detect incipient machine faults before they e.g. cause production losses. The goal is to eliminate unplanned repairs.

2) To detect the process states that increase machine failure probability.

3) To estimate the efficiency of the machine. The performance degradation may e.g. dramatically increase energy usage.

The development of on-line diagnostics features for electric drives is not a straightforward task. There are several topics that all require intensive research work. These include reliable algorithms and classification methods for automatic fault detection, generic diagnostics and data management concepts, sensors for condition diagnostics and methods for sensor level data transmission.

The primary objective of this project was to research generic diagnostics and data management concepts and sensor level data transmission methods for electrical drives diagnostics. The final goal of the research is to make the electrical drive condition diagnostics a standard functional feature, which integrates to the industrial information infrastructure utilizing standard software and hardware interfaces.

# 2. Research activities

The main research activities carried out in this project during years 2003–2006 and their main results are described in the following sections.

## 2.1 Uses for the frequency converter in the diagnostics of the motor

An electric drive has three primary components: the motor, the motor controller (e.g. a frequency converter), and the load (e.g. a pump or a compressor). All three interact through various mechanisms, for example, mechanically, thermally and electrically. Therefore, the drive should be considered as a whole. In this study, the usage of the information provided by the motor controller (which was assumed to be a frequency converter) in the diagnostics of the motor was considered. There are two important ways in which the frequency converter can be utilized in the diagnostics of the motor (and possibly the load) [2]:

1) Detection of transient states. Usually, the diagnostics algorithms assume stationary state. (However, e.g. some parameter estimation techniques require transient state.)

2) Acquisition of the rotational speed of the motor. This is needed in most spectrum analysis-based diagnostics techniques. Can be obtained from the measurement (if exists), or from the motor model (if applicable). In any case, at least the output frequency is known.

Some of the quantities measurable and/or calculable in an induction motor drive are depicted in Figure 2. The motor is assumed to be supplied by a voltage source inverter (VSI).

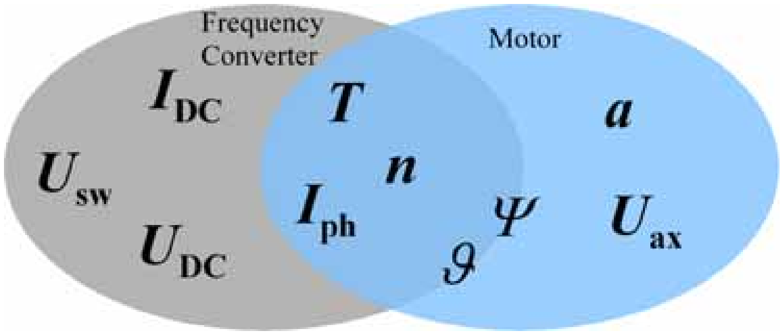


*Figure 2. Quantities measurable or calculable in a VSI (Voltage Source Inverter) induction motor drive. The placement of the symbols depicts where the quantity can be obtained.*

The detection of transient states was further studied. Transients can be caused by two main factors: a change in frequency converter command (rotational speed, output torque, or output frequency, depending on the mode of an operation), or a change in the load torque. The former is easy to detect by the converter, whereas the latter may pose problems.

The basis of the study was the fact that a change in load torque will create a change in motor the slip and input current. Motor input currents are measured by the frequency converter, and changes in the current RMS values can be monitored to detect transient states. The relationship between the output torque and the input current in an induction motor is relatively complex even in the case of a grid-connected motor, and in a frequency converter drive, where the frequency and the terminal voltage are not constants, accurate mathematical modelling becomes very cumbersome. Practical limitations arise from the fact that the accuracy of the current measurement is finite. It is defined by the number of bits used in the A/D conversion, and the nominal current of the drive. It can correspond to, for example, 0.1 A. Therefore, when the motor is lightly loaded or significantly less rated than the supplying converter, only relatively large changes in load torque can be detected using this method. However, when the ratings of the converter and the motor are approximately equal and the motor is loaded with a torque near its rated value, the method is effective.

## 2.2 Communication structures

As previously discussed, information in an electric drive is available from various sources including the motor (e.g. vibration measurement on the motor frame), the motor controller, and the load. Information from different sources must be generally measured at sufficiently close moments in time. For example, the rotation speed of the motor acquired from the motor controller (e.g. frequency converter) must be valid for a sequence of acceleration values obtained from the motor (or its load). There are two options to accomplish this: the motor and the controller can be connected to the information systems separately, or the drive as a whole via either the controller or the motor. The more natural choice in the latter case would be the utilization of the motor controller as a data-collecting unit as well as an interface to the information systems.

Utilizing the motor controller as a data collecting unit places additional requirements for its hardware and software. These are mainly dependent on the types of sensors from which it collects data [2]. However, in this scheme, the time synchronization of data from different sources is relatively trivial, and all the data concerning the drive is available to higher-level information systems via a single point. On the other hand, if parts of the drive are connected to information systems separately, no data storage memory is required in the motor controller. A mechanism for time synchronization is required, however, so that data can be time-stamped. On Ethernet networks, synchronization can be accomplished using e.g. the NTP protocol (Network Time Protocol) or the PTP protocol (Precision Time Protocol). Ethernet-compatible networks with the TCP/IP protocol stack enable the use of multiple higher-level protocols on the same bus. These protocols can be used, e.g., to configure the sensors' addresses [3]. An example of communication structures with motor controllers (frequency converters) acting as data collectors is depicted in Figure 3.

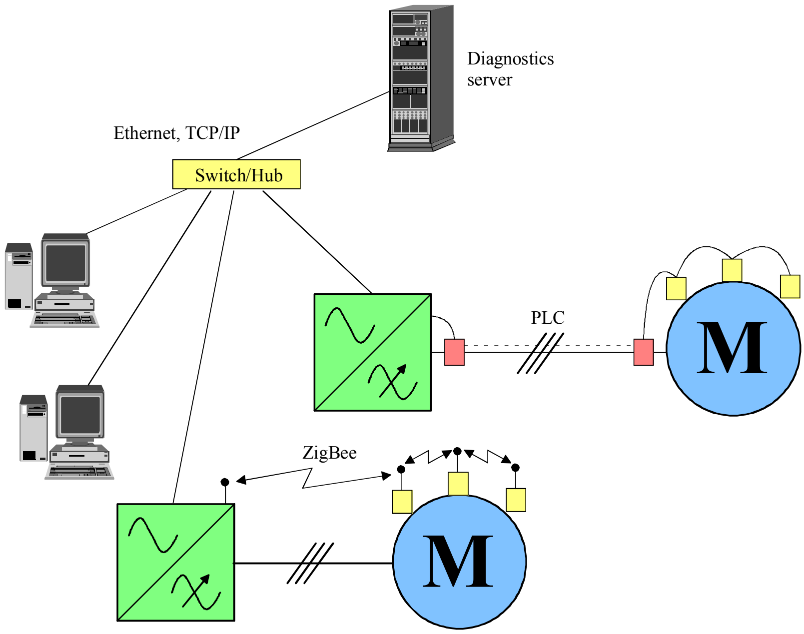


*Figure 3. An example of communication structures: Frequency converters acting as data collectors and communication system interfaces.*

The communication network must be designed so that its capacity is sufficient for the transfer of data. Data transmission requirements are ultimately defined by fault mechanisms and the analyses used to detect the faults [4].

## 2.3 Usability of wireless data transmission in diagnostics of electrical drives

Continuous condition monitoring of electric machines requires sensors to be attached to the machine. Additional instrumentation cabling is required to transfer data from sensors as shown in Figure 1. However, the cost and installation time for new cabling in industrial environment can be significantly larger compared to the cost and installation time of sensors. In addition cabling is prone to damage in harsh industrial environment. This is one reason why wireless technologies could be used to replace existing wires or in new sensor network installations. Other advantages in wireless data transmission are e.g.: the increased mobility of machinery, possibility to use temporary measurement setups, easy expandability of the wireless sensor network, and accessibility to the diagnostics data with a wireless mobile device. [5]

There are some drawbacks with wireless technologies. Wireless transmission is susceptible to many different phenomena, such as multipath propagation, interference and Doppler effect in fast moving machinery such as the rotor of an electric motor. These can cause errors or total blackouts in data transmission for periods of time. With proper technologies and design these can be avoided so that data transmission needs for the diagnostics and condition monitoring can be fulfilled, but latency in data transmission can be problematic in control applications. Following things should be taken in account when choosing proper wireless technology for application: network topology, number of nodes in network, transmission speed, and range and power requirements. Requirements and applications for wireless technologies are more closely studied in [5].

There is a wide range of wireless technologies available nowadays. They differ from each other in range, network topology, network size, power requirements, data rate, operating frequency and whether they are standardized or manufacturer specific protocols. Some of the most well known and widely used are e.g: WLAN, Bluetooth, GPRS, ZigBee, Insteon, Z-Wave, XMesh and LonWorks. ZigBee was chosen for closer study because it is designed specially for large scale, low power and low data rate sensor networks. ZigBee is a low cost, low power wireless technology specially intended for medium data rate (<100kbps) networks. Its high density of nodes per network capability makes it suitable for sensor networks used for motor measurements. ZigBee can be used to form a large sensor network for diagnostics and condition monitoring data transmission needs. In [6], a closer look for this technology was taken in the special case when there is a need to take measurements directly from the rotating shaft of an electric machine. These measurements could be, for example, rotor temperature or torque measurements. Conclusion is that ZigBee works well in this kind of situation and it could be very potential applicant for diagnostics and condition monitoring sensor networks in an industrial environment.

## 2.4 Inductively coupled power supply for wireless sensors

Powering of wireless sensors can be quite problematic. The use of batteries is a solution, but in industrial sensor networks, which could consist of hundreds or thousands of sensors, this is not an option. The changing of batteries takes time and some of the sensors can be located in difficult and dangerous locations. On the other hand, it does not make sense to use separate power wires for the sensor if the data transmission is wireless. However, in the case of electric machines there is always a power source for wireless sensors: the motor cable. Power needed by the wireless sensor can be scavenged from one phase wire using a simple current transformer. This solution removes the need of additional instrumentation cabling (Figure 1) and battery replacements for wireless sensors.

The structure of the inductively coupled power supply is quite simple. In addition to the current transformer, there is an electric circuit that transforms scavenged power into suitable DC voltage. The amount of supplied power depends on the motor current and the current transformer. On the other hand, the power consumption of wireless sensors depends on their operating mode, duty cycle, measurement type and wireless technology used. In the case of ZigBee-based wireless temperature sensor, the average value of power consumption in active mode was 70 mW and during the sleep mode $< 0.1$ mW. This results in average power consumption of approximately 2 mW, if the temperature is measured once per minute.

Performance of the inductively coupled power supply was tested with different motor currents and current transformers. From the measurement results shown in Figure 4, it can be seen that scavenged power is more than enough to power a ZigBee-based sensor. Tests proved the functionality of the inductively coupled power supply for wireless sensors. For complete results, see [7].

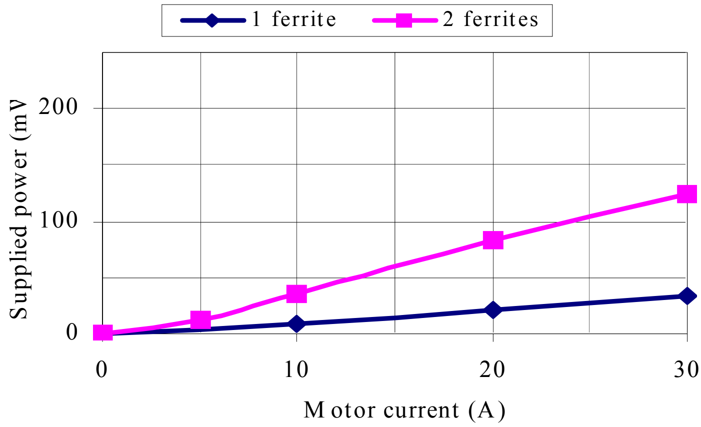


*Figure 4. Example of the test results for the inductively coupled power supply with two different size current transformers.*

## 2.5 The utilization of power line communications as a data transmission method in diagnostics of electrical drives

According to [8], reliable on-line diagnostics of an electric motor condition requires sensors installed at the motor, which, on the other hand, requires data transmission from the motor level to the upper level information systems. Generally, it is feasible to utilize a frequency converter or a motor protection relay as a diagnostics or data collection unit of an electric drive. The frequency converter or the motor protection relay has standard communications interfaces and it continuously measures or monitors motor state, such as, currents, voltages, rotation speed and motor parameters. The measured and monitored quantities depend on the type of frequency converter or protection relay. These quantities can also be utilized in drive diagnostics. However, a data transmission link between an electric motor and a frequency converter or a motor protection relay is required. This could be solved by utilizing the motor cable as a communications channel and power line communications (PLC) as a data transmission method.

The utilization of power lines for data transmission started in the 19$^{th}$ century. The motivation for PLC was the lack of communications networks. Instead, electricity distribution networks that connected power stations and cities were constructed intensively. The early history of power line communications is introduced in [9]. The idea of utilizing the motor feeder cable as a communication channel in the electric motor condition monitoring was first proposed in [10] and further studied in [11, 12].

During this project, the utilization of a standard PLC method, HomePlug 1.0 [13], in fixed speed drives was researched. The method encapsulates Ethernet frames (IEEE 802.3) into its own protocol and sends them forward. It offers broadband connections over power lines. According to the research carried out, the method works. However, the powering alternatives of power line modems at the motor end require more research work. The other research topic was characteristics of power line communications channels in industrial environment [14].

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# Diagnostics of quality control systems on paper and board machines

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## Abstract

The measurement information of traversing scanners is sparse and there are more variations in product quality variables than online systems show. Advanced control algorithms are implemented and quality problems are expected to be solved. Quality variables may be controlled either in machine or in cross direction of a web, but scanner measurement data is neither machine-directional nor cross-directional. A new approach for the measurement identification in cross direction and machine direction by using a Kalman filter and a Fourier transform is presented. The performance of quality control systems (QCS) can be evaluated with different indices for process control, maintenance, quality control and development purposes, during a system life-cycle.

# 1. Quality measurement and control scope

The product quality is captured on the machine (Figure 1). The machine roll, in the quality variables with their cross direction (CD), machine direction (MD) and residual variations, comes out from a paper machine. Quality variables are measured online by traversing scanners. The scanner measurement data is separated with a CD and MD separation model. The variations of quality variables in a web are attempted to be attenuated with closed CD and MD control loops. Maintenance activities affect the scanner measurements, CD and MD separation, CD and MD control performance through the calibration procedures and parameter adjustments.

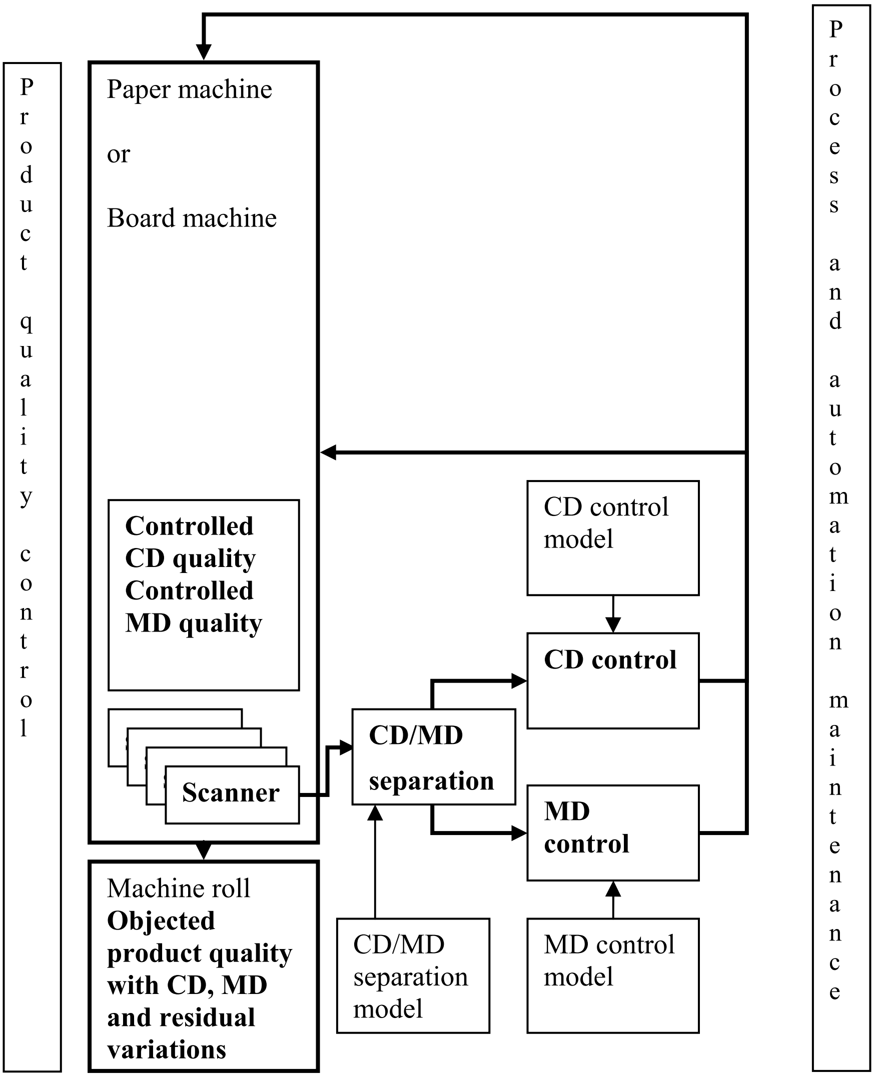


*Figure 1. The product quality is measured online by traversing scanners. The measurement data is separated into CD and MD components, which are used for closed CD and MD control loops.*

The quality of paper and board is characterized with many different properties, called quality variables, such as basis weight, moisture, caliper, ash content, colour, fibre orientation and porosity. It is common to describe the paper quality with its components: the mean value, the variation in cross direction, the variation in machine direction and the residual variation (Equation 1):

$$y_{ij} = y_{av} + e_i^{CD} + e_j^{MD} + e_{ij} \qquad \text{(Equation 1)}$$

| | |
|---|---|
| $y_{ij}$ | the quality variable value in a measurement matrix |
| $y_{av}$ | the mean value of all measurement matrix elements |
| $e_i^{CD}$ | the cross direction variation in a measurement matrix |
| $e_j^{MD}$ | the machine direction variation in a measurement matrix |
| $e_{ij}$ | the residual variation in a measurement matrix. |

CD variations are principally assumed to be only spatial and thus time invariant. MD variations are generally assumed to be temporal, they are time variant and independent of CD variations. The residual variation contains all remaining variations. The variation, seen by a scanner, measured from a zigzag path, thus represents the total variation. The variations of quality variables come from many different sources, such as raw materials, lacks in process machinery design, poor measurement sensors, ineffective control actuators, lacks in control design or start-up, process operation and seasons. CD and MD profiles are a visualization of scanner measurements [1]:

- "A cross direction profile is a graphical presentation of a paper property as a function of sampling position across the machine. A profile can show single-point values, composite values, or mean values based on a number of measurements."
- "A machine direction profile states the variation in property of a paper or a paperboard web along a straight line in the machine direction. The term is sometimes applied to the machine direction variation of the mean value of a property over the entire cross direction of the web, which more specifically is the machine direction mean profile."

# 2. Analysis of quality control systems

The paper and board quality variables – basis weight, moisture, caliper, ash, colour, gloss and fibre orientation – may be controlled in machine direction (Table 1). MD control loops are cascading, consisting of lower level PID loops and upper level advanced loops. Long time delays and time constants may be partly compensated by using model predictive control (MPC) algorithms. [2]

*Table 1. Controlled and manipulated variables in machine direction control.*

| CONTROLLED QUALITY VARIABLE | MAIN MANIPULATED VARIABLE |
|---|---|
| Basis weight | Thick stock flow |
| Moisture content<br>Coating moisture content | Main steam section pressure<br>Infra-red drying power<br>Air-impingement drying power |
| Caliper | Calender nip pressure |
| Ash (filler content)<br>Ash (coat weight) | Filler flow<br>Blade angle or blade loading pressure |
| Colour<br>Gloss | Flow of colorants, brighteners and fillers<br>Calender nip pressure |
| Fibre orientation | Jet-wire-ratio<br>Headbox pressure |

*Table 2. Controlled variables and manipulated actuator sets in cross direction control.*

| CONTROLLED QUALITY VARIABLE IN CROSS DIRECTION | MANIPULATED ACTUATOR SET |
|---|---|
| Basis weight, dry weight | Headbox slice screws<br>Headbox dilution valves |
| Moisture content<br><br>Coating moisture content | Steam box<br>Moisturizer<br>Infra-red drying profiler |
| Caliper | Induction heating profiler Calender nip |
| Coat weight | Coating profiler |
| Fibre orientation | Headbox slice screws |

Basis weight, moisture, caliper, coat weight and fibre orientation may be controlled automatically in cross direction with feedback control loops (Table 2). Optimization computing is utilized in large-scale multivariable CD control algorithms for hundreds of measurement points and dozens of actuators to minimize a CD profile error. The spacing between single actuators typically varies from 25 mm to 150 mm and it sets the lower limit of the CD controllability.

The purpose of the assessment of a quality control system is to determine the capability of that system to accomplish a specific mission, a quality control mission with its main tasks: product quality measurement, control room operation, MD and CD control. The guidelines of the standard IEC 61069-1 are applied to quality control systems and these systems may be assessed in six main property categories: **functionality, performance, dependability, operability, safety and non-task-related system properties**. The performance of quality control systems may be described with different performance indices. [3]

# 3. Paper quality measurement identification with a Fourier transform and a Kalman filter

The measurement with traversing scanners does not bring real CD and MD profiles. Common estimates for CD and MD profiles are the following ones: The measurement data box values of a scan are taken as a CD profile and the average of data box values in a scan brings a new point to a MD profile. There are some publications regarding the improvement of CD and MD separation, but they have not gained a lot of attention among suppliers.

With a frequency analysis we may find periodical phenomena in a dataset. With a Fourier transform it is possible to separate an analysed dataset into waves of different frequencies in considered dimensions. We are able to separate the quality measurement data into the waves corresponding CD and MD variations by using a two-dimensional Discrete Fourier Transform (DFT) and a Kalman filter.

A set of basis weight data has been recorded by a web analyser. The size of the analysed board web sample was app. 2.5 m x 200 m. The basis weight data is separated into CD, MD and residual components by using a two-dimensional Discrete Fourier Transform (DFT) and a Kalman filter (Figure 2).

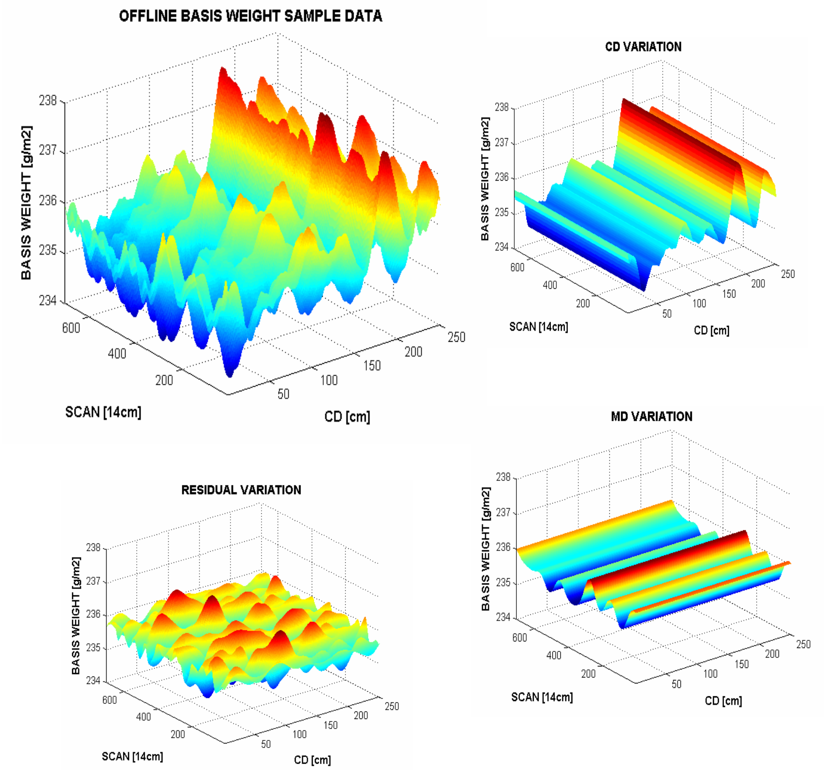


*Figure 2. Basis weight data, recorded by a web analyser, is separated into CD, MD and residual components by using a two-dimensional Fourier transform.*

A Kalman filter, in general, is an optimal way to pre-process noisy measurements for a model. In this case the model includes the most significant Fourier components of CD and MD variations. They are now used as the state variables in a Kalman filter. Mathematically this is a way of modelling a dataset with a Fourier based Kalman filter. The scanner measurement signal $y$ is pre-processed with a Kalman filter (Figure 3). In the Kalman filter loop, the following symbols are used:

| | |
|---|---|
| $x$ | the state vector of the model, the Fourier components |
| $A$ | the process model matrix, a phase shift operator |
| $H$ | the inverse Fourier transform matrix |
| $P$ | the error covariance matrix |
| $Q$, $R$ | the variances of the state and the measurements |
| $y$ | the measurement vector of a scan. |

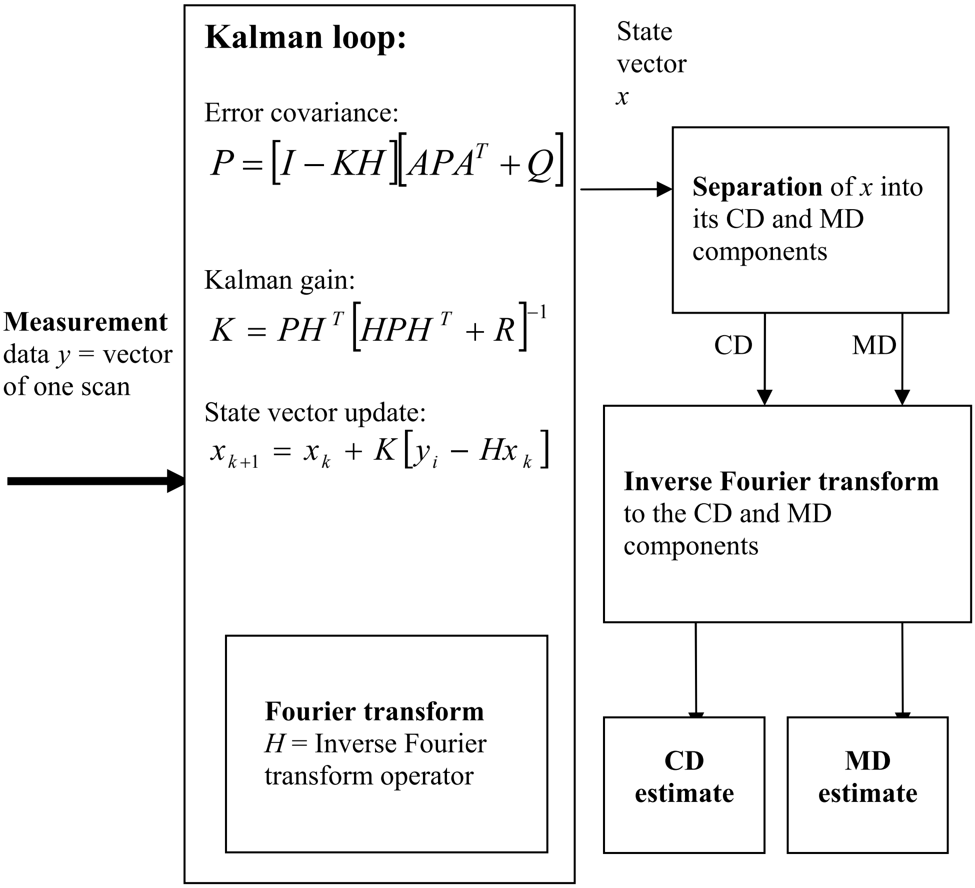


*Figure 3. A measurement vector of a scan is pre-processed in a Kalman loop and then separated into CD and MD component by a Fourier transform.*

The Kalman filter has been used to estimate the CD and MD profiles from the basis weight offline sample dataset. Firstly, a traversing measurement path has been defined to take single measurement points from the dataset. Secondly, the Kalman filter has been used to estimate the CD and MD profiles, point-by-point, according to the sampled measurement data. The estimated MD and CD profiles have been produced with Matlab scripts and presented with original profiles in (Figure 4). [4]

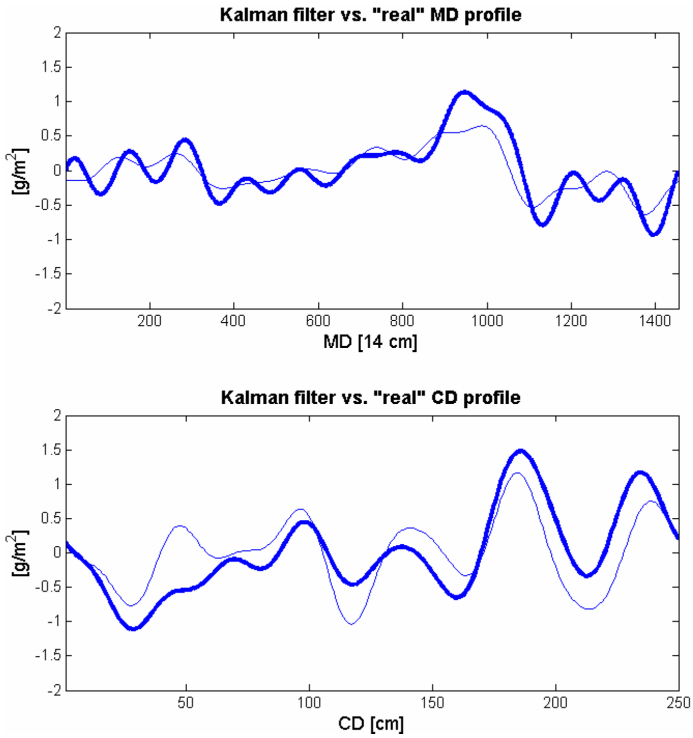


*Figure 4. The estimated (a slim line) MD and CD profiles follow original (a bold line) profiles in simulations.*

# 4. Developed system diagnostics

The life-cycle model of process control systems may be applied to quality control systems and it has been categorized into eight phases: specification, system design, implementation, mechanical installation, functional test, performance validation, production and decommission [5]. The factors, related to the dependability and performance of quality control systems, are discussed.

**The specification phase** shall describe the objective QCS as exactly as possible. In the pre-design phase a purchaser defines the process and operator requirements. In the user specification the purchaser defines measured, controlled and manipulated quality variables and main quality control principles. Along with the user requirements a preliminary validation plan for the whole life-cycle of a QCS is made up. After an investment decision, quotations are requested and the functional QCS description is developed by a supplier candidate. Scanners, sensors, process modules, other computer components and a network structure are specified. We should pay a special attention to the quality of the application software documentation because of the future maintenance and development needs. The quality control principles are discussed and defined loop-by-loop by process engineering, automation engineering and operator teams. QCS suppliers are encouraged to define the performance indices of sensors and purchasers are encouraged to require it.

**The system design phase** consists of three main areas: mechanical design, hardware design and software design. The mechanical design concerns possible process machinery changes which are needed because of the upcoming automation. In the hardware design detailed hardware components, like scanners with sensors, process control modules, system and field buses, as far as cabling, control room equipment and additional instrumentation, are determined and entered in hardware and network design specifications. In the QCS software design a main program structure, lower and upper control model loops are determined. Detailed program module descriptions are worked out. We should pay a special attention to the descriptions of customized upper level control modules because of maintainability.

**In the implementation phase** the QCS supplier acquires, manufactures, assemblies and tests the designed QCS concept. After an assembly a needed device configuration and customized application software programming are performed. In tests upper level MD and CD control loops, lower level control loops and other instrumentation loops are checked. A factory acceptance testing (FAT) is performed by the supplier in cooperation with the purchaser. The testing procedure shall cover all MD and CD control loops and the documentation of customized program modules shall be inspected. The purchaser's teams are encouraged to take advantage of the FAT as much as possible, and a more completed delivery can follow.

**In the mechanical installation phase** the QCS, according to the hardware, software and network design specifications, is installed in the purchaser's mill. A system platform with its scanners, sensors, computers, monitors, system racks, networks and cables are installed. The tested system and application software is loaded into the operator and process modules and servers. After the installation process machinery and piping trials, instrumentation calibration inspections, wired protection electronics trials, signal and loop testing (SLT) take place.

**In the functionality testing phase** a paper machine is run first with water in a cold commissioning. The alarm and interlock function limits of scanners are checked, the functionality of interlock functions and protections are tested and the power supply after break-downs confirmed. The scanner sensors and other related transmitters are pre-calibrated, the single lower level control loops are pre-tuned. The MD control loops with their single actuators and the CD control loops with their profilers are checked loop-by-loop. In a hot commissioning a paper or a board machine is started up with real pulps and chemicals. The QCS application software for every process section is checked, the control loop tuning and parameter optimizing are performed. The functionality in the MD and CD control loops of basis weight with their measurement signal processing and control parameter optimization is evaluated. Then follow the MD and CD control loops of moisture, caliper, coat weight, fibre orientation and the MD control loops of ash and colour. External foil samples and offline roll samples may be used as a reference for calibration. After the commissioning a system acceptance test (SAT) is performed. The performance indices are compared with the ones of the functional descriptions. The supplier is responsible for the SAT.

**The performance validation phase** consists of a technical validation of automation and a process validation. The technical validation of automation aims to show that the QCS works according to its specifications and is in a total control of its operators in all circumstances. The process validation aims to show that specified products can be manufactured. The capacity of a machine is increased to its nominal values by optimizing the operations and the automation.

I**n the production phase** the life-cycle of the QCS continues with every-day maintenance and development tasks. The purchaser takes care of the preventive maintenance of the QCS or it is performed by a service supplier. The organizing of a professional QCS maintenance team has an important role in maintenance supportability.

**In the decommission phase** the objective QCS is removed when it is no more needed. [6, 7]

## 4.1 Integration of process and QCS design

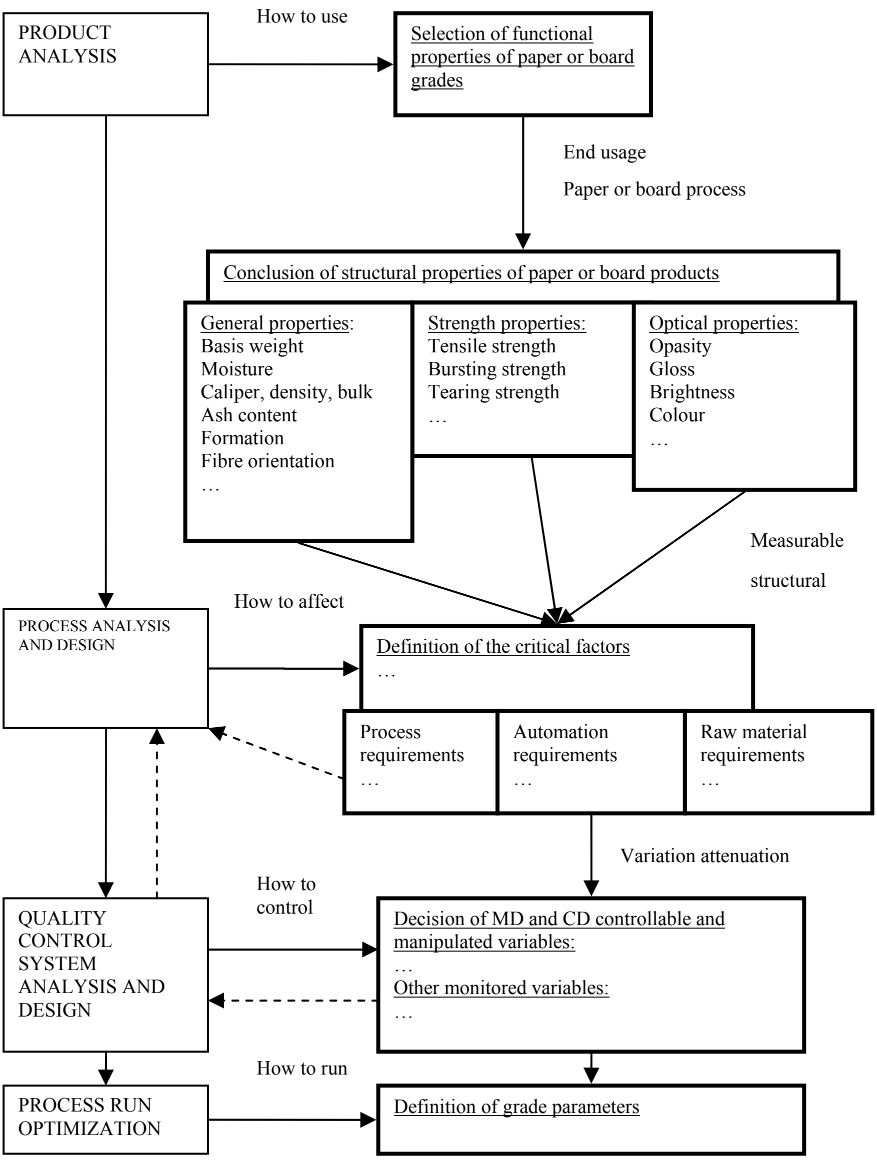


*Figure 5. The final control objectives are found out by starting to select the functional and to conclude the structural properties in the product analysis. In the process analysis the critical factors are defined, and finally the controllable and manipulated variables can be decided in the QCS design phase according to the automation requirements. [4]*

The basis of the quality control system analysis and design lies on a detailed product analysis, when we come from functional properties to final control objectives, see Figure 5. The functional properties of the desired paper grades are selected in the product analysis. According to the requirements – the end usage, the paper or board manufacturing process itself and the needed converting and finishing needs – the structural properties of the desired paper product are concluded. In the process analysis and design phase those critical factors are defined, which affect the selected online or offline measurable functional properties. These critical factors imply different requirements for the manufacturing process itself, for the raw materials and finally for the quality control automation. Due to the insufficient process or control performance some parts of the manufacturing process may be forced to become redesigned.

The main purpose of the quality control automation is the attenuation of the quality variations due to process disturbances. Severe process deficiencies cannot be compensated by the automation. In the QCS design phase the controllable and manipulated variables for the MD and CD control loops are decided. Due to the insufficient control performance some control strategies of the QCS may be forced to be redesigned. The final process run optimization is performed by defining the grade parameters for desired paper or board grades. Detailed set points and control behaviour characteristics are defined. [4]

## 4.2 Continual validation of quality control systems

The validation of a QCS refers to a duty in a mill's quality assurance, which begins in the specification phase of a QCS delivery project, reaches its culmination in the validation phase and continues in the production phase. The validation aims to show that the QCS works according to its user specifications. The purchaser is responsible for the validation of the QCS. In the process validation the performance of the production machinery with its QCS automation may be validated by utilizing offline web analyses [6].

**In a process control and maintenance aspect**, following performance indices are suggested to be used:

- The operation mode of a control loop, related to the standardized dependability concept up-state, when a quality control loop can perform its task, may be utilized. The operation mode – manual, automatic or cascade – of a control loop may be presented in user interfaces.
- The concept settling time of a quality control loop is related to the standardized dependability concept time to restoration and shows the time for a loop to return to its steady state after operator interventions, grade change program actions or process disturbances. A settling time is the time period when the basis weight comes back inside the limits after a set point change or after a disturbance effect in a control loop.
- Error integrals – IAE, ITAE, ISE, ITSE – are widely used performance indices. A bar visualization is a common way to show the absolute error integral IAE of a quality variable CD profile.
- Variances or 2-sigma deviations are widely used performance indices with CD profiles. This 2-sigma deviation shows the variation in a scan.

**In a quality control aspect** statistical concepts are used. The main object in quality control is the minimization of quality variable variations.

- The variation of a quality variable may be described with mean values and variances.
- The Harris minimum variance index may be held as a benchmark of the control loop performance. The Harris minimum variance index may be calculated when the controlled quality variable variance is measured and when the time delay and the variance of the disturbance in a quality control loop can be estimated. The use of the Harris minimum variance index is, especially, suggested with model predictive MD control loops.

**In a process and automation development aspect**, frequency analyses are efficient tools. Statistical indicators may be used, too.

- The power spectral density calculations may reveal the disturbances causes. The periodic phenomena are seen as narrow and high peaks in power spectral density curves. A power spectral density function may be calculated, for example, with the Fourier estimation methods.

- The long-term variances may be used to describe the performance and dependability of quality control automation and process machinery. The variances are highly dependant on the pre-processing of quality variable measurement signals. The quality control systems of different suppliers don't use same signal processing methods.

# 5. Industrial benefits of QCS diagnostics

End-users and suppliers are encouraged to pay attention to the CD and MD separation methods of scanner measurement signals. Powerful estimation and updating methods point-by-point, help to settle down controllable quality variables faster after disturbances. Predictive estimation methods with Kalman filters have been developed and tested with real data, in simulations. A new approach is suggested to be tested widely in industrial pilots.

By approaching quality control automation within a life-cycle model the factors affecting the dependability and performance of systems may be found out. With a careful specification phase and systematic, continual validation procedures, maintenance costs in the production phase can be reduced. The tight integration of process and quality control automation in the design phase helps to identify and avoid potential process and automation lacks. The performance assessment of quality control systems is rather complicated: different indices are needed for process control, maintenance, quality control, process and automation development purposes. By taking signal processing methods into account, the variations of quality variables may be compared with care.

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# Cost-effectiveness as an important factor in developing a dynamic maintenance programme

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## Abstract

Optimised decision making in maintenance programme development can lead to higher profitability. Within the Prognos project, procedures have been developed for improving the dependability of industrial systems by focusing on maintenance programme development and cost-effectiveness. The procedures have been mainly applied to a baling line of a factory producing chemi-thermomechanical refiner pulp.

## 1. Background and scope

Industrial systems are typically designed to operate on full capacity which means that their dependability must be as high as possible. Dependability is dependent on many factors and thus various measures may be needed to improve the dependability. In this study the focus has been on maintenance measures to decrease the number of failures or their consequences.

Our approach to improve dependability includes various procedures. Application of those depends on the target system and the phase of its life-cycle. The main steps of our approach are:

- Definition of objectives and appropriate measurements of those
- Definition of failure modes and criticality of those
- Definition of appropriate measures to decrease the number or consequences of failures

- Definition of appropriate and cost-effective maintenance tasks against failure modes defined in the second step.

The first step, the definition of objectives, is shortly described in Chapter 2. The second and third steps in our approach are the definition of failure modes and appropriate actions, which are completed by applying the well-known FMEA method. The criticality of the failures is assessed using the measurements of the objectives defined during the first step. This approach links the objectives directly to failures and this way also to actions. If the consequences are mainly economical, the criticality could be estimated by the annual costs per failure. This procedure is described in detail in references [1, 2]. Safety and environmental issues are not considered here, and they must be handled separately.

The fourth step, the definition of the maintenance tasks and the cost-effectiveness analysis, is described in Chapters 3 and 4.

## 2. Definition of objectives

The corporate objectives should be defined based on the individual critical success factors. Kaplan and Norton [3] have introduced the Balanced Scorecard (BSC) concept which translates the vision and strategy into objectives using next four perspectives: 1) financial, 2) customer, 3) learning and growth and 4) internal business process. The balanced scorecard gives managers a comprehensive view on the business and it is a combination of measures of past performance and measures of the drivers of future performance.

The maintenance objectives are occasionally set with no systematic approach used. However, the maintenance objectives need to be in line with the overall corporate (business) objectives. On the other hand, right measures should be used to illustrate the state of performance related to the corresponding objectives. Quality function deployment (QFD) method has been commonly used in transforming customer needs into engineering characteristics of a product. The analogy of transforming certain overall objectives into functional objectives has been used in translating the strategic objectives into specific maintenance performance measures, see reference [4]. On the other hand, the

BSC concept includes the idea of linking the different measures in a series of cause-effect relationships. Thus, the approaches can be utilised when defining the path from overall corporate objectives to maintenance objectives. For further information on implementing the BSC concept in defining maintenance objectives, measures and the relationships within an actual case, see e.g. reference [5].

# 3. Maintenance programme development process

The concept of a “maintenance programme”, as used in this article, refers to the description of a maintenance strategy for each piece of equipment of the target system, i.e. condition-based, use-based or corrective maintenance.

The maintenance programme development process includes several steps and the content of the steps depends on the phase of the life cycle of the target system. According to IEC 60300-3-11 [6], maintenance programmes are composed of an initial programme and an on-going, dynamic programme. The initial maintenance programme or recommendations regarding the maintenance tasks are often delivered by the manufacturer. Updating the on-going programme is based on the experiences of the effectiveness of the executed maintenance tasks. Updating the maintenance programme should be done if the criteria values of the defined performance indicators are not met or after any major changes to the system.

Effectiveness of the tasks can be estimated by measuring the performance regarding each objective.

The maintenance programme is generally developed by taking into consideration the characteristics of the system and the experiences gained. Maintenance decisions can be made on two time horizons – long-term or short-term. Long term planning comprises the development of the maintenance programme which includes the maintenance strategies and descriptions of the maintenance tasks. Short-term planning comprises the timing of the repair for early failures which have been noticed by condition monitoring. (See Figure 1.)

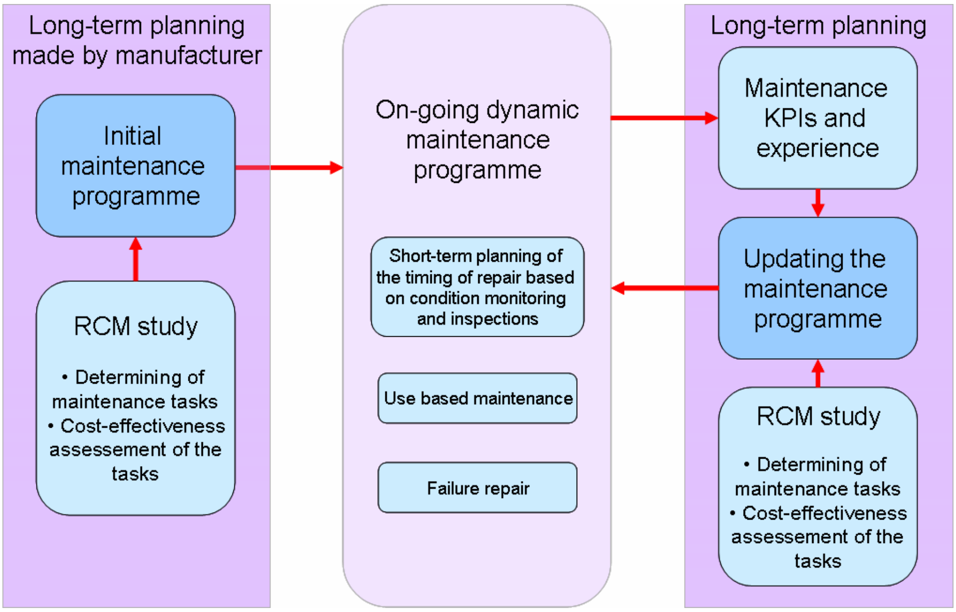


*Figure 1. Maintenance programme development.*

In general there are three kinds of situations in the maintenance programme development. 1) For a new factory or equipment, the initial maintenance programme is often offered by the manufacturer. It is typically based on certain assumptions about the operating conditions and duty type, as well as the production volume. 2) For a factory or equipment in operation, updating or more comprehensive maintenance programme development can be made based on experiences gained on using the system in known operating conditions. 3) Combination of the two previous cases, i.e. a situation where the target system is updated but not totally changed. An example is the Toro Loaders case study, which concerned a loader which was updated with a new feature enabling remote use of the loaders. A detailed description of the maintenance development activities applied in this case study is given in reference [7].

## 3.1 Selection and description of maintenance tasks

One method to define the maintenance tasks is by using reliability centred maintenance (RCM) as presented by e.g. Moubray [8]. The first part of the method involves identifying the failure modes of the system in focus, which is done using a failure mode and effect analysis (FMEA). By identifying the failure modes and mechanisms it is possible to find out appropriate maintenance tasks to prevent failures. By including a criticality analysis in the FMEA, failures causing most significant consequences can be found and thus first actions can be focused on preventing those. The criticality analysis method used in this project is described in detail in references [1] and [2]. However, it must be kept in mind that all failures can not be effectively prevented by maintenance. For that kind of failures other solutions must be found.

The next part of RCM involves determining the maintenance tasks by using the RCM decision logic. Moubray has used seven possible types of maintenance tasks, which are the outcomes of the decision logic.

In the baling line case, the RCM method was not applied as strictly as recommended by Moubray [8]. As a basis, all the recognised failure modes determined by the FMEA were used. The identification of one or more possible maintenance tasks for every failure mode was done by experts in workshops. In the maintenance task identification phase, the RCM logic was not used. Instead, the experts were allowed to freely brainstorm all the maintenance tasks they thought were possible. The identification of the maintenance tasks was done as accurately as possible, meaning that, for example, for visual inspections, the components to be checked were defined and their normal condition was described. The aim of this description was to make inspections more reliable.

In addition to identifying the maintenance tasks, time intervals must be determined for condition monitoring and use-based maintenance. In the baling line case, the appropriate time interval for inspections or condition monitoring was estimated using Moubray's [8] concept of nett P-F interval. The interval was determined by two variables – the time from detectable failure to functional failure, and the time needed by the maintenance organisation to make a planned repair. For use-based maintenance, the maintenance interval was estimated using the range of time to failure.

# 4. Comparing cost-effectiveness of maintenance tasks

RCM decision logic is used for determining the type of maintenance task according to the different failure modes. The RCM decision logic provides a question whether the task is technically feasible and worth doing. Answering ‘yes’ or ‘no’ to the first part is usually quite unambiguous, even if it might need some research. When the answer to the first part is ‘yes’, the latter part of the question is occasionally ignored, or given very little importance. The practical approach presented in this paper specifically focuses on providing the answer to the question of whether a task is worth of doing.

Maintenance tasks are always performed in order to prevent or repair a certain failure mode, and so it can be said that the tasks are profitable if they minimise the annual cost of that failure mode. Thus, selecting the most cost-effective task involves estimating the costs of alternative maintenance tasks. After the estimations have been made, one chooses the most cost-effective ones – but this is unfortunately easier said than done. There are typically one or more technically feasible preventive maintenance tasks, and it is important to remember that corrective maintenance is also an alternative which must also be included in any cost-comparison. For example, in the baling line case, comparisons were made between both preventive and corrective maintenance tasks.

The importance of preventive maintenance has been emphasised for a long time, and this has even led to over-maintenance in some cases. If the consequences of the failure are minor and the failure probability is quite low, it is probably cheaper to adopt corrective instead of preventive maintenance.

When considering an operating factory, the maintenance tasks’ costs can be estimated rather easily and accurately using both statistics and feedback from experienced personnel. The costs of alternative, unrealised tasks are much more difficult to estimate, and therefore also cannot be as accurate. However, for comparison purposes, the estimates do not have to be exact, but only of the correct magnitude in order to obtain a realistic impression of the more cost-effective alternative.

The costs of condition-based maintenance consist of:

1. condition monitoring or inspection tasks
2. repairs of early failures detected by the monitoring
3. immediate repairs (corrective maintenance).

The benefit of condition-based maintenance arises from the fact that possible failures that are detected early enough will enable the implementation of any necessary actions, with as low a production loss as possible. It is, however, known that all the failures can not be detected with either condition monitoring or inspections. It is possible to gauge the effectiveness of condition monitoring as the percentage of the number of early failures, out of the total number of failures.

Use-based maintenance tasks are made regardless of the condition of the target. The costs of use-based maintenance consist of:

1. execution of planned task
2. immediate repairs (corrective maintenance).

The cost factors associated with condition-based maintenance and corrective maintenance are illustrated in Figure 2. The timescale in the figure could be, for example, a year, and this was used in the baling line case. If no preventive maintenance is done, six failures in a year could be expected – all of which would need to be repaired immediately after they have been realised. If condition- based maintenance is applied, the condition of the target would be inspected once a month, and four of the six failures would be detected before there are any adverse consequences on the production. Those 'early failures' would also still need to be repaired, but early detection instead means that the task could be better scheduled, and would be more convenient than without inspections. As stated before, all the failures can not be detected by condition monitoring or inspections, and all the failures can not be prevented by predetermined maintenance tasks. The figures show these failures using arrows that go past the squares of planned maintenance, and they typically result in a failure which involves larger costs. The cost factors related to use-based maintenance, and similarly compared to corrective maintenance, are presented in Figure 3.

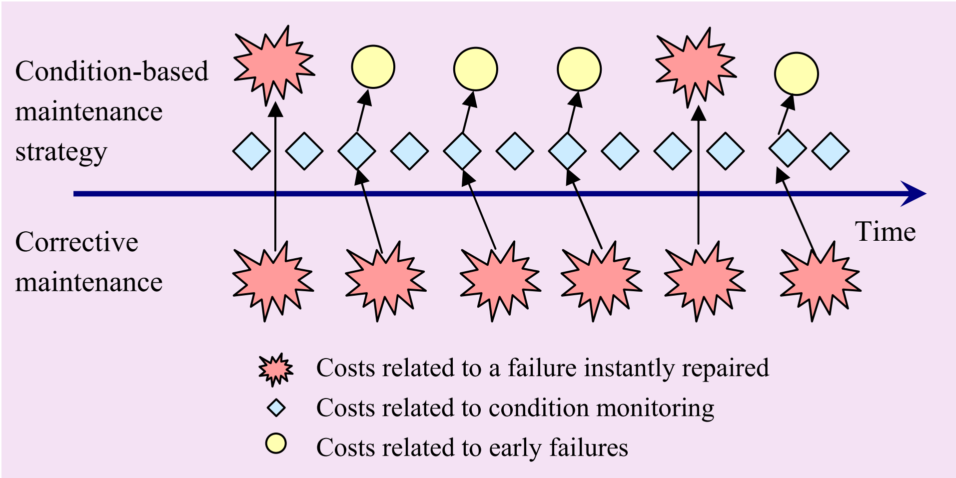


*Figure 2. Evaluating the cost-effectiveness of condition-based maintenance.*

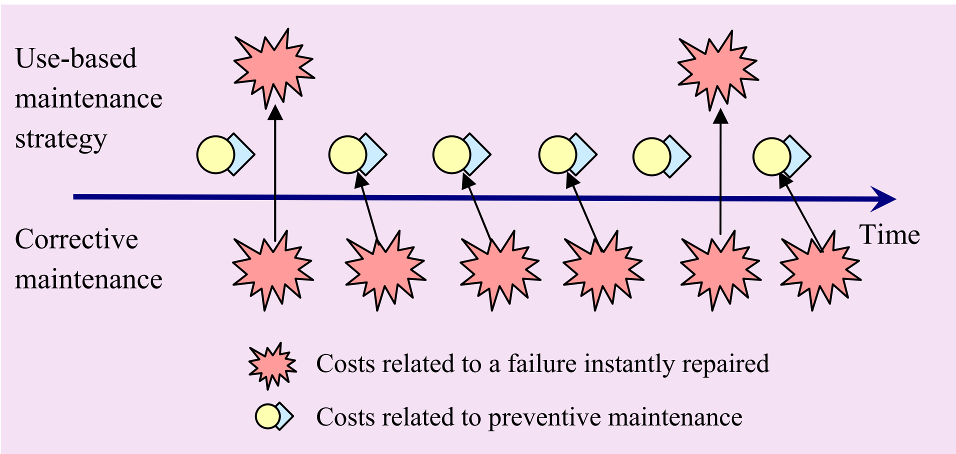


*Figure 3. Evaluating the cost-effectiveness of use-based maintenance.*

By comparing the costs of corrective and preventive maintenance, one is able to get information on the profitability of the preventive maintenance made as planned, compared to the option where no preventive maintenance is performed. The maintenance programme of the target system is analysed in a systematic way, but a lot of information is needed in order to evaluate the profitability of the maintenance tasks, as mentioned before. For example, the effect of preventive maintenance tasks on the decrease of failure probability must be well-known. On the other hand, the effectiveness of the condition monitoring or inspection tasks (as a percentage of the number of early failures out of total number of failures) needs to be evaluated purely based on experience. When utilising expert judgement, in general, the estimates are typically very subjective, as no accurate information is available. However, bearing in mind that the estimations needed partly consist of information on situations that are never realised, the information can be assessed in a rather reliable way.

## 4.1 Information needed for cost estimation

The main principles of comparing the costs of different maintenance strategies have been presented above. But before this comparison can be done, the prices of all the single maintenance tasks must be determined. Income losses due to stoppage or output decreasing, the salaries of employees, and prices of spare parts and investments needed for condition monitoring or modification, must all be considered for every task. Obviously, all the above mentioned factors are not relevant for all the task types, for example, failure repairs do not need investments. All the cost factors are presented in detail in Figure 4. The output decline as a factor of income losses is also included – to allow for a situation when a repair or maintenance does not require a complete stoppage, but the production rate is lower than normal. For investments, their lifetime in years is estimated, and then the average annual investment is calculated.

The average salary for the employees doing the maintenance tasks, and also an average hourly rate for stoppages, must be determined. In the case of the baling line, the hourly cost of a stoppage was determined by dividing the planned production volume for a day by 24 hours. The measurement for the production volume was given as tons of chemi-mechanical pulp, and the average price of a ton of chemi-mechanical pulp was also determined. By multiplying the hourly production volume with the production price, the average income loss for a stoppage of an hour was found. In the baling line case, the fact that all the stoppages do not cause income losses was also taken into account. After short stoppages the production loss can actually be compensated, and so it was decided that income losses were only to be included for stoppages longer than two hours.

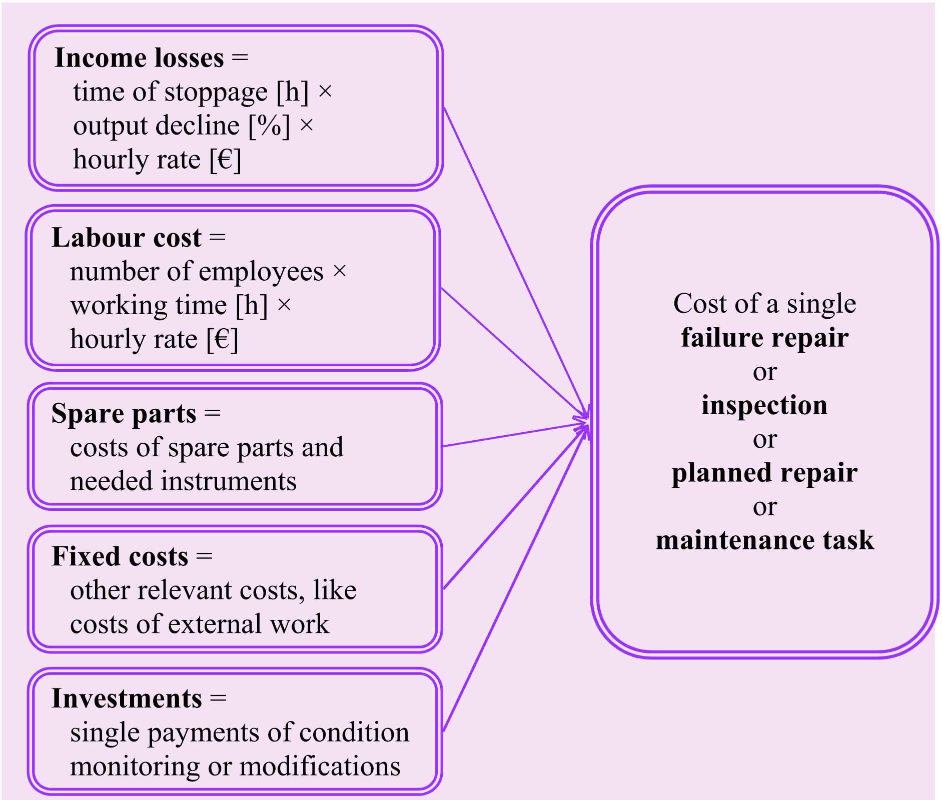


*Figure 4. Cost factors of maintenance tasks.*

The estimation of the cost of single maintenance tasks is, however, insufficient if the aim is to compare different maintenance strategies. In addition, also the number of different kinds of tasks that have to be performed when applying a certain strategy must be determined. We have estimated the number of tasks per year, but depending on the case, the time period can be chosen to be longer, or shorter. After the cost of single tasks and the annual number of tasks are estimated, the annual cost can be easily calculated. An example of cost the calculation for the situation described in Figure 2 is given in Table 1. The values of cost factors are merely examples – they are not real values from the baling line case.

In the example shown in Table 1, condition monitoring includes visual inspection done by an own employee, and an oil analysis done by an outside analyser, with a fixed price of 400 €. Through the use of inspections and oil analyses, an average of four failures per year can be expected to be detected in time – before functional failure. For this case, a stoppage would not be needed because of that particular failure, and no production losses are assumed. On average, two failures a year develop so rapidly that they would not be detected by the condition monitoring that is performed once a month. The last row of Table 1 shows the total annual costs of the two compared maintenance strategies, and for this case, it is easy to see that preventive maintenance is substantially more profitable than corrective maintenance.

In the baling line case, all the necessary information was obtained from expert judgement – using five full-day meetings. The expert group included three people who were familiar with the maintenance and failures of the baling line, and the meetings were led and documented by researchers who knew the method. The first two meetings dealt with FMEA, and the third (and beginning of the fourth) meeting focused on the determination of the technically feasible maintenance tasks, and time intervals of those tasks. The end of the fourth, and the fifth meeting was used for estimating the cost factors.

*Table 1. Example of costs in different maintenance strategies.*

| | **CORRECTIVE MAINTENANCE** | **PREVENTIVE MAINTENANCE** | | |
|---|---|---|---|---|
| | **Failure repair** | **Condition monitoring** | **Early failure** | **Failure repair** |
| Production loss [h×%×€/h] | 4×1×10 000 € | - | - | 4×1×10 000€ |
| Labour cost [prs×h×€/h] | 3×2×50 € | 1×1×50 € | 3×2×50 € | 3×2×50 € |
| Spare parts and materials [€] | 500 € | - | 500 € | 500 € |
| Other fixed costs (oil analysis) [€] | - | 400 € | - | - |
| Cost of one failure or task [€] | 40 800 € | 450 € | 800 € | 40 800 € |
| Number of failures or tasks in a year | 6 | 12 | 4 | 2 |
| Annual costs [€] | 244 800 € | 5 400 € | 1 600 € | 81 600 € |
| | | 88 600 € | | |

# 5. Industrial benefits

The method described in this paper is simple to perform, and includes many simplifications of the real world – each bringing with it various pros and cons. A major disadvantage is that the estimates of maintenance costs could be very inexact, because almost all the initial data is derived from inexact estimates. In the baling line case, for example, the cost of a “stoppage hour” was calculated using the average price of chemi-mechanical pulp for a certain time period, and it was assumed that there is continual demand for full capacity. In reality, the price and demand changes all the time. In the same way, the consequences of a failure vary widely, even if the failure mode is basically the same. In the baling line case, as typical failure costs as possible were estimated for all the failure modes.

Nevertheless, keeping in mind the previously mentioned disadvantages and restrictions, this method can offer useful information for the development of a cost-effective maintenance programme. One particular advantage of this kind of simple method is that it can easily be applied to real cases – no special software is needed, and results are easy to interpret. For example, in the baling line case all the cost information was collected and calculated within an Excel spreadsheet.

As was stated in the first section of this article, the method is most suitable for considering failures which result in operational consequences. However, the same computing principles can be used even if the consequences are more serious – concerning safety and the environment. The relevant cost factors must obviously be chosen to take into account the related consequences, but the cost of serious injury or death, for example, is difficult to determine.

The tool described in this paper offers a simple way of assessing the cost-effectiveness of the maintenance tasks. An expert judgement based assessment of the cost-effectiveness is typically rough. However, it has been shown that by systematically analysing the failure modes of the system and alternative maintenance tasks, one is able to include in the maintenance programme only the cost-effective tasks.

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# Online monitoring method for detecting coating wear of screen cylinders

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## Abstract

Screen cylinders are used to separate unacceptable fibres and sand, grit, pins, glass and other contaminants from pulp. In order to improve wear resistance, the feed surfaces of the screen cylinder wires are hard chrome plated. Coating failure results in rapid wear of the substrate and the cylinder needs to be replaced. If the wear of the chrome plating could be monitored and the coating failure detected early enough to prevent wear of the substrate material, recoating of the cylinder would be possible. Experimental research was carried out to study the possibilities of various methods such as electrochemical measurements, resistance measurements and fibre optical sensors for monitoring the wear of chrome coating. A method was developed for embedding a conductive wire for resistance measurements or the optical fibre underneath the chrome plating. It was demonstrated that both methods could be used to detect the coating failure, whereas the electrochemical measurements were not found suitable in this application. Further development work is required to adapt the methods into industrially applicable form. The methods could be utilised also in other applications than the screen cylinder. The benefits will be highest in applications where coating failure results in rapid failure or quality loss and where recoating, instead of component replacement, would give significant cost savings. In the case of screen cylinders, the costs can be reduced even to one third of the cost of replacement by recoating.

# 1. Background and scope

Screen cylinders are used to separate unacceptable fibres and sand, grit, pins, glass and other contaminants from pulp. The screen cylinder panels are made from closely spaced stainless steel wires. There is a narrow slot between the wires to let the acceptable fibres pass through when the pulp flows against the screen cylinder during the screening process. In order to improve the wear resistance of the cylinder against the erosive operational conditions, the feed surfaces of screen cylinders are hard chrome plated. However, when the chrome plating wears through, rapid wear of the substrate takes place and the cylinder needs to be replaced. In case the wear of the chrome plating could be monitored such that the coating failure could be detected early enough to prevent wear of the substrate material, recoating of the cylinder would be possible and feasible and would result in significant cost savings when compared to replacement of the cylinder.

The objective of the screen cylinder case of the Prognos project was to identify and develop a method which would enable on-line monitoring of the chrome plating wear. The research work was carried out in co-operation with Metso Paper, the industrial partner participating in this case of the Prognos project. A screen cylinder wire specifically tailored for the purpose could act as the on-line sensor. Tailoring of the cylinder wire could involve changes in the coating thickness and area, substrate material, wire profile and size, and possibly a multilayer structure or embedded sensors. The measured signal should give a clear on/off response for the failure of the chrome plating and, if possible, it should also give an indication of the progress of the coating wear to enable wear prediction.

# 2. Methods

A literature survey was carried out on erosive wear of coatings and methods to monitor coating wear in order to identify potential methods for further study and development [1]. Direct wear measurements such as weight or volume loss or dimensional changes are suitable for off-line use whereas indirect methods are often more feasible when on-line monitoring of wear is required. Indirect methods such as acceleration, acoustic emission or ultrasonic measurements could be suitable in certain applications but in this case these were not considerd viable due to the noise and disturbances from the process conditions. On-line corrosion monitoring methods could be applicable for monitoring wear under slurry erosion. Other possible methods include radionuclide technique, fibre optic sensors and smart sensors based on capacitive, resistive or conductive principles. On the basis of the literature survey and other background information a few potential methods were selected for further study.

Electrochemical corrosion monitoring methods are used to assess the electrochemical activity associated with corrosion, yielding results which can be used to estimate the corrosion rate or to identify situations that are likely to promote corrosion [2]. Electrochemical noise (EN) arises from the random fluctuations in potential and current during an electrochemical process. The electrochemical potential is related to the driving force of the reaction whereas the current is related to the corrosion rate (kinetics of the reaction). One of the advantages of the use of EN measurements is the fact that localized corrosion processes, which may be difficult to monitor with other techniques, tend to give particularly strong EN signals, and the method can be used to predict the type and severity of corrosion that is taking place. Electrochemical current noise can be measured between a pair of identical electrodes, or on a single electrode under potentiostatic control [3, 4, 5]. In screen cylinder the electrochemical properties of the substrate and the chrome plating are different and hence electrochemical measurements could be a possible monitoring method, e.g. using adjacent cylinder wires as electrodes.

Other potential methods selected for further study included resistance measurements with a conductive wire, and fibre optical sensors. The first experiments on the use of optical fibres as sensing elements date back to the early 1970s. The common feature of fibre optic sensors is that they contain an optical fibre, at least one optical source and a modulation scheme by which the parameter that is being measured introduces a change in the optical signal, which can be sensed at the detector and employed through the signal processing scheme. More detailed descriptions of the various fibre optic sensors and their possibilities can be found e.g. in the review articles in refs. [6, 7] and in the numerous references in them. A distributed sensor system could in some applications possibly even allow the determination of the location of the coating damage. Both in the case of resistance measurements with a conductive wire and fibre optic sensors, the sensors need to be embedded underneath the chrome coating.

# 3. Results

The work was carried out in three stages. First preliminary studies were made regarding the possibility to utilise electrochemical measurements, resistance measurements or optical fibres for detecting chrome coating failure on steel. Further studies included hard chrome plating experiments with embedded sensors and testing of the measurement systems in a wear test under reciprocating sliding. The performance of the monitoring methods was finally tested by carrying out erosion tests in a slurry containing abrasive particles. In the erosion tests also pieces from an actual screen cylinder panel were used as samples.

## 3.1 Preliminary studies

### 3.1.1 Electrochemical measurements

Since the difference in electrochemical properties of carbon steel and hard chrome is much larger than that between stainless steel and chrome, commercially available hard chrome plated carbon steel was used in the preliminary experiments. Other samples tested were uncoated carbon steel (Fe52), plastic, 316 stainless steel and pure chromium and nickel. Electrochemical noise measurements (EN) were carried out using two isolated samples as working electrodes together with a reference electrode. In this way it was possible to measure simultaneously both the current between the samples and the potential of the electrode pair with respect to the reference electrode. The tests were carried out in a decanter filled with water. Initially tap water was used but to ensure that the results are relevant to operational environment also process water from a paper mill was used.

The measurements showed that it was possible to make a difference between stainless and carbon steel. However, in tests with artificial failures in the coating the failure could not be detected. Further tests made by electrochemical impedance spectroscopy (EIS) showed that the different materials could be separated from each other based on their polarization resistance but the chrome plated sample behaved in a similar manner as the uncoated carbon steel. This is probably due to small faults in the chrome plating which make the substrate accessible for the corroding ions. Hence, the electrochemical measurements were not considered to be suitable for on-line monitoring of the wear of the chrome plating in this form. However, a sandwich type multilayer coating could be a possibility if it would contain an isolated layer below the chrome coating, the layer having electrochemical properties which are sufficiently different from those of the chrome coating.

### 3.1.2 Resistance measurements

If a conductive wire such as Cu with an insulation layer on it could be embedded underneath the chrome plating, it could be used as a sensor to detect the coating failure by resistance measurements. As soon as the coating fails also the insulation layer and the Cu-wire will become damaged. This results in changes in the electrical circuit which should also show up in resistance measurements.

For the preliminary tests carbon steel rod was used with an insulated Cu-wire with a diameter of 150 microns wrapped around it before chrome plating. As expected, the insulation on the Cu-wire caused problems in the electrolytic coating process and hence various pretreatments were tried including nickel deposition as well as application of electrically conductive silver and nickel paints on the sample before chrome plating. The diameter of the Cu-wire was of the same order as the coating thickness which also contributed to the adhesion problems. Despite the adhesion problems, it was possible to make a sample in which the chrome plating covered also the Cu-wire and held it satisfactorily attached for being used in a wear test. A reciprocating sliding wear test was carried out with this sample using another chrome plated steel rod as the counterpart. The resistance of the Cu wire as well as the resistance between the Cu-wire and the counterpart material was measured during the test. Both the breakdown of the insulation layer and the breakage of the Cu-wire could be detected.

The test showed that the resistance measurement is a potential method as far as the Cu-wire can be embedded properly underneath the chrome plating. For this an electrically conductive intermediate layer on the insulated Cu-wire is required. The thickness and adhesion of the layer must be good enough. The insulation layer on the Cu-wire has to be able to stand the conditions during the coating process without being damaged. Problems encountered due to the large dimensions of the wire as compared to the coating thickness could be minimised by embedding the wire in a groove made into the substrate surface. This would prevent the wire from causing a high protrusion on the surface and hence also reduce the mechanical stresses the wire will be subjected to during use.

### 3.1.3 Fibre optical sensors

A fibre optical sensor could be used in a similar manner as the Cu-wire in the resistance measurements. In this case the measured signal will be the light travelling in the fibre. Research on optical fibres and embedding the fibres in a metal matrix have been carried out for several years at VTT [8]. The size of the fibres is in the same range as that of the Cu-wire and the chrome plating thickness, which means that in order to be able to embed the fibres underneath the chrome plating, a groove is needed in the substrate surface. Fibres with a 20 µm Cu layer on them are available, the total diameter of the fibre being 165 µm. The Cu-layer on top should make the chrome plating of the optical fibres easier than that of the insulated Cu-wires.

The simplest arrangement for the measurements would be to measure the intensity of the light transmitted through the fibre. The light transmitting capacity of the fibre is affected by deflection caused e.g. by external pressure or wear. As the chrome coating wears the fibre becomes bare and will be subjected to the process environment. This will change the pressure and other loads on the fibre and affect the intensity of the transmitted light. When the fibre finally breaks the intensity drops to zero. In case reflected light would be measured instead of transmitted light, the light will be reflected back from the breakage of the fibre and the location of the failure could be determined. Before the optical fibres could be used in test measurements, coating experiments were needed to produce suitable samples.

## 3.2 Coating experiments and sliding wear tests using embedded sensors

After the preliminary tests the work was focused on embedding either a conductive wire or an optical fibre underneath the chrome coating. Due to the relatively large diameter of the fibres in comparison to the coating thickness a groove was needed in the substrate for embedding the fibre. Various methods for fastening the fibre into the groove were considered, and trials with a special soldering were made. To ensure coating adherence coating tests were made for steel rods with and without soldering using various pretreatments before hard chrome plating. The pretreatments included methods for cleaning and degreasing the surface of the sample first with ethanol or acetone, using also ultrasonic cleaning, and then removal of possible surface oxides either mechanically or by chemical or electrochemical etching. Electrolytic chrome deposition was carried out using a commercial electrolyte. A few trials were also made using an intermediate Ni or Cu layer before chrome plating to improve adhesion.

After several pre-treatment and coating trials without an optical fibre, a few coating tests were also made with a fibre soldered into the groove. Soldering both on the whole length of the groove and only at both ends of it was tried. Deposition of chrome on the steel surface and also on thicker areas of the soldering succeeded rather well but at the edges and thinner parts of the soldering layer the coating adhesion was poor. On areas where there was no soldering the optical fibre did not stay properly in the groove and also the coating was not properly growing on it. Hence new ways for getting the fibre embedded were needed. Small Ni tube was available, with an outer diameter of 0.35 mm and inner diameter of 0.30 mm. The tube could be used as a shield for the optical fibre or the Cu wire if they were inserted in it. Trials were made to place the tube in a groove on the substrate surface, fastening it by the same soldering material. In addition, a narrower groove was also made, slightly less in width than the diameter of the Ni tube. The tube was then fitted in it by pressing it into the groove so that it deformed slightly. Chrome coating of these samples was successful, and the tube was held tight in the narrower groove even without soldering. This way it was possible to embed either the insulated Cu wire or the optical fibre underneath the chrome plating.

The ends of the Ni tube were protected against bending by slightly larger steel tubes which were fastened at both ends of the samples. During the coating process the ends of the tubes were protected by silicone tubes to prevent chemical attack by the electrolyte in these areas. The monitoring system was then tested in reciprocating sliding tests in the VTT Rectester, measuring both the resistance of the Cu wire and the intensity of light transmitted through the optical fibre during the test, see Figure 1.

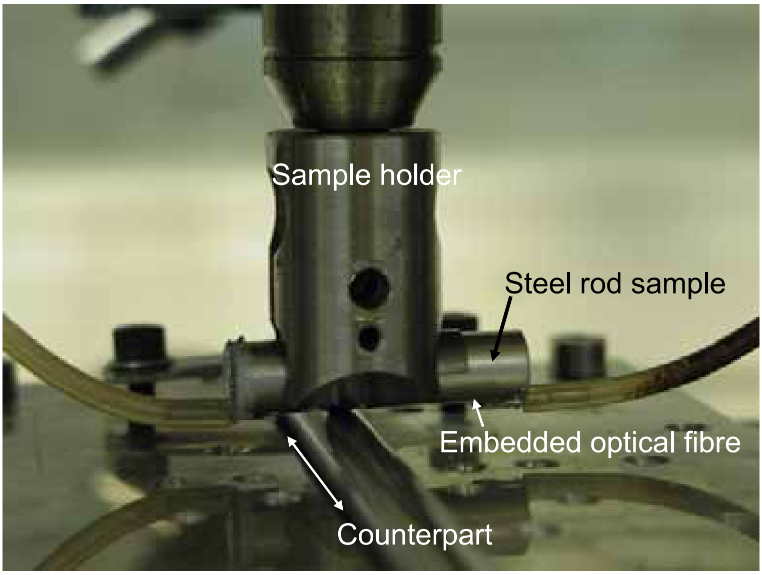



*Figure 1. Reciprocating sliding test arrangement. A sample, with an embedded optical fibre, is held in a sample holder (top) and pressed against a counterpart sample fastened on a test table, which is moved back and forth causing sliding action. Since the fibre is very thin, it is protected by silicone tubes attached to both ends of the sample.*

In the case of the Cu wire the breakdown of the insulation layer during the wear test was detected from the change in resistance between the sample and the wire. The breakage of the Cu wire itself, however, did not result in any noticeable change in the measured resistance of the Cu wire, due to the both broken ends of the wire being in direct contact with the surrounding material, this causing a short circuit between them. In the case of the optical fibre, the transmitted light intensity measurements showed a distinctive drop when the chrome coating and the Ni tube had worn through and the fibre started to get damaged. The light intensity decreased rapidly with the damage.

The tests showed that both embedded conductive wires and optical fibres can be used as sensors for detecting coating failure. Since the wires or fibres are embedded in a groove underneath the chrome coating, the time when the signal will indicate coating damage depends on how deep the wire or fibre is placed. In the tests carried out also the substrate material beside the groove had worn significantly after the coating failure, see Figure 2. Due to the test arrangement and sample geometry, the effect of the wear rate of the substrate material on the wear of the optical fibre was significant. In erosive conditions, such as in the screen cylinder, the fibre will be subjected to the erosive action of the slurry as soon as the coating and the thin Ni tube have failed.

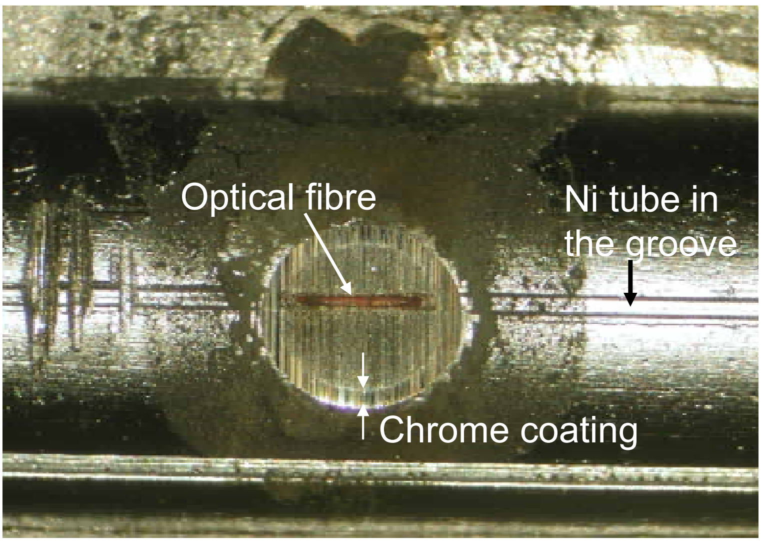



*Figure 2. Sample from the sliding test. The optical fibre, embedded under the chrome plating in a Ni tube, is visible in the middle of the round worn area. The thickness of the chrome coating can be seen at the edges of the worn area.*

## 3.3 Erosion tests

The third stage in the work was to verify the monitoring concept also in an erosive environment. The tests were carried out in the erosion test equipment of

VTT, see Figure 3. The equipment consists of a pot filled with slurry during the test, and the samples are placed in it in a circumferential sample holder. During the test the slurry is moved by a rotor in the centre of the pot. For monitoring purposes holes were made in the cover of the equipment for the optical fibres or wires.

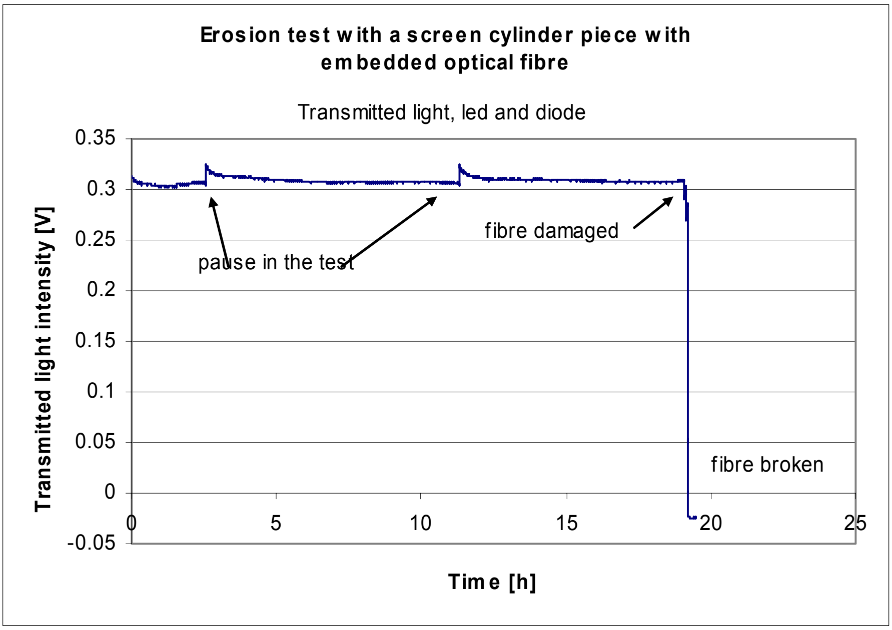
The first tests were made with similar samples as those used in the Rectester, i.e. chrome plated carbon steel rods with grooves and Ni-tubes for embedding the fibres. The fibres were protected by silicone tubes all the way along their free length in the erosion test equipment and also to some extent outside the pot as well. The test was started using a slurry with rather fine alumina sand, but due to limited time available for the test, it was then accelerated by adding iron particles into the slurry resulting in rapid coating damage.

*Figure 3. Erosion test equipment consisting of a test chamber and a rotor in the middle. The samples are held near the test chamber walls in a sample holder.*

The resistance measurement was only performed for the Cu wire itself but as the wire was damaged and broke, it short circuited with the sample and no proper change in the resistance could be measured. Hence, it was concluded that in order to be able to use the resistance measurement for detecting coating failure by an embedded Cu wire, the resistance needs to be measured between the Cu wire and the steel substrate. In this way the measurement would show a change at the moment of the failure of the insulation layer of the Cu wire.

Two types of measurements were made with optical fibre, i.e. both the intensity of the transmitted light and the weakening of the reflected light were measured. Due to the requirements of the latter method the length of the fibre used was nearly 30 km, and the length of the fibre to the sensor element (i.e. the sample) was about 10 km. Both measurements gave a clear indication of the damage of the optical fibre after the coating failed. However, whereas the response in the reflected light measurement was very distinct and more or less on/off type, the change in the intensity measurement of transmitted light was more gradual.

Finally, a sample was prepared from a piece of screen cylinder panel received from Metso Paper, by embedding an optical fibre in one cylinder wire. Coating of the 316 stainless steel screen cylinder pieces proved to be difficult, requiring special procedures before succeeding. One of the steel rod samples with embedded fibre was tested together with the screen cylinder piece. For the test a simple low cost arrangement with a LED as the light source was constructed. In the test alumina sand with tap water was used as the slurry. Again, the change in transmitted light intensity was gradual showing that it took nearly 2 hours for the fibre to get completely broken, from the moment it started to get damaged after about twelve hours test duration. The coating on the screen cylinder sample wore faster than the coating on the steel rod and the sample monitored by the LED system lasted about 19 hours. The sensitivity and resolution of the LED based system was much less than that of the laser based system and the response to fibre damage after coating failure was clear but of an on/off type instead of being capable to detect a gradual change, see Figure 4.



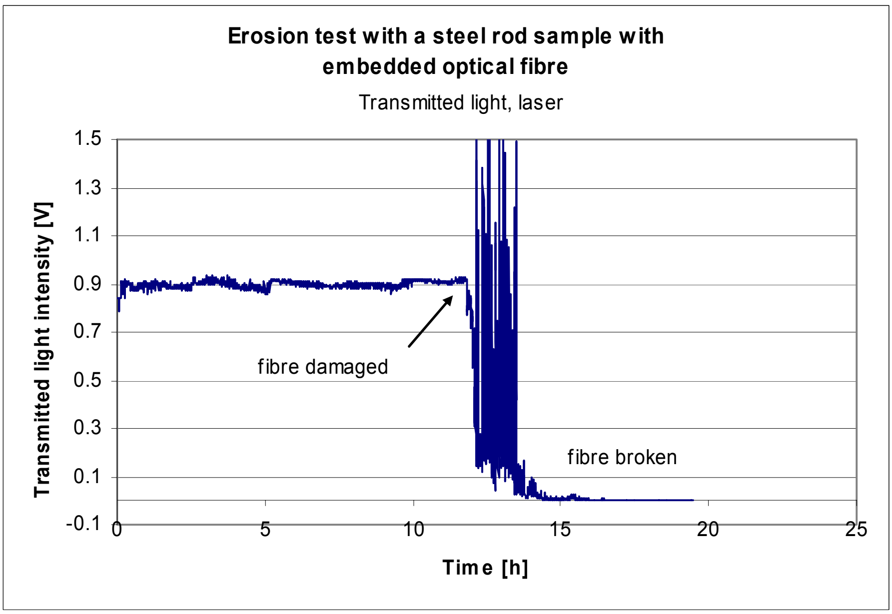




*Figure 4. Results of the transmitted light intensity measurement during erosion test of chrome coated samples with embedded optical fibre. Fibre damage after coating failure could be detected by a sudden or gradual drop in transmitted light intensity, depending on the sensitivity of the measurement system.*

# 4. Industrial benefits

In many applications coatings are used to improve the wear resistance of components. If coating wear can be monitored and coating failure detected early enough, maintenance actions can be taken before any major wear of the substrate material occurs. In practice, however, monitoring of coating wear is often based on visual inspection or off-line measurements. In this work it was demonstrated that both resistance measurements, using a conductive wire as the sensor, and fibre optical sensors can be embedded in the material underneath the coating and utilised for detection of coating failure. Optical fibres offer possibilities both for an on/off type detection and for detection of a gradual change in the signal at the final, critical wear stage. In applications where several fibres or wires could be embedded at different depths, it could also be possible to obtain an indication of the wear rate or depth. Further development work is required to adapt the methods into industrially applicable form. With on-line monitoring the need and proper time for service actions and recoating could be determined without extra inspections. The benefits will be highest in applications where coating failure results in rapid failure or quality loss and where recoating, instead of component replacement, would give significant cost savings. Metso Paper as the industrial partner in this project has indicated that in the case of screen cylinders, the costs can be reduced even to one third by recoating instead of replacing the cylinder.

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# Appendix A: Prognos project: figures and participants

In the following some figures and facts of the Prognos-project, Prognostics for Industrial Machinery Availability are given.

Duration: 10/2003 – 12/2006
Volume: ca. 2.3 M€
Funding: TEKES 59%, VTT 21%, Industry 20%
Research budget by research organisation:

| | |
|---|---|
| VTT Technical Research Centre of Finland | 1 604 700 € |
| Lappeenranta University of Technology* | 300 000 € |
| University of Oulu | 185 700 € |
| Tampere University of Technology | 185 700 € |

*includes the budget of Kymenlaakso University of Applied Sciences.

The manager in charge of the project: prof. Kenneth Holmberg, VTT

Project coordinator: Dr. Aino Helle, VTT

Chairman of the project steering group: Mr. Seppo Tolonen, Pyhäsalmi Mine Oy

Steering group member representing Tekes, the Finnish Funding Agency for Technology and Innovation: Mr Mikko Ylhäisi

VTT representative in the steering group: Lic. Tech. Helena Kortelainen

Each research organisation and all industrial partners were represented in the steering group.

## Industrial Cases

The research in the project was based on industrial cases listed below. For each case the research organisation responsible for the case is given with the person responsible in brackets. Also the industrial partners of each case are mentioned.

**Case Charging Crane**
Tampere University of Technology (Ville Järvinen), major contribution also by University of Oulu
Rautaruukki Oyj

**Case Underground Loader**
VTT Technical Research Centre of Finland, Networked Intelligence (Jarmo Keski-Säntti)
Pyhäsalmi Mine Oy and Sandvik Mining and Construction Finland Oy

**3D Visualisation for the above two Cases**
VTT Technical Research Centre of Finland, Virtual Models and Interfaces (Kari Rainio)

**Case Grease Lubrication**
VTT Technical Research Centre of Finland, Smart Machines (Risto Parikka)
UPM Kymmene Oyj, Rautaruukki Oyj, Pyhäsalmi Mine Oy

**Case Servo Motors and Industrial Robots**
VTT Technical Research Centre of Finland, Smart Machines (Jari Halme)
Foxconn Oy and LSK Electrics Oy

**Case Electric Motor Control**
VTT Technical Research Centre of Finland, Networked Intelligence (Jarmo Keski-Säntti)
ABB Oy Pienjännitetuotteet and UPM Kymmene Oyj

**Case Ventilation Air Fan**
Tampere University of Technology (Ville Järvinen)
Pyhäsalmi Mine Oy

**Case Primary Air Fan**
Tampere University of Technology (Ville Järvinen)
Foster Wheeler Energia Oy

**Case Paper and Cardboard Industry**
Remote Diagnostics Concept: Lappeenranta University of Technology (Jero Ahola)
Quality Control System Diagnostics: Kymenlaakso University of Applied Sciences (Merja Mäkelä)
ABB Oy Sähkökoneet, Vacon Oyj, UPM Kymmene Oyj

**Case Baling Line**
VTT Technical Research Centre of Finland, Risk and Reliability Management (Susanna Kunttu)
M-real Oyj, Joutseno BCTMP and Oy Botnia Mill Service Ab

**Case Screen Cylinder**
VTT Technical Research Centre of Finland, Smart Machines (Aino Helle)
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# Appendix B: List of publications

The publications produced during the Prognos -project this far are listed here. Internal project reports as well as confidential reports have not been included in the list below.

## Lappeenranta University of Technology

**Articles in international journals**

Ahola, J., Vartiainen, E., Lindh, T., "Phase Retrieval from Impedance Amplitude Measurement", Accepted for future publication in the IEEE Power Electronics Letters.

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Spatenka, P., Lindh, T., Ahola, J., Partanen, J., "Requirements for Embedded Analysis Concept of Bearing Condition Monitoring", Norpie 2004, 12–14 June 2004, Trondheim, Norway.

Lindh, T., Ahola, J., Spatenka, P., Rautiainen, A.-L., "Automatic bearing fault classification combining statistical classification and fuzzy logic", Norpie 2004, 12–14 June 2004, Trondheim, Norway.

Rautianen, A.-L., Tiainen, R., Ahola, J., Lindh, T., "A Low-Cost, Measurement and Data Collection System for Electric Motor Condition Monitoring", Norpie 2004, 12–14 June 2004, Trondheim, Norway.

Mäkelä, M., Ratilainen, M., Pyrhönen, O., Haltamo, J., Tarhonen, P., “Model Predictive Control Technology in Paper Quality Control: a Case Study of a System Update”, Paptac 91st Annual Meeting, Pulp and Paper Technical Association of Canada, Paperweek 2005, 7–10 February 2005, Montreal, Quebec, Canada, pp. B95–B99.

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Tiainen, R., Kämäri, A., Särkimäki, V., Ahola, J., Lindh, T., “Utilization of Ethernet Communications in Electric Drive Diagnostics – Requirements and Protocols”, will be published in the Proceedings of NORPIE 2006, Lund, Sweden, 12–14 June, 2006.

Tiainen, R., Särkimäki, V., Ahola, J., Lindh, T., “Utilization Possibilities of Frequency Converters in Electric Motor Diagnostics”, will be published in the Proceedings of Speedam 2006, Taormina, Italy, 23–26th May, 2006.

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Mäkelä, M., Manninen, V., Heiliö, M., Myller, T., "Performance Assessment of Automatic Quality Control in Mill Operations", in proceedings of Control Systems 2006, Tampere 5–8 of June, Finnish Society of Automation, Helsinki 2006, pp. 275–280.

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Mäkelä, M., Missä mennään metsäteollisuuden automaatiossa, Kunnossapito 5/2006.

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Manninen, V., Paper machine quality measurement identification by using Kalman filters, Master's thesis, December 2006, advance notice.

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Vähäoja, P., Lahdelma, S., Kuokkanen, T., Experiences in Different Methods for Monitoring the Quality and Composition of Solid Matter in Rolling and Gear Oils. In: Proc. of the 18th Int. Congress of Condition Monitoring and Diagnostic Engineering Management (COMADEM 2005), Cranfield, England 31.8.–2.9.05. Pp. 463–473.

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Järvinen, V., Dynamics of Acceleration Sensors Fixed to Rotating Frame, In the Proceedings of 11th World Congress in Mechanism and Machine Science (IFToMM), April 1–4, 2004, Tianjin, China. Vol. 5, pp. 2129–2133.

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Kivikunnas, S., Keski-Säntti, J., Ruuska, J., Standardoinnin tarve ja hyödyt tuotantoprosessien suorituskykyjärjestelmissä, Seminaariesitelmä, AUTOMAATIO 05 Seminaaripäivät 6.–8.9.2005, Helsingin messukeskus. Suomen Automaatioseura ry, pp. 329–334.

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## VTT Technical Research Centre of Finland, Smart Machines

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Holmberg, K. & Helle, A., Tribology as basis for machinery condition diagnostics and prognostics. To be published in International Journal of Performability Engineering (IJPE).

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Parikka, R., Helle, A., Monitoring of grease lubrication, In the Proceedings of Nordtrib 2006, Helsingør, Denmark, 7.–9.6.2006. Also published in TRIBOLOGIA – Finnish Journal of Tribology, Vol. 25 (2006), 3, pp. 3–10.

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Title

# Prognostics for industrial machinery availability
## Final seminar

Abstract

Operational reliability of industrial machinery and production systems has a significant influence on the profitability and competitiveness of industrial companies. A three year research project Prognos – Prognostics for Industrial Machinery Availability was started in October 2003 with the objective of generating methods for improving and maintaining industrial machinery availability by developing tehniques which enable prognosis of the operational condition, failure probability, and remaining operating life of the machinery and production lines. The project has been a joint research effort of VTT Technical Research Centre of Finland and three technical universities, with financial support from Tekes and 13 industrial companies. Industrial cases selected on the basis of the strategic needs of the industrial partners in the Prognos-project formed the basis of the work carried out by the research organisations. The results of the research and development include methods, tools and knowledge covering many areas and technologies including tools from maintenance planning to component level monitoring, diagnostics and prognostics. A general schematic description of prognostic concepts made in the project assists in figuring out the different areas of existing methods, available data and possible further development needs in any specific cases considered. The results of the project have been published in more than 90 publications, including 7 M.Sc. theses and one doctoral thesis. This symposium publication and the final seminar give a summary of the work performed and the results obtained in the three year project.

Keywords
Industrial machines, cranes, robots, electric motors, loaders, fans, paper machines, remote monitoring, condition monitoring, diagnostics, prognostics, operational reliability, control systems

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Technological development has resulted in increased complexity both in industrial machinery and production systems, at the same time with the increasing demand in the society for improved control of economy, reliability, environmental risks and human safety. Operational reliability of industrial machinery and production systems has a significant influence on the profitability and competitiveness of industrial companies. Diagnostic and prognostic tools have been developed in a three year research project Prognos – Prognostics for Industrial Machinery Availability during the years 2003 to 2006.

Industrial cases selected on the basis of the strategic needs of the industrial partners in the Prognos-project formed the basis of the work carried out by the research organisations. The results of the research and development in the Prognos project include methods, tools and knowledge covering many areas and technologies including tools from maintenance planning to component level monitoring, diagnostics and prognostics. During the project, the results have been published in more than 90 publications, including 7 M.Sc. theses and one doctoral thesis. This symposium publication gives a summary of the work performed and the results obtained in the three year project.

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