REVIEW OF “FAULT DETECTION, DIAGNOSIS AND DECISION SUPPORT METHODS” IN INDUSTRY

Rambabu Kandepu[a], Tor Inge Waag[b], Karl Magnus Laundal[c], Anis Yazidi[d]

[a], [b],[c], [d] Teknova AS, Norway

[a]rka@teknova.no, [b]tiw@teknova.no, [c]kml@teknova.no [d]aya@teknova.no

ABSTRACT
This paper focuses on some specific industrial cases in the area of condition monitoring, fault detection, diagnosis and decision support system methods. The paper briefly describes the cases, describes the existing methods, if any, and lists the specific challenges.

Keywords: Condition monitoring of industrial equipment, Review of industrial methods.

1. INTRODUCTION

Fault detection and diagnosis has been an active and important field for petrochemical plants. It has not been given the same level of attention in other process industries; especially metallurgical and material processing plants. But as the competition is growing in the world market, the fault detection and diagnosis is becoming important in all types of industries to reduce unexpected situations and to avoid unplanned shutdowns. The other important parameter for the motivation in this direction is health and safety issues arising from unexpected faults.

The work presented here is a part of an initiative taken by Teknova to work together with local industries in southern Norway with a focus on methods and tools for fault detection, diagnosis and decision support systems. The first step in this initiative is to survey the existing methods and tools in practice. The survey was focused to categorize the methods in three categories: measurement methods, fault detection & diagnosis (condition monitoring) and decision support system. The survey is intended to look at the methods applied for identifying faults both in process and operating equipment. However, most of the work presented here is focused on the equipment aspects.

In order to have a fault detection & diagnosis (or condition monitoring system) it is very important to have enough measurements from a process or equipment. However it is not always possible to measure key variables/parameters to monitor a process or equipment well enough. Especially the process plants being surveyed were metallurgical plants, where the operating temperatures for some process operations exceed 2000°C. Furthermore, the corrosive environment, dangerous fluids/gases and closed systems make it even more difficult to measure the key variables. For some types of equipment, e.g. pipes handling different types of fluids, it may be cumbersome to have manual periodic monitoring equipment. There can be situations where it is better to have contact-free sensors with regard to health and safety issues. Even though there are lots of advancements in various measuring technologies, the application of these advanced technologies for metallurgical plants has to overcome a lot of challenges.

In some cases, it is almost impossible to apply any technology to measure key process variables or performance parameters of equipment. In these situations, modeling plays an important role to develop soft sensors to estimate the immeasurable variables. In traditional process industry, where application of models for control and state estimation purposes has not been a practice, it is a challenge to make the transition. Especially, in situations where mathematical models cannot be applied and knowledge based and/or data-based models are useful, it is even harder to make engineers interested in developing and implementing these kinds of models.

For some cases, there are measurements available, but it is a challenge to have dedicated human resources to use the measurements for the purpose of condition monitoring of the equipment. It appears very common that there is a lot of historical data of the process measurements which is not being used for any purpose. The field of industrial diagnosis is not being applied at the same level in different process plants. The reasons can be many; the size of the plant, the age of the plant and the experience from before, availability of human and economic resources etc. Even in the case where there is an interest for using the data to gain useful knowledge, it is a challenge to convince other engineers/operators to have a transition from more human control to less human control in the plant.

Decision support system plays an important role once a fault is detected. For the plants operated by operators, it is very important to have an optimal design of decision support systems; design of Human Machine Interface (HMI) screens, placement of screens, color design, alarm level design and display etc. For some critical equipment failure and unexpected process operating conditions, the decision support system plays a key role for the operators and engineers to make important decisions in a short time interval.

1.1. Overview of the state of the art

At this juncture, we shall give a brief overview of the most prominent state of the art techniques used in the field fault detection and diagnostics. In one hand, fault detection and diagnosis methods fall into two main families, namely, Quantitative methods

(Venkatasubramanian et al 2003a) and Qualitative methods (Venkatasubramanian et al 2003b). In the other hand, other taxonomies divide the later techniques into History based approaches and Model based approaches (Venkatasubramanian et al 2003c). The cross-combination of these aforementioned taxonomies results into four classes illustrated in Figure 1.

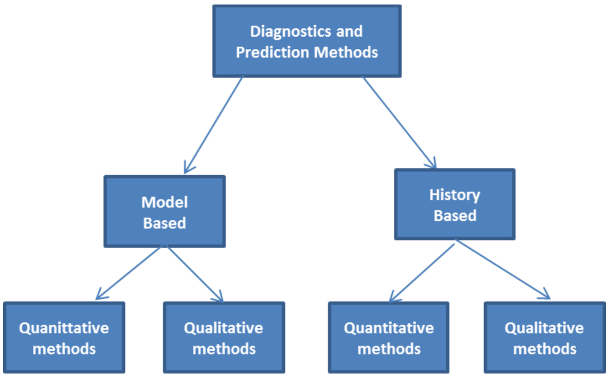

Figure 1: Classification of failure detection and prediction techniques.

Failure isolation refers to the ability of the diagnostic methodology to discriminate between the different types of failures and trace their root causes (Dash and Venkatasubramanian 2000). Fault isolation seeks to identify a cause-effect relationship that is susceptible of explaining the reason behind system deviation. In this perspective, Fault trees (Lapp and Powers 1977) have been extensively used for failure isolation. They are based on backward reasoning where the symptoms of the failure are first identified and then traced back using backward chaining to a possible root cause that can justify the process's mal-functioning.

Bayesian networks are a popular technique for fault diagnosis which bears similarities with the fault tees (Przytula and Thompson 2000). Statistical knowledge of the process and failure occurrences are summarized in a graph which edges represent cause-effect relationships. In the absence of statistical knowledge, the graph can be constructed by knowledge experts that specify the conditional probabilities of the occurrence of a system event given observations (symptoms) in a form of tables attached to each node. Bayesian networks have shown great permit in complex systems where human expert attention might easily become overwhelmed by the overabundant possible root causes of a failure. Usually, the hypothesis that dominates the other hypothesizes in terms of probability is identified as the root cause of the failure. Nevertheless, a sorted list of the eventual root causes of the failure ordered by their respective probabilities given the symptoms can assist the human expert in the presence of uncertainties. Case Based Reasoning (Guiu et al 1999) is a widely used technique for identifying faulty situations by leveraging historical knowledge of the process. In Case Based Reasoning, the status of the monitored process is compared to previously encountered failure situations from historical data accumulated over experience. A distance similarity measure is employed in order to situate the current status vis-à-vis previously encountered failures. The later distance is usually computed in form of a weighted combination of the difference between the current status of the monitored process variables and the historical process data. Nevertheless, the main shortcoming of Case based reasoning is its inability to predict and recognize novel classes of failures that are not present in the historical data. It is worth mentioning that Bayesian Networks and Case based reasoning belong to the class of qualitative based methods. Knowledge based Expert Systems (Becraft and Lee 1993) are another widely used method for failure diagnostics and prediction. Knowledge based Expert Systems are constructed via collaboration between a knowledge engineer and domain experts. The simplest form of knowledge based expert system is defined by antecedent part and a consequence part which maps these system observations to a fault mode. These rules reflect the expert knowledge experience about the system. There are three main challenges when constructing such expert systems: the issue of completeness of the set of rules to cover all states of the system, the eventual huge number of rules and the possibility of creating conflicting rules. Neural networks (Hoskins and Himmelblau 1998) are a form of quantitative methods that are based on the history of the process. Neural Networks are particularly useful in the absence of a model of a physical model of the process being monitored. Neural networks are able to extract hidden knowledge from process data by deducing a mathematical mapping between the inputs of the process and the classes of failures. When it comes to failure diagnostics and prediction, the Neural Network is fed by training data from the different failure modes as well as from the normal operations modes. The Neural network consists of different layers of neurons where the input of one layer serves as output to the next layer. Back-propagation is probably the most successful technique for updating the weights of the neurons in a Neural Network. In Back-Propagation update mode, the weights are adjusted using a gradient approach in order to mitigate the error between the computed output of the neural network and the expected output from the labeled training data. The main shortcomings of Neural Networks are twofold. First, Neural networks give good performance in already known situations while usually fail to predict novel failures for which there is no training data. In addition, it is not possible to express and extract the learned rules of the neural networks in a human readable form.

Machine Learning techniques have been also widely deployed in the area failure diagnosis and prediction. The adopted Machine Learning techniques can be broadly divided into two main classes, namely Regression techniques and Classification techniques. Regression paradigms aim to deduce mathematical expressions that fit the training data. Principal Component Analysis /Partial Least Squares (Wold et al

1984) have received a lot of attention when it comes to creating a statistical model of the failures occurrences by reducing the dimension of the space containing the variable of the monitored process and then applying multivariate regression techniques in order to relate the process input variables to the output variables. Gaussian Processes (Rasmussen and Williams 2006) have recently emerged as intriguing technique for non-linear regression that started to gain popularity. Pattern recognition classifiers have also been used in the field. These techniques include Support Vector Machines (Pöyhönen et al 2002) and Decision trees. In some cases, the different classes of faults cannot be separated in a low dimensional space by a linear classifier; therefore Kernel based techniques are used to map the low dimensional space into a high dimensional space where the faults classes are separable. Other statistical methods include Clustering and Data Mining techniques. Clustering and Data Mining techniques are two forms of quantitative based techniques that have found many applications in the field of failure diagnosis. It is worth mentioning that clustering is a form of unsupervised learning in contrast to classification techniques such as Support vector machines and decision trees that are forms of supervised learning. In Data Mining, association mining rules is a known method (Agrawal and Srikant 1994) that permits to discover frequent episodes in event sequences which are able to predict the failure in advance.

Model based techniques are based on deep knowledge of the mathematical model that governs the monitored process. Kalman filters (Frank et al 2000) are probably the most popular model based techniques for failure prediction and diagnostics. The advantage of Kalman filter resides in their recursive update form which makes it computationally and memory efficient. In fact, Kalman filter relies on the last measurement in order to create an estimate of the state of the system and does not consequently require storing the whole historical data of the process.

Residual based methods (Gertler and Monajemy 1995) resort to the concepts of residual generation which represents the difference between various functions of the outputs and the expected values of these functions under normal (no-fault) conditions. The procedures for residual generation vary from hardware redundancy (voting schemes) to complex state and parameter estimation methods.

The following industrial cases are presented in the sections to follow; Condition monitoring of pipes, Condition monitoring of valves, Condition monitoring of heat exchanger tubes, Water leakage detection & control and Failure prediction of hydraulic systems.

2. CONDITION MONITORING OF PIPES

One of the industrial cases reported in this paper is about condition monitoring of pipes belonging to a plant in the process industry. The objective is twofold: to perform cost-effective condition based monitoring, and to fulfill government imposed rules about health, safety and environment.

In the case studied, the company has a large number of pipes in use, with an accumulated length of many kilometers. For pipes carrying hazardous substances, condition monitoring is mandatory. The owner of the plant is responsible for a safe operation, and has to come up with adequate procedures. This chapter describes an effort to meet these requirements. The majority of the pipes are thin-walled, most of them with 3 to 6 mm wall thickness.

The methods considered, in addition to visual inspection, are ultrasonic wall thickness, x-ray, and pressure testing. For the critical pipes at this plant, acceptance criteria for wall thickness loss after ultrasonic inspection are defined as follows:

- 0-5% is OK within measurement uncertainty.
- 5–10% Increasing attention during subsequent inspections.
- >10 % Physical check-out, disassembly, X-ray inspection, replacement.

A plan for measurement points has been made, limiting the total number of check points to 1000, taking into account the consequences of leakage, and experience with location of problem spots. Locations at the pipes with highest flow velocities have been chosen, such as the outside of pipe bends, and especially bends immediately downstream from pumps, see Figure 2.

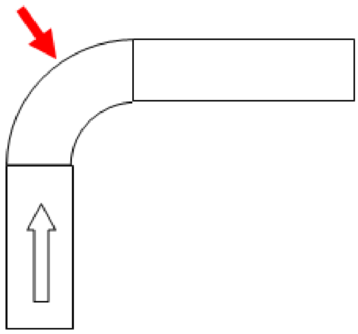

Figure 2: Location of inspection points at the outside of a bend.

Also, points for inspection are selected downstream from reductions in cross-section, near the first weld, where the flow velocity is increased, see Figure 3.

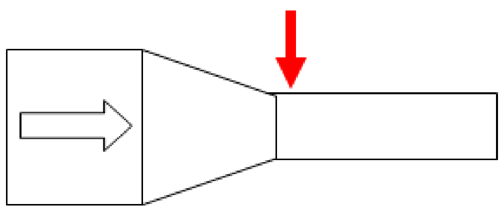

Figure 3: Location of inspection points after reduction in cross-section.

With completely fluid-filled cross-sections, points are selected at the top, bottom and on the sides (at the 3, 6, and 12 o'clock positions), see Figure 4.

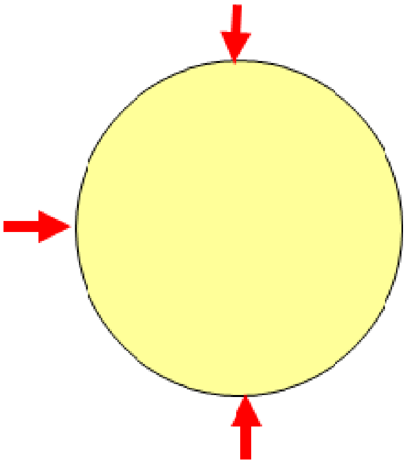

Figure 4: Location of inspection points for completely fluid filled pipes.

With partly filled pipes, inspection is made at the bottom and at the normal liquid level, see Figure 5.

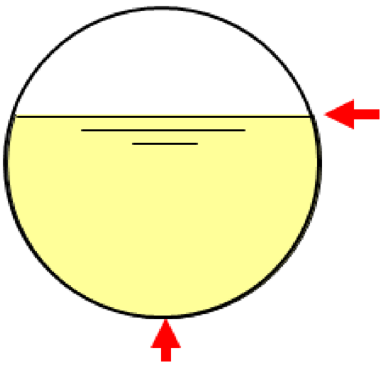

Figure 5: Location of inspection points for partially fluid filled pipes.

At water locks, several points along the axis near the bottom are chosen, and with bends in the vertical plane trapping air, the first point in the flow direction near the liquid to air contact is chosen, see Figure 6.

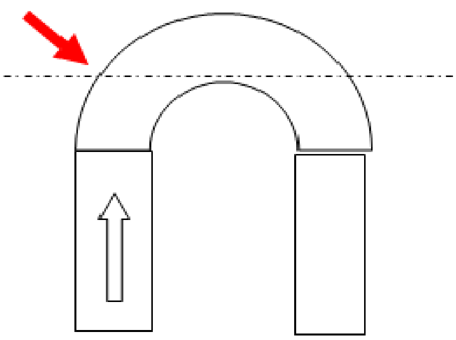

Figure 6: Location of inspection points at air traps.

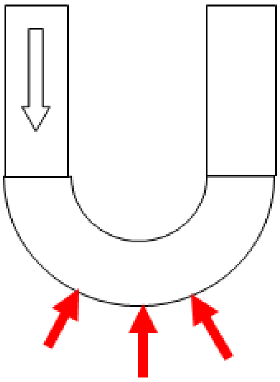

Figure 7: Location of inspection points at water locks.

These points are marked, as shown in Figure 7, after inspection in order to compare subsequent measurements and make trend plots for close checking of material loss in the 5 – 10% range. Even an inspection plan of 1000 points is a formidable undertaking. Results shall be archived, and the measurement locations should be marked very precisely for subsequent inspection and comparison.

Pressure testing should be avoided, since it could lead to leakage of hazardous material and exposure of humans. In cases with harmless fluids it can be used if care is taken to protect the operators well.

2.1. Ultrasonic wall thickness measurement

For the wall thickness measurements, the primary method used is recording of travel times for pulse-echo ultrasonics (NDT Handbook). This means that a short pulse train of ultrasonic energy is generated and transmitted from a piezoelectric transducer, and the instrument switches to listening mode after a short dead time. An echo of the transmitted pulse is then detected when the input level rises above a manually or automatically set threshold, or the detection can be based upon the time difference between multiple echoes travelling back and forth between the front and back wall several times.

The length of the pulse train and the minimum dead time determines the minimum wall thickness that can be measured. The time difference between multiple echoes gives a better estimate of wall thickness than the time to the first echo, provided that the subsequent echoes are strong enough.

The above case, with wall thickness 3 to 6 mm, and a goal of detecting a 5% material loss, requires fairly high-frequent and wide-band ultrasonic signals. Ultrasonic transducers should be selected for having well damped, short pulse trains. The center frequency should preferably be above 5 MHz with a pulse signature consisting of less than 2.5 oscillations before the signal is reduced to below 20% of the maximum amplitude. This corresponds to a 0.5 microsecond pulse length, which with good margin ensures a minimum detectable wall thickness of 1.5 mm, given an approximate sound velocity of 6 mm per microsecond.

Other methods, such as autocorrelation and inversion methods can also be used to find the desired time differences, and may give more accurate results than estimating ultrasonic travel times from simple thresholding of the received pulse amplitudes. These methods require more skilled signal analysis, but will give more precise results, especially with repeated surveys after a certain time interval, e.g. 6 or 12 months. To gain the most from repeated measurements, the same probe should then be located at exactly the same position as the first measurement, not only close to a point marked by a pencil, but preferably guided by firm side supports glued to the pipe.

For location of cracks or bad welds, there are other ways to configure ultrasonic inspection, using two or more transducers, or using non-normal angles of incidence. One of the principles used is then to direct the ultrasound away from the probe position, and if the material to be inspected is homogeneous and free from cracks, nothing will be reflected or scattered back to the probe. Reflected energy detected within a certain time window will therefore indicate defects located at a distance corresponding to this travel time.

Another powerful technique is called TOFD, Time Of Flight Diffraction. This method makes use of the full waveform of the ultrasonic pulses transmitted and received. The set-up is a separate transmitter and receiver, e.g. on each side of a weld to be inspected. The transmitter-receiver pair is moved along the weld and closely spaced recordings are made. The waveforms are plotted in grey-scale and interpreted in terms of diffraction theory, similar to wave optics. This makes visualization of small defects possible.

3. CONDITION MONITORING OF VALVES

When a process plant has a very high number of valves, it becomes a challenge to monitor them. Especially when valves are used to control critical fluids and even a small leakage in a valve cannot be tolerated, it becomes even more challenging. The following are the challenges in order to have online condition monitoring of valves:

- Too many valves of different types from different suppliers
- Different types of valves carrying different types of fluids
- Offline testing may be an option but it will lead to down time for the plant
- Predictive maintenance is preferred over periodic maintenance

To develop a condition monitoring system for valves, various aspects have to be taken into account. Suitable sensors are required depending on the type of valve, purpose of valve and criticality of valve for plant operation. Once the sensors are identified, an optimal wireless data logging system is required to collect data from the valve sensors, and to process and analyze a the data. Decision support system is to be designed to help operators identify a faulty valve with sufficient information; location of valve, type of fault, severity of fault, manufacturer with contact details etc.

4. CONDITION MONITORING OF HEAT EXCHANGERS

There are several commercial Non-Destructive Testing (NDT) condition monitoring methods available for heat exchangers; Ultrasonic testing, Visual inspection, Magnetic particle inspection, Helium leak test and Eddy current testing (Melingen 2010). All the techniques are briefly described, with more attention given to the Eddy current testing, as it is being used as the standard method by the company which presented the case.

4.1. Ultrasonic testing

A transducer sends a high frequency ultrasound pulse through the material and based on the reflected wave characteristics, the condition of the heat exchanger can be quantified. The advantages of ultrasonic testing are the following; it is sensitive towards both surface and subsurface discontinuities, the depth of penetration deeper compared to other methods, it can measure corrosion through thick walls, and furthermore it can also quantify the size of pits. However there some challenges to use this method; reliability of the method can be affected by poor surface finish, thick paint, and temperature. Only skilled personnel can perform the testing.

4.2. Visual inspection

Rigid/flexible fiber-optic boroscopes can give information about the condition of tubes/plates in heat exchangers. This method can be less expensive but it has its own limitations related to quantifying different types of faults.

4.3. Magnetic particle inspection

This method utilizes the magnetic properties of the heat exchanger material to detect a crack. The method is easy to apply and gives quick results. This method can be used for detecting cracks on the surface.

4.4. Helium leak test

Helium is used as trace gas in this method. The gas is pumped to the heat exchanger and a spectrometer is used to detect any leakage. It gives accurate results regarding the leak but it cannot be used to detect other faults than the leakage.

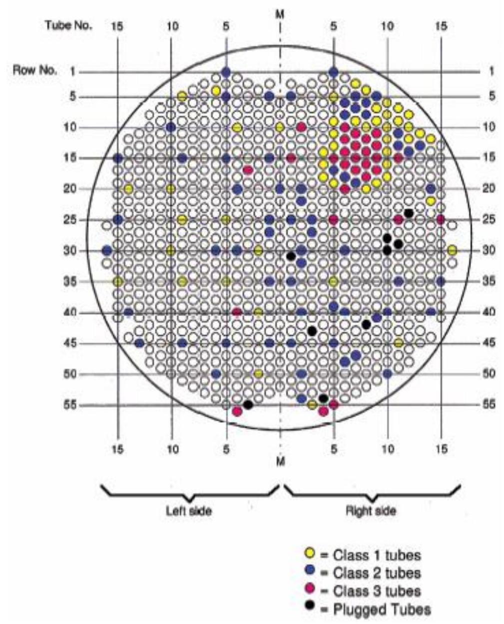

Figure 8: Decision support system from Force Technology

4.5. Eddy current testing

Eddy current based technology is being used to detect faults in thin heat exchanger tubes. The condition monitoring using eddy current based technology has several advantages, some of them are listed below:

- Very effective to detect cracks
- Gives immediate results
- Lot of data is available from test which can be analyzed to predict time for the next maintenance/replacement
- Portable equipment and contact-free
- The user interface system, for example from Force Technology (Force Technology) is very intuitive to find the severity of the fault and location of faulty tubes, see Figure 8.

However there are some challenges which are listed below:

- Calibration of the equipment is very specific to the material. Hence the equipment can only be used for inspection of particular equipment. If shall be used for other equipment, lot of calibration is necessary
- The results of inspection are sensitive to the thickness of the material.

Figure 9: Manifolds for cooling system at Eramet furnace. Ultrasound flow meters are mounted on the inlets and outlets, and water leakages are detected by investigating flow differences.

5. WATER LEAKAGE DETECTION AND CONTROL

In metallurgical plants, for instance Eramet Norway, it is necessary to handle molten materials in different unit operations. As the operating temperature can be as high as 2000°C, it is necessary to have a cooling system for the operating equipment and it is common to have water as the cooling liquid. In this circumstance, it is very critical not have any water leakage from the cooling system onto the molten material as the leakage would lead to explosions. Such explosions are of great concern for the safety of operators. Explosions caused by water leakage will also lead to equipment loss and possibly long term shutdown of the plant (even if the equipment is working, the plant may be shut down while the accident is investigated). The Norwegian government requires the plant to have a reliable system to identify, quantify and handle water leakages. The regulations also state that the water leakage alarms should be handled separately from other technical alarms due to the potential for serious dangers.

As the cooling system supplies cooling for different types of equipment, there can be a large number of water circuits. As a first measure to avoid leakages, it is important to use only clean water. This will minimize clogging and corrosion of pipes, and also ensure good cooling of the furnace hood. Monitoring of individual circuits for a leakage requires heavy instrumentation.

One system which was considered, but found unsuitable, was based on infrared imaging. IR images would be able to tell where a leakage occurs. However, automation of such a system is complicated, and since a large area has to be covered, many expensive cameras would have to be installed. Instead, a system has been implemented with two ultrasound flow instruments for each water circuit – one at inlet and one at outlet, see Figure 9. The difference in the flows at the inlet and outlet is compared to an estimate of the standard deviation over a specified time, to detect a fault. This statistical analysis is required to distinguish leak detection from measurement noise in a robust manner. Leaks down to 40 l/h can be determined using this method without or very few false alarms.

A good decision support system is designed to make sure that the leakage circuit is controlled/closed once a water leak is detected in a particular circuit. The flow instruments provide an opportunity to quantify leakages, and thus differentiate between critical alarms and alarms indicating small leakages, which do not require immediate action. These alarms are indicated by different colors in the HMI. The display observed by the operator also gives a clear message about which circuit is failing. It is important to train operators with operational procedures, what to do in the event of a water leakage in the cooling system corresponding to a critical equipment.

Overall the following are identified as the key challenges to have an optimal condition monitoring system for a process/equipment in the plant:

- Measuring key process/performance variables due to challenging process operating conditions
- Enough motivation for developing and implementing models for the application of fault detection and diagnosis
- Dedicating human resources for data analysis, and a challenge for a transformation from a more human control to less human control in process plants
- Optimal and intuitive decision support system design

6. FAILURE PREDICTION OF HYDRAULIC SYSTEMS

Off-shore industry relies heavily on hydraulic drilling equipment. Failure Prediction of hydraulic systems is an area of research which has recently attracted a considerable amount of research (Angeli and Atherton 2001). These systems are prone to wear over time leading to performance degradation and, ultimately, to failure. Due to the high cost of downtime in off-shore industry, detecting the wearing out of a component should take place at an early stage in order to avoid prominent failure.

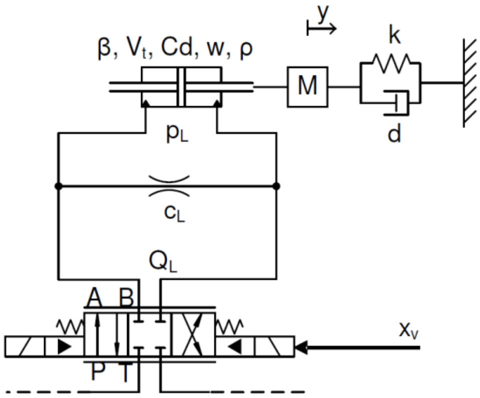

Figure 10: Nonlinear hydraulic-mechanical system with control valve and Nonlinear hydraulic-mechanical system with control valve and and hydraulic cylinder exerting forces on the object to be handled. Total load mass M, equivalent spring coefficient k and damping.

Too low forces in drilling operations might result in loss of grip while too high forces might jeopardize the drilling pipe. In a recent study pertinent to hydraulic drilling pipes (Choux and Blanke 2011), the authors devised an approach for prognosis that involves monitoring changes in two key parameters of the hydraulic system, namely leakage coefficient between the cylinder chambers and friction coefficient against the piston displacement. This stems from the fact that an increase of friction or the leakage coefficient lead to loss of grip. The nonlinearity of the hydraulic drilling equipment constitutes an inherent difficulty, which requires proper modeling techniques. In order to reduce the complexity of the nonlinear model, a general approach to decompose a nonlinear model into a linear hydraulic model connected to a mass-spring-damper system was introduced in (Choux et al 2009). Figure 10 is borrowed from reference (Choux and Blanke 2011) and depicts a nonlinear hydraulic-mechanical drilling pipe that is decomposed according the approach presented in (Choux et al 2009). Most of the legacy research resort to on-line model based fault detection techniques. In this sense, the current techniques are concerned with detecting deviation between the physical model of the hydraulic system (Choux and

Blanke 2011) and the real time data. To achieve this task, different online change detection techniques were employed including artificial neural networks (Muenchhof 2007), statistical abrupt change detection (Choux and Blanke 2011), Kalman filters (Chinniah et al 2008) and expert systems (Angeli and Atherton 2001).

CONCLUSIONS

Several industrial cases are presented in the paper with the focus of condition monitoring of equipment, failure prediction techniques and decision support systems. Further work will be focused on developing techniques for these specific cases with the cooperation of leading universities and R&D institutions.

ACKNOWLEDGMENTS

Authors acknowledge the participated industries for their support and contribution in this work. Further the financial support from Competence Development Fund of Southern Norway, Vest-Agder and Aust-Agder counties is acknowledged.

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