OPERATION WAS A SUCCESS, BUT THE PATIENT DIED – CALL FOR MORE ADVANCED PROCESS DIAGNOSTICS

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Abstract: The old cliché in the title of this paper is irritating, but describes all too well end-users' common experience of process diagnostics. Expensive tools are not in systematic use, exhaustive process models become outdated and information produced is scattered and detached from operational routines. At the same time, development of computational capability, information and communications technology and user interfaces, among other things, enable reliable easy-to-use hybrid diagnostic solutions to be made. In this paper, the topical need for modular, easy-to-use, situational and contextual process diagnostic approaches is discussed. Examples are given in the field of pulp and paper industry. Insight into process knowledge and its user-friendly representation in form of models and diagnostics tools, in particular, is provided.

Keywords: diagnostic, modelling, learning algorithms, multivariable systems

1. INTRODUCTION

Papermaking is a good example of today's modern production process. Paper production lines are efficient, flexible, reliable and highly automated. The number of personnel has decreased while the scope of individual responsibilities has widened. Production is scheduled as a part of the whole value chain and increasingly, optimised together with several production facilities. As a result, timely correct actions are extremely important for both human individuals through organisational functions as well as automated machines.

In the field of medical science, it is well known that sometimes an operation can be a success, but still the patient dies. This means that although symptoms are carefully diagnosed and a cause of illness is found, this does not always solve all the patient's problems. This analogy applies to the role of process diagnostics in modern papermaking.

Applications dedicated to mechanical condition monitoring, for example, have advanced significantly from helping to detect symptoms of an incipient failure towards supporting the diagnoses and action planning. However, papermaking is not only about mechanical vibrations. A mechanically very stable paper machine can still run poorly. The production is not only about wide scale process stability either. A very stable paper making line can still produce low quality paper or even pure waste.

A part of process automation and diagnostics development has taken place through advanced data integration, calculation capability and user interface possibilities provided by modern Information and Communications Technology (ICT) and automation system technology. The key issues behind the most remarkable sustainable development have been context and situation specific solutions with deeper knowledge of business processes, raw materials used, process behaviour, potential failures, effects of such failures and actions taken both to prevent the failures as well as to correct or repair them. In effect, models of the process and human behaviour have been incorporated into automated solutions.

The present authors propose that process diagnostics should be approached from a holistic, contextual and situational viewpoint. Modern process diagnostics should more support the focal actions, and less provide an additional, nice-to-know layer of information (c.f. Happonen and Koiranen, 2004).

2. UTILIZATION OF DESIGN KNOWLEDGE AND MODELS FOR DIAGNOSTIC PURPOSES

Process models can be considered at several levels. At unit processes and equipment level, physical and chemical models are valuable. Detailed design of material flows and mixing can be done, for example, with Computational Fluid Dynamic (CFD) models and simulations. Based on this, also simplified models for dynamic simulators can be created. Today, dynamic simulators are often used in designing automation and control tasks for unit processes. They are also needed in designing and tuning of multivariable, predictive controllers.

Regardless of modelling method selected, designing of the process sets up a nominal performance limit that cannot be improved without changing the design. The holistic design of disturbance elimination typically requires optimisation of task distribution between process and machinery design and control design. In the mixing process of a paper machine, for example, consistency disturbances could be managed through a holistic approach to process and control design. In reality this potential is often neglected (Kokko, 2002)

Regardless of designed target level true process performance will decrease from the nominal level because of such issues as actuator wearing, sensor fouling, other faults and also changes in operational targets. One of the main purposes of process diagnostics is to support the operators and maintenance personnel to maintain the process performance close to the nominal and to prevent and solve process problems more efficiently.

When process design knowledge, including the relevant models is fully available, it can and should be used for the benefit of process diagnostics. In many cases, however, this is not possible. Often the target process is so old that the design knowledge is outdated, lost or it never even existed in explicit form for certain process parts. In many cases process and machinery design have been divided to many suppliers. In such a situation the available design knowledge is a function of many partial optimisations. Typically this kind of shared design does not give optimal performance although it may give minimum cost estimate while ordering.

It is well known in the literature (e.g. Venkatasubramanian, *et al*., 2003) that the process diagnostics sets slightly different criteria for process models than process design and control tuning tasks.

In particular process models needed in diagnostics purposes should be:

- contextual to be able to acknowledge process conditions;
- adaptive to keep the model up to date, to reduce configuring work and to detect new faults when the old ones still exists;
- informative to give the information needed about the situation;
- dynamic to deal with process transitions and with production changes;
- easy to duplicate for large amount of similar process components;
- stochastic to deal with noise and inaccurate process models;

These requirements can be derived from the needs of end-users. In order to be useful a diagnostic solution has to be smart enough to take circumstances and other explaining issues into account when supporting decision making. The user of a diagnostic tool should also be guided into the right direction towards the actual reason.

Even if the simulators and models developed at design phase could not be utilised in diagnostics, the design knowledge is still valuable while configuring the diagnostic tool. It is important to know how to divide the complex process into logical unit processes, to be able to list all the key components in various unit processes, to know how to diagnose them and to know the criteria between good and deficient performance. The authors maintain that it brings significant benefits to apply a-priory knowledge of the most critical unit processes or the most probable sources of faults compared to methods utilising pure data mining techniques.

3. DIAGNOSTIC PROCEDURE IS THE BASE FOR DIAGNOSTIC SOLUTIONS

Human understanding is largely based on understanding social, contextual meanings (Happonen, *et al*., 2003). Such meaning structures are, in effect, continuously updated models. Similarly, reliable and useful process diagnostics is based on "shared meanings" within the whole target process, including such sub-processes as mechanic, thermodynamic, hydraulic and human processes. It is important that the diagnostic system supports the human way of understanding these complex structures.

A typical first step in a process diagnostic routine of a production process is to detect that the process behaves poorly. The next step is to describe the symptoms of the fault. Already based on the symptoms, an experienced individual may recognise the situation and immediately knows what to do. If the situation is unknown, mill personnel need to investigate the situation to find out reason for poor operation. First the mill personnel need to make sure that raw materials are good enough, the process is operated correctly and other general conditions are fulfilled. Then the production line is divided into smaller unit processes according to the symptoms and verified whether or not they are behaving normally. In this point the reason is identified to be in the process or somewhere else.

If the fault is identified to be in the process, it is tracked into a replaceable or repairable component. The component can be, for example, a physical part like a bearing, a piece of software or device like control valve. Figure 1 illustrates how to track faulty component from a complicated process. The process is returned into normal operation by changing or repairing the right components. If the fault is identified to be somewhere else, there is no need to investigate this particular process.

The key design principle of diagnostic tools is that they should support mill personnel in diagnostic procedure by investigating automatically and continuously such key process elements as usage, raw materials, field devices, control loops, unit processes and the automation system itself.

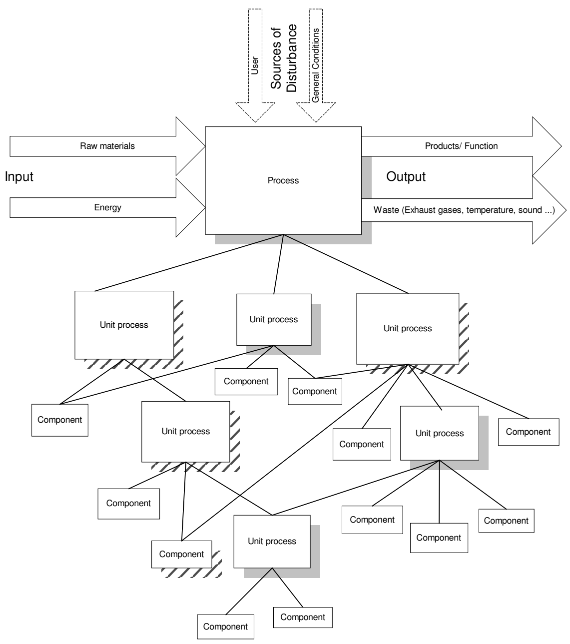

Fig. 1. An example how to track a fault in complicated process to a replaceable or repairable component. One faulty component may affect to several unit processes.

This design principle differs significantly from tools associated with earlier diagnostic systems utilising artificial intelligence, for example. Such systems often focused on automating functions that were earlier done by mill personnel. As a result, and often due to technical limitations, such systems were mainly able to provide information that was self-evident to users, but could not help in new or complex situations.

It is relatively easy to make a small-scale diagnostic solution focusing on certain limited part of a process but as the history shows, it is extremely challenging, but not impossible, to create a fully automated, holistic diagnostic solution for larger process entities. As discussed in the previous sections, a good starting point is that a significant amount of the information needed in diagnostics is already available in the process design phase.

4. EXAMPLE OF A HOLISTIC VIEWPOINT - PROCESS DIAGNOSTIC AND MONITORING TOOLS

As well as a diagnostic procedure can be divided into alternative paths and components; the same approach can be inherited into wide-scale diagnostics systems. A control valve or a pump, for example, can have a well-defined, unique role in a process. A number of control valves, however, have also several common types of performance criteria. As a result, it is beneficial for an easy-to-use diagnostics system to dedicate a diagnostics module for such a sub-system as control valves or pumps.

Traditionally sophisticated diagnostic tools and condition monitoring has mainly been available for rotating machinery and expensive devices. During the last ten years solutions have increasingly been developed also for intelligent field devices, basic control loops and DCS itself. Also various tools and expert systems based on advanced methods have been developed (Chiang, *et al*., 2001, Venkatasubramanian, *et al*., 2003). These systems are based on advanced mathematics like PCA, soft computing or frequency analyses.

A new generic approach introduced in this paper makes it possible to add unit process level and traditional field devices into the domain of diagnostic and condition monitoring in a unified, holistic way. These diagnostic tools and methods together automate the diagnostic procedure by monitoring all devices at every level of the process hierarchy continuously. Diagnostic information generated by different applications become useful when it is integrated using well-known integration techniques e.g. XML to create a plant wide diagnostic and condition monitoring application.

This kind of application tells continuously to the user how different process components at different hierarchy levels are performing. When there is a problem, the application can show all poorly operating components at different process levels. This way it is easy for a user to see what components might be responsible for problems detected at high-level indicators and what parts of the process are affected. The criticality of the situation is visualised by how the fault affects to the upper level indicators.

This kind of diagnostic approach is inherently modular. A successful configuration of such a solution requires knowledge about what tools and methods to use with different kind of devices at different hierarchy levels and what measurements are needed for successful diagnostics of different kind of devices. In principle, any proven traditional method for a certain need could be accepted. In practice, the present authors maintain that the holistic viewpoint taken increase awareness of end-user needs. As a result, also new methodological improvements are presented.

5.NEW METHODS FOR MODELING AND DIAGNOSING UNIT PROCESSES IN ORDER TO REDUCE COMPLEXITY

Several manufacturers of process industry equipment provide monitoring tools for their devices and unit processes. By taking these tools into active usage, it is possible to obtain condition monitoring for the most common and most critical devices.

However, as discussed above, there are several reasons why the utilisation of condition monitoring of processes typically stays far below 100%. The main reason is perhaps complexity; there are few standards and this, in combinations with numerous different devices and manufacturers, makes life difficult for plant personnel.

With general condition monitoring tools we can monitor devices that have previously not been monitored. However, existing general tools sometimes require tailor-made calculations, or detailed models, some algorithms employ complex algorithms with advanced mathematics, they may be operating-point specific, and they are often difficult to understand from plant personnel's point of view. Principal Component Analysis and Partial Least Squares, for example, are well known methods for academics and specialists, but too often tools utilising such methods require knowledge of mathematical analysis.

Simple methods that measure distances to alarm and warning limits are sometimes problematic and even misleading. They frequently tell more about the way a device is operating rather than the performance of the device.

The selection between data driven and analytical condition monitoring is challenging. Full data driven methods are problematic, since they require iterative learning and on-line experts in the interpretation of alarms and results. On the other hand, analytical methods (e.g. first principle modelling) tend to require too much expert work during start-up.

Multivariable Histograms (Fig 2) is a model structure that is well suited for monitoring purposes. It is open, non-linear, stochastic, and simple. Moreover, multivariable histograms model is suitable for on-line calculations, since model training is extremely simple being adding observations to histograms. Another important feature, forgetting, is also easy to apply on this model structure.

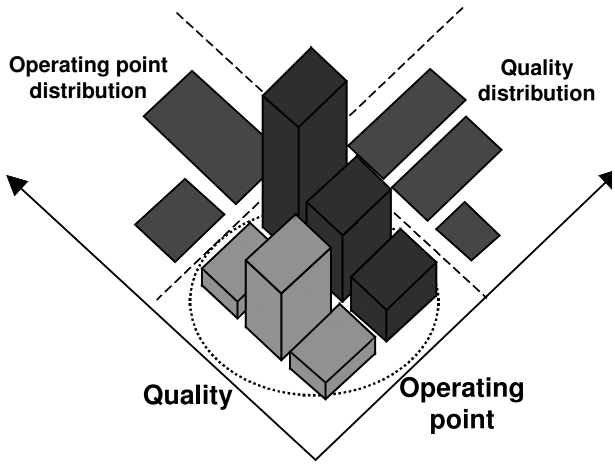

Fig 2. A multivariable histograms model consists of one monitored variable (e.g. quality) and explanatory variables (e.g. operating points).

Based on the multivariable histograms model structure, we developed a method for condition monitoring, called Conditional Histograms Monitoring (CHM). The name refers to the way the method evaluates performance: the measured quality, which is a histogram, is compared to a conditional histogram. The conditional histogram is evaluated from the reference model, conditionally from the current state (Friman, 2003). CHM is one of the key components in the diagnostics; in particular in ensuring those low-level components are working properly.

A CHM monitoring task employs two models; the first model represents long-time performance, and the second short-time performance. The two models are updated in the same way, but a forgetting factor is applied for the short-time model. By comparing the two models, we obtain the difference in device performance for actual compared to long-time operation.

For similar devices, it is useful to employ a common model for describing long-time performance. Hence a reliable model is quicker obtained.

In order to incorporate process knowledge casual relationships are utilised. This means that each variable is selected as either dependent or explanatory. For process experts, explanatory variables and casual relationships are usually trivial, but they bring intelligence into the model, something that cannot be obtained from measured data sets. By connecting CHM monitoring blocks into a hierarchical structure, where a dependent variable in one monitoring block is an explanatory variable in the next process stage, we obtain an intelligent structure, which is useful for diagnostics purposes.

During normal monitoring, one single trend for each device is monitored. The trend tells the percentile (0-100%) of each monitored signal, with extreme values 0% and 100% meaning that the entire short-time distribution is below or above the conditional distribution. Trend values close to 50% means that actual distribution and conditional distribution overlap, i.e. the device is working consistently. When the level of percentile trend has significantly changed, detailed reports may be requested. First we may check the distributions of explanatory variables; i.e. we check if the way of operation has changed. Then we normally investigate, which are the operating points that work poorly.

CHM has proven its capabilities in condition monitoring of various devices including pumps, fans, heat exchangers, and valves. It is a general method and there are no limitations in device types that can be monitored. Its flexibility compared to mass-and-energy-balance calculations has proven to be very useful. Very often some key measurement is missing, but some indirect measurement can often be used. For example, levels can sometimes replace pressure measurements; electric current can replace electric power measurements for monitoring purposes. Due to flexibility, almost any device can be monitored, and due to simplicity the method has been well received since histograms are informative and easy to understand.

6. EXAMPLE CASE: A PULP DRYING MACHINE

An automated, process wide diagnostic system was recently installed in a pulp-drying machine (Huovinen, 2004). For diagnostics purposes, the process is divided into logical unit processes, such as stock preparation, short circulation and drying section. Each of these units is further divided into the most important control loops, process devices, and other available measurements, which are monitored with, appropriate diagnostic tools and methods.

At the same time, unit process specific and process specific performance indicators are calculated independently. These indicators include such measures as productivity, energy consumption, quality indicators and their deviation, calculated efficiency and other application specific variables.

The information produced by low-level diagnostic tools and higher-level performance calculations is mapped together and visualised to the user with a traffic light tree (Figure 3). The topology of the tree is based on the hierarchy of the process, so it is easy for the user to understand where the fault is and how it affects into different parts of the process. The colour of the traffic light tells the status of the monitored component. The main objective is to visualise the diagnostic information same way despite the method that produced it and "hide" the complexity of the different diagnostic tools and methods from the user. The traffic lights are updated continuously, so user has real time view of the diagnostic results.

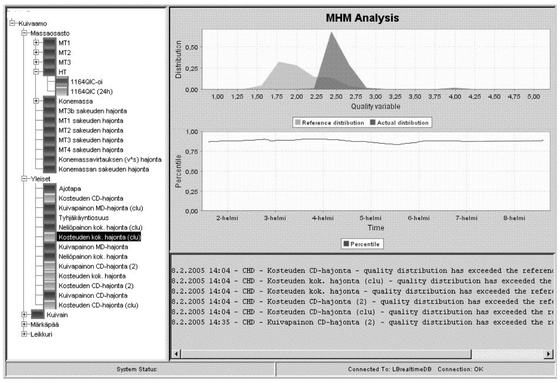

Fig 3. A traffic light tree makes it easy to utilise the information provided by various diagnostic methods. A Condition Histogram tool shows that the cross directional deviation of moisture has increased.

Each diagnostic module has a method specific display that gives more information to the user about monitored component. This information is, however, needed only when there is something wrong with the component.

In traditional diagnostic solutions, the values of performance indexes typically depend strongly on changing circumstances like production speed and different product qualities on the process rather than "real" performance of the process. However, these circumstances are normal and recurring. Therefore, common operation points can be identified from process data using clustering method (Hietanen, 2003, Nyuan, *et al.*, 2004). When the operation points are known, it is easy to create a multivariable histogram model between operation point and measured process performance.

This way it is possible to eliminate the disturbance caused by changing circumstances and to reveal the real process performance. Model structure of the conditional histograms also reveals those operation points where the performance is not acceptable.

The installation described here is used by a service organisation and it has already proven itself useful, not only as trouble-shooting tool, but also as an early warning system and research instrument when optimising the process performance. For example, knowledge about dependency between operation point and performance indexes allows unfavourable operation points to be avoided as much as possible.

In Figure 3, for example, the diagnostic system reports that conditional histogram analysis has detected that cross directional deviation of moisture at the end of the drying machine is bigger than before at the same operation point. This means that web moisture is higher at the other edge. This is not yet serious but badly tilting moisture profile will cause problems at the cutter and layboy. However, thanks to the diagnostic system, the plant personnel can be alarmed about the situation and they can solve the problem before production loss takes place.

Normally high-level performance indexes are the only interesting variables and they are closely supervised. However, developing faults are often visible in secondary measurements telling how the system affects to its environment for a long time before it has any effect on production. For example sound, mechanical vibration, energy consumption, temperature or waste may tell a lot about system health if they are interpreted correctly.

By monitoring primary quality variables only, developing faults cannot be detected until these variables are clearly affected, because the control system tries to keep the quality variables constant as long as possible. This kind of situation means production losses, because low quality product cannot be sold with good price. This is why also low-level diagnostic is needed: to detect faults already before they affect to quality variables and production.

7. CONCLUTIONS

Today, if process knowledge, new methods and intelligent integration of various diagnostic tools are utilised, it is possible to implement a comprehensive, holistic automated diagnostic system. The main benefits come from user-oriented integration of diagnostic tools and, thanks to the new methods, flexibility to increase the amount of equipment in the domain of condition monitoring.

Through application integration, a computer can process this information and make a compact easy to read summary for the user. This means that the domain of process diagnostics is changing from separate applications to comprehensive and useful system helping plant personnel to plan maintenance activities and to solve process problems as well as to increase the performance of the process.

Today the amount of measured variables is increasing rapidly. Automation systems can collect and process huge amount of data compared to earlier systems. At the same time process operators has to take care of much wider process areas than before. There is an increased need to assist operational personnel in process and device monitoring.

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