Insight into the basic techniques and special challenges associated with the application of automatic diagnosis to critical rotating equipment

Machine diagnostics that consider both process and condition monitoring data yield superior results: Concepts for developing cost justification with machinery monitoring

The past 20 years have seen continuous progress in the technological means available for monitoring the condition of Rotating Equipment. For years, machine protection relied almost exclusively on indirect state, or condition, variables such as vibration. Yet, more recent systems have been taking account of direct mechanical state variables such as piston rod position or thermodynamic variables like pressure volume (p-V) curves for e.g. reciprocating compressors. This is no longer being done exclusively for the purposes of machine protection, but in order to gain the most comprehensive information on the condition of a machine and its components.

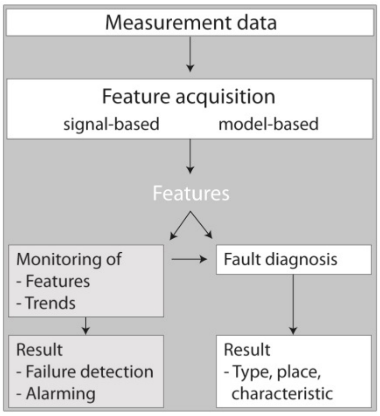

Fig.1: Diagnosis process diagram

Traditionally, the role of machine protection is to prevent damage to components that occur between scheduled maintenance inspections from causing catastrophic damage to a machine. Maintenance personnel will shut down a machine and disassemble it to get a comprehensive idea of the state of its components. In such cases, machine protection parameters are usually only determined based on a single threshold value, so that the only available information is either the 'OK' or the 'Alarm' status. The operator often lacks any information whatsoever on how the parameter used for machine protection purposes is trending. For example, he or she may not know whether the machine is operating at levels close to or well below an alarm threshold. Yet many machine operators are now unsatisfied with these kinds of basic safety mechanisms, where only a single variable (for example, frame vibration) is analyzed. At the very least, machine protection parameters in the 21st century should be recorded in such a way that their evolution overtime (trending) is discernable. To be able to derive added value from ongoing analysis, a measured variable's curve has to be evaluated, and machines usually have to be equipped with a finer net of sensors to obtain information on the condition of as many components as feasible.

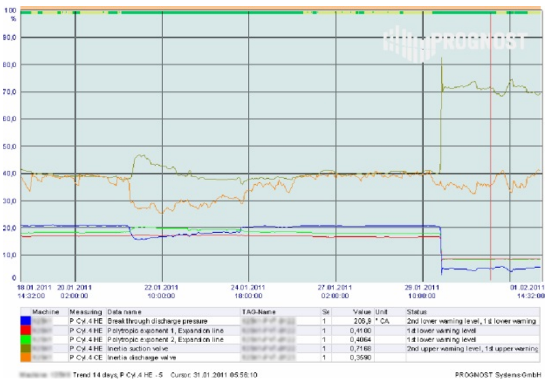

Fig.2: Plot of characteristic p-V values

Ideally, the state of any component can be judged based on a single parameter. The state of a bearing, for example, could be determined solely and unequivocally based on its temperature. However, this is impossible to do in many cases, so instead various parameters are monitored to obtain the greatest degree of certainty on a machine's state. The more complex a machine, and the more components need monitoring, the more parameters are drawn into the picture.

The problem is that increased numbers of measurement variables and analyses also make the interpretation of parameter developments more difficult. Often, an expert needs to be brought in to reliably interpret the plethora of monitoring parameters and assess a machine's state. Proper instrumentation, often referred to as an 'expert system', is likewise required.

This is where automated diagnosis systems come into play. These systems provide the expert with a kind of 'artificial intelligence' that can automatically diagnose a machine based on the data monitored. The level of detail included in the diagnosis (for example, in terms of which component is faulty and possible remedies) will depend on the number of parameters being monitored and on the quality of the diagnostic method.

In recent years, PROGNOST Systems, in collaboration with operators, has acquired extensive experience in the area of implementing diagnostic systems, ascertaining that certain diagnostic methods prove to be more effective than others.

Diagnostics

In the modern world, the term 'diagnosis' is widely used in various different disciplines. Originally, 'diagnostics' (from "*dia*": through, throughout, separated; and *"gnosis*": knowledge) referred to the process of acquiring knowledge for the purpose of distinguishing between objects. The term is often extended to mean not only the process of identifying features but also the adoption of measures.

Machine diagnostics can also be understood in this way. The purpose of technical diagnosis is to detect faults early enough to be able to infer suitable corrective measures, thereby increasing a system's safety, availability, lifespan and reliability, while also minimizing maintenance and operating costs. A fault refers to a deviation from a normal state, either on account of operational conditions or failures, outages or defects.

A clear distinction should be drawn between *machine diagnosis* and *machine monitoring* or *analysis*. In machine diagnosis, data collected by machine monitoring systems is evaluated by referring to the typical features associated with (incipient) faults. The quality of this diagnosis depends on two factors:

1. The measurement data collected (type, number, location)
2. The method used for feature acquisition

At the feature acquisition stage, features relevant to fault detection are extracted from the multitudes of measurement data collected. The fundamental assumption in this methodology is that changed features will also reflect any fault, i.e. that a defect will indeed cause a change in at least one of the parameters.

Signal based and model based methods

Signal based methods apply signal analysis to measurement data in order to derive features that will serve as diagnostic indicators for certain types of faults. *Model based* processes make use of mathematical models to exploit existing correlations between measurable signals. Feature characteristics and their variations arrived at by means of signal or model based methods (for example, an instance where different temperatures are recorded for two bearings identical in type) are checked in the context of threshold monitoring to see whether they fall outside tolerance ranges, thereby providing a means for detecting faults. In fault diagnosis, faults are identified on the basis of symptomatic deviations in feature characteristics with respect to an 'OK' state. This often gives rise to a

classification problem, as symptoms are classified into individual fault categories. This classification might be achieved by traditional statistical pattern recognition methods, or by knowledge based methods that apply “Fuzzy Logic”, or using “Artificial Neural Networks” (ANN), etc.
Diagnosis of a fault involves determining type, location, causes and consequences, along with projections on how the deviation might evolve and suggestions for appropriate corrective measures (maintenance) to be undertaken.

Automated diagnosis and pattern recognition methods

There are various methods used in automated diagnosis. Pattern Recognition refers to methods for detecting regularities and similarities in a data set. This method is a higher cognitive system and is under scientific investigation in the IT field. Processes are under development whereby measured signals are automatically classified into categories. These processes are based on pattern recognition, i.e. the recognition of features common to all objects in a given category (damage pattern), which distinguish them from the objects in other categories.

There is also the Fuzzy Logic method. This pattern recognition method was developed in the 1960s under the name *Fuzzy Set Theory*. It allows for the processing of less precise, fuzzy features, using qualifiers such as 'a little', 'more or less' or 'quite' rather than precise inputs like 'warning yes/no'. Before the theory was developed, objects belonged to clearly defined groups; they either belonged to a set or they did not. Fuzzy sets allow us to model the degree to which a given object belongs to a set. The degree of an object's inclusion in a set can be expressed with statements like 'true most of the time' or 'not true at all'.

An innovative mixture of “Fuzzy” methods with “Pattern Recognition” is the PROGNOST® “Confidence Factor” to detect damages on gears and rolling element bearings. Confidence Analysis is a “blurred” or “fuzzy” pattern recognition technique that quantifies the similarity of the measured vibration peaks to the expected fault peaks. The Confidence provides a strong indicator of whether a measurement really does represent a real fault or damage. If the Confidence is low, it most likely means that the specific fault is not present, but if the Confidence is high, then it is likely that the fault indicated is real.

Artificial Neural Networks are computational models whose structural and functional aspects are conceived along the lines of the neural networks of living organisms. By skillfully interconnecting large numbers of simple electrical circuits (neurons) in a network, these models aspire to achieve computational power comparable to that of the human brain. The concept is applied to situations where little knowledge is available on a problem that needs to be solved. An example would be facial recognition systems, where data from public surveillance cameras is automatically matched against a visual database of persons wanted by the police. ANNs are also found in measuring and control technology, where they might be used to automatically set threshold values after having generated a forecast of how the monitored process will evolve.

The basic idea behind Rule Based diagnostic systems is to collect and process knowledge and represent it using 'if (antecedent) and 'then' (consequent) operators. Rule based systems consist of a database of facts, the rules and a system of control. Control systems are designed to identify suitable rules, to apply selected rules and to update the database.

Rule based diagnosis

One of the problems with using 'hard and fast' rules is how to leave an allowance for a machine's operational fluctuations, specifically variations in operating conditions and loads. Such rules need to be precisely defined, with a separate set of rules developed for each operating status. This is because a certain level of vibration might be fine for operating state 'A', but might represent a fault while in 'B' state. Giving equal weighting to all the features of a rule set (for example, three features, each receiving a weighting of 33%) would not be an accurate depiction of reality, since each variable has to be weighed differently.

For example, increased vibration levels on compressor cylinders are a 'more reliable' indicator of impending damage to a valve than the pressure readings taken at the suction and discharge manifolds. Despite this, these features usually receive equal weightings. Assigning pressure readings and cylinder vibrations equal weightings of 33% (as would be done using rule based methods) is a distortion of reality, since pressure readings only start to deviate in the event of a significant valve leakage, which might result in an erroneous diagnosis.

Another hurdle concerns the monitoring of the sensors installed in the machine: namely, ascertaining precisely which physical variables will be available in the form of measurement data. It is also important to note whether the system features pressure sensors; if not, the diagnosis must run without them. In any event, a given set of rules has to be individually tailored not only to the various operating states but also to the machinery available.

One thing all diagnostic methods share in common is the fact that whether they are acceptably accurate will always depend on the availability of a certain amount of data. Lack of long term trend data (for example, on account of a machine being taken out of operation as soon as its measurement data starts to deviate from the norm) will compromise the accuracy of a diagnosis or even preclude automated diagnosis altogether. This is why

PROGNOST® systems do not perform automatic diagnosis in the event of emergency shut downs, since they usually mean that only data from few rotations is available.

Diagnostic methods for reciprocating compressors

A reciprocating compressor's operating principle and flexibility present difficult problems in terms of automatic diagnosis systems. Compared to other rotating equipment, reciprocating compressors involve greatly varying stress levels for many components.

1. While the crankcase predominantly contains rotating parts, the section from the crosshead slide to the cylinder contains only oscillating components that are either in constant motion, like the piston, or else parts that are engaged only cyclically, like suction and discharge valves.
2. There are many ways to flexibly adjust throughput (the quantity of compressed gas) to suit the requirements of a given process (load control), from regulating rotation speed, to clearance pockets, to step less valve unloader systems. All control variations have a great impact on the measured data used for diagnosis.
3. Gas compositions may vary while machines are in operation. The impact of differing molecular weights for different gases on the way a machine behaves is often detected by the monitoring system.

All these underlying conditions, from step less unloader systems to pulsations, give rise to physical phenomena that would need to be taken into account by the monitoring system. In order to rise to the aforementioned challenges, PROGNOST Systems GmbH developed in their PROGNOST®-NT automatic diagnosis system for detecting operating conditions that affect the measurement data used for diagnosis. This was done to ensure that automatic diagnosis is also available for machines with varying load steps. In addition, automatic functions for setting threshold values that form the basis of pattern recognition have been improved. Initially, the traditional pattern recognition method involving saved patterns was used exclusively, but the introduction of fuzzy logic methods allowed for superior diagnosis classification. It was possible to apply the two methods to all damage categories and benefit from both of their advantages. In the case of some damage patterns, such as loosened connections giving rise to mechanical clearance between piston rod and crosshead, the addition of rule based diagnosis has made it possible to further increase the probability attached to a given diagnosis.

Technology in action

The following example illustrates the case of a reciprocating compressor in a refinery in hydrogen service. The machine is monitored by a separate acceleration sensor for each crosshead slide and cylinder, and is also capable of p-V diagram analysis with dynamic pressure sensors. p-V curves are monitored for more than 10 different parameters, the most significant five of which are shown in Figure 3.

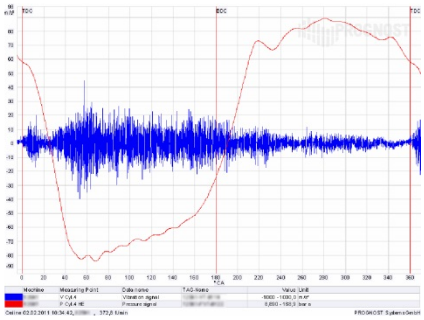

Fig. 3: Time signals for one revolution showing vibration acceleration and dynamic pressure of a reciprocating compressor cylinder

Figure 3 clearly shows that the figures shown for cylinder four registered only slight changes over a two week period. However, throughout 29th January 2011 radical changes began to be observed. The pressure curve measured is given in Figure 4, which also shows the vibration acceleration measured on the cylinder.

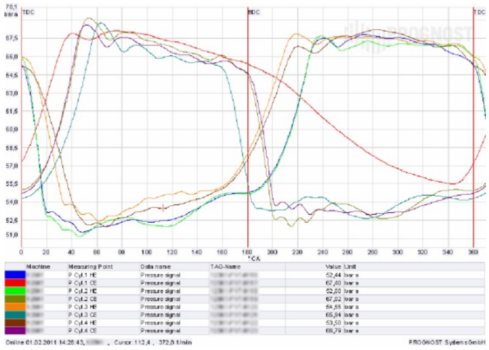

Fig. 4: Dynamic pressure curves for all 4 cylinders over one full revolution, clearly pointing to a damaged discharge valve

At first glance, there does not appear to be anything out of the ordinary about the signals. The only things of note are the increased vibrations at crank angles of approximately 40 - 210° and the relatively large pressure differential to suction pressure during the early intake phase. Yet there was already an automatic diagnosis based on this information.

Based on the available information for cylinder four, the PROGNOST® system diagnosis module detected a fault in the 'sticking suction valve' category. There was an additional diagnosis report, pointing to a damaged discharge valve on the crank end side of cylinder one.

IMP…	01.02.2011 14:24:00	125K1	Cyl.4	Damage class: 'Sticking Suction Valve, Head end', Cylinder 4 correlation: 61.0 %
IMP…	01.02.2011 14:24:00	125K1	Cyl.1	Damage class: 'Damaged Discharge Valve, Crank end', Cylinder 1 correlation: 60.3 %

Fig. 5: User notification

The rate of coincidence with all the patterns available for the “Sticking suction valve” category determined using fuzzy logic methods was 61 %; for “Damaged discharge valve” it was 60.3%. This figure reveals that the system only detected a limited number of features belonging to this particular damage category. Therefore, it could be concluded that the damage is still in its early stages. Yet experience has also shown that in the case of a low coincidence rates of below 80% there might be crossovers into different damage categories; in other words, the diagnosis is not precisely defined at this point. However, a glance at the dynamic cylinder pressure curves for all the cylinders a few minutes later clearly confirms the diagnosis concerning the cylinder one discharge valve. The pressure curve exhibits almost no re-expansion and fails to reach suction pressure levels. Based on an inspection of the valves during the following machine stop, the diagnosis of the sticking valve could also be confirmed due to the level of greasy substances found in the valves. A sticking valve is often the earliest phase of a future valve failure and should proactively be replaced prior to a complete failure.

This second example is based on the above mentioned “Confidence Analysis” with the results of the signature calculation and the confidence graphed in a “Confidence Plot”. The plot is a data mining tool to identify false alarms and faults which are present but still are in a good status (False Pass). The signature amplitude is normalized relative to the threshold values and the amplitude is plotted vertically and the Confidence horizontally. The plot is populated with the most recent amplitude / confidence pairs for each signature in the database. This plot is a convenient method to display whether a significant signature is present and also that the amplitude is larger than normal indicating that a component fault is developing.

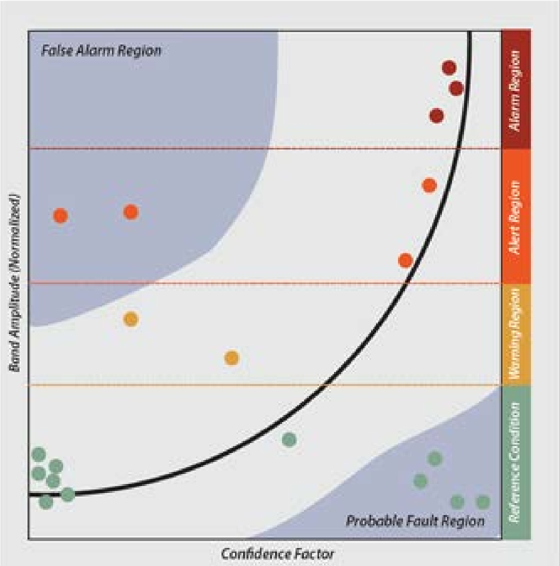

Fig. 6: PROGNOST®-Predictor Confidence Plot

The four corners of the scatterplot correspond to different possible situations. Points in the bottom left corner are signatures with low amplitudes relative to alarm levels, and a low confidence. These signatures are in a “good” status. The bottom right corner contains signatures with low amplitudes relative to alarm levels, but a high confidence. These points are false passes and require immediate attention and likely have alarm thresholds that are set too high. These signatures, if left unattended, would be missed alarms in a typical monitoring system since their alarm thresholds are too high to alarm even though a fault signature is present. The user should analyze each of these points and adjust alarm thresholds as necessary to monitor the upcoming failure. The top left corner contains signatures with high amplitudes relative to alarm levels, but a low confidence. These points are false alarms that need analyst attention and possibly their alarm thresholds increased. The top right corner contains signatures with high amplitudes relative to alarm levels, and a high confidence. These signatures should be managed carefully to avoid machine failures since they show true component faults. The scatter plot is divided into alarm regions Warning, Alert, and Alarm. The user can define additional informational regions. For each trend a signature amplitude and confidence is computed. If the new pair of values falls into a defined region that status is assigned to the trend.

The Confidence is a pattern recognition technique that quantifies the similarity of the measured peaks in the spectrum to the expected signature pattern. The Confidence provides a strong indication of whether a spectral measurement actually represents a real component fault. If the confidence is near 0, it means that the specific fault is likely not present in the spectrum, but if the confidence is near 1, then the fault is likely real. The Confidence captures the existence of a fault independent of the amplitude or severity of the fault.

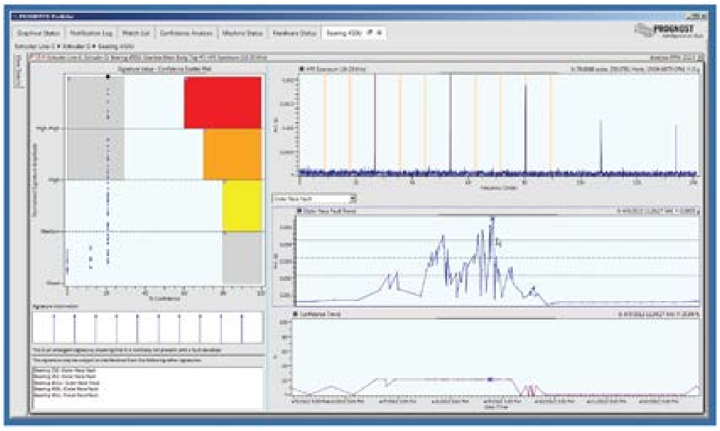

Fig. 7: This plot shows a low confidence factor despite of high band amplitude. This means that these amplitudes do not belong to the failure represented by the bands in the upper spectrum since only a few peaks match with this failure pattern.

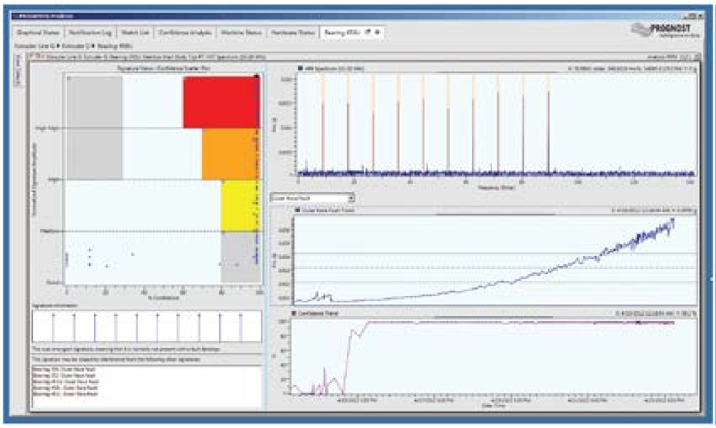

Fig. 8: This plot shows a high confidence factor and high band amplitude which result in an alarm. All bands show matching peaks inside.

Conclusion

This case study shows that it is possible to diagnose independent failures on one machine when simultaneously using the combination of pattern recognition, fuzzy and rule based methods. Owing to their operating principle, reciprocating compressors are especially complex machines that make automatic diagnosis difficult. There are many different methods for recognizing patterns in the measurement data of a monitoring system. The experience of PROGNOST Systems has shown that automatic diagnosis is possible, but that it also requires paying proper attention to the system's features and settings. This ensures that performance affecting factors such as varying operating loads and gas compositions can be eliminated.

This combination of traditional pattern recognition methods, fuzzy logic and rule based diagnosis has yielded the best results in recent years, and as a maintenance decision making aid, has helped mechanical engineers to draw faster conclusions based on more precise assessment and analysis of the state of a given machine.