EnergiTools® - A Power Plant

Performance Monitoring and Diagnosis Tool

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Abstract

Throughout the world, power generation organizations are moving into a more competitive environment. Power plant operation economics are therefore becoming very important. The industry is now required to optimize the power generation of existing plants by increasing the efficiency of equipment and by chasing "lost megawatts".

The diagnostic of performance problems has at the same time become a more complex and intricate task. Although the behavior of power plant components has not changed, because the physics has remained the same, modern power plants are complex conglomerates of interactive components, systems, and instruments. Even though modern plant information systems provide plenty of data, performance engineers have to turn it into relevant information using appropriate methodologies.

Westinghouse EnergiTools® is a performance diagnostic tool that combines the power of on-line process data acquisition with advanced diagnostics methodologies. The system uses analytical models based on thermodynamic principles combined with knowledge of component diagnostic experts. An issue in modeling expert knowledge is to have a framework that can represent and process uncertainty in complex systems. In such environments, it is nearly impossible to build deterministic models for the effects of faults on symptoms. A methodology based on causal probabilistic graphs, more specifically on Bayesian belief networks, has been implemented in EnergiTools® to capture the fault-symptom relationships. The system also has the ability to use neural networks for processes that are difficult to model analytically. An application is the estimation of the reactor power in nuclear plant by interpreting several plant indicators.

EnergiTools® is used for the on-line performance monitoring and diagnostics at Vattenfall Ringhals nuclear power plants in Sweden. It has led to the diagnosis of various performance issues with plant components. Two case studies are presented. In this first case, an overestimate of the thermal power due to a faulty instrument was found, which led to a plant operation below its optimal power. The paper shows how the problem was discovered, using the analytical thermodynamic calculations. The second case shows an application of EnergiTools® for the diagnostic of a condenser failure using causal probabilistic graphs.

Introduction

With the increasing competition in power generation, the electrical industry is required to optimize the production at existing power plants. Investing in new equipment is one response to this challenge. Optimizing production by chasing "lost megawatts" in existing installations is, however, a more cost-effective approach. For this reason, performance monitoring and diagnostics are increasingly important.

The diagnostics of plant performance are critical to minimize plant operational costs. Early detection and diagnosis of equipment problems allow the plant staff to quickly implement corrective actions. This allows the plant to improve megawatt production. In addition, maintenance actions can be determined while the plant is still in operation, allowing the plant to have the necessary replacement parts available prior to an outage. Such preventive actions potentially avoid extended maintenance shutdowns or operation in a degraded condition for an extended period of time.

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Performance monitoring and diagnosis has traditionally relied heavily on the experience and intuition of experts. Recent advances in diagnostic methodologies and in information technologies have enabled the development of innovative diagnostic support software tools, like the Westinghouse EnergiTools®, to augment the efforts of these plant experts.

EnergiTools® includes traditional analytical models, which are based on thermodynamic principles. Its use in the context of the traditional performance monitoring and diagnosis will be illustrated in the next section. EnergiTools® also offers several advanced diagnostic support paradigms:

- **A unit level diagnostic** provides a system level view of the plant, where plant-level problems are identified. If there is a problem, EnergiTools provides an estimate of where the plant’s heat rate is being increased. It quantifies each component’s performance, the effect of its degradation on the heat rate, and the corresponding loss in megawatts.

- **For processes that are difficult to model analytically,** EnergiTools® has the ability to use neural networks. An example is the estimation for the nuclear reactor power. Here, a neural network is used to correlate reactor power with key plant measurements. This estimate, along with other inputs, can be fused to provide the best estimate for reactor power.

- **A component level diagnostic** provides a detailed component level root-cause analysis. This portion of the tool uses recent advances in diagnostic methodologies and in decision theory. It is actually the main purpose of this paper. The rationale behind this methodology will be described, and the benefits will be illustrated in case studies representing realistic operating conditions.

**Traditional performance monitoring and intuitive diagnosis**

Complex plant configurations are monitored by observing data records from sensors placed at various plant locations. Typically, data is continuously collected, and experts monitor the readings. From these readings, they assess the health of the plant. If there are unusual readings, the experts use their diagnostics skills to determine the cause of the problems. While experts can be good at this detective work, there are problems associated with using human expertise to monitor complex...
systems. A typical application may involve up to several hundred sensors, so that the task of real-time monitoring can be overwhelming and could produce unacceptable rates of false alarms or misdiagnosis. Modeling software tools have been developed to help engineers in their diagnosis. Many early performance evaluation software used only analytical methodologies. Those systems were run regularly by performance engineers with off-line plant data. Besides supporting the performance engineers in the calculations, these tools did little to guide their diagnostics activities. As the example below illustrates, the diagnostic activities place great reliance on the experience and intuition of plant personnel.

In spring 1998, the unit 3 of Vattenfall Ringhals Nuclear Power Plant was already using EnergiTools® for its automatic performance monitoring. Figure 1 shows the user interface with a small portion of the Ringhals 3 model. The operational department of Ringhals unit 4 had a feeling they were losing output power. Since units 3 and 4 are twin units, they decided to use unit 3 performance monitoring tool in off-line mode to analyze the situation of unit 4.

Unfortunately, unit 4 is not very well equipped in terms of instrumentation. The available data was the turbine first stage inlet pressure, the feedwater temperature, the condensate flow, and the feedwater flow. The performance engineer thought that the problem could be related to fouled feedwater Venturis, which had previously been experienced on unit 3. This was the first problem to be analyzed. The approach was to analyze which indications supported the idea of fouled feedwater Venturis. A comparison between the condensate flow and feedwater flow over time is shown in figure 2.

The comparison indicated that there was actually a mismatch. However, more evidence was needed to be able to identify that the mismatch was related to the Venturis and not to a drift in instrumentation for the condensate flow. Hence, the trend of the turbine first stage inlet pressure over time (figure 3) was analyzed.

Since the pressure before the turbine first stage is a very good indication of turbine load, it corresponded very well to the condensate flow. Another indication to study was the feedwater temperature over time (figure 4). Since this reflects the pressure before the turbine first stage, a drop in feedwater temperature would indicate a falling turbine load.

The final proof that unit 4 was actually losing output power due to a fouled feedwater venturi came from a calculated heat balance. EnergiTools® was used to perform this "what-if" analysis. Issues that can be studied include, for example, how a changed cooling water temperature affects the output power, or how a reduced thermal power affects the output power, as well as pressures and temperatures in the turbine train.

In this particular case study, the idea was to evaluate how well calculated data, with thermal power reduced to 99.5%, would fit to actual measured data. Of special interest were the following parameters:

- turbine first stage inlet pressure,
- feedwater temperature, and
- condensate flow.

It turned out that the calculated values from EnergiTools® matched the measured data very well. This made Ringhals performance engineer feel confident that there was really a problem with a too low thermal power and that the problem was related to fouled feedwater venturis. The output power was about seven megawatts below nominal power.

Since Ringhals unit 4 was approaching outage, arrangements were done to clean the Venturis. If the problem had not been noticed, the plant would have gone back into operation below

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nominal power. During one production year, a seven megawatts loss equals to a substantial amount of money!

Automating performance diagnosis

Analytical diagnostic algorithms can be integrated in performance monitoring tools. With the computing power available today, one could think to emulate human experience and intuition by intensive automatic execution of performance calculations with varying plant data.

Unfortunately, such strategies are not good at figuring out multiple failures. Using these methods in conjunction with regular on-line monitoring, i.e. every few hours, can provide useful information, since multiple failures and degradation rarely occur within a short time frame. Using automatic analytical methodologies off-line and running them every few weeks or months might provide unreliable results.

Another issue with analytical strategies, such as data qualification methodologies, is that they do not deal well with non-linear behaviors, which exist in thermohydraulic processes.

Replacing the traditional automatic diagnosis methods with expert systems can provide information about the underlying causes of problems and give clear indication on the rationale behind the diagnosis.

Expert system for the performance diagnosis

An expert system relies on a knowledge base, which maintains a set of rules and relationships between faults and symptoms. Usually, symptoms can easily be observed, whereas their causes, the faults, can not be easily observed.

The graph below (figure 5) models some of the faults-symptoms relationships for a condenser. A possible problem with a condenser is that the cooling water intake system may have accumulated dirt that will affect the flow rate, in turn reducing performance of this component. This failure is called condenser fouling and can only be observed directly by visual examination of the inside of the component, which would obviously affect the plant operation. The simplified faults-symptoms graph shows two observable symptoms: the higher than normal electrical amps consumption for the cooling water pump and the increase in condenser pressure.

Once the faults-symptoms relationship has been identified, an inference strategy has to be defined. In other words, how does the expert system figure out what set of faults caused an observed set of symptoms?

Figure 5: Condenser faults-symptoms graph

Over the years, there have been considerable efforts to develop expert systems to diagnose power generation equipment. With a few exceptions, the majority of the systems have relied on rule based reasoning.

Rule based diagnosis

In a rule-based expert system, reasoning is carried out through the logical chaining of “if-then” rules, which are acquired from an expert. In the condenser model (figure 5), we would have rules like the following:

if “pressure increase” and “cooling water pump amps” are too high
then “condenser fouling” is true

Though the language is very simple, it is quite powerful when modeling experts' reasoning, and several impressive rule based expert systems were constructed. But rule based systems have limitations in the expressiveness of rules. In the condenser example, if all the symptoms related to the bad “pump performance” are true, then the inference rule above indicates that there must also be “condenser fouling”!

Missing, noisy, or faulty plant data add another degree of complexity to the problem. They incorporate uncertainty in the rule-based system, extending the rules to the format:

if “symptom” with certainty x
then “fault” with certainty y

Unfortunately, the decision theory proves that it is not possible to capture reasoning under uncertainty with inference rules. The reason is that the inference rules are context free while coherent reasoning under uncertainty is sensitive to the context in which facts have been established. In other words, having a symptom with certainty x does not imply that the fault certainty is y, because the fault certainty is impacted by the status of all the other symptoms related to that fault. In addition, what is...
known about one fault will also impact the knowledge about other faults that share common symptoms.

Bayesian belief network

At first look, the reasoning under uncertainty looks very difficult. However, classical probability theory has been extended to a very precise mathematical framework for decision making. Bayesian Belief Network is such a framework. It uses the concept of a priori and context-sensitive knowledge, as well as conditional probabilities and related inference rules.

Within this framework, our condenser fouling problem (figure 5) would be rewritten as follows. Let's assume that from experience, we have the following a priori knowledge:

- a condenser fouling has a probability of 1% \( P(f) = 0.01 \)
- a pressure increase has a probability of 4% \( P(pi) = 0.04 \)

In addition, some context sensitive knowledge relates the faults to the symptoms:

- the conditional probability to have a pressure increase in case of fouling is 99% \( p(pi|f) = 0.99 \)

Keeping in mind that the observable fact is the symptom "pressure increase", the Bayesian inference rule provides the probability of the fault, given the symptom:

\[
P(f|pi) = \frac{P(pi|f) P(f)}{P(pi)} = \frac{0.99 \times 0.01}{0.04} = 0.25
\]

In other words, when the only observed symptom is that pressure increase is too high, the probability that it is caused by a condenser fouling is only 25%! One might be surprised to have such a low fault certainty. It is actually because having a 4% a priori probability for the pressure increase clearly indicates that this symptom is not caused by only the condenser fouling, which has a much lower a priori probability (1%).

Condenser diagnosis using Bayesian belief network

The small example above only has one fault and its single symptom. This is appropriate to present the theory, but it does not really demonstrate the power of the concept. Let's apply Bayesian belief network to the condenser diagnosis, using the faults-symptoms graph presented in figure 5 together with appropriate probabilities.

Bayesian belief network produces appropriate fault diagnosis when presented with sets of complete and coherent symptoms. In Figure 6, the expert system is presented with symptoms of condenser fouling. The conclusion is that there is a high likelihood (64%) that condenser fouling exists, whereas the other faults have a low (35% for pump performance) or very low chance to exist (0.5% for the instrumentation failure).

In the next test case (figure 7), the expert system is presented with the set of symptoms relevant to the pump performance problem. Although two of the symptoms are shared by the condenser fouling fault, the system correctly identifies the pump performance as being the most probable fault (98% certainty).

In real operating condition, faulty or noisy instruments may produce erroneous symptoms. In some cases, for example when some sensors are not available, symptoms might be missing. In such conditions, many diagnosis systems might produce wrong conclusions. As will be illustrated below, our Bayesian belief network framework also provides realistic diagnosis in this type of situation.
The condenser pressure increase is normal (i.e., no pressure increase), whereas the other symptoms are clearly present. As demonstrated in figure 8, the expert system maintains a diagnostic similar to the previous case (figure 7). The pump performance is still considered to be the most probable fault, with however a lower probability (78% versus 98%).

Figure 8: Poor pump performance with one wrong symptom

In the first case, an erroneous symptom has been introduced.

Fig. 9: Condenser fouling symptoms with one observed fault

The condenser pressure increase is normal (i.e., no pressure increase), whereas the other symptoms are clearly present. As demonstrated in figure 8, the expert system maintains a diagnostic similar to the previous case (figure 7). The pump performance is still considered to be the most probable fault, with however a lower probability (78% versus 98%).

Figure 8: Poor pump performance with one wrong symptom

In the first case, an erroneous symptom has been introduced.
A second test case shows a situation where some a priori knowledge is existing about faults. It is known for a fact that the instrumentation is out of order. Figure 9 shows how the expert system reacts when presented with the set of symptoms associated with the condenser fouling. The conclusions are similar to the case of figure 6, but with reduced certainty. The condenser fouling fault is now credited with 39% probability versus 64% in figure 6.

Bayesian Belief Network in EnergiTools®

The Bayesian Belief Network framework has been implemented into EnergiTools® to support the component diagnosis functionality. A diagnosis scenario using EnergiTools® will be described. The graceful behavior in case of missing or erroneous symptoms will be illustrated as well as the process of refining the diagnosis.

Figure 10 illustrates a condenser fault diagnosis, as produced for a practical case by EnergiTools®. More faults and symptoms are defined than in the previous section example. Nevertheless, in this particular case, the three potential faults identified by EnergiTools® relate to the pump performance and fouling. The faults-symptoms relationships are similar to those previously identified (figure 5).

The next step is to verify why EnergiTools® believes that the faults are relevant. This is accomplished by looking at the associated symptoms. Figure 11 shows the symptoms associated with the pump performance fault. Note that five states (normal, low, medium, high, and very high fault) are used for each fault or symptom. This allows for a finer tuning than when an item is either true or false. It appears that the possibility of a pump performance problem was mainly derived from the very high increase in condenser pressure. The two other symptoms for the pump performance are actually unknown (20% chance for any of the five states), because they are not instrumented or their measured values were rejected due to an instrumentation failure.
The diagnosis engineer has then to figure out possible values for the missing symptoms. If he finds out that the "pump amps" is somewhat high, he could manually enter a distribution for this symptom, as illustrated in figure 12.

Fig. 12: Setting an observed symptom - CW pump Amps too high

<table>
<thead>
<tr>
<th>Root Cause</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro Fouling</td>
<td>0.553</td>
</tr>
<tr>
<td>Poor Pump Performance</td>
<td>0.476</td>
</tr>
<tr>
<td>Micro Fouling</td>
<td>0.047</td>
</tr>
<tr>
<td>Vacuum Pump Problem</td>
<td>0.001</td>
</tr>
<tr>
<td>Air in Leakage</td>
<td>0.001</td>
</tr>
<tr>
<td>High Hot Well Level</td>
<td>0.001</td>
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</tbody>
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Fig. 13: Condenser fault probabilities with high CW pump amps symptom

Running the diagnosis with this additional fact yields a new fault distribution (figure 13) with two highly probable faults: macro fouling and pump performance.

If the diagnosis engineer finds out that the "pump amps" is normal, EnergiTools® would provide another fault distribution (figure 14). This time, the only fault to be considered is the condenser micro fouling.

Fig. 14: Condenser fault probabilities with CW pump amps symptom set to normal

<table>
<thead>
<tr>
<th>Root Cause</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Micro Fouling</td>
<td>0.515</td>
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<tr>
<td>Vacuum Pump Problem</td>
<td>0.006</td>
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<tr>
<td>Air in Leakage</td>
<td>0.006</td>
</tr>
<tr>
<td>High Hot Well Level</td>
<td>0.005</td>
</tr>
<tr>
<td>Macro Fouling</td>
<td>0.004</td>
</tr>
<tr>
<td>Poor Pump Performance</td>
<td>0.003</td>
</tr>
</tbody>
</table>
Conclusion

With the increasing competition in power generation, the issue of performance monitoring and diagnosis is becoming increasingly important. Performance monitoring and diagnosis has traditionally relied heavily on experience and intuition of experts. Recent advances in diagnostic methodologies and in information technologies have enabled the development of innovative diagnostic support software tools, such as the Westinghouse EnergiTools®.

EnergiTools® includes traditional analytical models, based on thermodynamic principles, for the performance calculation and identification of possible component performance degradation. Several artificial intelligence paradigms have been integrated to support the root-cause diagnostic activities. One of the techniques used for the component diagnostic is based on the Bayesian Belief Network.

Case studies based on data from the Vattenfall Ringhals nuclear power plants in Sweden are presented in this paper. Those practical examples demonstrate how well the EnergiTools® component diagnostic handles multiple faults and uncertainty, and how it provides realistic diagnosis even when only a subset of the possible observations is available. The Bayesian belief network framework brings a very useful contribution to the chase for “lost megawatts”.

Acknowledgement

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REFERENCES