Monitoring and Diagnostics Techniques for Gas Turbines and Their Remote Application to Assist in Optimizing Repair Outages

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Abstract
Detecting faults in a timely manner in plant critical equipment is increasingly important. Detection at an early stage can have multiple benefits, including the avoidance of unscheduled outages and possible equipment damage.

Being able to plan ahead to ensure correct resources are available when a scheduled repair outage is carried out, and being aware of the details of the faults that require repair is a further benefit, ensuring that repairs are quick, effective and efficient.

A remote monitoring and diagnostic system assists in
- the availability of personnel for monitoring
- enabling personnel to filter large quantities of data for significant events
- the identification of the faults that require repair

The case study details an evolving situation where combustion faults were identified which otherwise could have caused a trip and unscheduled repair outage.
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1. Introduction
Detecting faults in a timely manner in plant critical equipment is increasingly important. Detection at an early stage can have multiple benefits, including the avoidance of unscheduled outages and possible equipment damage.

Being able to plan ahead to ensure correct resources are available when a scheduled repair outage is carried out, and being aware of the details of the faults that require repair is a further benefit, ensuring that repairs are quick, effective and efficient.

To achieve this, continuous monitoring is required. This creates issues that need to be solved:
- Availability of personnel for monitoring
- Enabling personnel to filter large quantities of data for significant events
- Identifying the details of the faults that require repair

The availability of personnel for monitoring can be enhanced by providing access to the diagnostic and monitoring system throughout the organisation. This can best be achieved using a distributed architecture.

The filtering of large quantities of data for significant events is the task of the monitoring and diagnostics software. There are numerous techniques that contribute to this process. The techniques produce a spectrum of diagnostics from the detection that something is abnormal through to the complete diagnosis of a fault.

Identifying the details of the faults that require repair is a mixture of using the diagnostics provided by the monitoring and diagnostics system, using data exploration tools to get more information and in some cases examining the turbine itself. Various support tools are needed to ensure proper exploration of conclusions such as graphing and diagnostic message management. The ease of use of these tools is one of the key aspects to providing a successful monitoring and diagnostic system.

The case study details an evolving situation where combustion faults were identified which otherwise could have caused a trip and unscheduled repair outage. It is a COGEN site, so a trip would have impacted the process plant, as well as causing unscheduled loss of electrical generation. No personnel were available onsite for monitoring.

The remote monitoring and diagnostic system enabled the engineering support company to identify problems at an early stage, enabling planning for a scheduled repair outage to be made. The faults caused significant exhaust temperature spread changes that were insufficient for controller alarms to occur, but were identified by diagnostic system messages and corroborated through schematic displays and graphing.
2. A Distributed Architecture Maximises Staff Availability
A distributed model for remote monitoring and diagnostics gives the flexibility to construct the architecture most suited for an organisation. The analysis of the data acquired from a turbine is stored and analysed as close as possible to the source. This provides robustness of the system to communication failure.

The data acquisition server beside the turbine can supply information to clients directly, or to a remote server that then supplies it on to other clients. By caching data at each point in the network we minimise the total traffic through it. In addition, because the analysis is carried out at site we can transmit highly informative summaries that minimise the bandwidth required. An example of an existing architecture is shown in figure 1.

Figure 1- Example of a distributed architecture for Monitoring and Diagnostics

This decentralised structure means that many people all through the organisation can examine what has happened to the turbine and experts can be called in to help resolve problems when required. Often there are one or two people whose prime responsibility is to look after the turbine. These people are the ones that use the monitoring and diagnostic system the most.

When the maintenance of the turbine is contracted out in some form of Long Term Service Agreement, the fact that the full monitoring and diagnostic system is available on-site allows the operators and owners of the turbine to see the same information that is available to the company running the service agreement and work in partnership with them.
It should be noted that it is easy to modify the distributed architecture described above to provide a centralised diagnostic and monitoring centre if this is required. Variations where the monitoring and diagnostics is partially centralised and partly distributed can also be achieved.

**Figure 2 - Example of a hybrid architecture for Monitoring and Diagnostics**

3. **Diagnostics Provide Automatic Analysis of Large Amounts of Data**

There are many techniques for capturing knowledge about gas turbines such as simple limits, expression based checkers, temporal based checkers, rule bases, neural nets, mathematical numerical models, temporal reasoning systems and qualitative models. Each technique has a particular area of application. The techniques produce a spectrum of diagnoses from the detection that something is abnormal through to the complete diagnosis of a fault.

The controller provides alarm and trip limits, but non time critical analysis of data is better performed externally to allow the controller to focus on its function of controlling the turbine. The data for analysis comes from the turbine control system, plant control system and any specialised hardware that can be connected, such as vibration monitoring or emission monitoring systems.

The data sampling frequency will depend on the type of faults to be detected and the amount of storage available. Typically a once-per-second sampling provides the appropriate compromise for an overview of many tags over many years. The diagnostic information may relate to an immediate incident or refer to a longer time frame.
3.1 Management of Diagnostics

It is important to have concise summaries of diagnostics that can be explored in depth if necessary. In the examples below, the messages are colour coded according to severity (red - critical, orange - fault, purple - warning, event – cyan, information – green, controller message – grey). The diagnostic listing can be filtered to show only certain severities and types of diagnostics as shown in figure 3.

Figure 3 - defining a diagnostic query

Often, an engineer initially wants to know what has occurred and is not interested in a time listing until they choose to drill down. The “number of occurrences” option allows this, and can be applied to diagnostics that have triggered over many months. Figure 4 shows the number of critical massages relating specifically to gas fuel over a period of 10 months. Expanding a particular message shows the time and date that each message occurred.

Figure 4 - Number of occurrences of critical gas fuel diagnostics over 10 months
When turbines are being continuously monitored there is a need to know about particular problems that have previously been reported and if plans to rectify the problem have been put in place. This information needs to be available at the time the message is displayed. The monitoring and diagnostic system can attach notes to messages indicating that further information is available. These notes are available to all users. An example is given in figure 5. The system can also link diagnostics directly into the turbine manual pages.

**Figure 5 - Sample note attached to a diagnostic message**

```xml
<Diagnostic Message> Speed Ratio Valve Position (FSGR) too high. Limit 50.00 %
<Filter Date> 14/07/2008
>Status> On
<ReasonCode> Aware
<ReviewDate> 01/10/2009
<OffDate> 00/00/0000
<SetBy> JA
<Incident Date> 24/03/2008
<Notified> JA
<NotifiedDate> 24/03/2008
<NotifiedBy> JA
<ReportLocation> \Server_1 \Site_A\2008\March\Site_A_24_March_2008.doc
<Description> The gas fuel supply pressure is fairly low, as the gas fuel speed ratio valve is set at a quite a high level of opening (around 50% to 70%), and above the Tiger limit of 50%.
```

It is also possible to filter the messages so that they do not appear in a normal diagnostic query, as shown in figure 6. This allows faster interpretation of the diagnostic list and makes new messages more obvious.

**Figure 6 - Filtering query results to remove known problems**
3.2 Simple Checking Mechanisms

Simple checking mechanisms derive their power from the fact that there are lots of them and they are relatively easy to set up. In many cases existing data can be analysed and the checkers created automatically. A measure of how well each one fits an expected profile highlights individual diagnostics checkers that need to be set up manually.

A key part of the effectiveness of simple checkers is knowing the state of the turbine. This provides the context in which accurate bounds for an individual check can be made and the correct status of digital inputs can be determined. For example, the fuel valve should not be open when the turbine is off.

States need not be mutually exclusive and can be used to usefully segment the diagnostic space across different turbines and turbine types. An example of states that might be defined is STOPPED, CRANK, FIRE, FULL SPEED NO LOAD, PART LOAD, BASE LOAD, SHUTDOWN, TRIP, GAS FUEL, LIQUID FUEL, MIXED FUEL.

3.2.1 Reporting of Digital and Alarm Changes

The most basic diagnostic function is to provide an alarm and event historian for messages generated by the control system. In figure 7 there is a list of process alarms from a Speedtronic Mk V produced over the course of three days, indicating problems with both steam and gas supply. Of note is that there are millisecond time stamps from the controller since the data is collected on the printer port of an HMI and is event driven, rather than polled, allowing messages to be queued until they are acquired by the monitoring and diagnostic system.

Figure 7 - Speedtronic controller alarms from the printer
These messages are integrated with diagnostics from the monitoring and diagnostic system itself. Figure 8 shows over the period of an hour and a half that there are wheelspace temperature issues, low steam and fuel supply, a rapid increase in compressor discharge temperature and eventually we see the gas fuel pressure increase as the gas compressor is started up. This particular incident relates to supply issues of steam and gas to two turbines on one site. At the next outage the distribution of the gas supply was altered to provide a more even supply to both turbines. This minimised the need to run the gas compressor and thus saved money.

**Figure 8 - Speedtronic Controller alarms are integrated with other diagnostics**

3.2.2 High/low Limits on Analog Values
The next level of diagnostics involves looking at the normal range of many tags in each defined state of the turbine. These limits are set below the alarm and trip limits of the controller and help to define what is considered to be “normal” operating for a turbine in a given state. Knowing what is normal for a class of turbines can identify problems as soon as the diagnostic system is attached to a particular turbine. Limits can be obtained automatically by looking at the distribution of values for a given tag and deciding from the shape of the distribution where the limits should be. Figure 9 shows a distribution with the automated limit values in green.
Limits need to have deadbands applied to stop chattering of diagnostics when the value of a tag slowly crosses a limit. Figure 10 shows a 5 second excursion for a vibration sensor that tripped a turbine. The next section gives more detail of the underlying problem.

3.2.3 Follows Abstraction

The follows abstraction can be applied to many different sets of tags and is defined as

\[ \text{signal } X \text{ must be within a given tolerance of signal } Y \text{ with no excursions lasting more than a given time } T. \]

In the example in figure 11, the follows abstraction is applied to two vibration sensors on the same bearing. These are overall vibration measurements and it is expected that they are roughly in line with each other. This is the case until the excursion for sensor 4.
This example tripped the turbine and returned both sensors to valid values. The contract executive for the site remotely looked at the monitoring system and could see from the diagnostics that it was reporting a faulty sensor 4 at the time of the trip, but not afterwards. Firstly, it was determined that the turbine could be restarted immediately. A controls engineer was dispatched to modify the control system to only trip out if both sensors 4 and 5 were reading high and the replacement of sensor 4 was scheduled for the next outage.

### 3.2.4 Other Simple Checking Abstractions

Other simple checkers can be defined, similar to the follows abstraction described above:

- **Pairs abstraction** - signal X must be given within a given tolerance of signal Y at all times.
- **Inverse follows abstraction** - signal X must be out with a given tolerance of signal Y with no excursions lasting more than a given time.
- **Inverse pairs abstraction** - signal X must be out with a given tolerance of signal Y at all times.

These abstractions can be applied to signals and reference sets, adjacent thermocouples, digitals that are mutually exclusive and many other pairings of tags. They are, like the analog checkers, state dependent. They also can be tuned by analysing existing data to provide parameter values.

### 3.2.5 Gradient Checker

The gradient checker looks at a signal expected to be relatively constant and detects deterioration over long and short periods. There is also a variant of this that checks for step up and down in tag values. The example shown in figure 12 details the deterioration in steam flow over the course of two months. This deterioration was picked up remotely and the progress of the deterioration was monitored to determine when to shut down and clean the steam nozzles.
The graphical representation shows the maximum, minimum and average of the steam flow over 5 minute intervals. Using this technique of displaying tag value over longer period of time allows the handling of large time spans stretching 10 years or more without swamping the computer system with vast amount of once-per-second data. These graphical summaries are saved and distributed remotely allowing efficient use of bandwidth and computer processor.

High time resolution events are still visible, as the maximum and minimum then deviate from the average. In the example above, the steam is stable for much of the time with the maximum, minimum and average close together. However, near the end the steam flow plugs and then the plug is forced out causing a 0.0 minimum and a 3.8 maximum in a 5 minute time period when the average is a steady 1.5.

Any period of time in this graph can be drilled down to retrieve the original once-per-second data, and this can be replayed through the system as if it were live.

3.3 More Sophisticated Diagnostics
A monitoring and diagnostics system has many forms of knowledge embedded in it. These can look at normal behaviour and highlight deviations from it or can diagnose specific faults. This provides a spectrum of diagnostics from knowing something is not normal through to completely diagnosing a fault. In some cases it is not possible to distinguish between faults from the sensor input available.

This embedded knowledge depends on the appropriate sensors being available. Even with few sensors (for example 80 analogs from a Speedtronic Mk IV) it is possible to detect and diagnose many problems.

The sum of all the embedded knowledge produces many diagnostic messages that must be presented in a user friendly way. By treating the messages as tokens and then applying temporal pattern matching on these tokens, a hierarchy of diagnostic messages is produced that classifies the messages and highlight the important ones.
The system can determine the cause of the set of diagnostics observed at any one time and present this as the diagnosis. These are a set of diagnostics that determine this conclusion, a set that are accounted for by the conclusion and a further set that is probably “noise” which indicate detected abnormalities in the same area as the conclusion exists.

Figure 13 shows a diagnostic breakdown where a GE Frame 5 - 2 shaft turbine becomes unstable due to the second stage nozzles running out of control because the actuator has not enough power to move them against the airflow. This was caused by the use of a steam helper turbine on the compressor shaft. The fix, consisting of a larger actuator motor, was engineered and implemented at the next outage. In the mean time the turbine was throttled back to avoid the conditions where it was out of control.

**Figure 13 - example diagnostic breakdown**

- **Diagnosis**
  - The second stage nozzles actuator has saturated.

- **Faults Present Leading To This Conclusion**
  - The current to the nozzle servo (YANZ) is too high.
  - The reference signal to the second stage nozzles (TSRNZ) is too high
  - The actual position of the second stage nozzles (TSNZ) does not follow the reference (TSRNZ) within 30 seconds.

- **Other Faults Present That Are Accounted For By This Diagnosis**
  - The compressor shaft speed (TNI) is too high.
  - The output shaft speed (TNI) does not follow the reference (TNR) within 50 seconds.

- **Other Faults Present In The Same Area (2ND_STAGE_NOZ)**
  - Vibration on bearing BB4 too high

The kinds of embedded knowledge include:

- Rule Bases
- Performance models for heat rate and power
- Compressor Efficiency Models
- Measuring NOx Levels Against Targets
- Factored Running Hours and starts
- Qualitative Fuel System Models
- Neural Net Combustion Models
- Vibration analysis
- Other specialised modules for specific problems
3.3.1 Diagnostics Rules
A rule system where knowledge is expressed in an if-then-else format is a convenient way to represent many diagnostics. The rules can chain together to produce sophisticated conclusions. These rules are further enhanced by embedding time related (temporal) primitives within them. Figure 13 in the section above shows an example of this.

3.3.2 Neural Nets
Neural nets predict the value of their output based on the value of their inputs using learned weightings of links within the model. They are useful where numerical models are hard to define, such as in exhaust flow and pattern. There needs to be careful selection of the training set taking account of seasonal variations. Figure 11 shows a neural net applied to the expected exhaust combustion pattern. The green represents the expected upper and lower boundary and the actual orange is outside these, indicating a problem.

Figure 13. Neural net applied to exhaust temperatures

3.3.3 Compressor Efficiency
Calculation of the compressor efficiency and noting the baseline efficiency at the last off-line water wash shows when an off-line water wash would be effective. Figure 14 shows compressor efficiency deterioration that was recovered by an off-line water wash.
3.3.4 Performance Models for Heat Rate and Power
To meaningfully compare the power output and heat rate at different times, correction factors need to be applied, especially for ambient temperature and pressure. Figure 15 shows performance model values over a two year period, with associated baselines where off-line washes have been carried out. Performance values are an overall indicator of the general health of the turbine and are monitored remotely. Comparison with other turbines in the fleet also assists in highlighting problems.

Figure 15- Performance model values over a two year period
3.3.5 Factored Hours and Starts

Typically a turbine manufacturer will provide guideline for when maintenance is due and this will be based on the number of hours, starts and type of running for the turbine. It is useful for the monitoring and diagnostic system to provide this information, along with known target, scheduled and factored dates for the next maintenance, as shown in figure 16.

**Figure 16 - Factored hours, starts and schedules**

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<tr>
<td>Base load (Distillate)</td>
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<tr>
<td>Heavy Fuel</td>
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<tr>
<td>Peak load</td>
<td>0.0</td>
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<td>10</td>
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<tr>
<td>Peak load Start/Stop Cycles</td>
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<tr>
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<tr>
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<tr>
<td>Trips @ Severity Factor 4</td>
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<tr>
<td>Target Date</td>
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<tr>
<td>Provisional Scheduled Date</td>
<td>29/03/2007</td>
</tr>
<tr>
<td>Factored Date</td>
<td>13/03/2008</td>
</tr>
</tbody>
</table>

3.3.7 Flame Vector

The combustion pattern in the exhaust is displayed for a single instant in time in figure 17. Creating an exhaust temperature residual vector allows easy tracking of combustion stability across long periods of time. The values of the thermocouples are combined to form a vector. The length and direction of this vector gives an indication of the combustion pattern that can be trended over long periods of time. Figure 18 shows a 5 day fleet wide flame vector pattern showing online washes (red), moves to part load (orange and red) and significant change in combustion pattern (purple).
Figure 17 - Instantaneous exhaust temperature pattern

Figure 18 - Fleet wide flame vector over 5 days
3.3.8 Vibration Analysis
As well as what is regarded as behavioural monitoring and diagnostics, the monitoring and diagnostic systems also provide analysis and diagnostics for vibration data inputs.

Diagnostics include:
- Unbalance
- Misalignment
- Hydraulic Instability – for Oil Whirl and Oil Whip
- Rub
- Blade Damage

Figure 19 shows a significant change in vibration on a bearing that has two vibration sensors attached, A and B. The plots at the top show Nyquist plots of the instantaneous values of the vectors for the first three harmonics for A and B with the orbit plot for the bearing in the centre. The graphs show the phases and amplitude of the first three harmonics for 90 minutes at the time of the incident. This was caused by a fracture in a turbine blade.

Figure 19 – Harmonics showing significant vibration incident
4. Support Tools to Assist in the Identification of Faults
Various support tools are needed to ensure proper exploration of conclusions such as graphing and diagnostic message management. The ease of use of these tools is one of the key aspects to providing a successful monitoring and diagnostic system. Figures 20-24 show examples of the kinds of tools available.

**Figure 20 - X-Y plots of bearing vibration sensors where there are two sensors per bearing**

**Figure 21 - Footprint comparison of vibration over several startups**
Figure 22 - Distribution of values for vibration tags for base load state over 24 hours

Figure 23 - Maximum vibrations and spreads for each startup for the past three years
5. Case Study - Combustion Problems on a GE Frame 6 Gas Turbine

This gas turbine is a Combined Heat and Power installation located on a chemical production site. The turbine runs continuously at base load. It has DLN1 for NOX reduction and also supplies steam for use in the chemical production process.

Turbine Services monitors the turbine on a daily basis from the UK office, and reports are sent to the customer for any problems detected. Turbine Services engineers are also on call if problems occur at any time. They can use the TIGER® monitoring and diagnostic system on their laptops to check on turbine status, even if away from the office or at home. Repair and maintenance is carried out by Turbine Services under a Long Term Service Agreement.

The on-call Turbine Services engineer received an SMS message on his mobile phone from TIGER at about 8pm on Monday 5th May indicating the turbine had unexpectedly dropped out of DLN mode and gone to lean-lean combustion. The engineer called the site, to discuss and then analysed remotely with TIGER. The engineer concluded that the drop out to lean-lean mode had been caused by changes in gas fuel pressure which had triggered a combustion flashback.
The diagnostic messages indicate that the turbine dropped out of DLN mode (premix combustion) and into lean-lean mode. It also indicates exhaust over temperature and problems with the gas fuel valve occurred.

This shows a large upward transient associated with the flashback, followed by a change in spread level and behaviour.
Further analysis using trend and data graphs and the combustion can pattern screen also showed that after the turbine switched back again to premix combustion (DLN mode) there had been a step change in exhaust temperature spread from 25 to 35 Deg C, and the spread pattern had changed. It was also now changing in line with ambient temperature and consequent turbine power changes as shown in figures 26 and 27.

Although this was still well below alarm limits, it indicated the flashback may have caused some damage, which had increased the spread and changed the spread pattern.

Further analysis also indicated that the gas speed ratio valve was operating sub-optimally, and that a poor response by this to a gas fuel supply pressure change had probably caused the flashback to occur, by failing to keep the gas fuel intervalve pressure steady for the gas control valve. The detailed analysis of all these problems was assisted by the ability of TIGER to load up archived historical data and replay it as if the event was actually occurring as shown in figures 28 and 29.

Accordingly, it was agreed with the customer to carry out a hot gas path inspection the following week, as the turbine already had a planned shutdown scheduled for work on the heat recovery steam generator.

Turbine Services has mobile workshop and spares containers, which are deployed to site to support maintenance and repair activities. These were immediately mobilised and conveyed to site. Manpower was also mobilised, ensuring all resources were available on site in time for the shutdown.

During a three day shutdown, it was discovered that secondary nozzle tip damage had occurred on cans 10, 1 & 2 and the inner gas (pilot) tubing at secondary nozzles 10 & 1 had been dislodged/broken from the nozzle tip. Further inspection also revealed that transition piece number 1 was found to have its inner floating seal dislodged. Figure 30 shows the details.

*Figure 27 – Data graph of exhaust temperature spread*

This shows a large upward transient associated with the flashback, followed by a change in spread level.
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**Figure 28 – Combustion can pattern screen before the flashback**

![Combustion can pattern screen before the flashback](image)

**Figure 29 – Combustion can pattern screen after the flashback**

![Combustion can pattern screen after the flashback](image)
A replacement transition piece complete with inner and outer seals was installed and the three primary nozzles for can 1, 2 and 10 were reassembled along with a replacement set of secondary nozzles and associated piping. In addition the speed ratio gas valve servo and <S> processor TCQA card were also replaced. The turbine was then restarted successfully.
6 Conclusion

A monitoring and diagnostic system allows early detection of abnormalities in the operation of a turbine. When the monitoring and diagnostic system is accessible remotely throughout an organisation, key staff can be called upon to contribute to the problem analysis and solution. The monitoring system itself uses many different techniques to analyse the operation of the turbine. The combination of these techniques, and the ability to further explore the data, results in a powerful application to solve problems and optimise repair outages.

References


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