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AN INNOVATIVE FLEET CONDITION MONITORING CONCEPT FOR A 2MW GAS TURBINE

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ABSTRACT

Deterioration of gas turbine component condition leads to degradation of performance, efficiency, reliability and safety. Accurate monitoring and advanced analysis of gas turbine performance offers great potential to minimize life cycle costs and maximize performance and availability and thereby revenues. Implementing advanced performance monitoring tools for a fleet of engines can save millions of dollars by improving availability and reliability of the machines. OPRA Turbines has more than 100 of its OP16 2MW class gas turbines installed worldwide. Using B&B-AGEMA's GTPtracker software, an online real-time condition monitoring and prognostics system has been developed. A detailed model of the OP16 engine has been used to simulate deterioration and failure effects, generating signatures for condition assessment on component level. The signatures are stored in the GTPtracker monitoring database in the form of rule sets that can be correlated also to condition monitoring information from different disciplines such as vibration and lubrication. Performance data matching a rule set indicates specific component deterioration and failure modes. Rule set matches are automatically detected and translated into maintenance decision support information, thereby helping to minimize life cycle costs. The concept is used for both diagnostics, detecting and isolating current engine problems, and prognostics for predicting problems by extrapolating trend functions. The system is highly flexible and end user configurable. The paper gives an overview of the system and methodologies applied with generic examples. For the OPRA OP16 gas turbine, two case studies are presented demonstrating specific component deterioration detection and sensor fault isolation.

NOMENCLATURE

EGT	Exhaust Gas Temperature	[K]
GPA	Gas Path Analysis	
GUI	Graphical User Interface	
NGV	Nozzle guide vane	
PR	Pressure ratio	[-]
PW	Power	[kW]
PWc	Corrected power	[kW]
PT2	Total inlet pressure	[bar]
SFC	Specific fuel consumption	[kg/kWh]
TT2	Total inlet temperature	[K]
TT3	Compressor exit total temperature	[K]
TT3c	TT3/ θ	[-]
TT45	Gas generator exit temperature (twin spool)	[K]
TT45c	TT45/ θ	[-]
VIGV	Variable inlet guide vanes	
Wc	Corrected mass flow	[kg/s]
δ	PT2 / 1.01325	[-]
θ	TT2 / 288.15	[-]

INTRODUCTION

For condition monitoring to diagnose, track and predict the health of gas turbines, three separate major areas can be identified: performance, vibration and the lubrication/oil system. While the monitoring of vibration and the oil system is common with other types of rotating machines, the monitoring of the gas turbine aero-thermodynamic performance has several specific elements. Many publications describe how performance measurement data can be translated into information on the physical condition of components and parts (Doel, 1992; Visser, et al., 2006; Volponi, 2014).

While simple gas path analysis methods provide information on the health of the whole system (for example in terms of EGT and power output margins), more advanced methods generate condition information at component or part level. This offers much more potential for optimizing the maintenance concept but requires models establishing the relations between the conditions of individual components and gas path measurements.

An early publication by Urban (1972) presents the relationships that need to be included in these models in Figure 1.

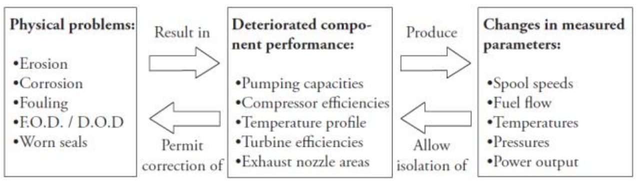


Figure 1 Relations between physical degradation mechanisms and observable performance parameters (source Urban (1972)).

Besides the aero-thermodynamic models capable of describing these relations, methods are also used that employ empirical models generated from longer term history of performance and maintenance to establish the relations. These include genetic algorithms, neural network and other 'machine learning' methods (Bin, et al., 2000; Sampath, et al., 2002). The problem with these methods is that they cannot detect or predict problems that have not yet occurred. Still they may form a valuable complement to the physical model-based method to identify correlations among effects that are not covered by the models.

Advanced model-based gas path analysis (GPA) tools exist that can accurately detect problems on component level, providing valuable maintenance decision support information (Aretakis, et al., 2002; Mathioudakis, et al., 2000; Visser, et al., 2004). However, these tools mostly require manual interaction by skilled engineers. Several concepts applying this concept continuously and on-line exist but add significant complexity and problems with reliability (Volponi, 2014). Recently, neural networks, fuzzy logic and similar machine learning machine learning methods relying on large amounts of field data have been proposed to mitigate reliability problems (Tang, 2018; Zaccaria, 2018) but still suffer from complexity.

However, to have continuous online engine condition analysis, even with a limited level of reliability, would provide huge benefits in terms of maintenance (cost), reliability and availability. For the OPRA OP16 gas turbine, it is concluded a method is required that offers robust advanced GPA capabilities for online monitoring, with limited complexity.

OPRA OP16 GAS TURBINE

OPRA Turbines develops, manufacturers, markets and maintains gas turbine generator sets. The generator sets are powered by the robust and efficient OP16 gas turbine, which is rated at 1.85 MWe. The generator package is delivered as a containerized solution that includes the OP16 gas turbine, fuel systems, generator, control system, air intake and ventilation system. The generator sets can be provided in a variety of configurations to meet specific customer requirements. These sets can be installed as single or multiple units, covering installation requirements from 1.5 to 10 MWe power output.

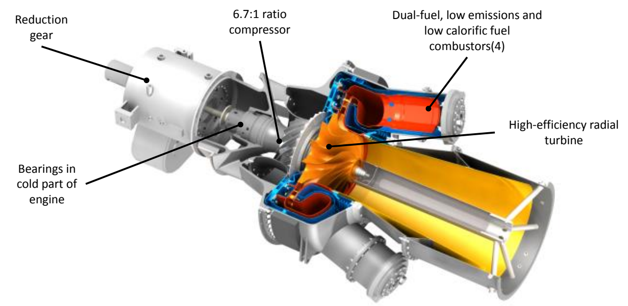


Figure 2. The OPRA OP16 gas turbine (courtesy of OPRA Turbines).

The OP16 (Figure 2) is a single-shaft all-radial gas turbine for industrial, commercial, marine and oil & gas applications. Since its market introduction more than 130 generator sets based on the OP16 gas turbine have been delivered worldwide. The OP16 gas turbine features a single stage centrifugal compressor with a nominal pressure ratio of 6.7:1. The moderate pressure ratio reduces the need for gas compression prior to introducing the fuel into the gas turbine. The radial turbine wheel, which is mounted back-to back with the compressor, has been aerodynamically optimized to achieve a high efficiency. The compact compressor/turbine configuration permits the use of an overhung rotor assembly where the bearings are located on the cold side only. The all-radial configuration makes the OP16 robust and insensitive to foreign object damage and fuel contaminants. The combustion system consists of four reverse flow can combustors, making maintenance access convenient and establishing a uniform temperature and flow distribution into the turbine. The OP16 has a high exhaust gas temperature making it suitable for combined heat and power (CHP) applications. Typically, the power output is controlled by exhaust gas temperature. For more details of the OP16 and its application in CHP installations refer to Axelsson (2015).

OPRA'S REMOTE CONDITION MONITORING SYSTEM

Today there is a clear trend that gas turbine users choose long term service agreements with different options and choices from a range of packages. These packages vary in extent and can include scheduled maintenance, unscheduled maintenance and/or engine overhaul. Being able to accurately monitor and perform advanced analysis will minimize the life cycle costs and maximize the performance and availability of the units. Therefore, OPRA has implemented a remote condition monitoring system for its OP16 fleet.

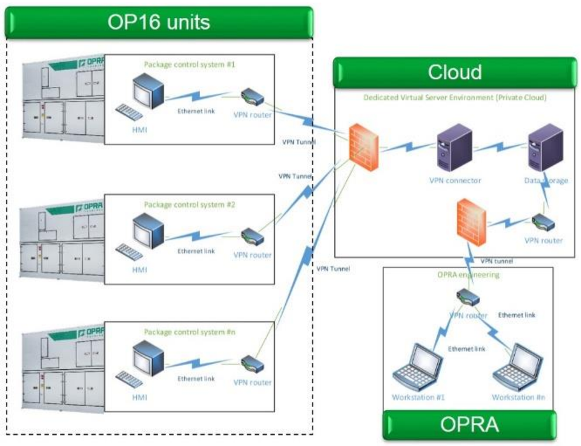


Figure 3. Set-up of OPRA's remote condition monitoring system.

A remote condition monitoring system offers the clients many benefits including:

- High availability by improving the maintenance planning and avoid unplanned outages
- Reduced fuel consumption by preventing undetected performance degradation
- Enhanced safety by reducing the risk of catastrophic failures
- Access to all the data enabling quick and accurate response on issues from the OEM

A schematic of the set-up of OPRA's remote monitoring infrastructure is shown in Figure 3. The system is implemented in a purpose designed and dedicated cloud environment. Within the data center the servers responsible for the connectivity and application are separated on several virtual servers. This ensures security, integrity and reliability of the infrastructure.

The units in the field send data to a central database server. On the customer site the remote monitoring exists of two parts; a router that provides the provision to establish the remote connection in a secure manner and an HMI computer collecting the data and forwarding it to the central database server. To enable secure transfer of the data from the sites to the centralized database a VPN tunnel is established. In this approach the centralized VPN connector is the client connecting to the VPN server running on the routers. This approach limits the impact of a VPN server being attacked.

The diagnostics center is located at OPRA's headquarters in the Netherlands, where a team of engineers are monitoring and supporting the OP16 fleet. The GTPtracker is connecting to the database and updates the fleet status and provides information on critical events. By utilizing a software such as GTPtracker, which includes a high level of automation, the diagnostic engineers can focus on providing correct advice to the customers and/or service team rather than processing data.

SURROGATE MODELS

A concept has been developed to separate the physical gas path analysis models from the on-line monitoring methods using surrogate models. The general idea is to derive a model with only the relations required for the online GPA from a comprehensive (off-line) thermodynamic cycle model.

The off-line cycle model must be capable of

1. predicting reference engine performance for the entire operating envelope. This includes operation conditions such as
   - power setting (e.g. EGT, Torque load, fan speed),
   - ambient and inlet conditions (pressure, temperature, humidity),
   - fuel type,
   - variable geometry settings (e.g. VIGV).
2. predicting the effects of specific deterioration modes, failures and faults on performance.

Reference performance data must then be aggregated into relations between expressions of performance parameters that correct for the inlet operating conditions (represented by δ and θ) as much as possible. The off-line cycle model is used to validate various expressions in their success of successfully 'capturing' performance for varying operating condition is a single line, or if not possible, a set of lines for different variable geometry positions or fuels for example. This should optimally lead to a single base line relation between semi-non-dimensional expressions for power and a power setting variable like EGT for example. The method applied is similar to the 'model based parameter correction' method described by Kurzke (2003) and the 'empirical parameter correction method' described by Volponi (1998).

In Figure 4 an example is given of the derivation of a baseline equation for the power output of a 2-spool turboshaft. Using the GSP Gas turbine Simulation Program (Visser and Broomhead, 2000). The top graph shows actual power curves versus TT45c (i.e. gas generator exit temperature divided by θ) for a range of operating conditions. The second graph shows corrected power, calculated using the expression

$$PWc = \frac{PW}{\partial^{a}\ \theta^{b}} + c.\delta + d.\theta + e$$

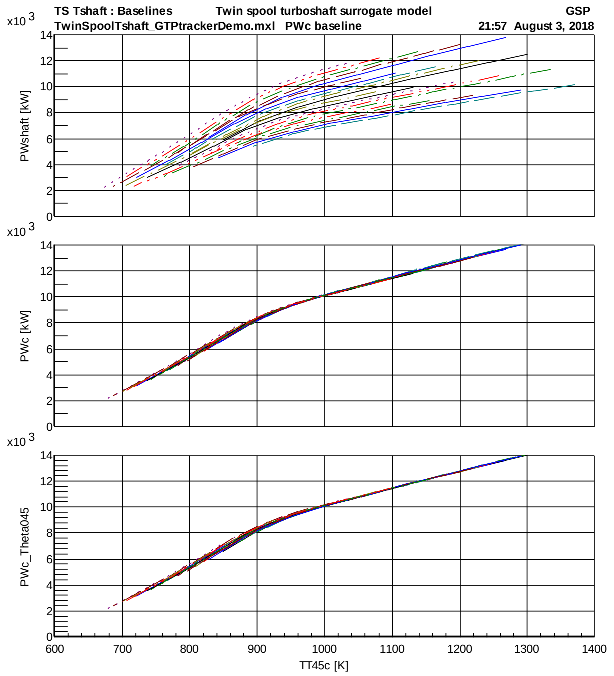


Figure 4 Development of baseline for power for a twin spool industrial turboshaft

For standard ISA corrected (or 'referred') power, a=1, b=0.5 and c=d=e=0. Often however, these constants need to be slightly adapted to make all curves (for different conditions) better coincide (within a predefined margin) into a single PWc curve in the area of interest, so performance for all operating conditions can be represented indeed by a single curve. The deviation margin due to varying operating condition usually must be within 1% to avoid interference with deviations due to component condition changes. In the example of Figure 4 only b is changed from 0.5 (for PWc) to 0.45 (PWc_Theta045) resulting in a better coinciding in the high power (high TT45c) range which is preferred for gas path analysis and diagnostics. This relation can subsequently be curve fitted. The polynomial fit only needs to match the PWc curve in the range of interest (in this case above a TT45c of 1000 K), which often is at or near base load operation (i.e. 1100 K), where full steady-state, required for accurate comparison with base line performance, is reached. In this example, a linear fit perfectly represents reference power above the 1000 K level, providing an accurate (<0.5%) baseline for baseload operation:

$$PWc_{ref} = 9900 + (\mathrm{TT45} - 980) \cdot 12.9$$

It is clear that for this example an additional relation would have to be added if analysis at part load would be required.

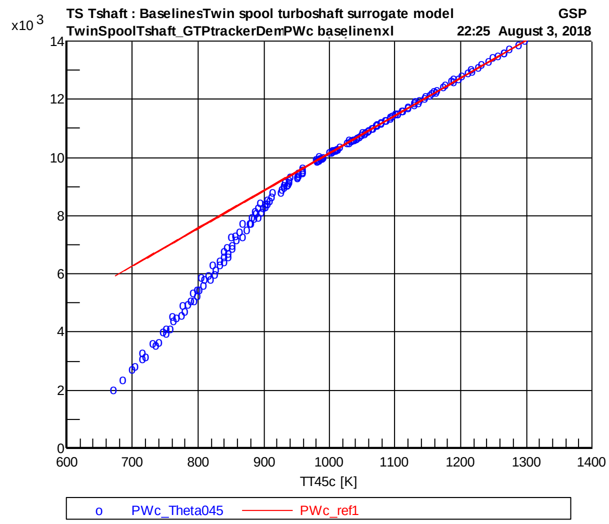


Figure 5 Surrogate model curve fit

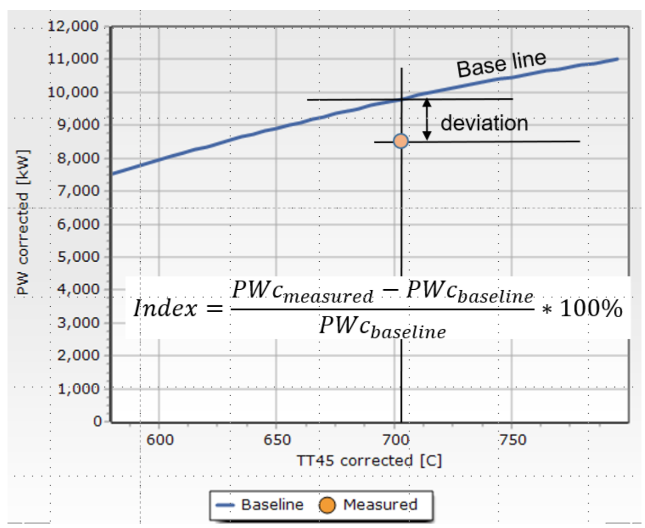


Figure 6 GTPtracker condition index example

CONDITION INDICES

In GTPtracker, online measured operating condition data is fed to the surrogate models and compared to the value of the corrected parameters calculated from actual measured performance. The deviations are indications for component condition parameters such as efficiency, pressure loss or flow capacity. In GTPtracker, deviations from the surrogate baseline model are named 'condition indices', as shown in Figure 6.

To identify specific problems in the engine, combinations of indices must be analyzed because only a single index deviation may be caused by several different problems. The analysis of combinations of indices is done online using GTPtracker rulesets.

RULESETS

Rulesets in GTPtracker are combinations of conditions for indices. For example, matching a ruleset may require the power index to be lower than -5%, while also an index for the compressor pressure ratio must be lower than -4 % and another index for some temperature must also lie in a certain range. This could then mean the compressor can be isolated as being the cause of the performance deviation.

A cycle model capable of simulating deterioration and faults in the gas path such as GSP (Visser and Broomhead, 2000) can be used to determine or validate the rulesets. It is important to verify if indeed the ruleset uniquely relates to the specific problem. Experience from the field may subsequently be used to finetune the rulesets. The rulesets must also be set to capture effects beyond the measurement uncertainty to minimize false alarms.

DIAGNOSTICS

With well configured and validated rulesets, diagnostics can be performed on component level, either manually but also automatically and continuously on new incoming data points. The rulesets are related to maintenance types. Depending on the ruleset maintenance type, items are added to the maintenance calendar providing maintenance decision support. Figure 7 depicts the process. The surrogate reference model performance indices are compared with the measured indices; deviation patterns are compared against the rulesets providing diagnostic information. Rulesets can be developed using the off-line model deterioration and fault effect simulations.

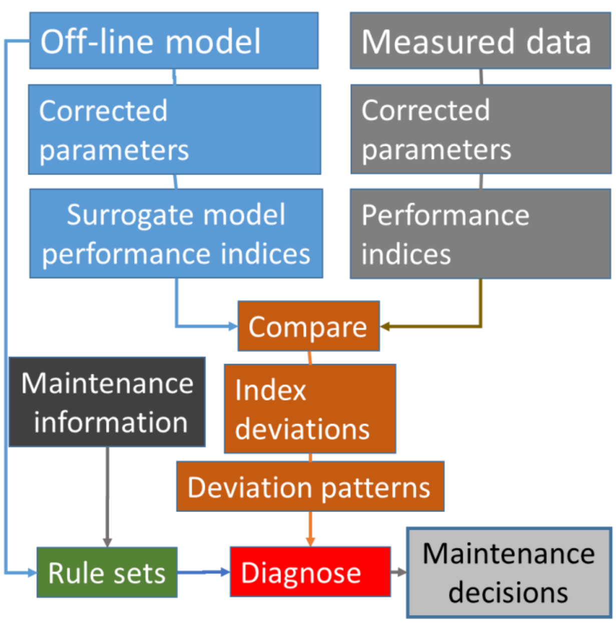


Figure 7 From baseline model and measured data to maintenance decisions

TRENDING

A Kalman-filter based trending function is used to obtain the most likely trend from measured and calculated time series parameters that are subject to noise, sensor faults and other irregularities. For the Kalman filter, equations similar to those used for the Optimal Tracker described by Provost (2015) have been used. This Kalman filter is 'smoothing out' random noise looking both at the actual level and the slope (time derivative). The level and slope smoothing factors ('a1' and 'a2') should be optimized for the specific nature and noise of a signal. The Optimal Tracker (optionally) relates a2 to a1, leaving only a single constant (a1) to fine-tune the trend function. In Provost (2015) the benefits of the Optimal Tracker Kalman filter for time series analysis of industrial asset performance signals are further described.

The Kalman filter algorithm is configurable for each parameter separately, using a user-friendly GUI showing the trend result. In addition to a1 (and optionally a2), constants can be specified controlling the impact of outliers, discontinuities etc.

In Figure 8 an example is shown of the Optimal Tracker trend function for an SFC index (note that these are simulated data with SFC varying due to Monte Carlo simulated noise on both component model efficiency and sensor error). Here a2 is set to -1 (enabling the Optimal Tracker relation for a2) and the delta limit is set to 4 resulting in a reset of the trend (suggesting a discontinuity) towards the right end of the plot.

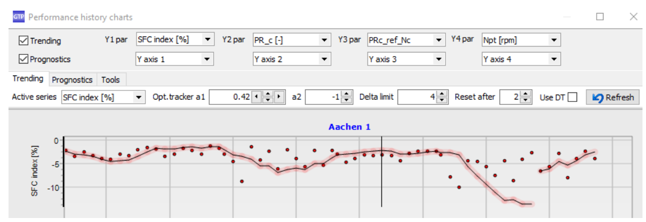


Figure 8 Example of data points, trendline and the controls for configuring the trend line Kalman filter function

In general, only time series parameters that are not affected by operating conditions that are changing in the time series, are suitable for trending. These are ISA corrected (surrogate model) performance parameters or the condition indices for example. Other examples are vibration signals or oil system parameters.

Another way of excluding effects of operating condition variation is filtering out only point of interest such as base load or steady state. The GTPtracker Query filter offers the user a flexible way of selecting specific point types for this purpose.

PROGNOSTICS

Automatic prognostics is performed every time new data points are added to the time series. For a user specified number of most recent point, a regression is performed and extrapolated. If the extrapolation hits a user specified limit within a specified period, a ruleset check is performed. When meeting a ruleset, the same action as with diagnostics is taken, adding items to the maintenance calendar for maintenance decision support.

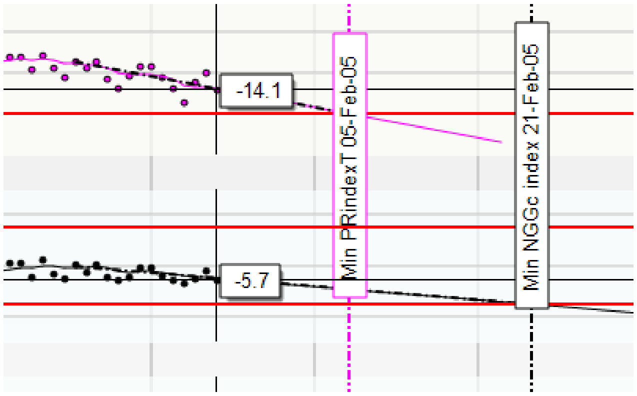
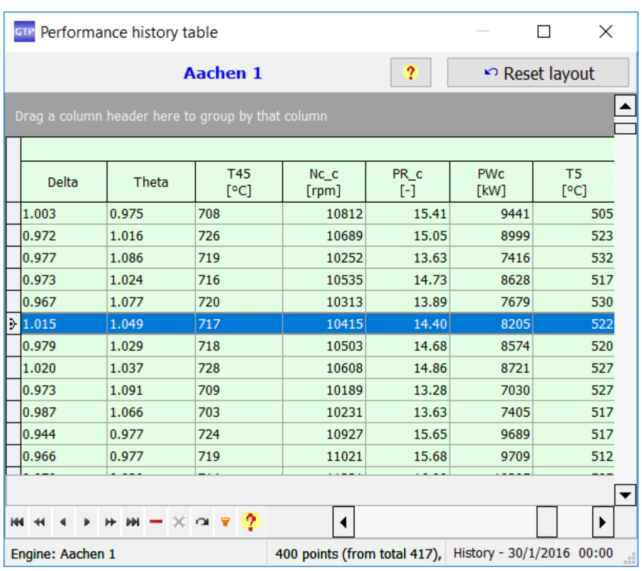


Figure 9 Prognostics using the condition index trends

In the example of Figure 9, the prognostics is shown at work on 2 condition indices (in this case power and efficiency). Both trends show a negative slope which is extrapolated and exceed the red line alert limit at a specific date. As mentioned in the Trending section, also for prognostics, only specific parameters or point types that are independent of varying operating conditions, are suitable for prognostics.

ANALYSIS TOOLS

For analysis of performance history, it is important that values and trends of several parameters can be shown simultaneously when browsing the data. Also, component operating points must be easily assessed and show in conjunction with other parameters. In GTPtracker, all tables and graphs are synchronized on the selected point in time. Moving the selection point through one graph or tables, moves the point in all tables. With multiple windows or monitors, this way a powerful tool is provided to engineers analyzing events in performance historic data. Moving to a point in the performance table in Figure 10 for example, immediately shows the operating point and active speed line in the compressor map in Figure 11.



Delta	Theta	T45 [°C]	Nc_c [rpm]	PR_c [-]	PWc [kW]	T5 [°C]
1.003	0.975	708	10812	15.41	9441	505
0.972	1.016	726	10689	15.05	8999	523
0.977	1.086	719	10252	13.63	7416	532
0.973	1.024	716	10535	14.73	8628	517
0.967	1.077	720	10313	13.89	7679	530
1.015	1.049	717	10415	14.40	8205	522
0.979	1.029	718	10503	14.68	8574	520
1.020	1.037	728	10608	14.86	8721	527
0.973	1.091	709	10189	13.28	7030	527
0.987	1.066	703	10231	13.63	7405	517
0.944	0.977	724	10927	15.65	9689	517
0.966	0.977	719	11021	15.68	9709	512

Figure 10 Performance history table

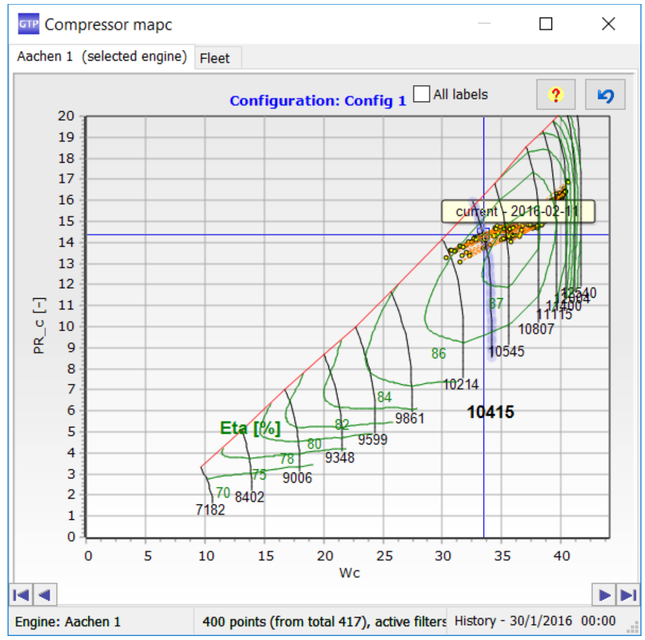


Figure 11 Compressor performance history

DATA PROCESSING

GTPtracker data processing has 3 stages (Figure 12).

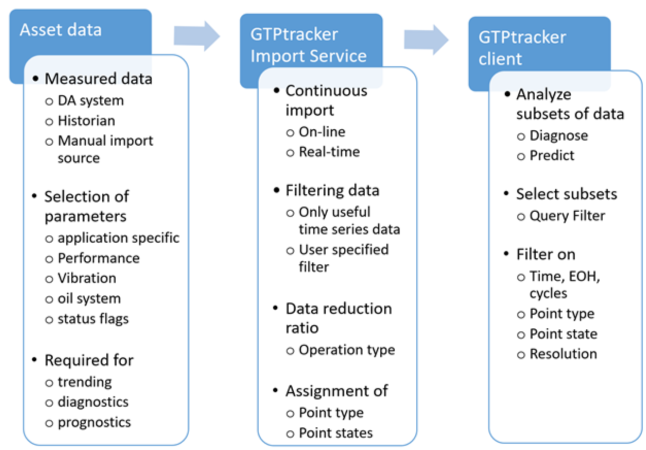


Figure 12 GTPtracker data processing scheme

- Importing data from industrial assets such as power plants or other energy systems. A specific selection of parameter values are imported from a data source, such as a data acquisition or historian database.
- Filtering data: the data are filtered to only obtain data significant for the analysis. This means data points where no parameters is changing significantly relative to its prior and next neighboring points are skipped. The criteria for this filter are user specified. The filtering process runs continuously on the GTPtracker server.
- Analyzing the data in the GTPtracker client: a subset of data is selected using the Query Filter function to select specific periods, ranges of engine operating hours (EOH) or cycles, point types and/or states. More

detailed filters can be specified by SQL code query rules. In addition, query resolution can be defined to obtain only one point per user specified number of seconds, minutes, hours, days etc.

ONLINE DATA ACQUISITION

GTPtracker has various ways of importing data. Both manual and on-line data importing are possible. Interfaces using SQL querying of historian databases are available for several established industry standard historian database / asset monitoring systems. For older systems, CSV text files can be imported continuously online via the FTP protocol. The GTPtracker Server and Import configuration service application runs on a Windows server and continuously extracts and filters data from the historian.

For individual analysis cases, data can manually be imported from CSV files.

RULE SET GENERATION

Using the GSP baseline model of the OP16 engine, a few simple deterioration cases have been simulated to demonstrate the concept of the ruleset-based diagnostics. In The solid curves in Figure 13 show the predicted effects of 5% drop in compressor efficiency (point 2) and a 5% drop in turbine efficiency (point 3) relative to the reference performance (point 1). The operating condition is base load which is at a fixed exhaust gas temperature EGT (the EGTc set point is 100%). Shown is the effect on compressor pressure ratio PR_c, ISA corrected shaft power PWc and the change of compressor exit temperature dTT3c.

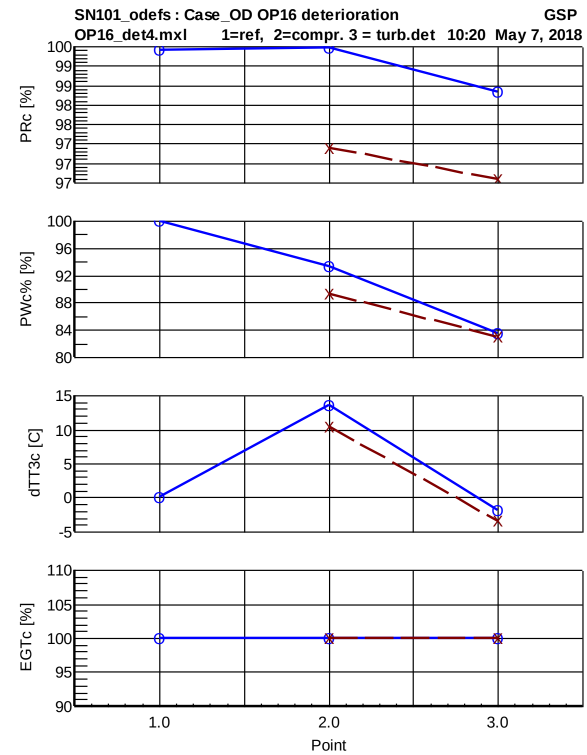


Figure 13 OP16 deterioration simulation results

It is clear the two different cases are easy to isolate from each other. With only compressor deterioration, pressure ratio remains about constant, power drops and TT3c increases. This means a ruleset could be derived looking at PR_c and TT3c, isolating the compressor as the problem component when a drop in corrected power is accompanied by only a rise in TT3c and not a drop in PR_c.

However, usually turbomachinery deterioration cannot just be represented by a decrease in efficiency, especially with a compressor also flow capacity is negatively affected. Turbine flow capacity may increase slightly due to the increase in flow cross areas caused by corrosion and/or erosion in the NGVs. The dashed curves in Figure 13 show the case of compressor deterioration with -5% efficiency and -2.5% flow capacity change (point 2). Point 3 is -5% turbine efficiency and +2.5% flow capacity.

Now the problem is different, especially for PR_c. We must accept that the compressor deterioration is an unknown combination of efficiency and flow capacity reduction, somewhere between the solid and the dashed curve cases in Figure 13. However, a ruleset can still be derived isolating compressor from turbine problems.

In Figure 14 a part of a GTPtracker ruleset table is shown, with 2 rulesets that both become active if the power index is lower than -2 or -3 %. The power and pressure ratio indices in the table are directly related to the corrected parameters used in the simulation described above. Two exclusive areas for the PR index and TT3c are defined that would either suggest the compressor or the turbine as the root cause of poor performance.

Rulesets for configuration: OP16 Config 2

Name	Description	Component	Maintenance ty
Compressoı	Compr.Gen.Deteı	Compressor	water wash

Fieldname	Display label	Unit	Below	Above
PW index [%]	PW index	[%]	-2.00	
PR index [%]	PR index	[%]		-3.00
TT3_2 [°C]	TT3_2	[°C]		280

Name	Description	Component	Maintenance ty
Turbine det		Turbine	Inspection 1

Fieldname	Display label	Unit	Below	Above
PW index [%]	PW index	[%]	-3.00	
PR index [%]	PR index	[%]	-3.00	
TT3_2 [°C]	TT3_2	[°C]	280	

Figure 14 GTPtracker rulesets example

Figure 14 only shows a subsection of all the rulesets for the GTPtracker OP16 configuration. The number and detail of rulesets that the user can specify is unlimited.

Naturally, the rulesets should be finetuned based on experience and refinement of the deterioration models in the GSP cycle model. Sensor error rules may be added using sensor redundancy, avoiding gas path deterioration false alarms.

CASE STUDY I

Detection of sensor error is important to avoid wrong control system- or human action. This section demonstrates detection by GTPtracker of a drifting fuel flow measurement in an OP16 gas turbine unit in the field.

Using the end-user configurable functionality of GTPtracker to identify the operating state of an engine from imported data, base load steady-state points are distinguished from other operating states using limits on measured rotational speed, exhaust gas temperature, power output and bleed valve opening, appropriate to the OP16. Usually, the base load data points are subsequently filtered out to better trend and analyze engine performance, especially the parameters that depend on engine operating condition.

To eliminate the effect of operating conditions, performance indices are defined using the semi- end user configurable capability of GTPtracker. These include power, pressure ratio, thermal efficiency and EGT. Power and EGT indices are a ratio of the corrected value to the reference value derived from the OP16 baseline model.

Configuration of engine type: OP16

Constants | Baselines / maps | Rulesets

Name	Description	Component	Maintenance type
Fuel flow sensor	Fuel flow sensor drift		Fuel flow sensor reset

Fieldname	Display label	Unit	Below	Above
PWc_index [-]	PWc_index	[-]	1.050	0.950
EGTc_index [-]	EGTc_index	[-]	1.005	0.995
Eta_index [-]	Eta_index	[-]	0.800	1.200

Figure 15 Ruleset for detecting a drifting fuel flow measurement

Drifting of a fuel flow measurement is characterized by constant power and EGT index trends and a change in the trend of thermal efficiency index. Constant power and EGT indices imply that the engine is producing the same power for a given EGT meaning that all components forming the gas flow path are performing at a nominal level. Changing of the fuel flow alone in such a scenario can only be caused by a faulty measurement resulting in a corresponding drift in the measured thermal efficiency. These conditions are developed into a ruleset shown in Figure 15 which says that if the power and EGT indices stay within a specified limit and the thermal efficiency index goes out of a specified limit, fuel flow measurement fault is suspected. The limits are defined based on a combination of OP16 cycle simulations, measurement accuracy and experience. The ruleset detected a drifting fuel flow measurement at an operational OP16 gas turbine engine, automatically adding an item to the maintenance calendar. To investigate further, the trend of performance indices over the past weeks was filtered out using the query filter. A near constant trend of power index and EGT index was observed, while the thermal efficiency index showed a steady increase over time (Figure 16). The fuel flow measurement was thus, identified as the suspect and replacing of the fuel flow sensor was added to the on-site maintenance plan. Replacing the sensor restored the engine performance parameters. It can be seen in Figure 16 that towards the end, the thermal efficiency goes back to its nominal value.

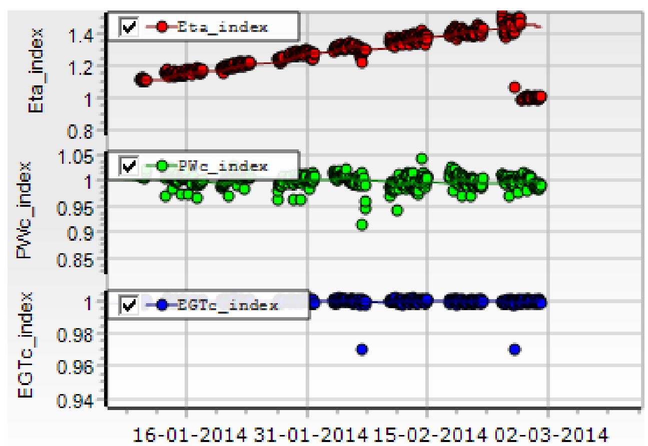


Figure 16 Trend of performance indices: thermal efficiency index (Eta_index), power index (PWc_index) and EGT index (EGT_index)

CASE STUDY II

To ensure clean compressor inlet air, it is necessary to install filters at the gas turbine inlet. As the filters progressively get clogged, the pressure loss in the inlet increases, resulting in reduced gas turbine performance (efficiency and power). Moreover, failing to replace a filter on time can cause it to burst, potentially leading to foreign object damage in the gas flow path. This case study demonstrates the use of prognostics in GTPtracker to predict when an inlet air filter would need to be replaced. This helps in efficient planning of maintenance activities, avoiding damage to the gas turbine and retaining engine performance.

Figure 17 shows the trend of the index for inlet air filter loss of an OP16 gas turbine engine operating on-site. *dPfilter_index* is the ratio of measured pressure drop across the air inlet fine filter to a reference value, usually the pressure drop measured during engine commissioning. As can be seen from the graph, the inlet pressure drop across the filter stage is increasing over time. A ruleset is created that generates the maintenance action of replacing the inlet filter when the index exceeds a defined limit (in this case 3). The prognostics function predicts that the filter will have to be replaced within a few months and adds an item (at 22 May) to the maintenance calendar as shown in Figure 18. Depending on the type of maintenance required and the time available to perform it, the status of a maintenance action can vary. In this case, since the fault is only *predicted* by prognostics, and there is some time available to carry out the required maintenance, the status of the maintenance action is assigned as “Predicted” by GTPtracker. The user can change the status to “Scheduled”, “Suggested”, “Urgent”, “Anomaly” etc. after further analysis, changes in observed trends, and maintenance planning.

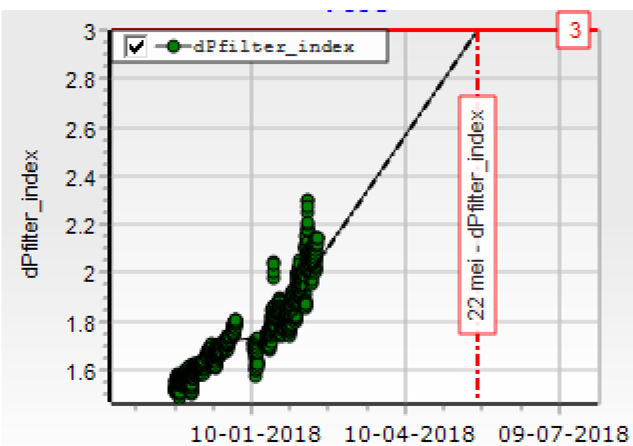
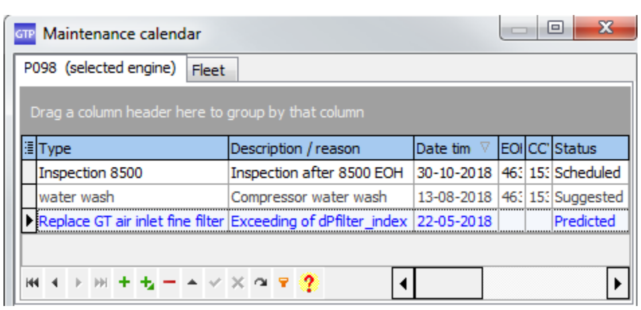


Figure 17 Prognostics showing when the air inlet filter will need to be replaced



Type	Description / reason	Date tim	EOI	CC	Status
Inspection 8500	Inspection after 8500 EOH	30-10-2018	46:	15:	Scheduled
water wash	Compressor water wash	13-08-2018	46:	15:	Suggested
Replace GT air inlet fine filter	Exceeding of dPfilter_index	22-05-2018			Predicted

Figure 18 Updated maintenance calendar upon prediction of required inlet air filter replacement

CONCLUSIONS

- An innovative online condition monitoring system has been developed for the OPRA OP16 gas turbine using the GTPtracker monitoring and tracking tool.
- The connection of the condition monitoring process with accurate cycle models capable of simulating deterioration via a surrogate models and rulesets for diagnostics offers an optimal compromise between complexity and functionality.
- The GTPtracker environment and configuration user interface provides a powerful tool for diagnostics engineers to optimize maintenance (minimize costs), reliability, availability and safety for the OP16 fleet.
- A customized version of the GTPtracker tool has recently been deployed for the OP16 engine.

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