The future of Gas Turbine Technology
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EXPERIENCE WITH CONDITION-BASED MAINTENANCE RELATED METHODS AND TOOLS FOR GAS TURBINES

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Contents

- **Overview of the CBM approach**
- **Tools and techniques developed by LTT/NTUA**
  - Diagnostic and prognostic methods
  - EGEFALOS®
  - Power Plant CBM s/w
- **Application examples**
  - Sensor fault diagnosis using PNN
  - VSV fault diagnosis using adaptive performance modeling
  - Burner malfunctions identification using a pattern recognition approach
  - Compressor & Turbine fouling diagnosis using adaptive performance modeling
  - Turbine subsystem malfunction identification from on-wing data
- **Summary-Conclusions**

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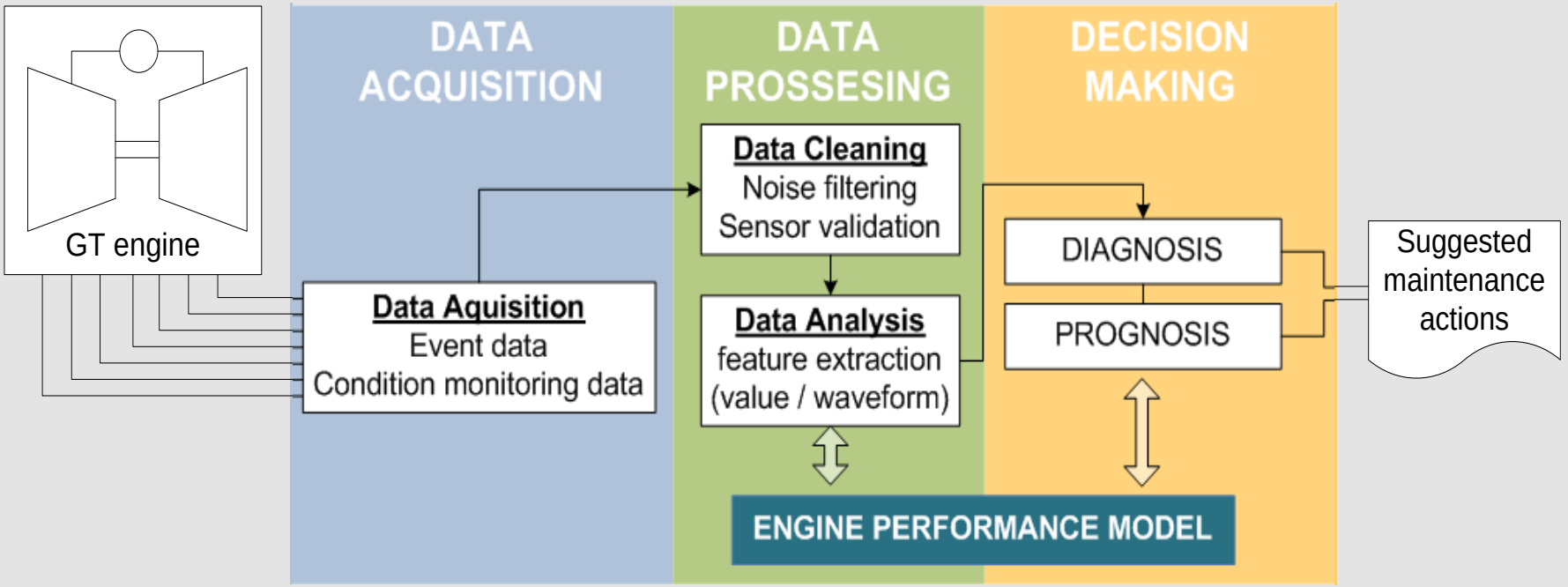
Overview of the CBM approach



CBM is a maintenance approach, where maintenance actions are suggested, based on information collected through condition monitoring

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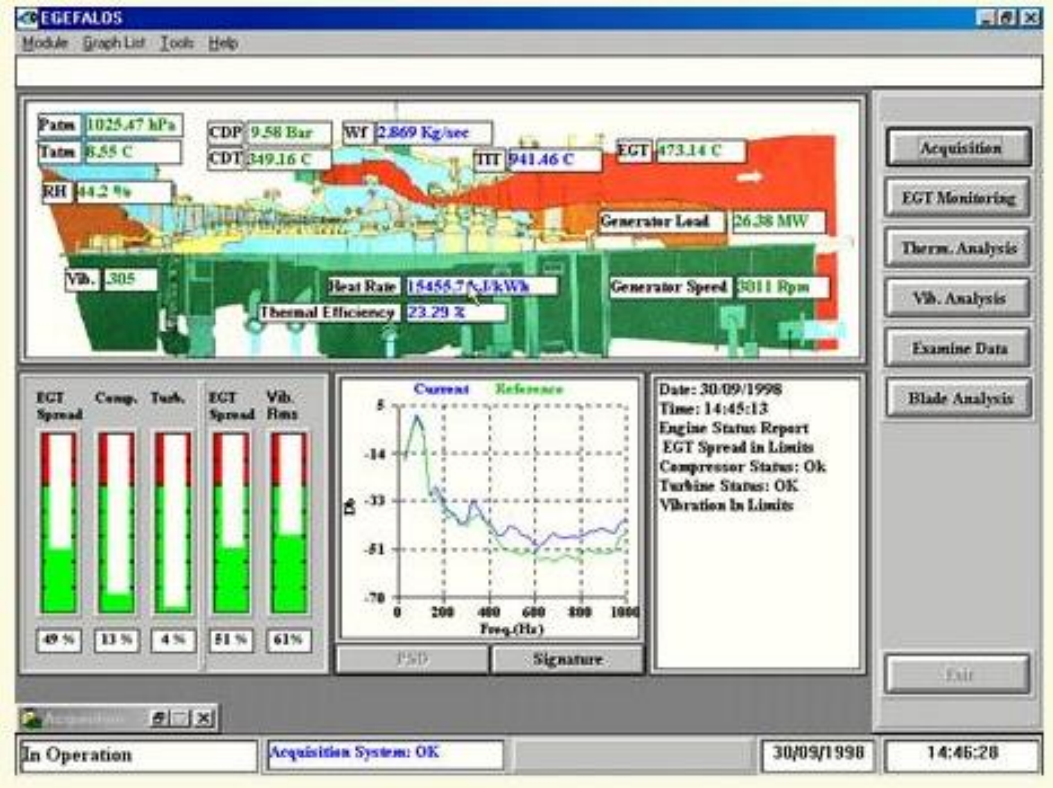
LTT/NTUA CBM related activities

Sensor faults	Model-Based Diagnostic methods	AI Diagnostic methods
•Pattern Recognition Methods •Model-based methods through optimization techniques • Probabilistic Neural Networks	•Adaptive Performance Modeling •Deterioration Tracking method •Combinatorial approach •Optimization technique •Performance model 'zooming' •Pattern recognition Methods •Wavelet analysis •Stochastic approaches	•Bayesian Belief Networks •Probabilistic Neural Networks •Fuzzy Logic •Artificial Neural networks •Dempster-Schafer technique **Prognostic methods** •compressor washing economic analysis and optimization.

LTT/NTUA is active for nearly 25 years in the field of gas turbines condition monitoring and diagnostics

EGEFALOS®

Engine **GE**neral **FA**ult **L**ogic **O**riented **S**oftware



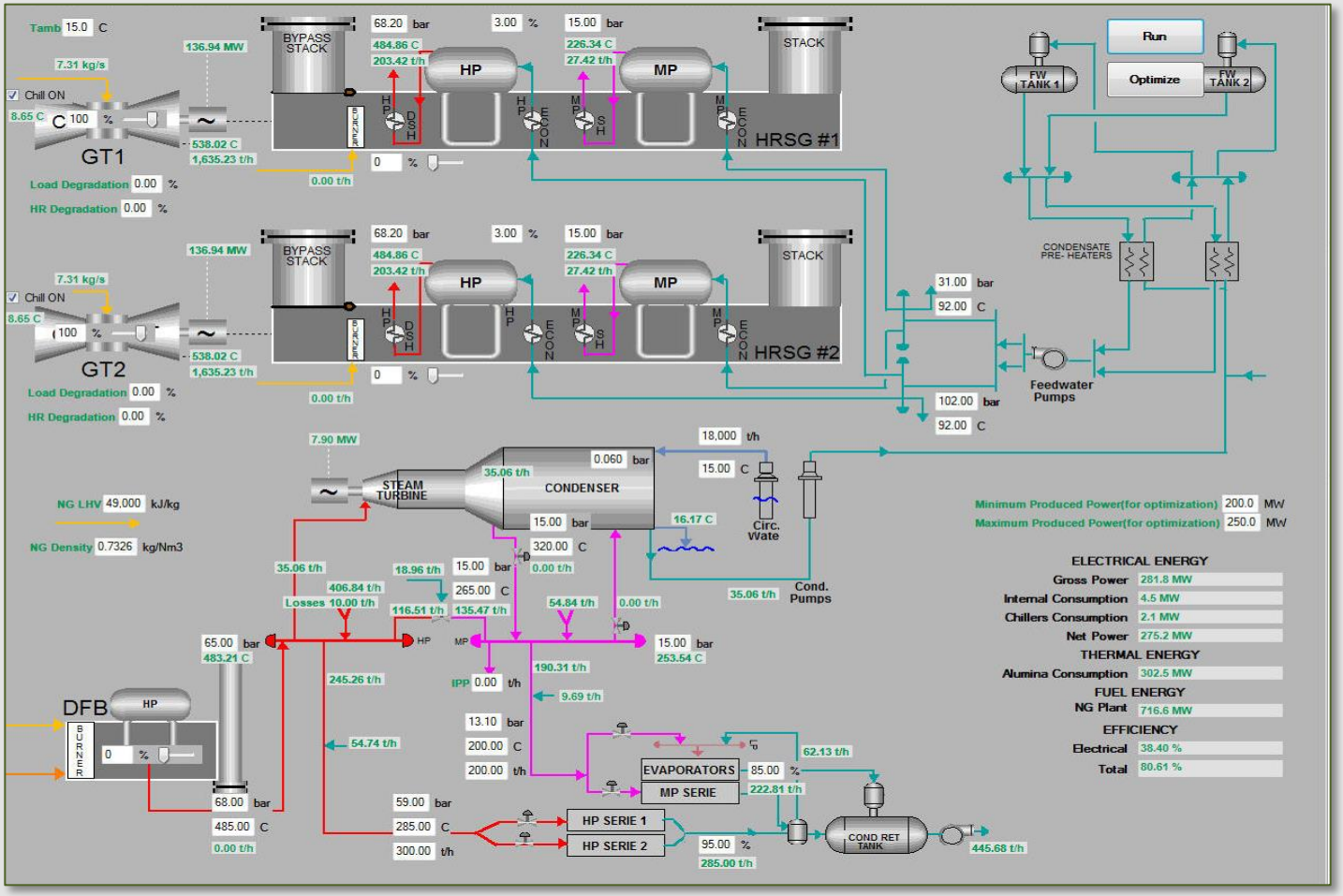
Main features

- Data acquisition
- Hot section monitoring
- Performance Data analysis
- Vibration monitoring
- Data Base management
- Blade analysis

Installed facilities

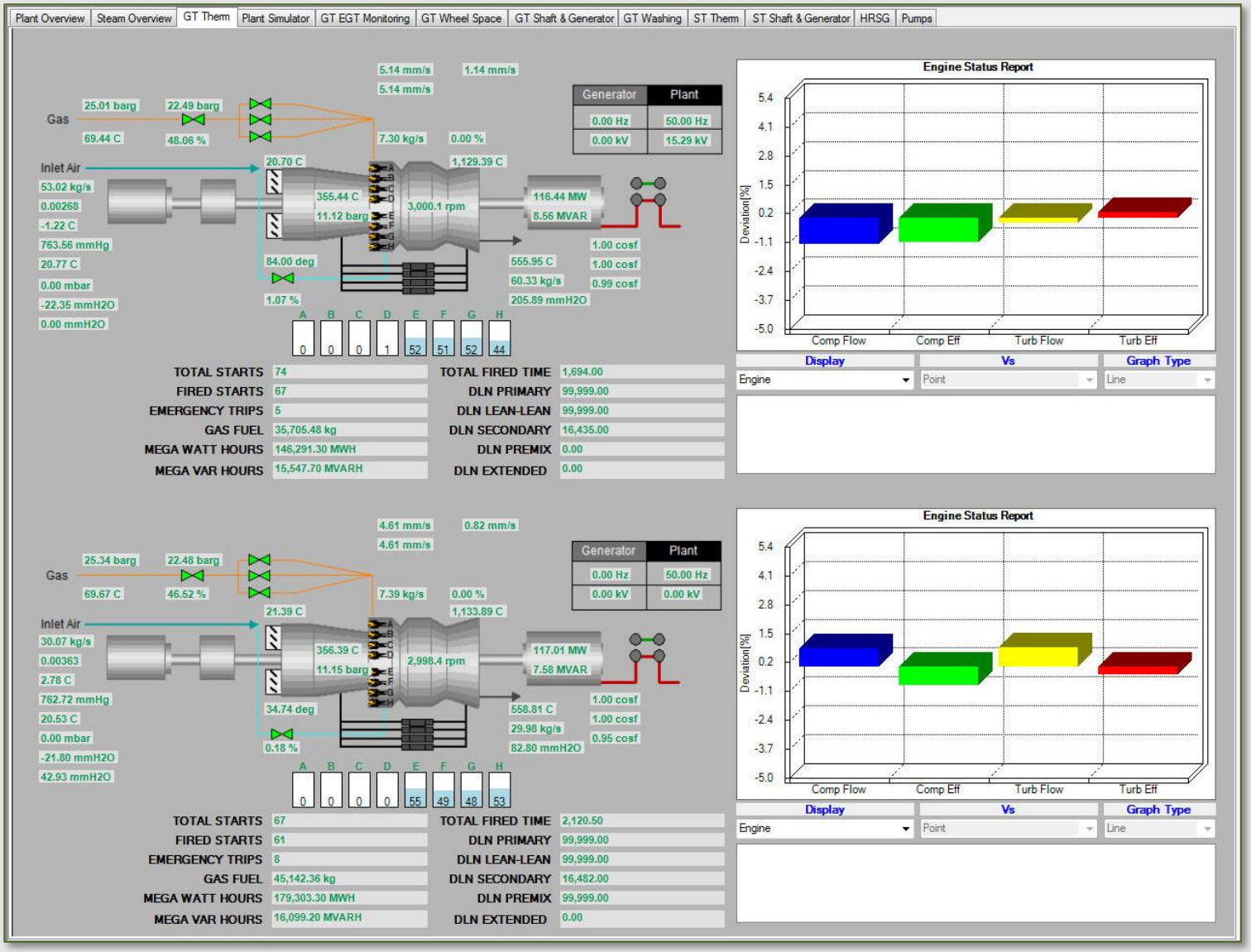
- ABB-GT10
  (Hellenic Refineries, Aspropirgos)
- J-79 TurboJet
  (HAF Engine Test Cell, Elefsina)
- FIAT TG-20
  (PPC Power Plant, Chania)
- GEC EM610B
  (PPC Power Plant, Lavrio III)

CBM software for a CCGT power plant

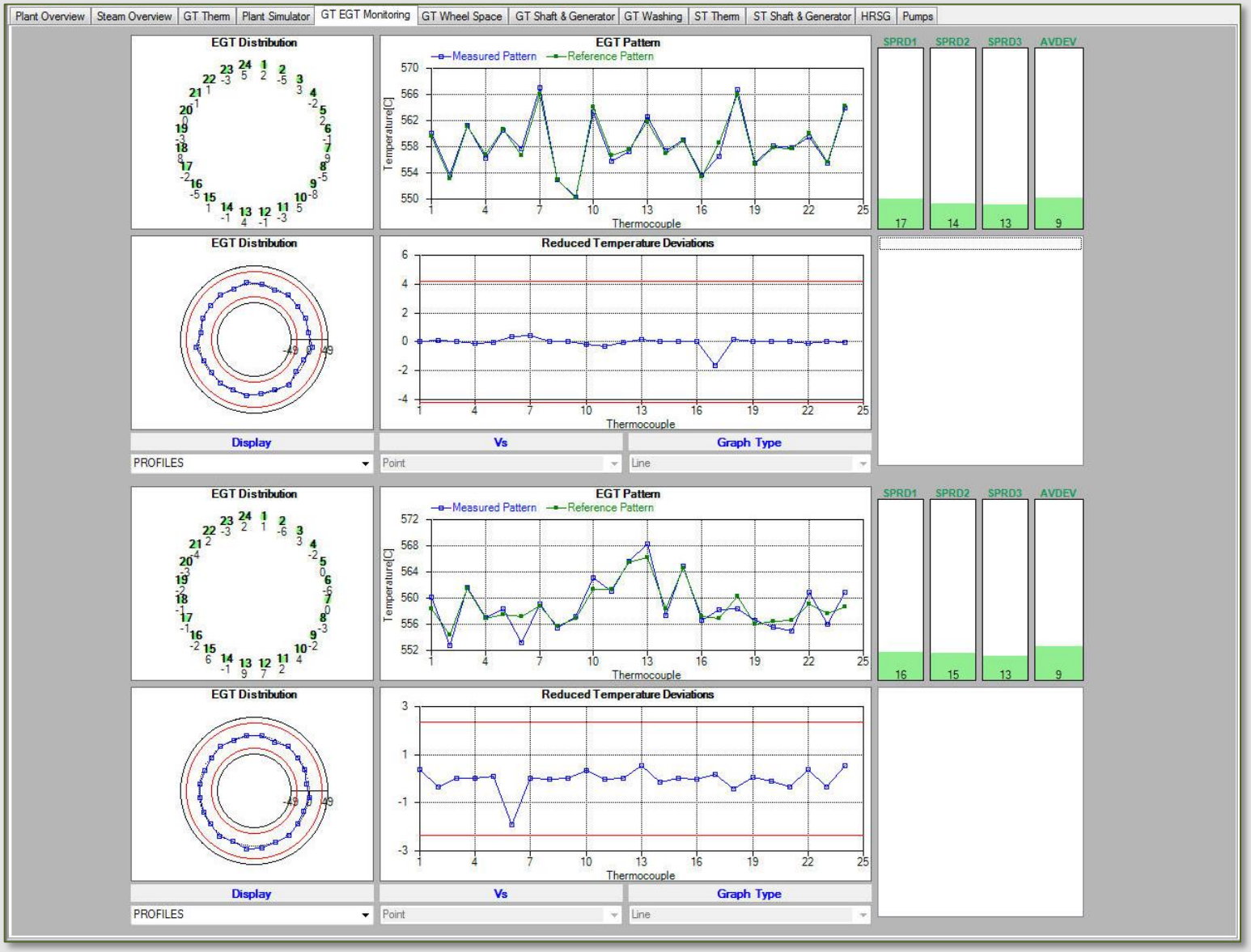


Online plant overview of a 334MW CCGT comprising two PG171 GE gas turbines and one SST-900 Siemens steam turbine

Gas Turbines diagnostic feature of the CBM software



EGT monitoring feature of the CBM software

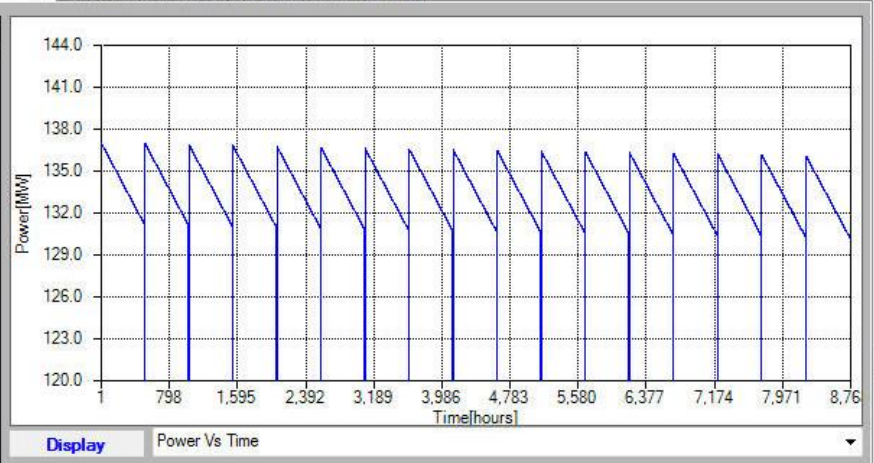


Compressor washing optimization feature of the CBM s/w

Plant Overview | Steam Overview | GT Therm | Plant Simulator | GT EGT Monitoring | GT Wheel Space | GT Shaft & Generator | GT Washing | ST Therm | ST Shaft & Generator | HRSG | Pumps

Parameter	Value	Parameter	Value	Parameter	Value
Total Time duration[days]	365	Time for Washing-01[hours]	510	Produced Energy[MWh]	1161762.9
Time difference between points[hours]	1	Time for Washing-02[hours]	1022.3	Fuel Cost[$]	91893385.3
Number of Washings[-]	16	Time for Washing-03[hours]	1535.8	Total Cost[$]	101288317.9
Washing duration[hours]	3	Time for Washing-04[hours]	2049.7	Total Profit[$]	3270346.8
Load degradation[%/month]	6	Time for Washing-05[hours]	2564.5	Energy Cost[$/MWh]	87.185
HR degradation[%/month]	0.83	Time for Washing-06[hours]	3079.1		
Load degradation due to aging[%/year]	0.7	Time for Washing-07[hours]	3594.2		
HR degradation due to aging[%/year]	0.3	Time for Washing-08[hours]	4109.6		
Nominal Power[MW]	137	Time for Washing-09[hours]	4626		
Nominal fuel flow[kg/s]	7.31	Time for Washing-10[hours]	5142.4		
Fuel Cost[$/kg]	0.41	Time for Washing-11[hours]	5658.4		
Market Price[$/MWh]	90	Time for Washing-12[hours]	6174.4		
Life Expectancy[years]	30	Time for Washing-13[hours]	6691.4		
Investment Cost[$/kW]	350	Time for Washing-14[hours]	7207.5		
Personel[ppl/MW]	0.2	Time for Washing-15[hours]	7723.4		
Salary[$/month]	1500	Time for Washing-16[hours]	8241.2		
Meintenance Cost[$/MWh]	6				
Filter Change Cost[$]	5000				
Washing Cost[$]	3000				
EOH increase due to Washing[hours]	20				
Time Interval Between Filter Change[days]	120				

Run | Optimize | Optimize Nr Washings | Nr Washings Based on Power Loss | Power Loss[%] 5



Example of the required number of washings estimation, over a specific period, for optimum total profit

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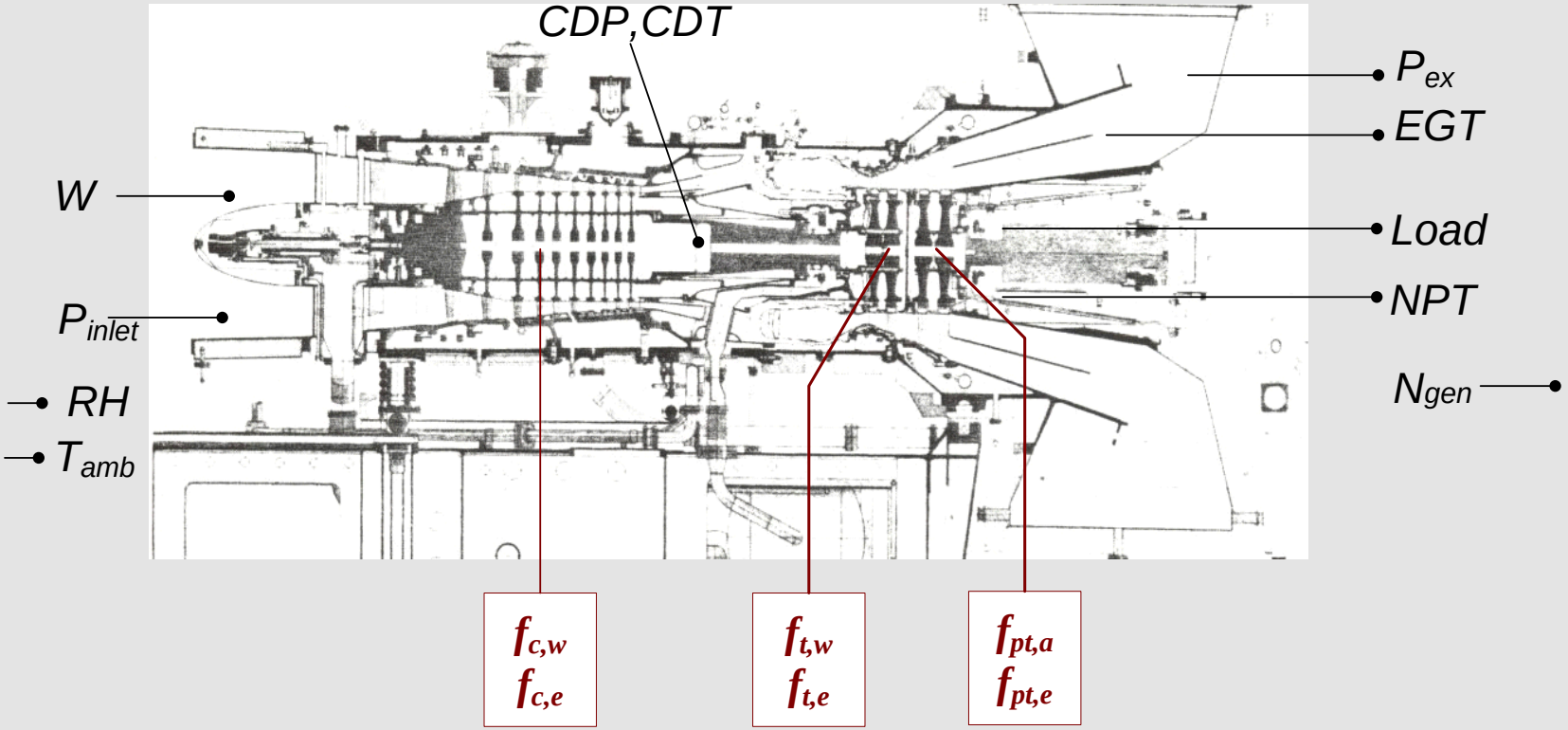
Sensor fault diagnosis using PNN

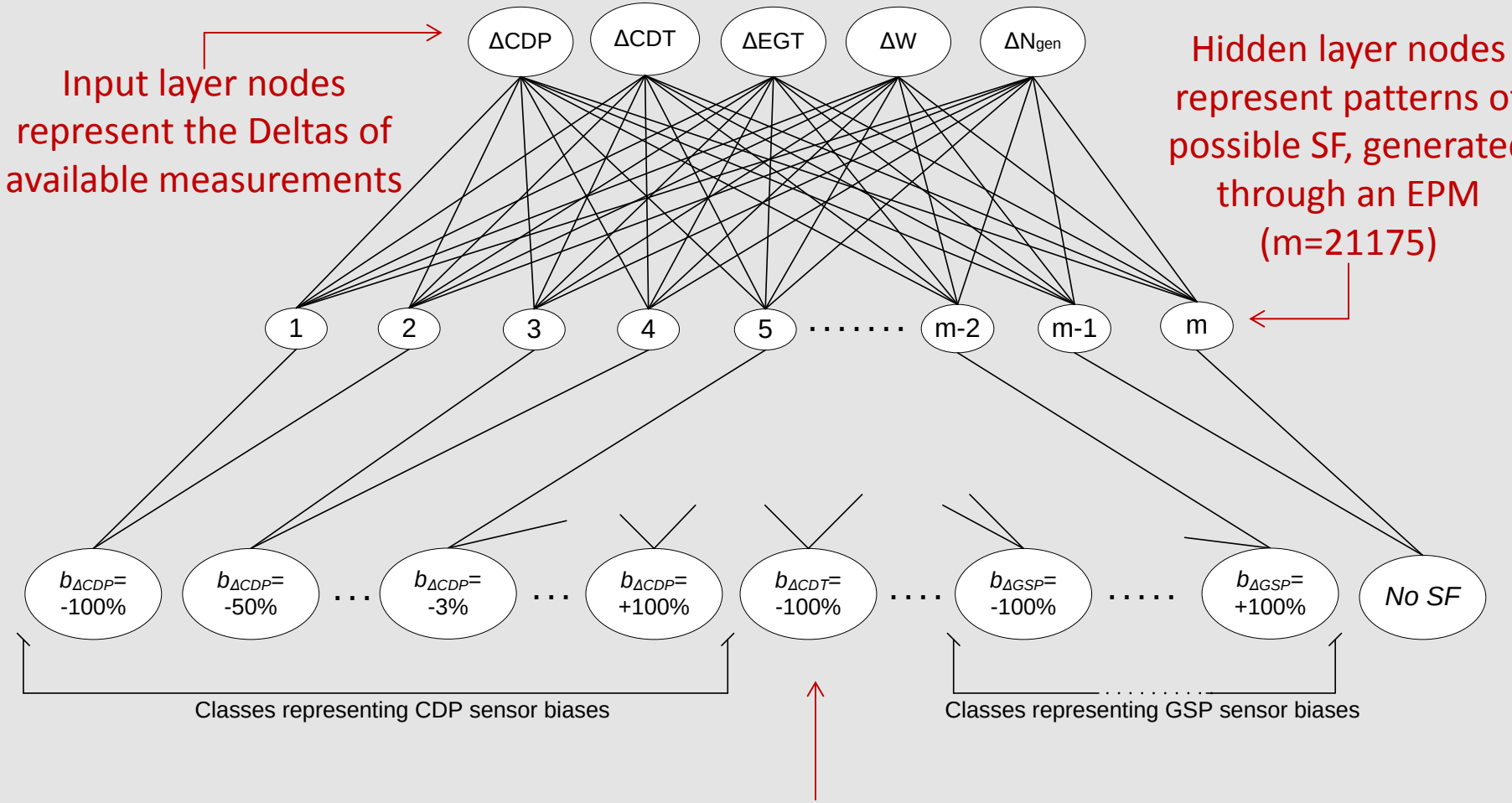
The ABB Sulzer type-10 example



16 MW, twin-shaft industrial GT, used by *Hellenic Petroleum S.A.*.

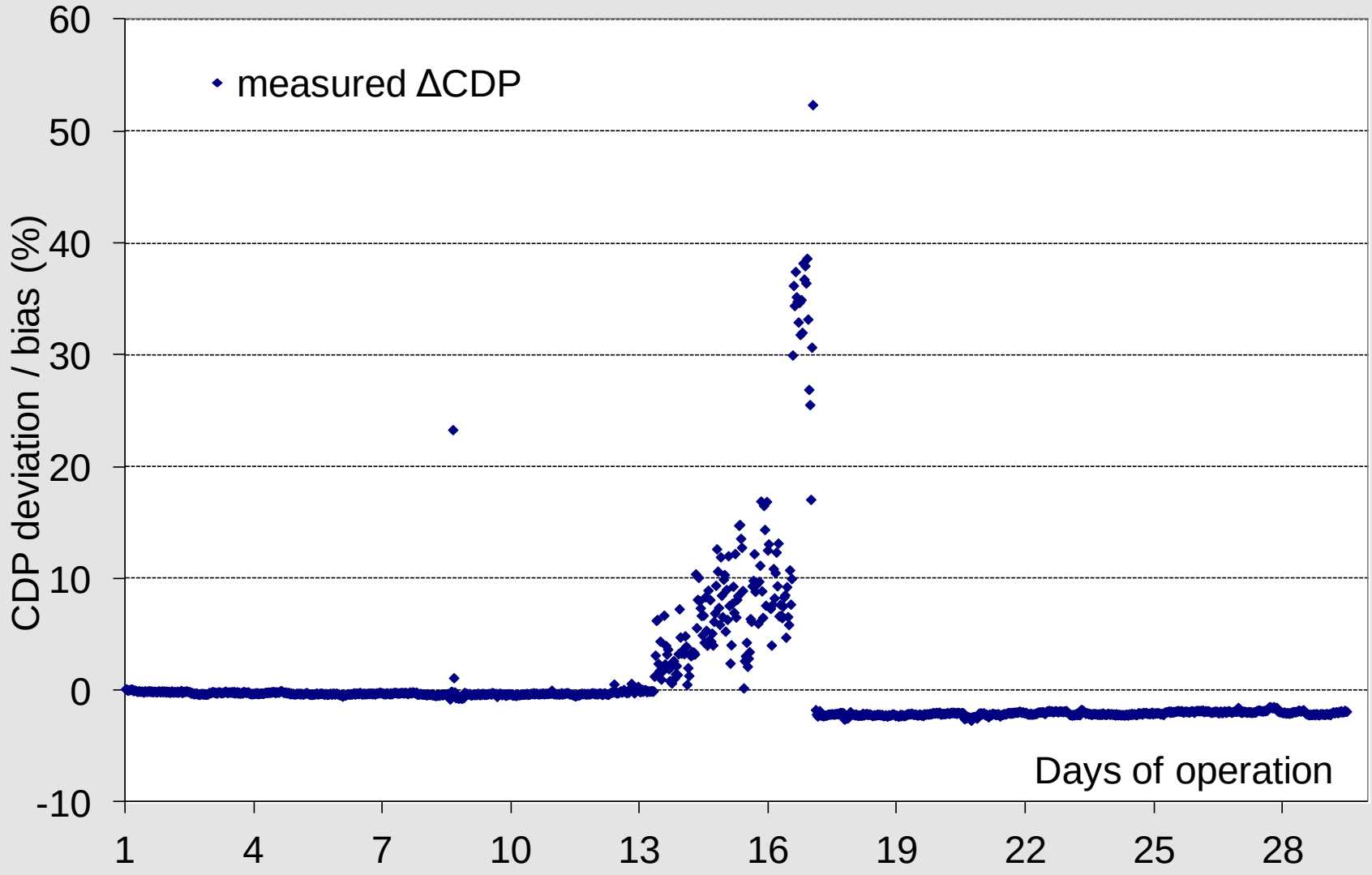
Sensor fault diagnosis using PNN

Probabilistic Neural Network architecture



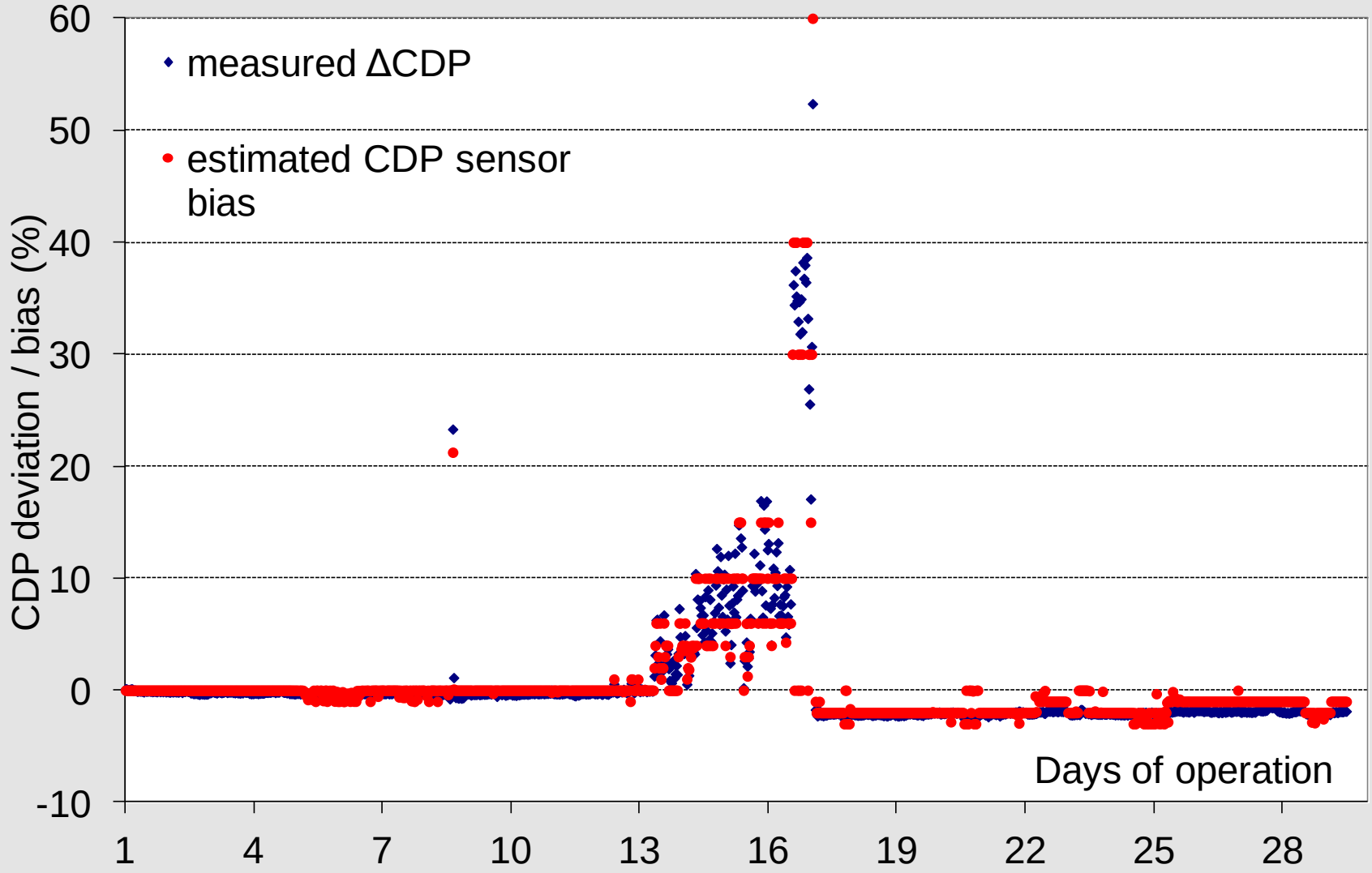
Sensor fault diagnosis using PNN

Measured Deviations and estimated sensor biases of **CDP** measurement



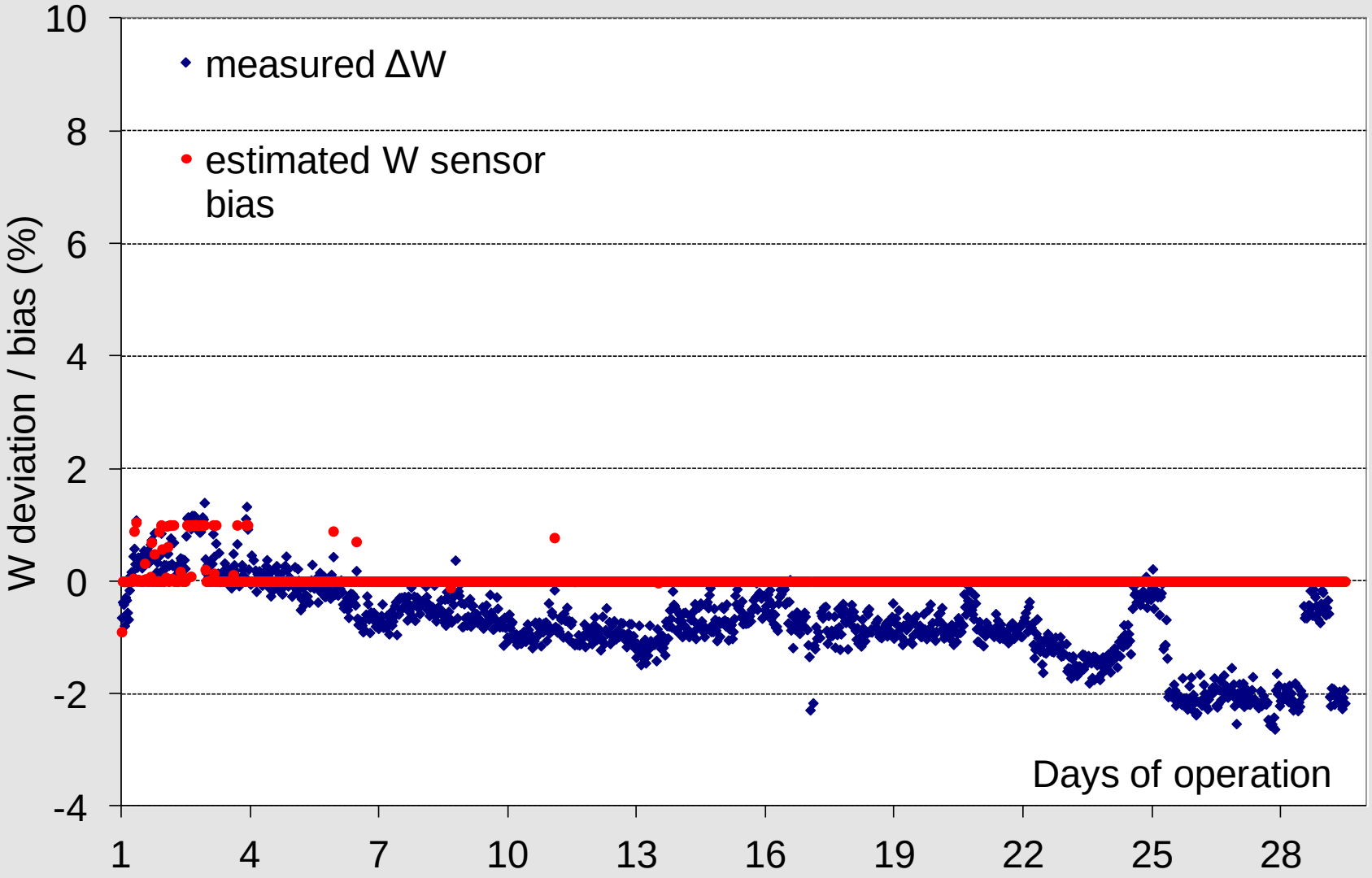
Sensor fault diagnosis using PNN

Measured Deviations and estimated sensor biases of **CDP** measurement

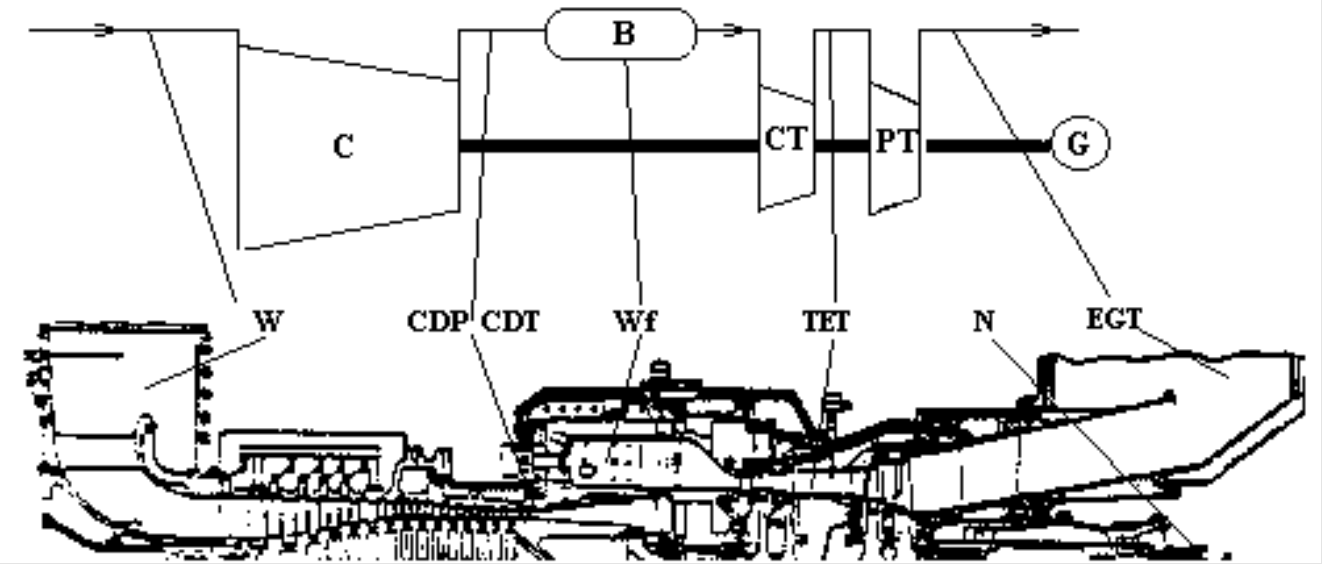


Sensor fault diagnosis using PNN

Measured Deviations and estimated sensor biases of **W** measurement



VSV system fault diagnosis

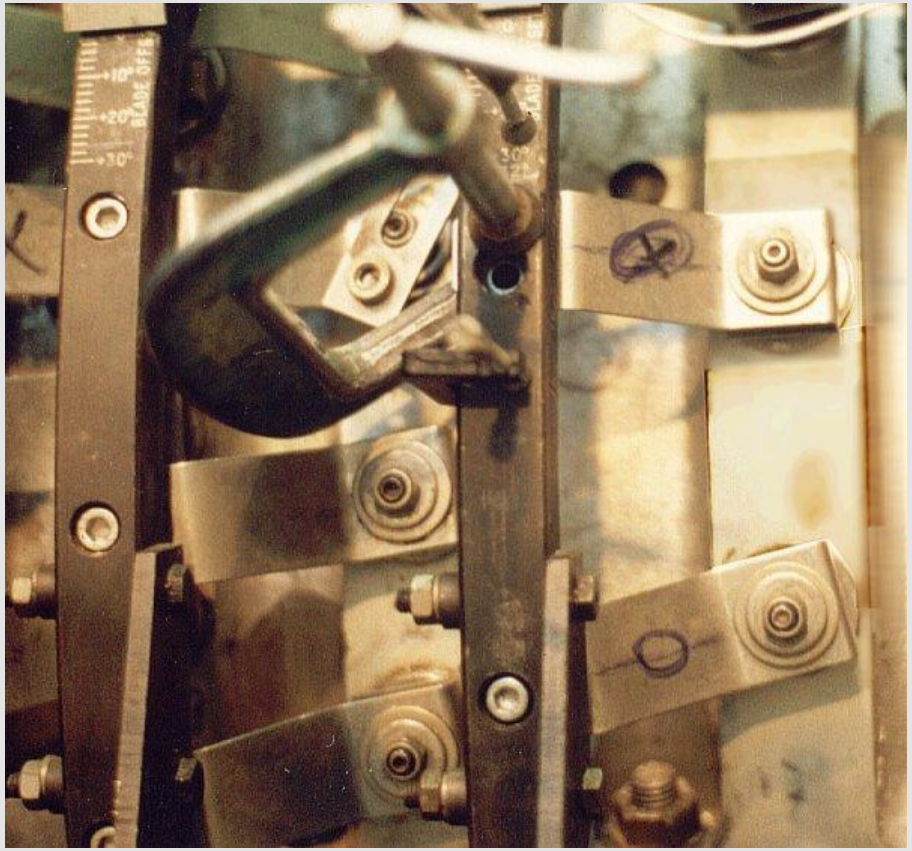


Application on a Medium Size GT in cooperation with the OEM, where diagnostic methods were validated versus implanted faults

VSV system fault diagnosis

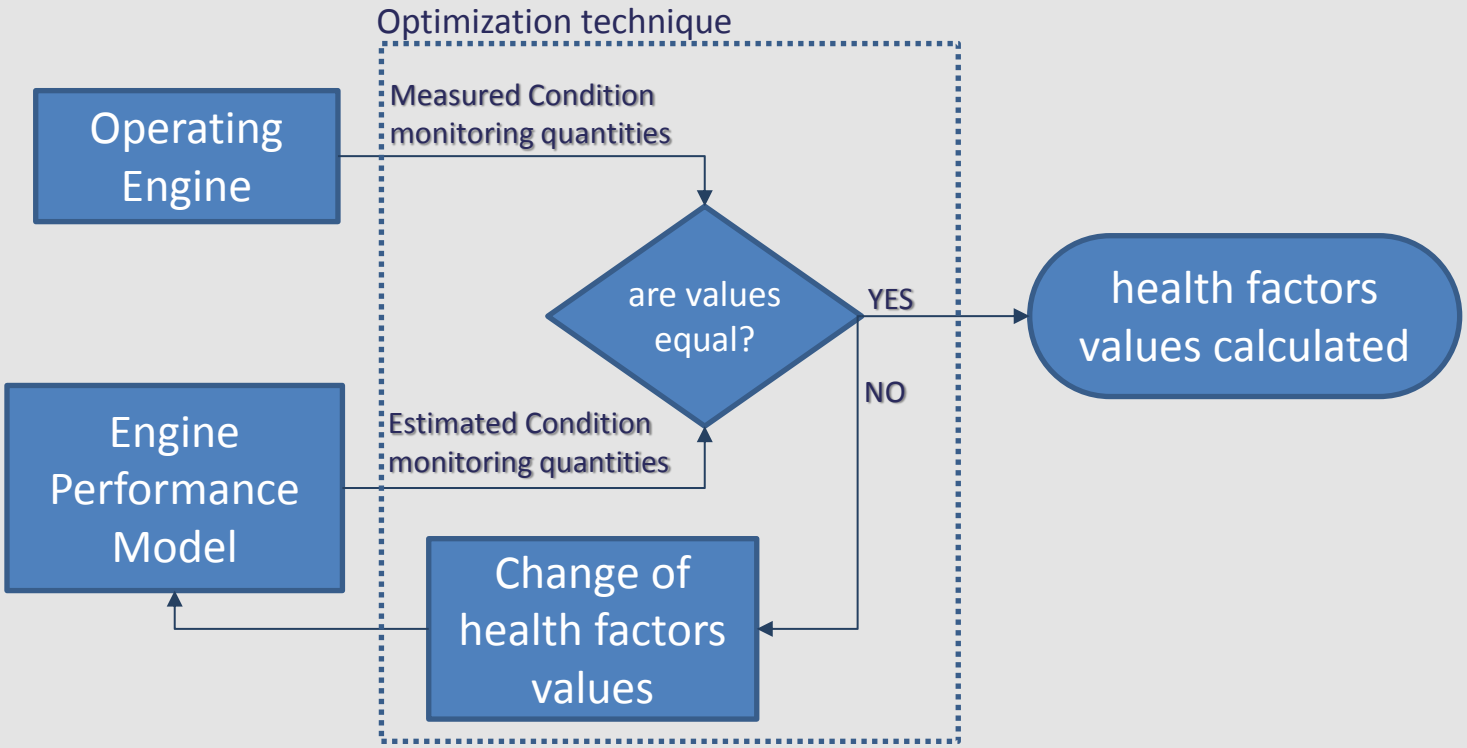
Performed tests of VSV faults

Test No.	Description	Details
1	Datum Test	Healthy Engine
2	IGV Fault	1 vane mistuned by 10˚
3-5	Stage-1 Fault	1 vane mistuned by 5^o, 10^o, 15^o
6-8	Stage-1 Fault	3 vanes mistuned by 5^o, 10^o, 15^o
9	Stage-4 Fault	1 vane mistuned by 10˚
10	Stage-4 Fault	2 vanes mistuned by 10˚
11	Datum Test	Healthy Engine



VSV system fault diagnosis

The Adaptive Performance Modeling method



Model-based, deterministic method for the diagnosis of aerothermodynamic faults

VSV system fault diagnosis

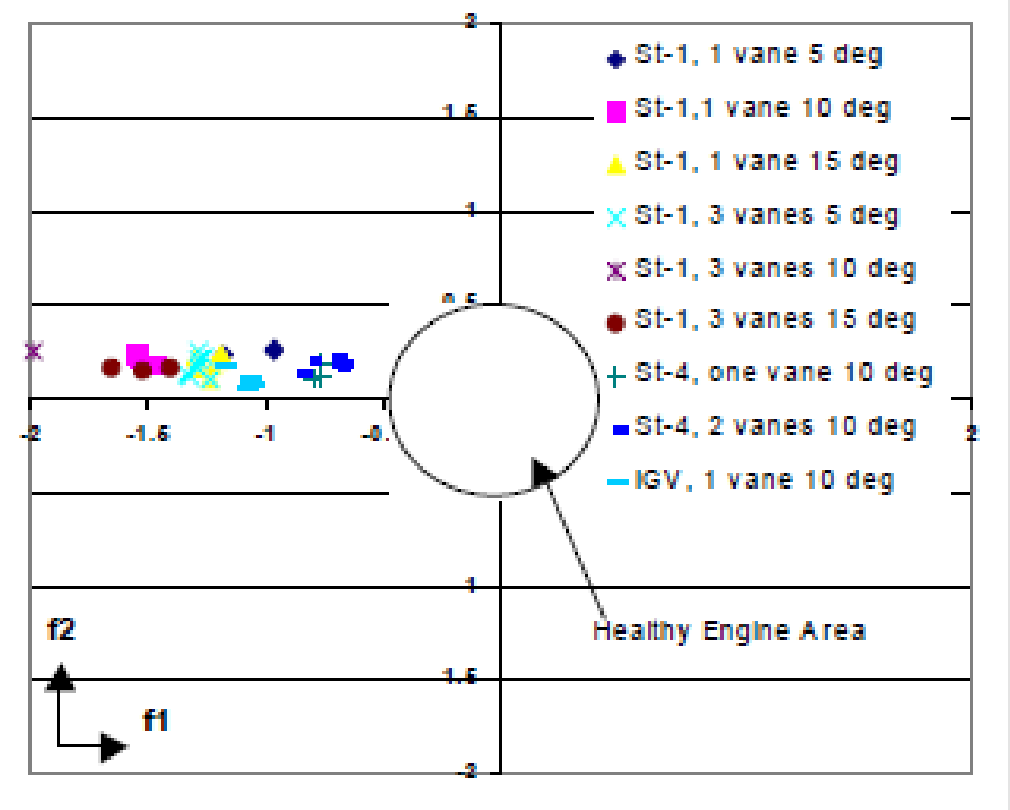
TORNADO compressor diagnostic plane

Compressor swallowing capacity:

$f_1=q_c/q_{c,ref}$

Compressor efficiency:

$f_2=n_{p,c}/n_{pc,ref}$



A decrease in compressor pumping capacity is detected, while its efficiency remains practically unaltered.

VSV system fault diagnosis

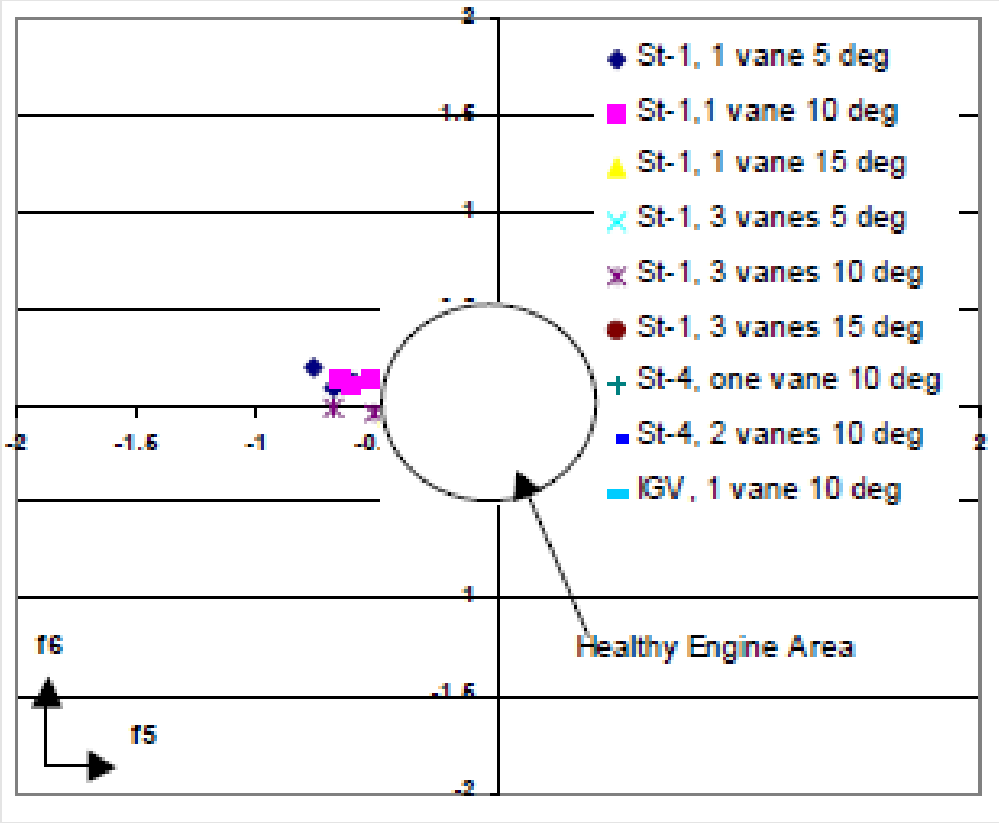
TORNADO turbine diagnostic plane

Turbine swallowing capacity:

$f_5 = q_T / q_{T,ref}$

Turbine efficiency:

$f_6 = n_{isT} / n_{isT,ref}$



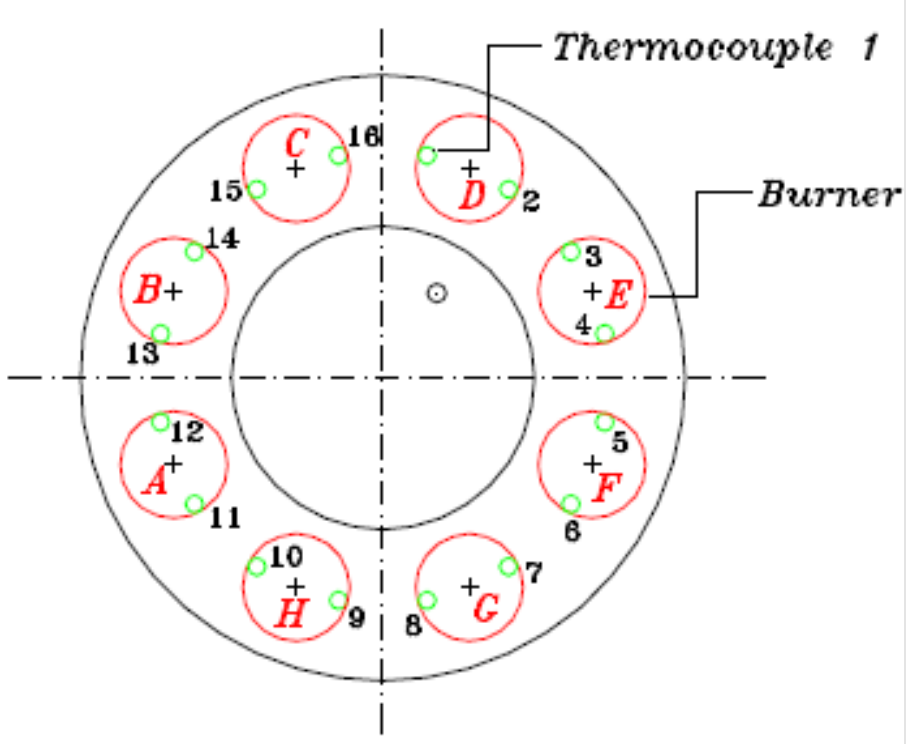
Points are much closer to the origin, while there is no visible trend of displacements.

Burner malfunctions identification

Implanted faults on the TORNADO gas turbine

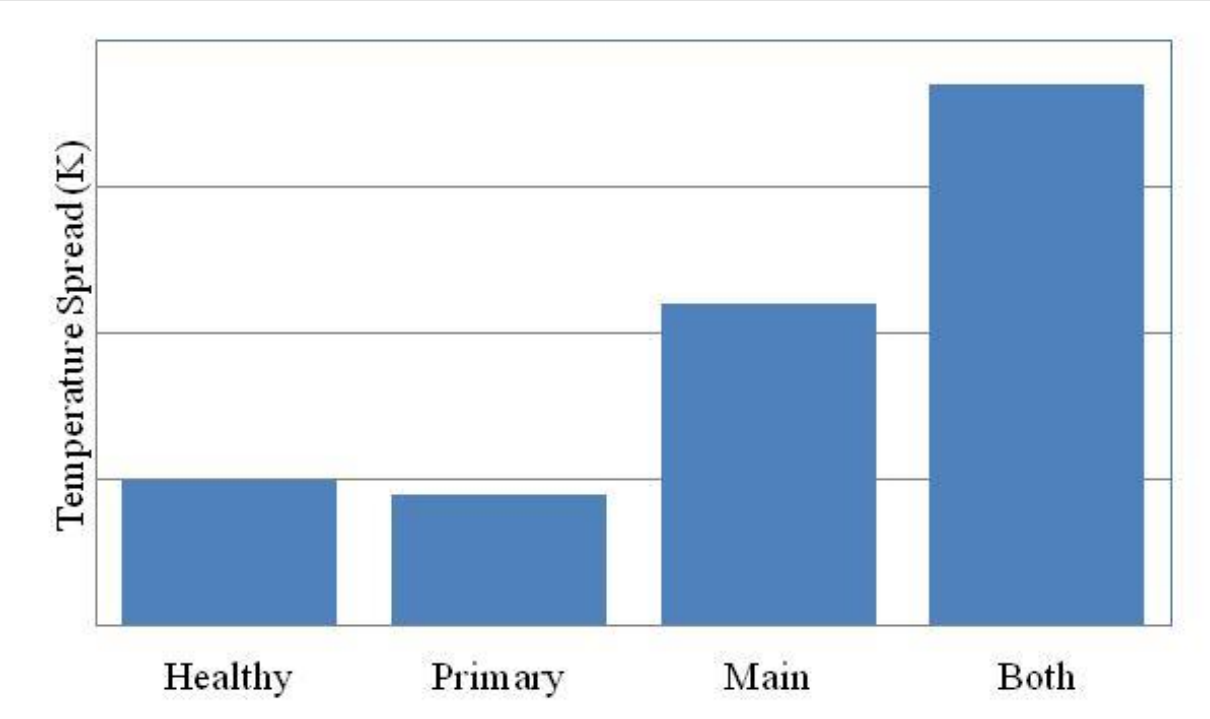
Fuel flow restriction by acting on the fuel supply of each burner, at three levels of severity:

i. Blocking the primary fuel nozzle (approx. 7% of fuel),
ii. Blocking the main fuel nozzle,
iii. Blocking both nozzles



Burner malfunctions identification

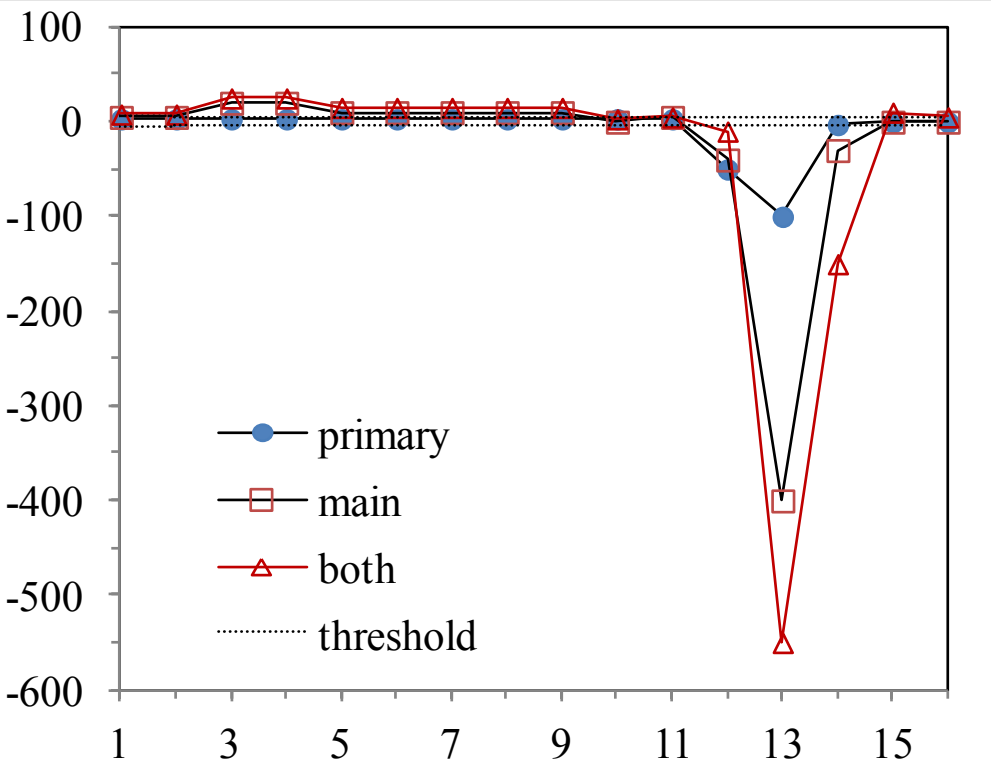
Common techniques for temperature profile monitoring are: temperature spread monitoring and deviations from average monitoring.



However, both parameters constitute a global index and do not necessarily reflect pattern changes.

Burner malfunctions identification

Pattern Recognition approach

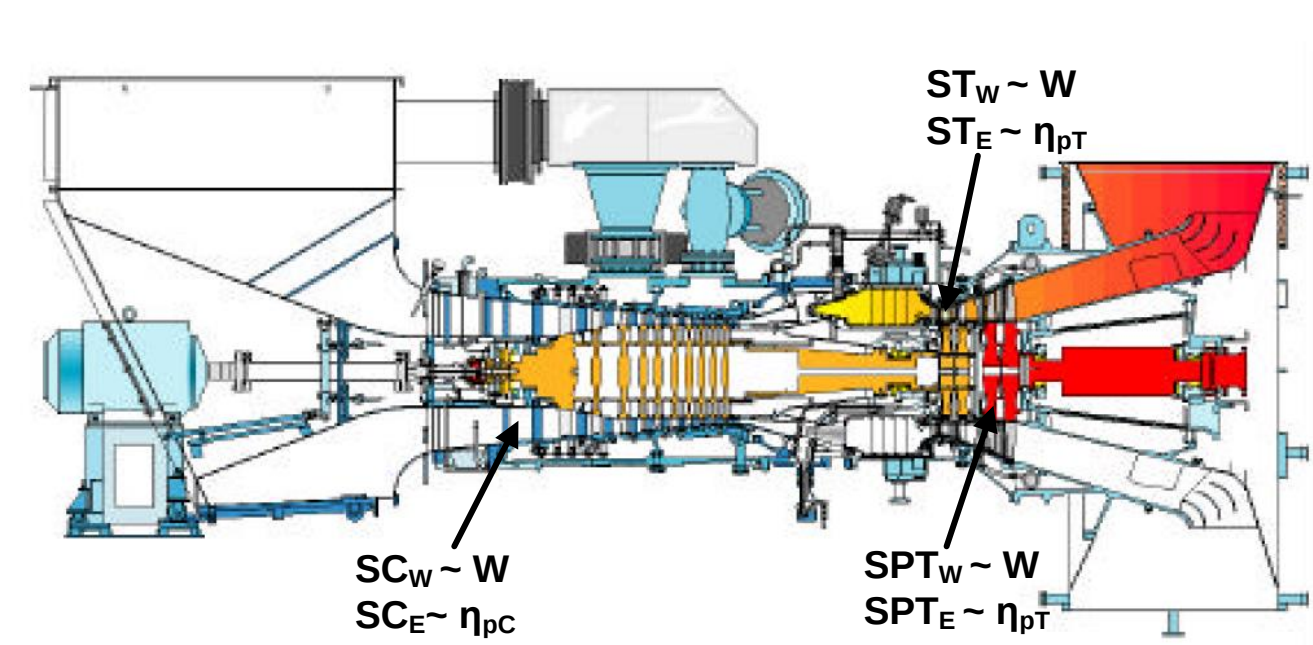


Temperature patterns are obtained from sensors placed at certain circumferential locations that correspond to a discrete spatial sampling of the continuous temperature distribution.

Changes of this distribution will produce changes of the pattern.

Turbine fouling diagnosis

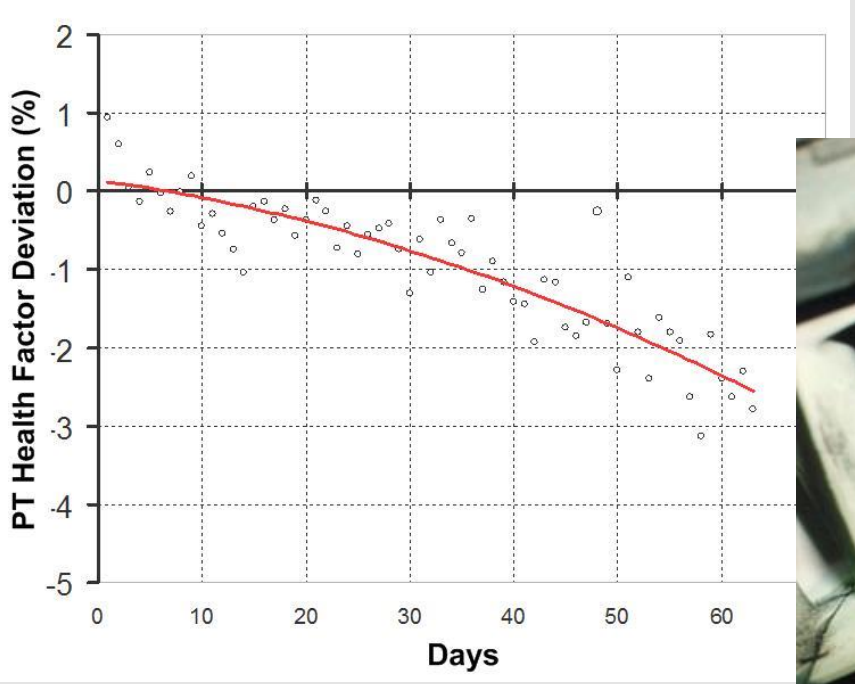
Twin Shaft Gas Turbine of 21MW



Application of the adaptive performance modeling technique on an Industrial GT in cooperation with the Operator for Fault Identification by post processing of Engine Measurements

Turbine fouling diagnosis

Twin Shaft Gas Turbine of 21MW

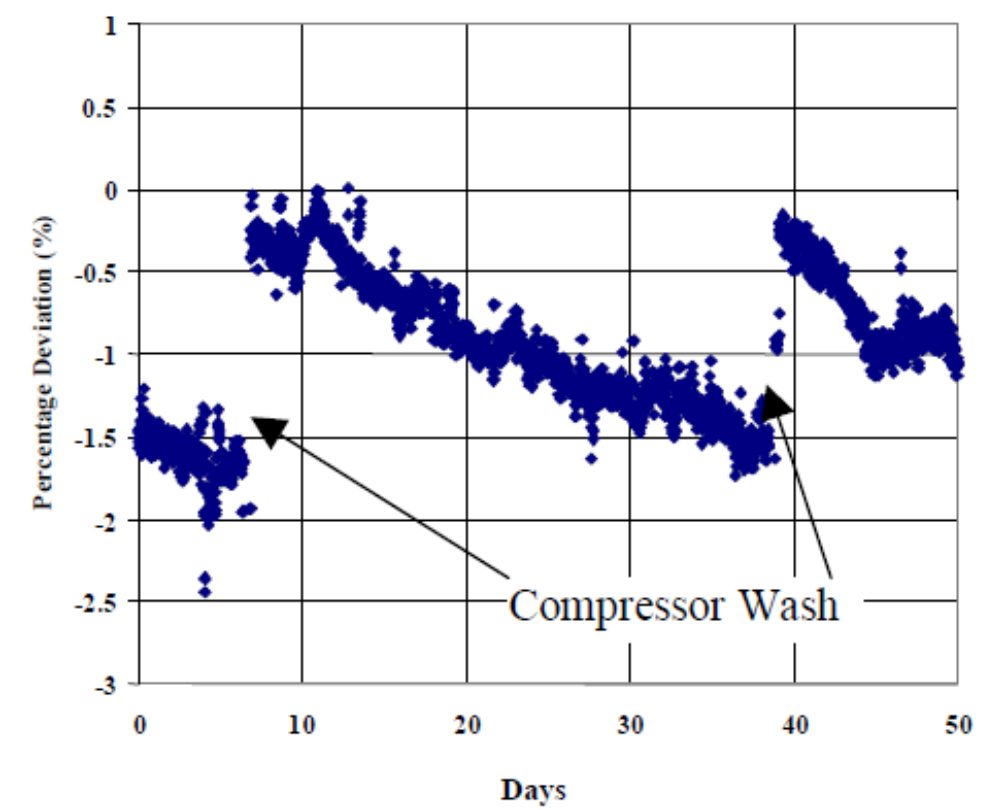


Fault : Deposits on both gas generator and power turbine blades due to anticorrosive additives of the fuel

The Faulty Components (Turbines) were correctly identified

Compressor fouling diagnosis

Twin Shaft Gas Turbine operating in a distillery



Compressor efficiency monitoring by application of the Adaptive Performance Modeling technique.

This approach has the advantage that is not affected by load variations.

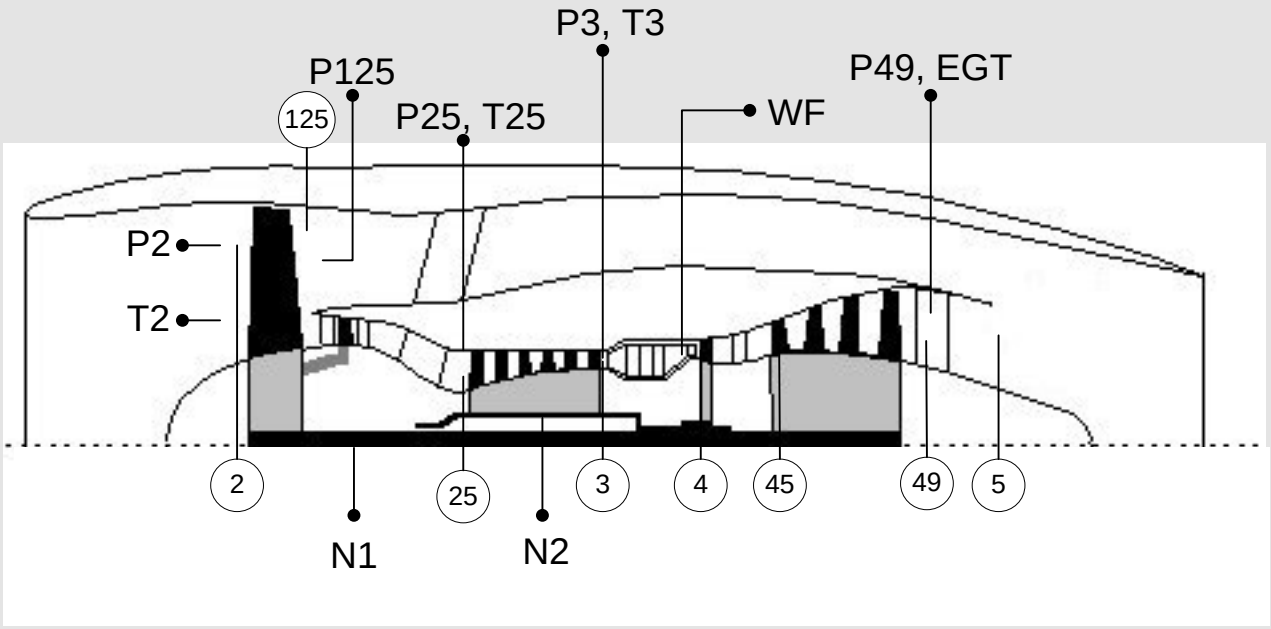
Compressor washing optimization

Application on a aeroderivative gas turbine of 42 MW

A/A	Washing strategy	No. of washings	Total profit (M$)	Change (%)	Change (k$)
1	Optimized	14	2.559	0	0
2	Typical equidistant	12	2.550	−0.359	−9.2
3	5% Power loss	15	2.553	−0.250	−6.4
4	4% Power loss	19	2.540	−0.752	−19.2
5	10% Power loss	7	2.475	−3.320	−85.0

Adaptive performance modeling coupled with a detailed cost analysis module to predict the impact of the compressor washing process on the power plant revenue, allows the optimization of the process with regards to power plant specific data.

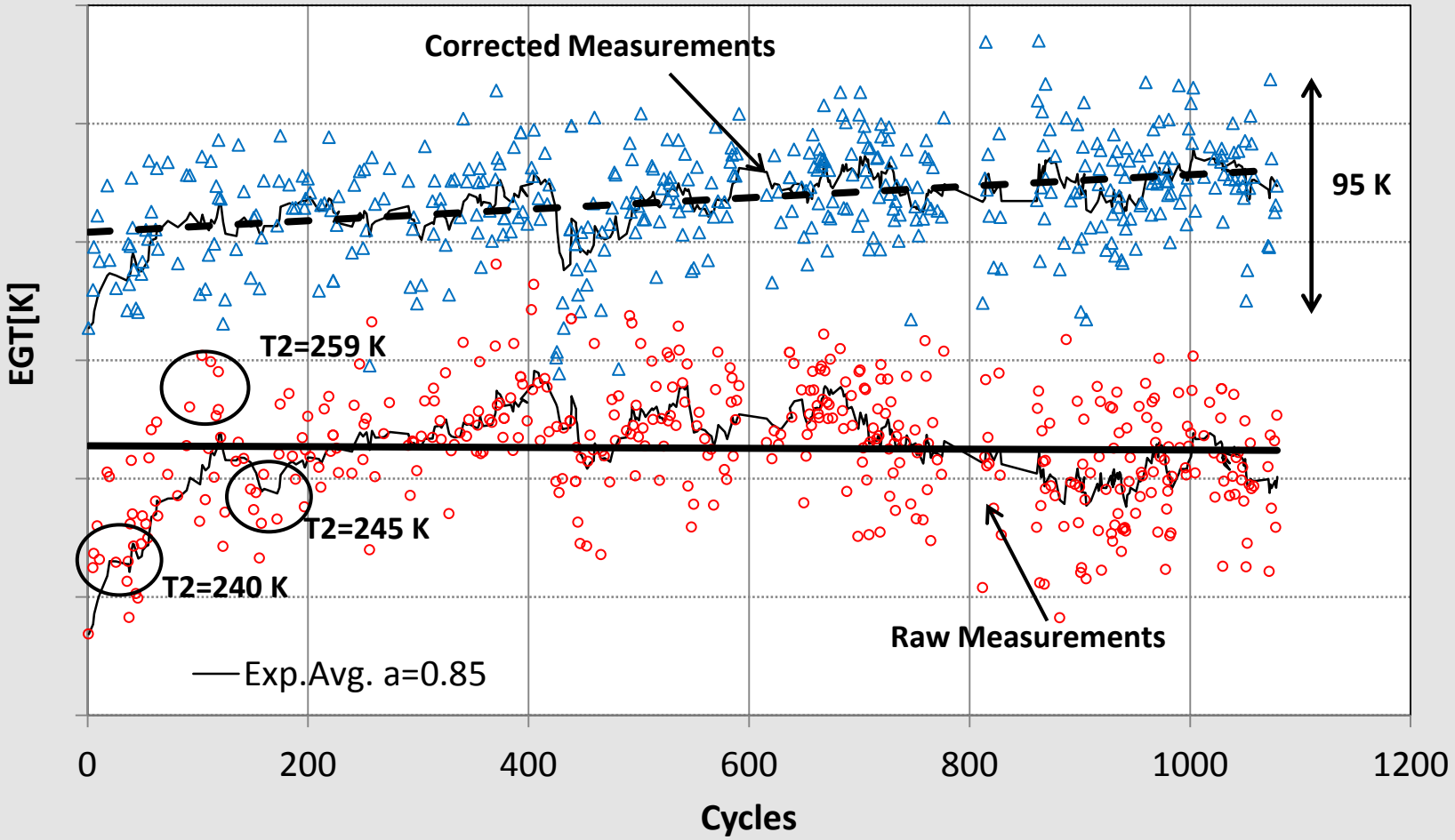
Turbine subsystem malfunction identification



On-wing available measurements of the high bypass ratio turbofan engine of a commercial short range aircraft

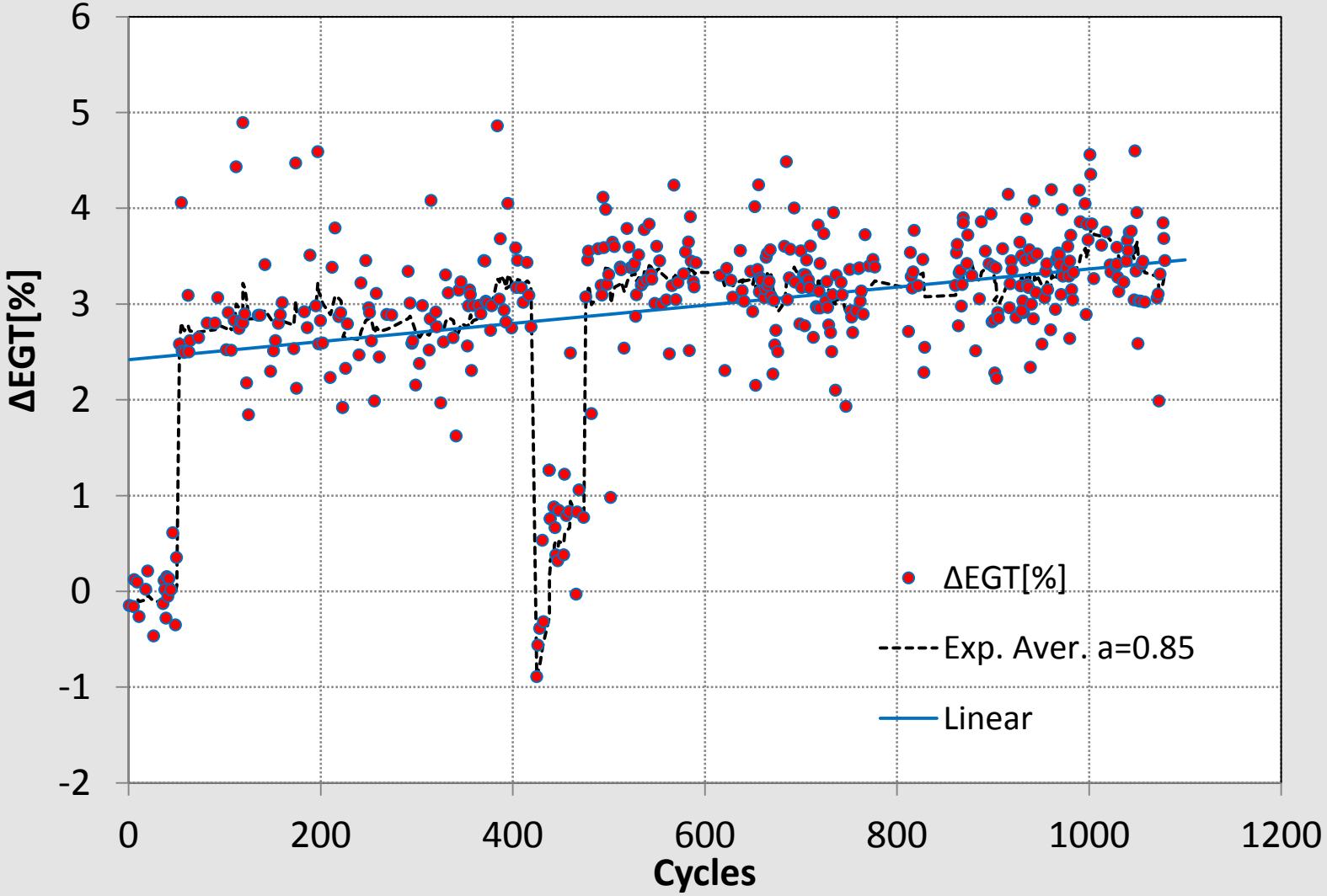
Turbine subsystem malfunction identification

Raw and corrected EGT variation with engine cycles



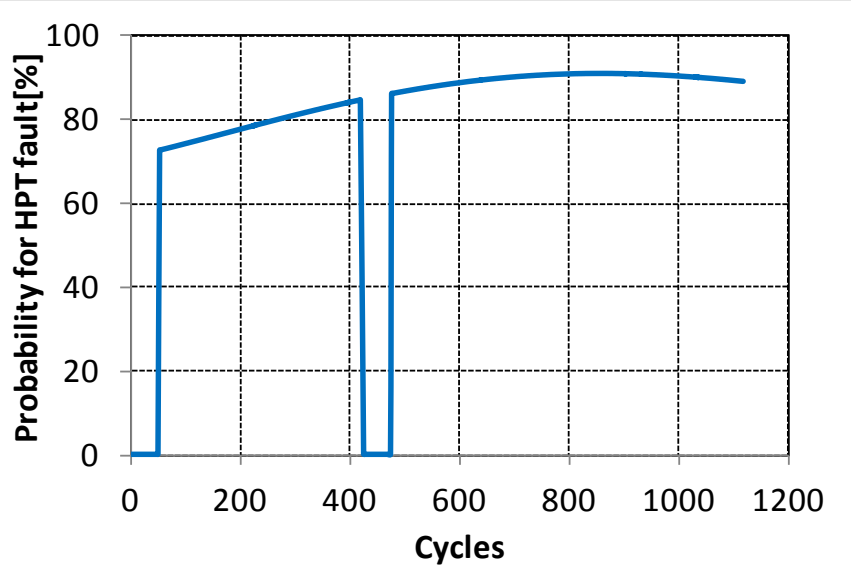
Raw and corrected measurements do not provide any information, since they include both operating point and ambient conditions effects

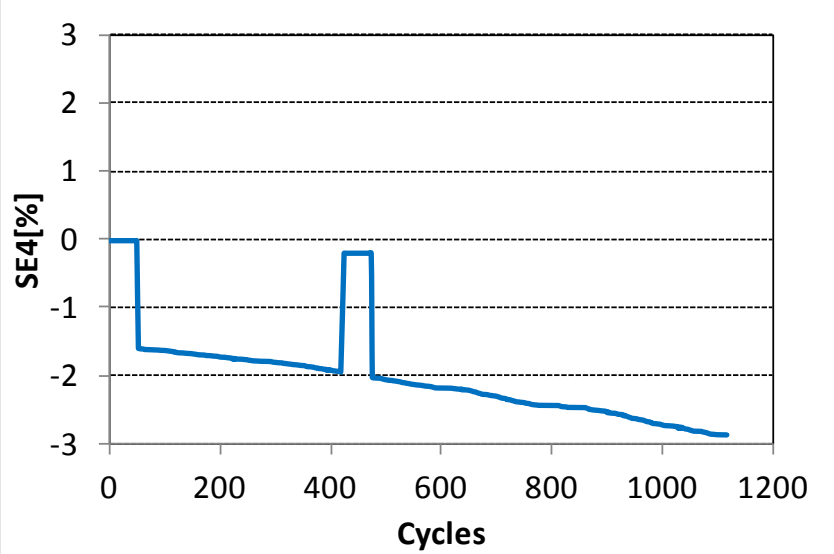
Turbine subsystem malfunction identification



Three sudden shifts are revealed when measurements deltas are calculated

Turbine subsystem malfunction identification





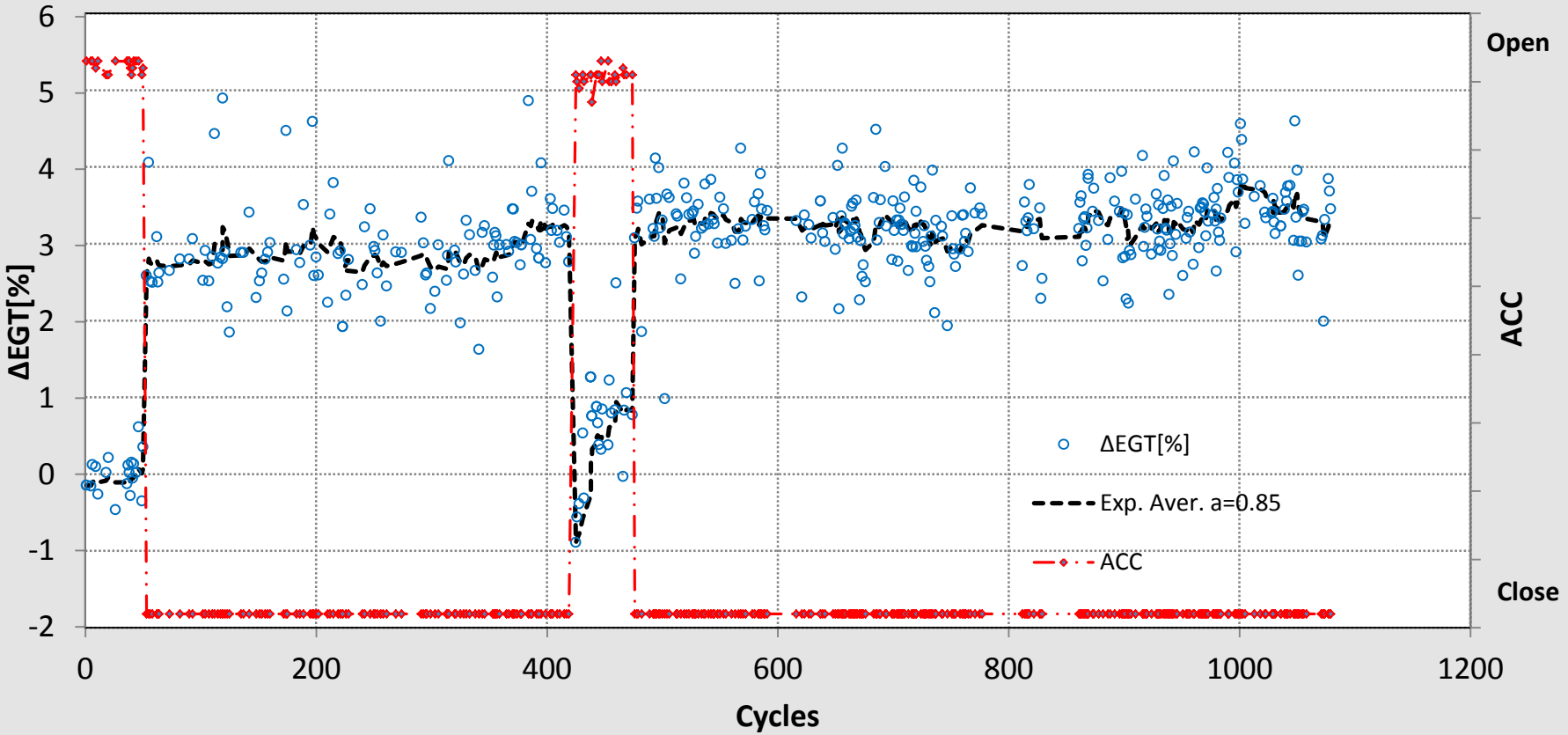
The method of PNN estimates that an increasing HPT fault occurs

The deterioration tracking method detects an increasing deviation of HPT efficiency

Two independently acting diagnostic methods detected a fault probably connected to an HP turbine sub-system.

Turbine subsystem malfunction identification

Active Clearance Control (ACC) subsystem fault



The specific engine is equipped with ACC

A failure of the bleed valve is expected to cause increased tip clearances, thus decreasing HP turbine efficiency, as detected by the diagnostic methods

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Summary –Conclusions

- An overview of methods and tools developed by the research group of LTT/NTUA has been demonstrated.
- The developed methods expand to the whole range of the CBM area and rely on aerothermodynamic measurements and waveform type data acquired from the engine.
- These methods and techniques support CBM s/w platforms that have been developed so far and are in service today.
- Application examples on a number of operating engines, stationary and aircraft, demonstrate that advanced diagnostic methods can lead to efficient engine health assessment.
- Efficient health assessment is crucial for applying corrective actions such as compressor washing and further implementing prognostic methods.