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SENSOR CHECKING USING MODEL BASED ENGINE PERFORMANCE TEST ANALYSIS AND NUMERICAL OPTIMIZATION

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ABSTRACT

One of the problems with gas turbine performance monitoring is the difficulty to differentiate between malfunction of the engine itself and the erroneous indication of a sensor. In this paper the results of an investigation about a sensor checking method which utilizes numerical optimization are presented.

Basis of the sensor checking method is the model based engine performance monitoring. With this performance monitoring approach the measured data are compared against a full thermodynamic model of the gas turbine. The comparison yields engine health factors that describe the differences between the model of the engine and the measurements. If all factors are equal to one then there is perfect agreement; if the compressor efficiency factor is 0.99, for example, then an efficiency deficit of 1% is diagnosed.

The idea of the sensor checking algorithm is the following. For each of the sensors an optimization is done in which the optimization variable is the sensor reading and the figure of merit is a model match indicator (a measure of how good the measurements fit to the model). Each of the optimizations yields a postulated sensor reading which goes along with the best figure of merit. When all optimizations are completed, then it is checked by which of the optimization runs the biggest improvement of the model match indicator has been achieved. The hypothesis of the sensor checking algorithm is that the sensor with the biggest model match indicator improvement is potentially showing the wrong value.

This sensor checking method is examined using data that are created by performance models of a new engine and two levels of engine deterioration. For the optimization a gradient search method is employed. A modified model match improvement indicator is described which reduces the false alarm rate of the basic method significantly.

1 NOMENCLATURE

f	factor
$f_{health,j}$	health factor for component j
FHV	fuel heating value
fom	figure of merit
M_{ind}	model match improvement indicator
$M_{ind,mod}$	modified model match improvement indicator
N_H	high pressure spool speed in figure 5: XN_HP_A
opt	optimum
P_2	compressor inlet total pressure
P_3	compressor exit total pressure
P_{44}	high pressure turbine exit pressure
P_{45}	low pressure turbine inlet pressure
q_0	square sum of ($f_{health,j}$-1)
r_i	reading of sensor i
ref	reference
SFC	specific fuel consumption
T_3	compressor exit temperature
T_4	burner exit temperature
T_{45}	low pressure turbine inlet temperature
T_5	exhaust temperature
W_F	fuel flow
W_2	compressor mass flow

2 INTRODUCTION

Sudden significant changes in the reading of a single sensor can be diagnosed without difficulty as a sensor failure. Slowly drifting sensor readings, however, are not so easy to detect and it is not obvious if there is a sensor problem or an engine problem. If a sensor malfunction is not detected then this leads to false conclusions about engine component performance and thus makes the entire performance diagnostic useless (ref. 1).

In this paper a method for detecting slow sensor drifts is examined with the assumption that only one sensor has failed; multiple sensor failure is not discussed.

3 MODEL BASED ENGINE PERFORMANCE DIAGNOSTICS

The sensor checking method is an extension of the model based engine performance diagnostics which employs a thermodynamic model of the engine to be monitored. As shown in ref. 3 it is possible to create an accurate aero-thermodynamic model of an engine from the limited amount of information which is available to any gas turbine operator. The details of such a model may not be correct, however, this is not important since the aim of performance diagnostics is mainly detecting the changes in component performance; the absolute level of the component efficiencies is of secondary importance.

The conventional test analysis makes no use of information which is available from known component maps, for example. It will give no information about the reason, why a component behaves badly. A low efficiency found for the fan of an aircraft engine may be either the result of operating the fan at aerodynamic overspeed or a poor blade design. To improve the analysis quality in this respect is the aim of „Analysis by Synthesis" (**AnSyn**). This method is also known as model based engine test analysis.

When doing analysis by synthesis a model of the engine is automatically matched to the test data. This is achieved with scaling factors applied to the component properties that close the gap between the measured data and the model. The principle is demonstrated in figure 1 which shows in a compressor map how the scaling factors for mass flow and pressure ratio are found during the test analysis. Efficiency scaling factors relate the analyzed efficiency with the efficiency read from the map.

The scaling factors may also be called component health factors f_{health}. A factor of 1.0 means perfect agreement between the model and the measurement. An efficiency scaling factor less than one indicates, that the component performs worse than predicted, thus indicating deterioration.

Generic engine performance models can be automatically adapted to any individual engine by applying the consolidated health factors to the base model. Thus it is possible to have always a model of reasonable accuracy while the engine deteriorates slowly.

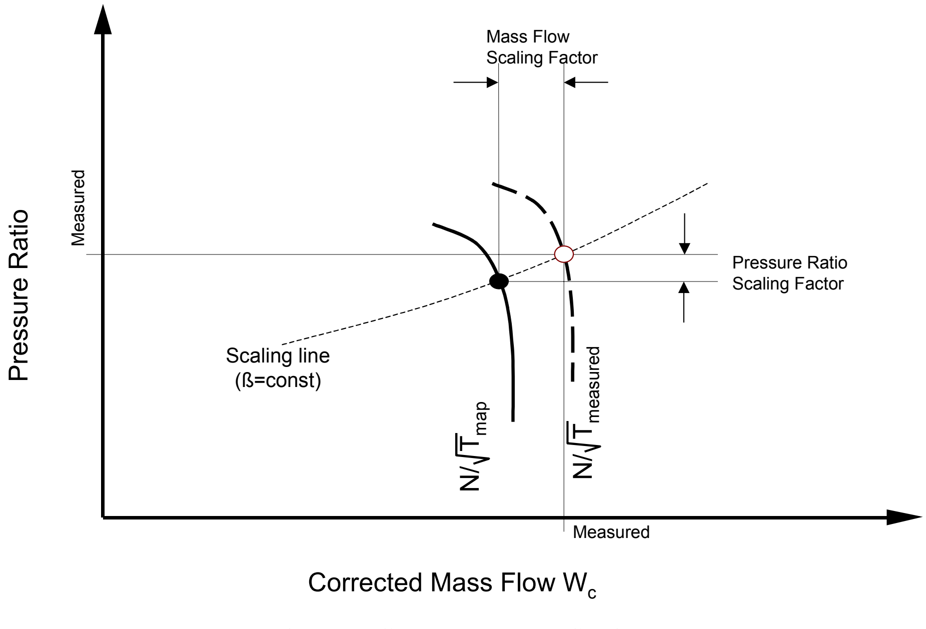

Figure 1: Compressor Map Scaling Factors

4 MODEL BASED SENSOR CHECKING USING OPTIMIZATION

4.1 Basic Idea

The sensor checking algorithm works as follows. At first the square sum q_0 of the deviations of all component health factors $f_{health,j}$ from 1 is calculated:

$$q_0 = \sum (f_{health,j} - 1)^2$$

Next for each of the sensors i an optimization is done in which the single optimization variable is the sensor reading r_i and the figure of merit is:

$$fom = \sum (f_{health,j} - 1)^2$$

Thus for sensor i a postulated reading $r_{i,opt}$ is found together with a figure of merit $fom_{i,opt}$. With other words, if the sensor would indicate the reading $r_{i,opt}$ then the deviations of all health factors from 1 would be minimal.

When all optimizations are done, then the differences q_0 - $fom_{i,opt}$ are checked. A big difference means that ignoring the reading of sensor i would improve the agreement between the model and all the other sensor readings significantly. Therefore the differences q_0 - $fom_{i,opt}$ are called here Model Match Improvement Indicators $M_{ind,i}$.

The hypothesis of the sensor checking algorithm is that the sensor for which the model match improvement indicator has the highest value is potentially indicating the wrong value. Ignoring this sensor reading yields a significantly improved match of all the other measurements with the model.

Keep in mind, however, if the measured value r_i deviates less than the measurement tolerance from the postulated reading $r_{i,opt}$ then no sensor error can be diagnosed.

4.2 Testing the Method

The quality of any sensor checking method can be quantified by the smallest sensor error which can be detected. Obviously sensor errors within the measurement tolerance can not be detected and therefore the sensor error threshold is always bigger than this tolerance.

With the method discussed in this paper besides the measurement tolerance also the quality of the engine model affects the magnitude of the smallest detectable sensor error. This problem is examined in the following with the performance program GasTurb 10 (ref. 2) in which the sensor checking algorithm is implemented.

4.2.1 Engine Model

For testing the sensor checking method a thermodynamic model of a two spool turboshaft engine similar to the General Electric LM2500 is used. The main parameters of the cycle are listed in table 1.

Shaft Power	21.55 MW
Pressure Ratio	18
Mass Flow	65 kg/s
Burner Exit Temperature T_4	1550K
Exhaust Temperature T_5	840 K
Thermal Efficiency	35%

Table 1: Main Cycle Parameters of the New Engine

Typical sensor positions in such a two spool turboshaft are shown in figure 2. On most engines not all of them are installed; indicators for the variable geometry positions (compressor guide vanes, bleed valves) may complement the sensor suite.

For a two spool turboshaft there are up to five air mass flow analysis options (depending on the sensors installed on the engine):

1. Mass flow is measured
2. Gas generator turbine flow capacity is known
3. Power turbine flow capacity is known
4. Match the mass flow to the measured power turbine inlet temperature T_{45}
5. Match the mass flow to the measured exhaust gas temperature T_5

4.2.2 Perfect Model, no Measurement Scatter

This first test of the sensor checking algorithm deals with the ideal world in which the model perfectly matches the measured data if all sensors indicate the correct value. Mass flow analysis option no. 1 is employed and the quality of the T_3 sensor (compressor delivery temperature) is checked as an example.

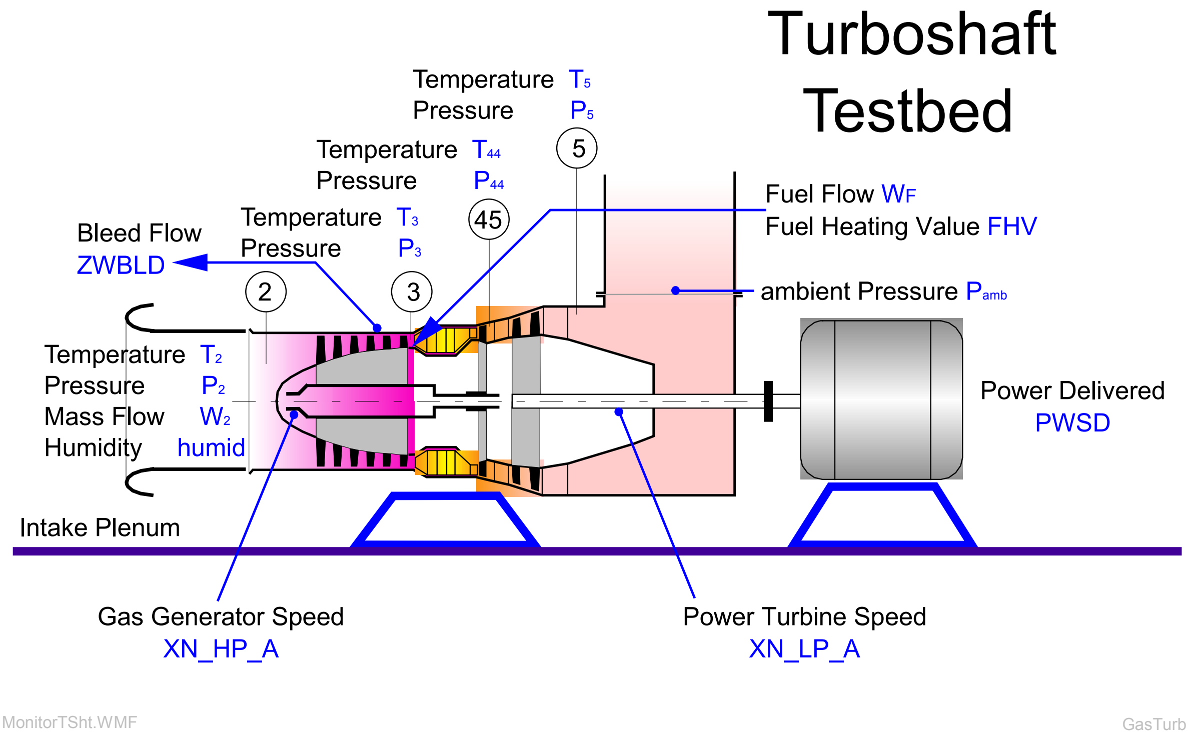

Figure 2: Measurement Positions on a Turboshaft

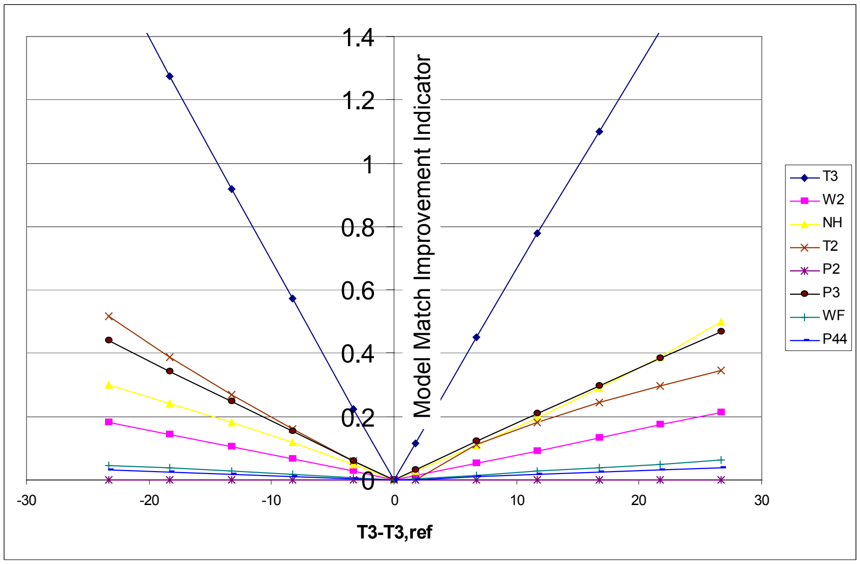

Figure 3: New Engine, Perfect Measurements

The test is performed in such a way that the T_3 measurement is set to various values off the correct value (the reference) and then the sensor error check is performed. The test is considered successful if the correct sensor is declared faulty and the correct sensor reading is postulated.

The result of the first numerical experiment is plotted over $T_3 - T_{3,ref}$ in figure 3 which shows that the biggest Model Match Improvement Indicator (M_{ind}) is that of the faulty T_3 probe. The M_{ind} of the N_H, P_3 and T_2 are less than half of that from the T_3 sensor.

Many more tests have been done with various sensors and different mass flow analysis methods. In general the sensor errors are identified correctly and there is no significant difference between the various flow analysis methods. It is understandable that fuel flow errors can not be distinguished from errors in fuel heating value. Of course a sensor error will only be detected if the sensor reading is used for the analysis.

4.2.3 Model of a New Engine, Measurements from a Heavily Deteriorated Engine

In reality there will never be a perfect model available; engines deteriorate and sometimes the model remains that of a new engine. Let us ignore for the moment the possibility of automatically adapting the model to the measured data.

Two levels of deterioration are considered in this paper and listed in table 2: Moderate deterioration leads to an increase in specific fuel consumption (SFC) of 1.4%. Heavy deterioration yields 5.5% increase in SFC

Feeding the calculated values from the heavily deteriorated engine model as sensor readings into the analysis procedure based on the model of the new engine yields as health factors exactly the numbers in the table.

	moderate deterioration	heavy deterioration
Compressor Flow Capacity	-0.5%	-2%
Compressor Efficiency	-0.5%	-2%
HPT Flow Capacity	+0.5%	+1%
HPT Efficiency	-0.5%	-2%
PT Flow Capacity	+0.2%	+0.4%
PT Efficiency	-0.3%	-0.9%

Table 2: Deterioration Assumptions

For the next numerical experiment the sensor readings are calculated with the model of the heavily deteriorated engine. The model of the new engine model is employed for the test analysis and the sensor checking. In effect an inaccurate model is used for the sensor quality analysis.

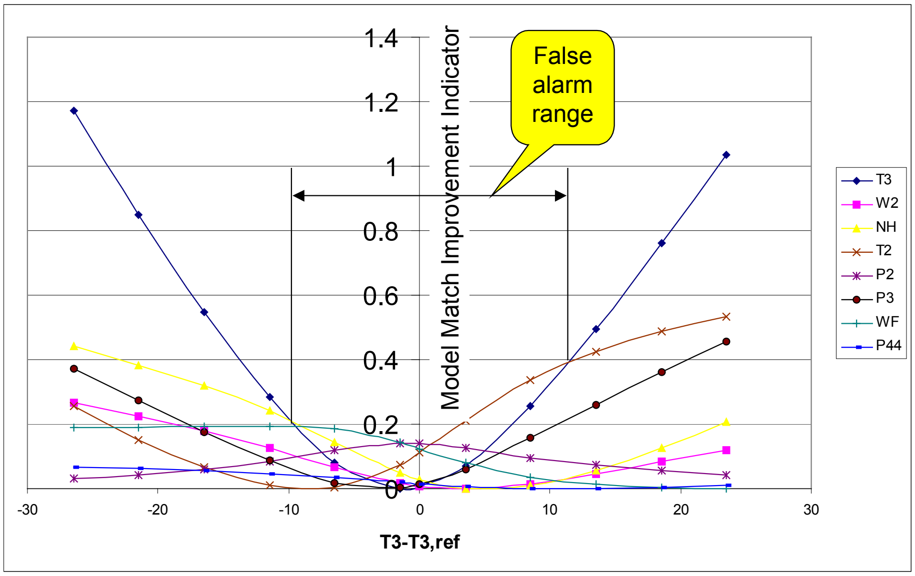

Figure 4: Model of a New Engine, Data from a Heavily Deteriorated Engine

The results plotted in figure 4 show a high false alarm range for this case. T_3 errors between -10 and +11K are diagnosed as fuel flow (WF) or T_2 errors and this insensitivity to sensor faults renders the method pretty useless.

However, the method can be improved by two means:

- As already mentioned above, a self adapting model can be employed which avoids that big discrepancies between the model and the (correct) measurements develop over time.
- A more meaningful Model Match Improvement Indicator is used

Let us concentrate on the second option and look at a typical sensor diagnostic plot as shown in figure 5, for example. There the deviation between the sensed and the postulated value is normalized with the measurement tolerance.

The M_{ind} as used above considers only how much the engine health factors deviate from 1.0 for the best model match. However, the optimization yields also a postulated value for each sensor which goes along with the best match of the model. Big differences between the postulated and the indicated values combined with small Model Match Improvement Indicator values mean that the postulated value is not reasonable.

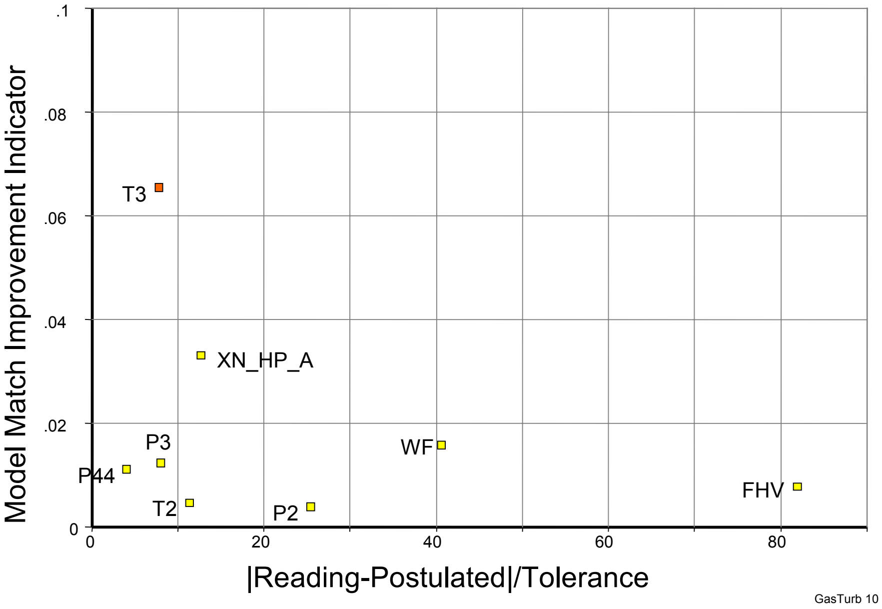

Figure 5: Typical Sensor Diagnostic Plot

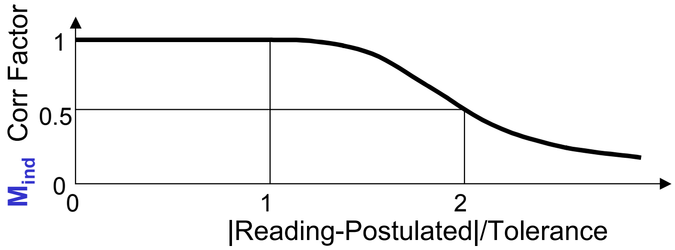

Figure 6: Empirical Correction Factor

The Modified Model Match Improvement Indicator $M_{ind,mod}$ takes the difference between the indicated and the postulated value into account. M_{ind} is modified by a factor to yield the Modified Model Match Improvement Indicator $M_{ind,mod} = f * M_{ind}$

Model Match Improvement Indicators with differences between indicated and postulated values lower than the measurement tolerance remain unmodified while others are factored downwards, see fig. 6.

Figure 7 differs from figure 4 by the definition of the respective Model Match Improvement Indicators. Compared to figure 4 we observe a significantly reduced false alarm range which means that much smaller T_3 sensor shifts can be detected.

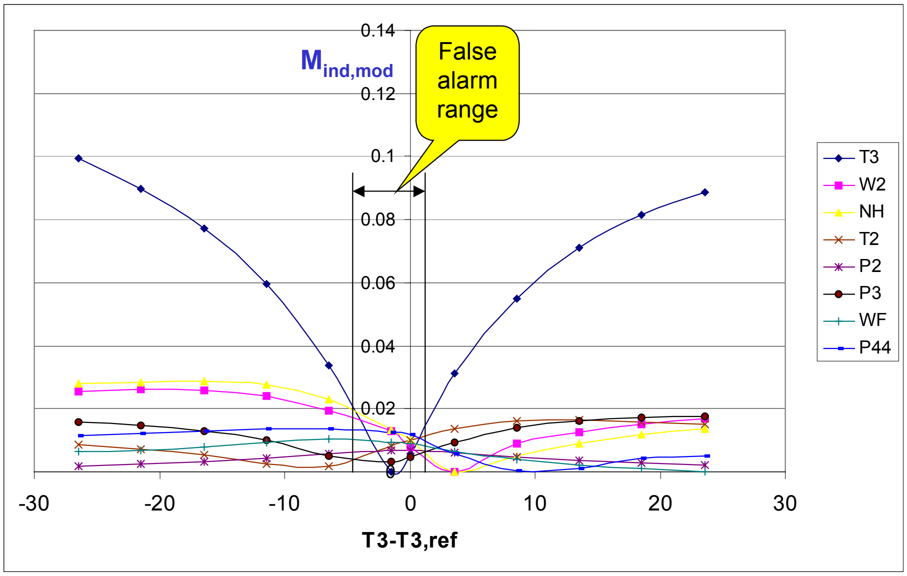

Figure 7: New Engine, Data from a Heavily Deteriorated Engine, Modified Indicator

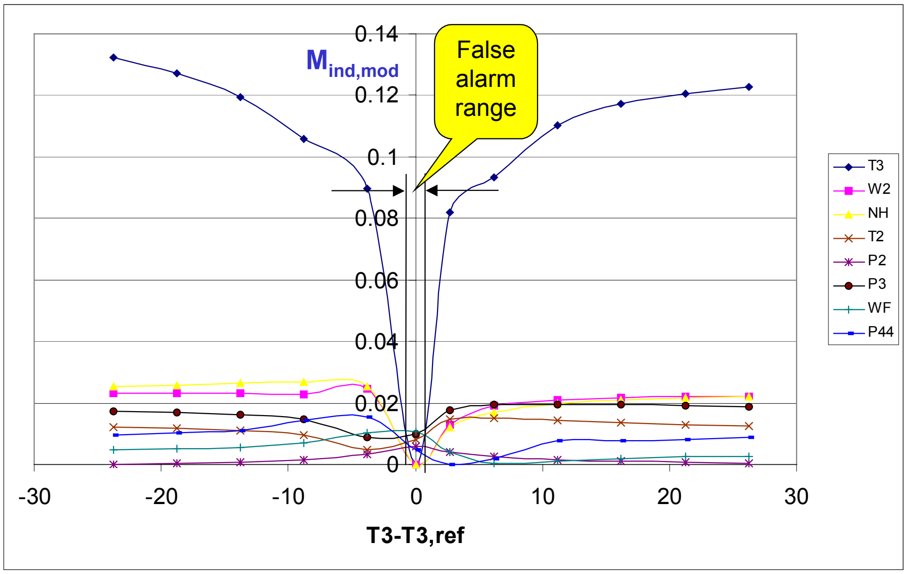

Figure 8: New Engine, Data from a Moderately Deteriorated Engine, Modified Indicator

If the difference between the model and the engine is smaller (if we consider only moderate deterioration) then the performance of the sensor check method is truly impressive as can be seen from figure 8. Remember, however, that no measurement noise is considered in the examples shown and therefore in real world applications the sensor malfunction detection will not be quite as good.

4.3 Variations of the Method

As shown above the formulation of the Model Match Improvement Indicator has a big impact on the sensor error detection rate. Similarly there might be other elements of the algorithm that affect the quality of the results or the computational effort required.

4.3.1 Alternate Figure of Merit

The expressiveness of the figure of merit for the optimization runs can be improved by taking into account known correlations between certain health factors. For example, compressors with poor efficiency have usually also a low flow capacity. Another option for improving the figure of merit is to introduce weighting factors for the deviation of the health factors from 1.0.

Furthermore - instead of comparing the health factors against the ideal value 1.0 - one can compare against the value found from previous sensor checking runs in which no sensor error was detected. This will definitely improve the quality of the results because it is equivalent to comparing against a self adapting model of the engine.

4.3.2 Optimization Aspects

The optimization task is a rather primitive one from a standpoint of mathematics: there is only one variable and there are no constraints. If the thermodynamic model of the engine is sufficiently robust then the only question is how to formulate the figure of merit fom.

The first version of the sensor checking algorithm in GasTurb (ref.2) did use as figure of merit

$$fom = \sum \left| f_{health,j} - 1 \right| .$$

The idea behind this formulation was that the optimum should be distinct as opposed to being a flat region. However, with this definition of fom the gradient search algorithm needed a high number of function evaluations. After changing the definition to

$$fom = \sum (f_{health,j} - 1)^2$$

the number of engine model evaluations needed did decrease significantly, typically from 300 to 200 in the examples discussed above.

5 CONCLUDING REMARKS

The sensor checking algorithm works fine in general, especially if a self adapting engine performance model is used. Thus the model based sensor checking method examined in this paper can be a valuable contribution to engine performance diagnostics. Due to the significant amount of computation required it is not suited for real time on line analysis, however, for detecting slow sensor drifts this is not required.

Many more tests of the algorithm with various sensors and mass flow analysis methods have been done during the preparation of this paper. Some included also random noise added to the simulated measurements. It was found that the threshold value for detecting a sensor malfunction depends on many things and needs to be examined in detail for each application.

Even if the algorithm does not give perfect answers in all cases, it can be a valuable element within a sophisticated performance diagnostic system.

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