

A GPA diagnostic system for aeroengine applications

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Abstract: In this research, a GPA (Gas Path Analysis) diagnostic system enhanced with GPA Index is described for gas path sensor and component fault diagnosis. A method of measurement correction is used in order that the measurement data obtained at ur standard ambient and operating conditions can be used for diagnostic analysis. The developed diagnostic system has been implemented into a Cranfield U niversity gas turbine per formance and diagnostic analysis software PYTHIA for gas turbine performance degradation analysis. The de veloped method and software have been applied to a model aero gas turbine engine to test the effectiveness of the system. The analysis shows that the developed diagnostic system can diagnose degraded sensor and compo nents effectively using performance deviation measured at ur standard ambient and operational conditions. The oretically, the idea of the diagnostic approach can be applied to different gas turbine engines.

Key words: aeroengine; gas turbine; diagnostics, GPA (gas path analysis); sesor

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Nomenclature

CFC	component fault case	T	total temperature
FCM	fault coefficient matrix	w	weighting factor
GPA	gas path analysis	x	engine (independent) component health par rameter vector
H, H'	influence coefficient matrix	x	predicted engine (independent) component health parameter vector
HOT	higher order terms	y	ambient and engine operating condition param eter vector
ICM	influence coefficient matrix	z	engine measurable performance parameter vec tor
K	maximum number of possible failed sensors	Γ	flow capacity
K_f	number of assumed failed sensors in a SFC	β	threshold for sensor fault detection
L	total number of sensor fault cases	λ	GPA Index
M	number of measurable performance parameters	σ	GPA convergence threshold
m_i	fuel flow rate (kg/ s)	ε	difference between real and predicted fault sig natures
N	shaft rotational speed relative to its design val ue	η	component isentropic efficiency
N_h	number of engine component health paramet ers in a fault case	Subscripts	
N_a	number of ambient and operating condition par ameters	amb	ambient
P	number of measurement samples	b	burner (burner 1)
p	total pressure (atm)	c1	fan (compressor 1)
RMS	root mean square	c2	HP compressor (compressor 2)
S	total number of component fault cases	HP	high pressure
S_f	total number of most likely fault cases	LP	low pressure
SFC	sensor fault case; specific fuel consumption		

m	measured value
t1	turbine 1
t2	turbine 2
Δ	deviation (%)
0	nominal operating point
3	LP compressor exit
5	HP compressor exit
11	LP turbine exit
#	pseudoinverse

Introduction

Gas path diagnostics techniques have shown great potential to improve the availability of gas turbines and cut down the maintenance cost of gas turbine engines. Li^[1] and Singh^[2] have provided comprehensive reviews on gas turbine gas path diagnostic techniques. The most important ones among these diagnostic techniques are gas path analysis (GPA) and its derivatives^[3,6], traditional optimization based nonlinear methods^[7], artificial neural networks^[8,10], genetic algorithms^[11-13], fuzzy expert system^[14,15] and diagnostics with transient measurement^[16].

Gas path analysis (GPA) and its derivatives are powerful diagnostic approaches, but have the disadvantages such as smearing effect always appearing in the diagnostic results, requiring the a priori information of degraded component(s) and measurement noise and bias free sensors. These problems have been discussed by many researchers, such as Mathioudakis^[17]. One of the GPA methods to reduce the smearing effect was a “concentrator” concept introduced by Provost^[18] in his Kalman Filter diagnostic approach. The reduction of the impact of measurement noise was also discussed by previous researchers^[19,20].

All the gas turbine diagnostic methods use the information of the deviation of gas path measurements to identify degraded engine components and this information comes from sensors. Sensors are prone to degrade and fail during hostile engine gas path environment. When this happens the diagnostic results obtained by using incorrect measurement information will be wrong and misleading. Different gas path sensor fault diagnostic approaches have been developed

in the past. Example of the engine performance based sensor diagnostic methods are those using Gas Path Analysis^[18,21], Pattern Matching^[22], artificial neural networks^[9,23], genetic algorithms^[11], Fuzzy Logic^[24], etc.

In this paper, an ambient and operating condition correction method is used to correct the measurement data to a standard ambient condition and a nominal operating condition. A GPA Index combined with a GPA diagnostic method is used to assess the accuracy of diagnostic prediction and is applied to sensor and engine component fault diagnosis. An integrated gas turbine diagnostic system including measurement correction, sensor fault detection and engine component fault diagnosis is introduced and tested with the application of the system to a model aero gas turbine engine implanted with a typical sensor and component degradation. The system is demonstrated with the use of Cranfield gas turbine performance and diagnostic software PYTHIA. Analysis and conclusions are made accordingly.

1 GPA for gas turbine diagnostics

1.1 Gas path analysis (GPA) and GPA index

A linear and nonlinear GPA approach developed at Cranfield^[6] is an effective gas turbine diagnostic method used to assess gas turbine faults. The idea of the method is as follows.

The thermodynamic relationship between engine gas path measurable parameters and component health and ambient and operating condition parameters can be represented with Equation (1).

z = h(x, y) (1)

where $z \in R^M$ is measurable performance parameter vector and M the number of the performance parameters, $x \in R^{N_h}$ is the component health parameter vector and N_h the number of component health parameters, $y \in R^{N_a}$ is the ambient and operating condition parameter vector and N_a the number of these parameters, and is a vector valued function. At a given operating point which is denoted by subscript “0”, Eq. (1) can be expanded in a Taylor series

$$\mathbf{z} = \mathbf{z}_0 + \left. \frac{\partial h(\mathbf{x}, \mathbf{y})}{\partial \mathbf{x}} \right|_0 (\mathbf{x} - \mathbf{x}_0) + \left. \frac{\partial h(\mathbf{x}, \mathbf{y})}{\partial \mathbf{y}} \right|_0 (\mathbf{y} - \mathbf{y}_0) + HOT \quad (2)$$

where HOT are higher order terms of the expansion and can be neglected. Therefore, a linearized gas turbine performance model can be expressed with Equation (3).

$$\Delta \mathbf{z} = \mathbf{H} \cdot \Delta \mathbf{x} + \mathbf{H}' \cdot \Delta \mathbf{y} \quad (3)$$

When there is no deviation from standard ambient condition and nominal operating condition, $\Delta \mathbf{y} = 0$. So Eq. (3) becomes

$$\Delta \mathbf{z} = \mathbf{H} \cdot \Delta \mathbf{x} \quad (4)$$

Therefore, the degradation of components expressed by the deviation of component health parameters can be predicted by inverting the influence coefficient matrix (ICM), $\mathbf{H}$ to a fault coefficient matrix (FCM), $\mathbf{H}^{-1}$ leading to Equation (5).

$$\Delta \mathbf{x} = \mathbf{H}^{-1} \cdot \Delta \mathbf{z} \quad (5)$$

The nonlinearity of the engine behaviour is taken into account by using an iterative process^[6] where the linear GPA is applied iteratively until a converged solution is obtained, Figure 1.

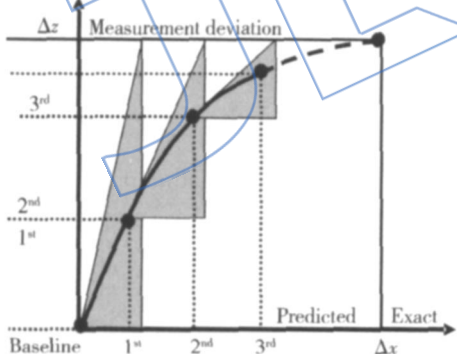


Fig. 1 Non-linear GPA^[6]

To ensure that the ICM is invertible and the solution is unique, it is required that the minimum number of the measurement parameters is the number of health parameters involved and the measurement parameters are uncorrelated (independent from each other). Redundant measurement ($N_h < M$) is beneficial for accuracy improvement but the Equation (4) is over-determined. An estimation of the solution, $\mathbf{x} = \mathbf{H}^\# \mathbf{z}$ of Eq. (4) in a least-square sense can be obtained

with the pseudoinverse of ICM defined as

$$\mathbf{H}^\# = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \quad (6)$$

The convergence of the non-linear GPA shown in Fig. 1 is declared when the predicted measurable performance is very close to the real measured performance. This criterion is shown in Equation (7) where the RMS of the difference between the predicted and real performance measurement is smaller than σ when convergence is declared

$$RMS = \sqrt{\frac{\sum_{i=1}^M \left| \frac{z_i - z_{m,i}}{z_{0,i}} \right|^2}{M}} < \sigma \quad (7)$$

where z_i is predicted measurement, $z_{m,i}$ measured data, $z_{0,i}$ nominal value at specified diagnostic condition, and σ is a very small number.

This diagnostic method is simple and fast in prediction although it has certain requirements that are difficult to meet such as:

- the influence coefficient matrix (ICM) is an accurate mathematical description of gas turbine performance around a specified operating point
- measurement bias and noise free sensors
- uncorrelated (independent) measurements being sensitive to engine degradation.

Another disadvantage of the GPA is the dependency on the a priori information of degraded components - conflicting answers may be provided if different degraded components are assumed due to lack of such information. Therefore, further interpretation of the prediction from the GPA may be very important in order to avoid being misled by the GPA. This job can only be done by experienced gas turbine diagnostics engineers.

In order to solve such a problem, the concept of a GPA Index which is the measure of the gas turbine diagnostic accuracy is introduced and is defined in Equation (8)

$$\lambda = \frac{1}{1 + \varepsilon} \quad (8)$$

where λ is the GPA Index, and ε a measure of the difference between the measured deviation and predicted deviation of engine gas path measure-

ments (fault signature) expressed with Equation (9).

$$\varepsilon = \sum_{i=1}^N w_i \left| \frac{\Delta z_i}{z_{0,i}} - \frac{\Delta z_{m,i}}{z_{0,i}} \right| \quad (9)$$

w_i are weighting factors taking into account the relative importance of the measurements. In this study, all of the measurements are assumed to have equal importance so they all take the value of 1.0.

The meaning of the GPA Index is shown in Figure 2 and explained as follows. First, the faulty engine components need to be assumed. Then, at specified ambient and operating condition, the GPA predicts the degradation of the assumed faulty engine components and such information is sent to the model engine to produce a predicted fault signature. The comparison between the real fault signature and the predicted fault signature produces the different ε and therefore the GPA Index. If the assumed faulty components are correct, the predicted fault signature will be very close to the actual fault signature so ε will be very small and therefore the GPA Index will be very close to 1. In other words, a GPA Index approaching 1 indicates a very accurate degradation prediction while a GPA Index close to 0 means a wrong prediction.

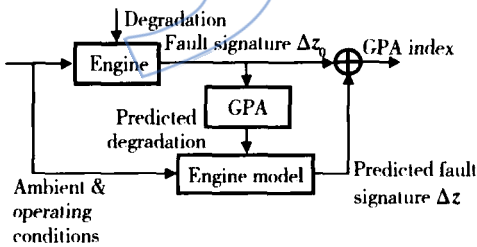


Fig 2 GPA Index Calculation

Theoretically, the GPA approach described in Figure 3 should provide a good degradation prediction when there is enough number of measurements ($M \geq N_h$). Unfortunately, the smearing effect may be so strong that the degraded engine components are difficult to recognize. Therefore, the concept of engine fault cases introduced by Zedda and Singh^[11] is used in this study.

To apply the GPA Index effectively to gas

turbine component fault diagnosis, the maximum number of simultaneously degraded engine components and the component fault cases (CFC) that cover all the combination of potential degraded components should be assumed. For example, compressor degradation can be one fault case and a combined compressor and turbine degradation can be another. A diagnostic approach to cover all pre-assumed engine fault cases is shown in Fig. 3 where highest values of the GPA Indices obtained among all fault cases would indicate the most likely engine degradation cases.

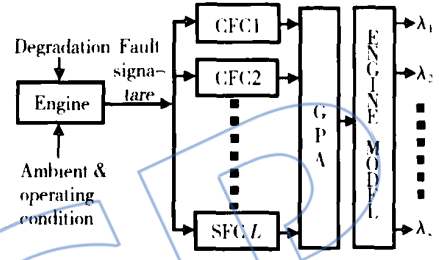


Fig 3 GPA Diagnostic system using GPA Index

It is recommended to use redundant measurements to predict engine degradation as the prediction accuracy can normally be improved. By using the concept of fault cases, the number of component health parameters, N_h , in each component fault case can easily become less than the number of available measurement parameters, M , and therefore the measurement redundancy can be obtained in all fault cases.

In a situation where more than one CFC cases are likely, weighted engine degradation is suggested and calculated as follows

$$\bar{x}_i = \sum_{j=1}^{S_f} x_{ij} \cdot \lambda_j / \sum_{j=1}^{S_f} \lambda_j \quad (10)$$

Where $\bar{x}_i$ is a weighted health parameter, x_{ij} the i th health parameter predicted in CFC case j , λ_j the GPA Index in CFC case j and S_f the total number of the most likely fault cases.

1.2 Sensor fault detection with GPA index

Gas path sensors may degrade or fail and then produce significant bias during gas turbine operations. Using correct measurement information is crucial in obtaining correct fault signature, producing accurate engine diagnostic results

and avoiding misleading messages to gas turbine maintenance engineers.

Similar to the concept of engine component fault cases, different sensor failure are classified into sensor fault cases (SFC), each of which excludes assumed failed sensor(s). Figure 4 shows a sensor fault detection approach using the concept of sensor fault cases. Assuming that among total M sensors, total number of K sensors may fail. Due to the nature of GPA approach that the GPA is not able to detect engine degradation without correct fault signature, the GPA should use unfailed sensors for diagnosis. Therefore, the number of sensor fault cases, i. e. the number of sub sets of sensors excluding assumed failed sensors is

$$L = \frac{M!}{K_f \cdot (M - K_f)}, K_f \leq K \quad (11)$$

where K_f is the number of sensors excluded. In other words, each of the sensor fault cases refers to a sub sensor set excluding K_f sensors and there are L sensor fault cases in total. By selecting one of the engine component fault cases, all of the sensor fault cases are searched by the GPA to produce a total number of L diagnostic results with L GPA Indices. If the failed sensors are excluded in the sensor fault case, the GPA approach will predict correct engine degradation and the GPA Index will be very close to 1. Otherwise, the predicted fault signature will be wrong and the GPA Index will be closer to 0. By comparing the values of the GPA Indices among all sensor fault cases, the sensor fault cases that have the largest GPA Indices would indicate the most likely sensor fault cases where failed sensors are excluded.

The application of such a sensor fault detection approach is based on the condition that there are redundant sensors. In other words, the number of sensors in any of the sensor fault cases must be no less than the number of engine component health parameters in the selected engine component fault case and such condition is expressed in Equation (12).

$$M - K_f \geq N_h \quad (12)$$

where N_h is the number of engine health parameters in an engine component fault case (CFC).

Sensor bias may have different quantities. If sensor bias is too large, the GPA searching process in Fig. 4 may diverge and no result will be provided. To avoid such a situation to happen, a threshold is introduced where all the measurement deviations are compared with the threshold and the deviations larger than the threshold indicate failed sensors. Therefore, complete sensor fault detection approach will go through the following two steps:

If measurement deviations are larger than the threshold β , the corresponding sensors are declared faulty and are excluded from the diagnostic process.

If measurement deviations are smaller than or equal to the threshold, the sensor fault detection system, Figure 4, is applied to check sensor health before the measurements are used for engine component diagnosis.

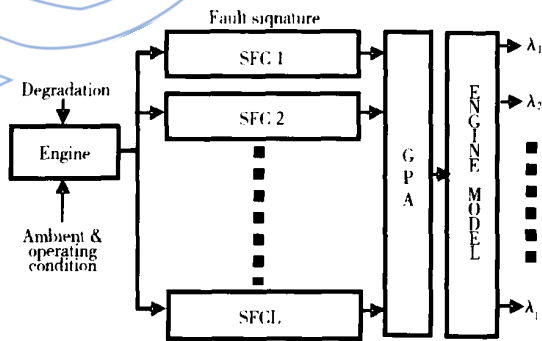


Fig 4 Sensor fault detection with GPA index

1.3 Measurement correction

Gas turbine gas path measurements are rarely done at a specified condition, such as at standard ISO ambient condition and at nominal engine operating condition, that is used as the nominal operating condition for diagnostics. The diagnostic analysis can be carried out at different ambient and operating conditions where measurement data are available. However, to make use of multiple measurement samples that might be taken at different ambient and operating conditions, it will be more convenient to correct all

measurement samples to a specified nominal ambient and operating condition. The idea of such a model-based measurement correction is illustrated in Figure 5.

Assume that condition a is the nominal operating condition where the diagnosis is carried out. Such a condition is normally taken as sea level standard ambient condition together with the engine providing nominal power output. Condition b is a condition slightly different from condition a where degraded engine performance is measured. For diagnostic purpose, measurements at b should be corrected to those at condition a in order to obtain performance deviation due to degradation and get correct fault signature. Assume that the performance deviation is $\Delta z_{i,a}$ at condition a and $\Delta z_{i,b}$ at condition b . The measurement correction against ambient and operating conditions from b to a is $\Delta z_{i,AB}$ for clean engine and $\Delta z_{i,A1B1}$ for degraded engine. In Fig. 5 it can be seen that

$$\Delta z_{i,a} + \Delta z_{i,A1B1} = \Delta z_{i,b} + \Delta z_{i,AB} \quad (13)$$

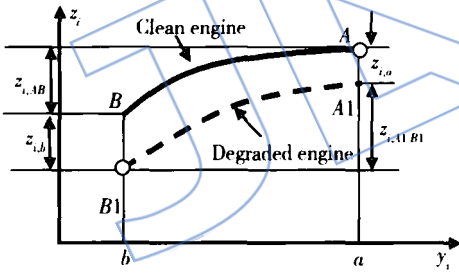


Fig 5 Measurement corrections against ambient and operating conditions

Therefore, the performance deviation at condition a can be calculated as

$$\Delta z_{i,a} = \Delta z_{i,b} + (\Delta z_{i,AB} - \Delta z_{i,A1B1}) \quad (14)$$

where

$$\Delta z_{i,AB} = z_{i,B} - z_{i,A} \quad (15)$$

$$\Delta z_{i,A1B1} = z_{i,B1} - z_{i,A1} \quad (16)$$

The clean engine performance may not vary parallel to the degraded engine performance from condition b to a but such difference is not taken into account in this study. So

$$\Delta z_{i,AB} = \Delta z_{i,A1B1} \quad (17)$$

and therefore

$$\Delta z_{i,a} = \Delta z_{i,b} \quad (18)$$

Due to the fact that point A represents available baseline performance, point $B1$ represents available degraded performance and line AB can be easily obtained by using engine test data or engine performance model, the fault signature at condition a can be obtained with Equation (19)

$$\Delta z_{i,a} = \Delta z_{i,B1} + \Delta z_{i,AB} \quad (19)$$

Due to the non-linearity of engine thermodynamic behaviour, it is very likely that $\Delta z_{i,AB}$ may be noticeably different to $\Delta z_{i,A1B1}$ when significant engine degradation happens, which is not taken into account in this study. More detailed discussion of this topic was given by Li and Singh^[25].

To reduce the impact of measurement noise on gas path diagnostics, a rolling average, Equation (20), is applied to the corrected multiple samples and an averaged measurement is obtained and used for further diagnostic analysis.

$$\bar{z}_i = \frac{1}{P} \sum_{i=1}^P z_i \quad (20)$$

where P is the number of measurement samples.

1.4 Integrated GPA diagnostic system

Taking into account the influence of ambient and operating conditions, sensor failure and engine component degradation, an integrated GPA diagnostic system is proposed. In such a system, the diagnostic process experiences three steps and they are illustrated in Figures 6.

- **Measurement correction** - the engine gas path measurement samples taken at different ambient and operating conditions are first corrected to the standard ISO ambient condition and a nominal operating conditions with clean engine (without degradation) model using the information of Δy to obtain the corrected measurement deviations ($\Delta z - \Delta z_y$). An averaged deviation (fault signature) is obtained by using Eq. (20) to reduce the impact of measurement noise.

- **Sensor fault detection with GPA** - The obtained measurement deviation (fault signature) is input into a sensor fault detection system

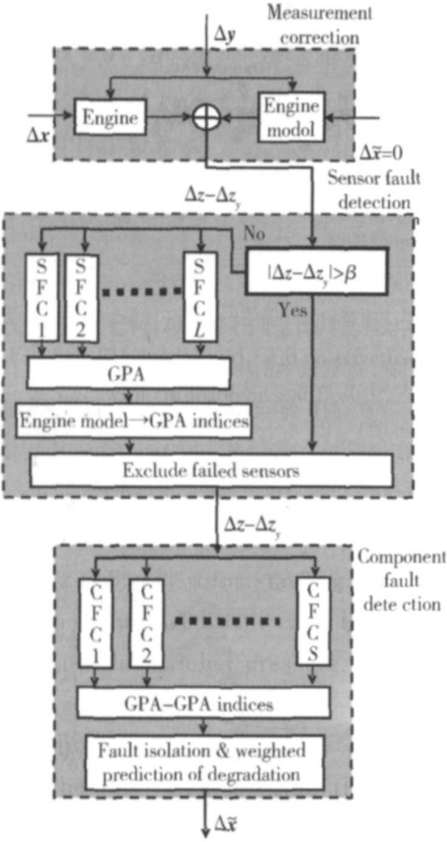


Fig 6 Integrated GPA diagnostic system

where faulty sensors are detected and excluded.

• **Engine component fault diagnosis** - the fault signature excluding the measurements from failed sensors is passed to an engine component GPA diagnostic system to find out the most likely degraded engine components. A threshold of GPA Index is specified to assess if a CFC case is likely (the value of the threshold used in this research is 0.85). If more than one CFCs are detected, weighted engine degradation will be obtained with Eq. (10).

The outputs of the diagnostic system are detected faulty sensors and isolated faulty engine components together with an estimation of the component degradation Δx .

Such an integrated GPA diagnostic system (Fig. 6) has been implemented into Cranfield gas turbine performance analysis software *PYTHIA* developed from *TURBOMATCH*^[26], the validity of which has been tested over many years.

2 Application and analysis

A representative two shaft model aero tur-

bofan gas turbine engine similar to EJ200 is chosen for the analysis. It has a fan (compressor 1), a HP compressor (compressor 2), a burner (burner 1) and two turbines (turbine 1 and turbine 2). When the engine works at different ambient operating conditions and at degraded conditions, the HP shaft speed is used as control parameter and kept constant. The configuration of the model engine is illustrated in Figure 7 and the basic performance parameters of the model engine are as follows:

total exhaust flow rate	76 kg/s
total pressure ratio	26
turbine entry temperature	1760 K
thrust	60 kN
specific fuel consumption	22 mg/N · s

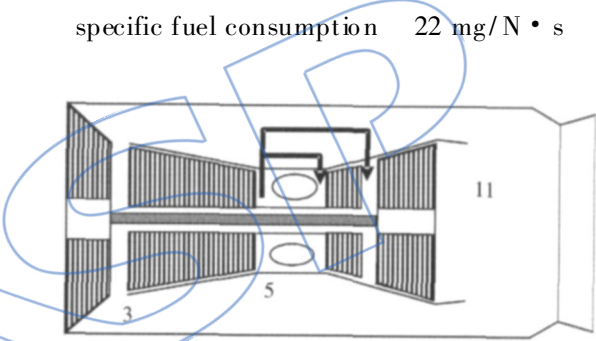


Fig 7 Model gas turbine configuration

To test the diagnostic system, it is assumed that the HP compressor of the model engine is degraded and a degradation of 3% reduction in flow capacity and 1% reduction in isentropic efficiency is implanted into the HP compressor. It is also assumed that the two compressors, the burner and the two turbines of the engine are potential degraded components and the maximum number of simultaneously degraded components can be up to two.

The selected instrumentation set for diagnostic purpose of the model engine is listed in Table 1 and the maximum number of potential failed sensors is 1.

The simulated measurements for the clean and degraded engine are provided by *PYTHIA* where two different ambient and operating conditions are given in Table 2. Due to the fact that measurement noise is inevitable and is the major non-repeatable uncertainty that can not be easily

corrected and has a negative impact on diagnostic results they are included in the analysis.

Table 1 Engine gas path instrumentation set

No.	Symbols	Parameters
1	T_{amb}/K	Ambient temperature
2	p_{amb}/atm	Ambient pressure
3	$N_{HP}/\%$	HP shaft rotational speed
4	T_3/K	Fan discharge total temperature
5	p_3/atm	Fan discharge total pressure
6	T_5/K	HP Compressor exit total temperature
7	p_5/atm	HP Compressor exit total pressure
8	T_{11}/K	LP turbine exit total temperature
9	p_{11}/atm	LP turbine exit total pressure
10	$m_t/(kg/s)$	Fuel flow rate
11	$N_{LP}/\%$	LP shaft rotational speed

Table 2 Two measurement conditions

Parameters	Condition <i>a</i>	Condition <i>b</i>
	(Standard ISO ambient condition with nominal HP shaft speed)	(Urr standard ambient condition with lower HP shaft speed)
T_{amb}/K	288.15	298.38
p_{amb}/atm	1.0	0.997
$N_{HP}/\%$	100	98

To simulate the noisy measurements from the model gas turbine engine, the performance of the model engine is first simulated and then the simulated measurable performance parameters are superimposed on by measurement noise. It is assumed that the measurement noise has Gaussian distribution and that the noise levels for the measurable parameters fall within the ranges provided by Dyson and Doel^[27]. The detailed application of the proposed diagnostic system to the model engine is shown as follows.

2.1 Correction of measurement data

The correction of gas path measurements against ambient and operating conditions is done without the consideration of engine degradation ($\Delta x=0$), Fig. 5 and 6.

To show the effectiveness of the measurement correction and the correction errors of the

fault signature, simulated measurement samples at Condition *b* (Table 2) for the engine implanted with the HP compressor degradation without noise and bias are used and three measurement deviations are compared in Figure 8. The first one marked as ‘Real’ is obtained at standard ambient condition with nominal HP shaft speed regarded as true fault signature, the second one marked as ‘Corrected’ is obtained by correcting the data from Condition *a* to Condition *b* (Table 2), and the third one marked as ‘No correction’ is the measurement deviation without measurement correction. It can be seen that the fault signature with measurement correction (marked as ‘Corrected’) is very similar to the ‘Real’ fault signature but slightly different in magnitude while the measurement deviation without measurement correction (marked as ‘No correction’) is completely different. It can be seen that the measurement correction is very effective although minor correction errors exist.

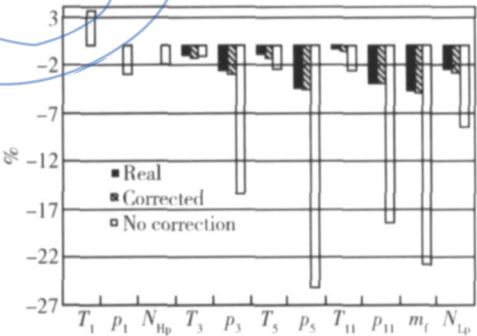


Fig 8 Comparison of measurement deviations

The simulated measurement samples with measurement noise for the clean engine working at Condition *a* and the measurement samples with measurement noise and bias for the degraded engine at Condition *b* are pre-processed with the measurement correction method (Fig. 5) and data averaging using Eq. (20) ($P=10$) before they are passed to the sensor fault detection system shown in Fig. 6.

2.2 Sensor fault detection with GPA index

It is assumed that one of the sensors p_5 is degraded and therefore has a significant level of bias (-5%) in the measurements when the en-

gine is degraded at Condition *b*.

To detect a potential failed sensor, 8 sensor fault cases (SFC) are pre-assumed and shown in Table 3. To test the effectiveness of the sensor fault detection system described in Fig. 6, one of the component fault cases is selected and 8 sensor fault cases are searched with the GPA. To see the difference of the results when different component fault cases are selected, all of the five single component fault cases (first two component fault cases in Table 4) are selected in the analysis. A comparison of GPA Indices obtained is shown in Figure 9. For example, the first group of five GPA Indices corresponding to SFC1 is the results of the first sensor fault case searched with the five component fault cases.

Table 3 Sensor fault cases

Sensor Fault Cases	Pre-assumed faulty sensor
SFC1	T_3
SFC2	p_3
SFC3	T_5
SFC4	p_5
SFC5	T_{11}
SFC6	p_{11}
SFC7	m_f
SFC8	N_{LP}

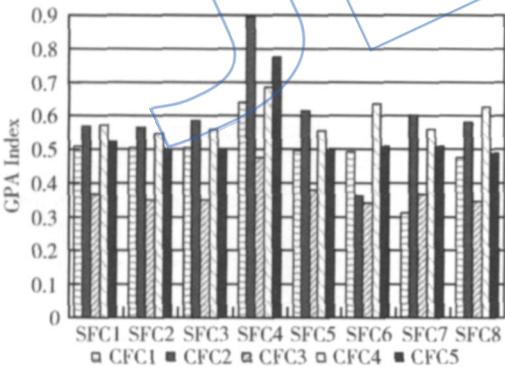


Fig 9 Sensor fault detection with GPA Index

It can be seen in Fig. 9 that although the selected component fault cases are different the GPA Indices in SFC4 always show relatively larger values compared to the values in other sensor fault cases. Among the five GPA Indices in SFC4, one of them has significant higher value than others. This is due to the reason that the correct component fault case (CFC2) and the correct sensor fault case (SFC4) are selected in

the sensor fault detection process. Therefore, the results strongly indicate that the sensor *p*₅ is very likely to have problem. It also shows that whichever the engine component fault cases is chosen for the sensor fault detection the indication of the result is the same. However, the results from the selection of some fault cases such as CFC2 is more obvious than the results from other fault cases such as CFC3. In addition, the detection of the failed sensor is not affected significantly by the measurement correction errors existing in the fault signature.

Table 4 Engine component fault cases

Component fault case	Pre-defined faulty components
CFC1	compressor 1
CFC2	compressor 2
CFC3	burner
CFC4	turbine 1
CFC5	turbine 2
CFC6	compressor 1+ compressor 2
CFC7	compressor 1+ burner
CFC8	compressor 1+ turbine 1
CFC9	compressor 1+ turbine 2
CFC10	compressor 2+ burner
CFC11	compressor 2+ turbine 1
CFC12	compressor 2+ turbine 2
CFC13	burner+ turbine 1
CFC14	burner+ turbine 2
CFC15	turbine 1+ turbine 2

2.3 Engine component fault diagnosis

Based on the above results and analysis, the measurement from sensor *p*₅ should be excluded and the rest of the measurements are used for further component diagnosis.

Based on the assumption that the maximum number of simultaneously degraded engine components can be up to two, all the component fault cases (CFC) are listed in Table 4. Using the GPA diagnostic system described in Figure 6, all the possible fault cases are searched with the GPA and the GPA Indices obtained from the diagnostic analysis are shown in Figure 10. It can be seen that fault cases CFC2, CFC6, CFC10 and CFC12 have the GPA Indices larger than the specified threshold 0.85 indicating that they are the most likely fault cases while the Indices for

other cases are relatively lower.

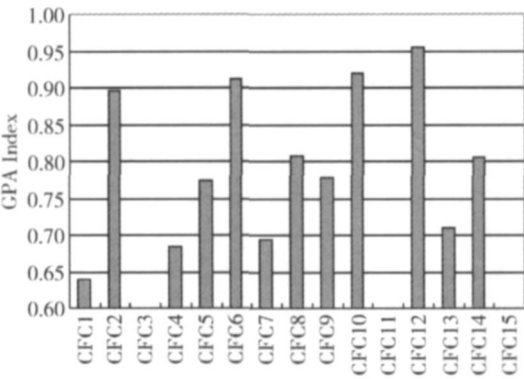


Fig 10 Comparison of GPA Indices for all fault cases

The predicted component degradations of the four most likely fault cases are compared and shown in Figure 11. It shows that although the trend of the prediction is similar but the solutions are slightly different. To take the advantage of all the solutions from these four cases, a weighted solution of the predicted engine degradation with the GPA Indices, Eq. (10), is obtained and shown in Figure 12, which shows that the compressor has the largest degradation while the degradation of other components are so little that they can be neglected. Therefore, it can be concluded that only compressor is the most likely degraded component.

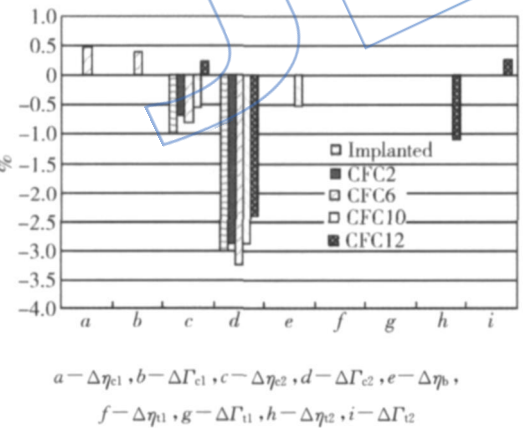


Fig 11 Predicted engine degradation (Implanted fault: Compressor 2 $\Delta\eta_{c2} = -1.0$, $\Delta\Gamma_{c2} = -3.0$)

Once the degraded component is isolated, the GPA is now applied only to the HP compressor (CFC2) to quantify the degradation and the result is shown in Fig. 12. By comparing the predicted component degradation (CFC2) with the implanted compressor degradation (Fig. 12), it

can be seen that the prediction error for compressor efficiency drop is about 0.33% and the prediction error for compressor flow capacity drop is about 0.14%. Such errors may be due to the impact of measurement correction errors and the remaining measurement noise after noise reduction.

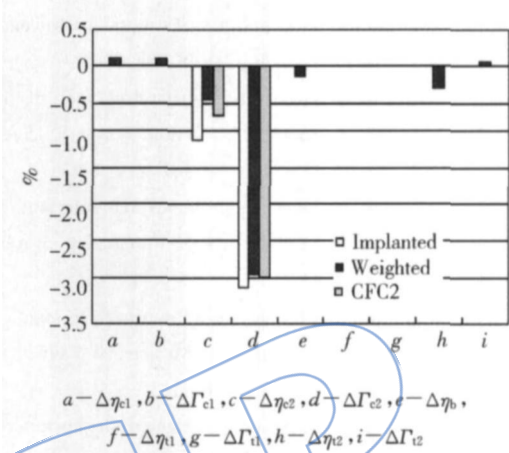


Fig 12 Comparison between implanted fault and weighted engine degradation prediction

3 Conclusions

In this study, a gas turbine gas path diagnostic system is introduced, which includes three steps in the diagnostic process. The first step is the data processing where measurement data are corrected to those at a specified ambient and nominal diagnostic operating condition together with data averaging to reduce the impact of measurement noise, the second step is sensor fault detection and the third step is the engine component degradation analysis. A GPA Index is introduced in the GPA diagnostic system and is effectively used in the detection of gas path sensor failure and the diagnosis of gas turbine component degradation. The diagnostic system implemented into Cranfield gas turbine performance and diagnostics software, Pythia, has been applied to a model aero gas turbine engine implanted with a biased sensor and a degraded component. The application and the analysis show that the diagnostic system has a great potential to accurately detect gas turbine component degradation with the presence of a biased sensor and

the introduction of the GPA Index offers enhanced confidence in accurate gas path diagnostic analysis.

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