Jet Engine Fault Detection with Discrete Operating Points Gas Path Analysis

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A common feature of all Differential Gas Path Analysis methods is the necessity of measuring a number of performance variables greater or at least equal to the number of diagnostic parameters which have to be estimated. Discrete Operating Conditions Gas Path Analysis (DOCGPA) is an extended version of the conventional GPA algorithms, providing–among other things–the capability to overcome this problem. In the present paper, we describe how this method can be coupled with an engine computer model, in order to perform component directed fault diagnosis. Application to a commercial turbofan engine demonstrates the effectiveness of the proposed method.

Nomenclature

[C] = influence coefficient matrix
EPR = engine pressure ratio
J = scalar defined in Eq. (8)
k = number of different operating points
[M] = information matrix
m = number of unknown component parameters
n = number of measured variables
[P] = covariance matrix of unknown components parameters
m = number of unknown component parameters
PEUI = performance estimation uncertainty index (equal to J)
[R] = covariance matrix of measures variables
tr{ } = trace of a matrix
u = operating condition vector
x = component parameter vector
y = measurement vector
Δ( ) = percentage change from an initial value
Σ = summation

Superscripts
T = transpose matrix
−1 = inverse matrix

Introduction

GAS Path Analysis (GPA) methods are the methods which deal with the study of the fluid (gas) aerothermodynamic changes, as it flows through the different parts of a gas turbine. The idea on which such methods are based is the fact that any change in the performance of the components, which are in contact with the gas path, will result in a change of the aerothermodynamic parameters. If this second change is traced, the original cause can, in principle, be detected. A review of the early GPA methods is given in Ref. 1. Recent work is presented in Refs. 2–4.

The most crucial problem which is recognized in the field is the following: In an effort to develop an effective diagnostic system based on GPA, practical limitations are encountered. These limitations appear when, in order to increase reliability on performance estimation as well as to isolate malfunctioning components of the engine, one has to increase the volume of information concerning its state. The usual approach to meet this requirement is the increase of the number of measured quantities, by installing additional sensors. In the case of engines under development, the main restriction is the cost of the additional instrumentation. In already existing engines, one additional restriction is faced, which concerns the integrity of the powerplant: Installation of new sensors cannot be undertaken by the user, unless this is allowed by the engine manufacturer.

A method of overcoming these practical limitations has been introduced[5] under the name of Discrete Operating Conditions Gas Path Analysis, DOCGPA. This method, which will be reviewed in the present paper from a more comprehensive and practical point of view, utilizes the ignored amount of independent information coming out of measurements realized by the already existing sensors, at different operating points. To make this additional information useful, engine performance models are necessary. Such models must correlate correctly the engine observed behavior with the "health" condition of its components, at all operating points.

In the following, we will present how engine performance computer models can be used to provide the data needed by DOCGPA in order to perform fault diagnosis, with application to particular engines.

Underlying Principle of the Method

Aging or specific engine failures reflect on engine performance deterioration, which results in deviations of the values of measured performance variables (pressure, temperature) from the ones corresponding to a healthy operation (baseline values). The performance deterioration is usually represented by the drop of the values of some characteristic component performance parameters (e.g., efficiencies, flow capacities). The correspondence between the set of deviations of the measured variables from the baseline and the set of component performance parameter deviations, constitutes the standard basis for the conventional GPA methodology.

The ordinary mathematical formulation of the above correspondence is expressed by a well-known linear equation, which is valid at each particular operating point:

$$\Delta y = [C] \cdot \Delta x \qquad (1)$$

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where

Δy = $n \times 1$ vector of measured deviations
Δx = $m \times 1$ vector of unknown component parameter deviations
$[C]$ = $n \times m$ influence coefficient matrix

In order to determine the Δx vector, we have to solve the system Eq. (1). A necessary condition for the solution of the system is $m \le n$, i.e., the number of measured quantities must be greater or at least equal to the number of the unknown parameters. If, however, we consider that the deviations Δx remain the same for different operating points of the engine, we can take advantage of the nonlinearity of engine performance characteristics in order to overcome this constraint.

In fact, any gas turbine configuration may be considered as a system for which the measured output y is a function of the system parameter vector x and the input vector u.

$$y = G(x, u) \tag{2}$$

The vector u determines the conditions which define the operating point (ambient conditions, load, control settings, etc.). Linearization of Eq. (2) with respect to x leads to the equation.

$$\Delta y = [C(u)] \cdot \Delta x \tag{3}$$

The conventional formulation of the GPA (Eq. (1)) is simply the application of the Eq. (3) at a particular operating point. If we apply Eq. (1) at k discrete operating points, we can write with the assumption of unchanged Δx:

$$\begin{bmatrix} \Delta y_1 \\ \vdots \\ \vdots \\ \vdots \\ \Delta y_k \end{bmatrix} = \begin{bmatrix} [C]_1 \\ \vdots \\ \vdots \\ \vdots \\ [C]_k \end{bmatrix} \Delta x \tag{4}$$

where

$$[C]_i = [C([u_i])] \quad i = 1, k$$

We see that we dispose now of the $k \times n$ measurements, while the unknown parameters remain the same. Equation (4) can then be used to determine Δx if the rank of the augmented coefficient matrix, (containing now $k \times n$ rows) is greater or equal to m. This condition is in general fulfilled for the case of a jet engine, due to the nonlinear dependence of the influence coefficients on engine operating point, as will be shown later. By choosing, therefore, a suitable number of discrete operating conditions, we can increase the number of equations in Eq. (4), thus allowing the determination of the desired m elements of Δx even though $n < m$ (parameters to determine are more than the measured variables).

The assumption of Δx unchanged for different operating conditions has been verified, at least, in some compressor fault cases. It has been reported[8] that tip clearance and leading edge erosion lead to shifting of the speedlines of the compressor maps, while similar behavior was observed as a result of overall blade airfoil erosion.[9] Shifting of the speedlines without a change in their shape means exactly that, for compressor parameters, Δx is the same for different operating conditions. The validity of the assumption for other component parameters or kinds of faults would still have to be verified. In any case, the method will work as long as the number ℓ of deviations, which depend on operating conditions, is less than n. This can be understood, since in that case the number k of operating points should simply be chosen such that $k > (m - 1)/(n - 1)$.

The handling of Eq. (4) in order to allow for measurement noise and get statistically valid results has already been presented.[5] The final equation is

$$\Delta x = [M]_k^{-1} \sum_{i=1}^{k} [C]^T_i [R]_u^{-1} \Delta y_i \tag{5}$$

where M is the so called information matrix

$$[M]_k = \sum_{i=1}^{k} [C]_{iT} [R]_i^{-1} [C]_i \tag{6}$$

and $[R]_i$ is the typical covariance matrix of the measured variables.

The uncertainty on the estimation of Δx is expressed by its covariance matrix P_k where

$$[P]_k = [M]_k^{-1} \tag{7}$$

The model represented by Eq. (5), which was built from k discrete operating points is called the order k GPA model.

For any order k model, along with its covariance $[P]_k$, we shall consider it as a measure of the corresponding diagnostic effectiveness. In the present work, we shall use as such measure the following norm:

$$J = (\mathrm{tr}\{[P]_k\}/m)^{1/2} \tag{8}$$

J is named performance estimation uncertainty index (*PEUI*).[5] Knowing that the trace of a matrix is the sum of its diagonal elements and that the diagonal elements of $[P]_k$ represent the variance in the estimation of each component of Δx, J is a kind of global rms error for the order k model. Clearly, the smaller the value of J, the more accurate is the estimate. In other words J indicates the amount of information which is useful when the number of the considered operating points increases.

Let's see now how an engine computer model can be used together with this method, in order to perform fault diagnosis.

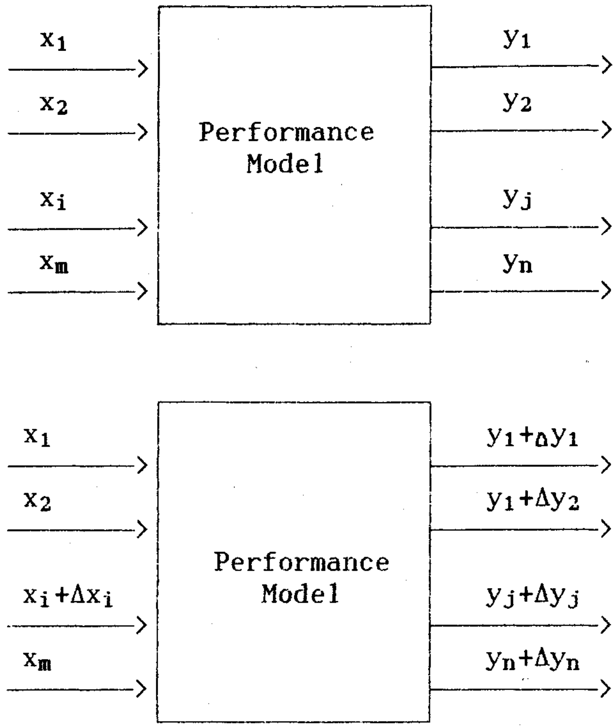
Performance Model and Influence Coefficients Matrix Calculation

The elements of the influence coefficient matrices $[C]$, at each operating point, can either be defined analytically (for example Ref. 6), using engine parameter interrelationships or by using an engine performance simulation code, if it is available. In this later case, $[C]$ can be produced in the following way: each independent parameter is sequentially perturbed and the corresponding percentage changes in measured variables are recorded. The derivatives involved and the influence coefficients are then numerically evaluated.

The advantage of such a procedure is that all secondary effects, such as bleeds, power extraction, etc., are inherently taken into account, without the need of developing complicated analytical expressions. On the other hand, if one possesses a modular computer model allowing for simulation of many types of engines, the technique can directly be applied, without the need to develop a new set of analytical expressions for each case. Last, but not least, there is no need for simplified assumptions (for example, choked nozzle operation) which may restrict the application of GPA in a limited region close to the full power operation.

Using this procedure, we can calculate the elements of the influence coefficient matrix at different operating points, having the possibility produce the information needed by Eq. (5) for fault diagnosis.

The outline of the calculation procedure is presented in Fig. 1. At this point, we must emphasize the requirement for high



$$c_{ji} = \frac{\partial x_j}{\partial x_i} \approx \frac{\Delta y_j}{\Delta x_i}$$

Fig. 1 Calculation of influence coefficients.

Table 1a Measurement vector

Index J	Symbol y_j	Quantity
1	N_1	Fan spool rotational speed
2	N_2	High Pressure Compressor speed rotational speed
3	FF	Fuel Flow rate
4	EGT	Exhaust Gas Temperature

Table 1b Component parameter vector

Index J	Symbol x_j	Quantity
1	n_F	Fan efficiency
2	n_{IPC}	Intermediate Pressure Compressor efficiency
3	n_{HPC}	High Pressure Compressor efficiency
4	n_{HPT}	High Pressure Turbine efficiency
5	n_{LPT}	Low Pressure Turbine efficiency
6	A_N	Effective Nozzle Area

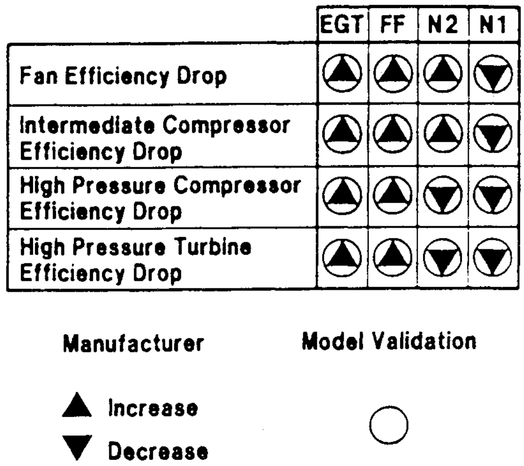


Fig. 2 Qualitative comparison between measured parameter deviations and results of the model.

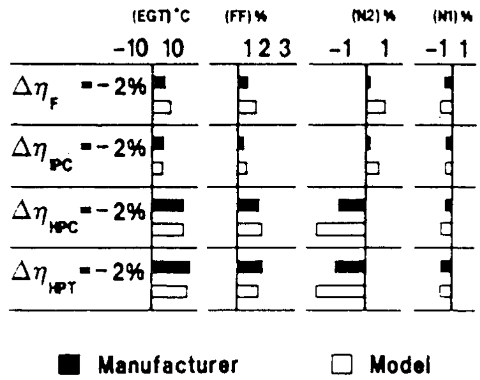


Fig. 3 Quantitative comparison between deviations predicted by the model and corresponding values provided by the manufacturer.

accuracy of the calculation procedure. In fact, the corresponding performance model must be able to predict accurately the engine behavior over the whole operating range, in order to compute with acceptable accuracy the influence coefficient elements. It should be mentioned that generalized engine models, especially when built by the engine user, do not always fulfill this requirement. In order to overcome these disadvantages, the models should be customized to the particular engine. In this respect, the present authors have proposed a method of making the engine models more realistic, by means of a map adapting technique.[7]

Application of the Method

In order to demonstrate the application and effectiveness of this method, we have selected the JT8D turbofan engine as a test case. We have adapted our general performance model to this particular engine, while information about faults is provided by the manufacturer.

Table 1 defines the vector of available measurements y and the vector of unknown component parameters x, as we have chosen them for this engine.

Before proceeding to the evaluation of parameters needed to diagnostic purposes, we must ensure that the engine model represents, with sufficient accuracy, the observed engine behavior. Validation of the model can be done for this particular engine by using the same measurements that will be used below for diagnostic purposes. A qualitative and a quantitative comparison between the model prediction and measurements is presented in Figs. 2 and 3. For the various situations mentioned in these figures, the direction of the variable deviations is checked first, and then their quantitative behavior. It can be seen from Fig. 2 that the deviation direction is identical for all cases, while, in Fig. 3, a good agreement exists between predicted and measured quantities.

The variation of certain elements of the influence coefficient matrix with varying EPR (different operating conditions) is shown in Fig. 4. This figure presents calculated values using the available performance simulation code. The nonlinear behavior of the influence coefficients with varying operating conditions is evident.

The independent information amount added, using measurements coming out of additional operating points, can be evaluated using the performance estimation uncertainty index, J, defined in Eq. (8). Making use of this index, we shall investigate below the possible improvements offered by the

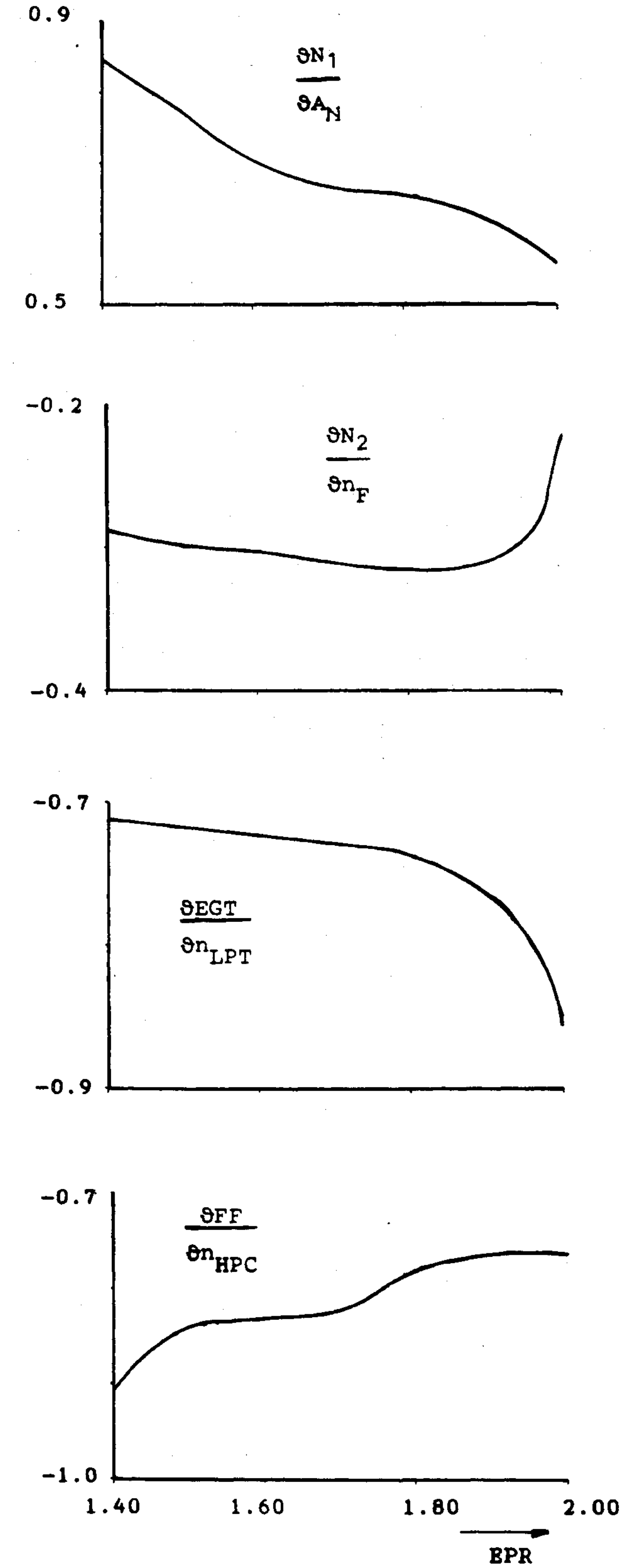


Fig. 4 Variation of influence coefficients with *EPR*.

consideration of different operating points, in respect to the GPA approach.

Calculations of the *PEUI* were performed, using our model for the particular engine under consideration, assuming that all measured values of the variables (N_1, N_2, *WF, EGT*) have been obtained with an accuracy characterized by a standard deviation equal to 0.2%, 0.2%, 0.5%, 0.5%, respectively, if not otherwise stated. These calculations correspond to different *EPR* values.

Table 2 Values of *PEUI* for various combinations of operating points and number of unknown parameters.[a]

EPR	*PEUI* value for $m = 6$	$m = 5$	$m = 4$
	2 operating points		
(1.4, 1.8)	19.1	4.6	2.7
(1.4, 1.9)	10.2	4.5	2.6
(1.4, 2.0)	18.3	4.1	2.9
(1.8, 1.9)	15.6	8.7	4.3
(1.8, 2.0)	39.6	8.5	2.7
(1.9, 2.0)	15.5	9.7	2.9
	3 operating points		
(1.4, 1.8, 2)	14.4	3.4	2.1
(1.4, 1.9, 2)	7.9	3.2	2.0
(1.4, 1.8, 1.9)	8.8	3.9	2.2
(1.3, 1.9, 2)	11.1	6.2	2.3
	4 operating points		
(1.4, 1.8, 1.9, 2)	7.7	3.1	1.8

[a]Engine operation, sea level, static.
[b]m = number of estimated unknown component parameter deviations.

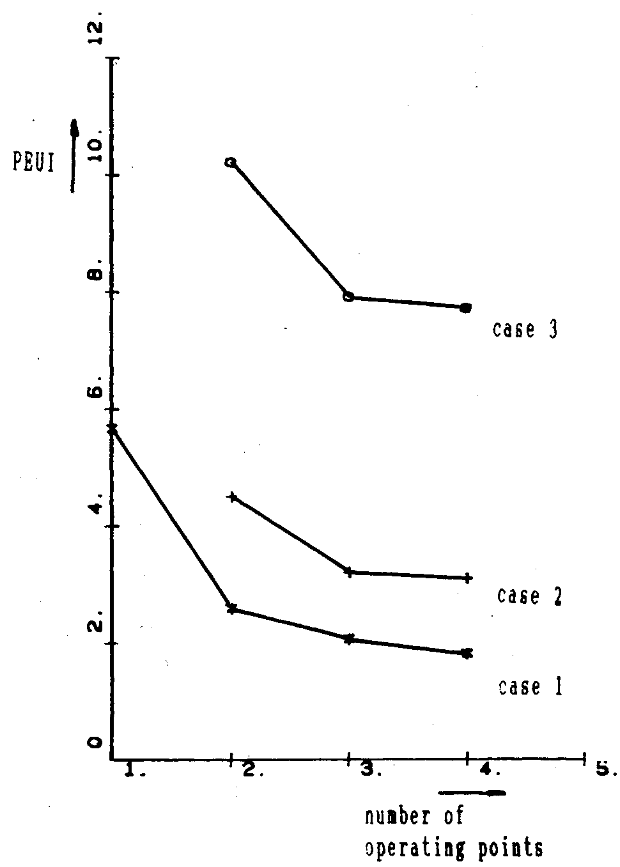


Fig. 5 *PEUI* vs number of operating points.

Table 2 presents the calculated values of the performance estimation uncertainty index, when we examine various combinations of *EPR* values, each time for the same number of operating points. For each combination, the number m of the estimated unknown component parameter deviations is varied, as well.

It can be seen from Table 2 that, for the same number of operating points considered, different *EPR* combinations give different *PEUI* values. We can also note that, in general, but with an amount of scatter that can be considerable, the best *PEUI* values are obtained when the chosen operating points are away from one another. The existing scatter becomes smaller, when the demanded additional information decreases (smaller values of m).

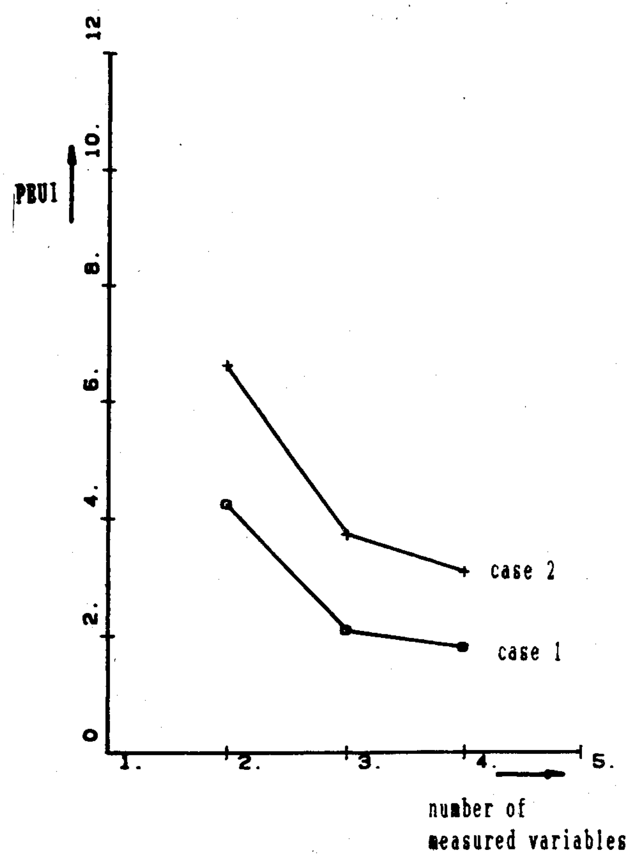


Fig. 6 *PEUI* vs number of measured variables.

The minimum values of *PEUI* for each case considered are presented in Fig. 5. We have named case 1, as corresponding to the estimation of four unknown parameters deviations. For this case, we have considered information coming out from one to four operating points. Case 2 has been formed as Case 1. Now five unknown parameters deviations are considered. The corresponding number of operating points varies this time from two to four. Finally, case 3 considers six unknown parameters deviations, while the number of operating points considered is again two to four.

It can be seen from Fig. 5 that both the overall accuracy and reliability are improved, when the number of operating points taken into account increases for a given estimated subset of the unknown parameter deviation vector. In the same figure, the capability of estimating more parameters than measured variables, as the number of different operating points increases, is demonstrated.

It must be pointed out here that values of *PEUI* were calculated on the basis of the assumed accuracy of the measurements. The answer to the question of what ranges of values of *PEUI* would be acceptable, would have to be related to the severity of the faults under investigation, namely, to the magnitude of the deviations they cause. *PEUI* should have a value smaller than the magnitude of the deviations caused by the faults we expect to identify, in order to have a reliable identification.

As a byproduct of the previous results, we can remark that disregarding the values measured by one or even two sensors (including the corresponding parameters among the ones to be determined), it is still possible to deduce them using the available information coming out of the rest of the sensors. Fig. 6 presents results for such a situation. It is possible, thus, to perform a check on the measured quantities disregarded during the calculation. Of course, such procedures are characterized by a loss of accuracy, but are useful for cross-checking suspicious measured values.

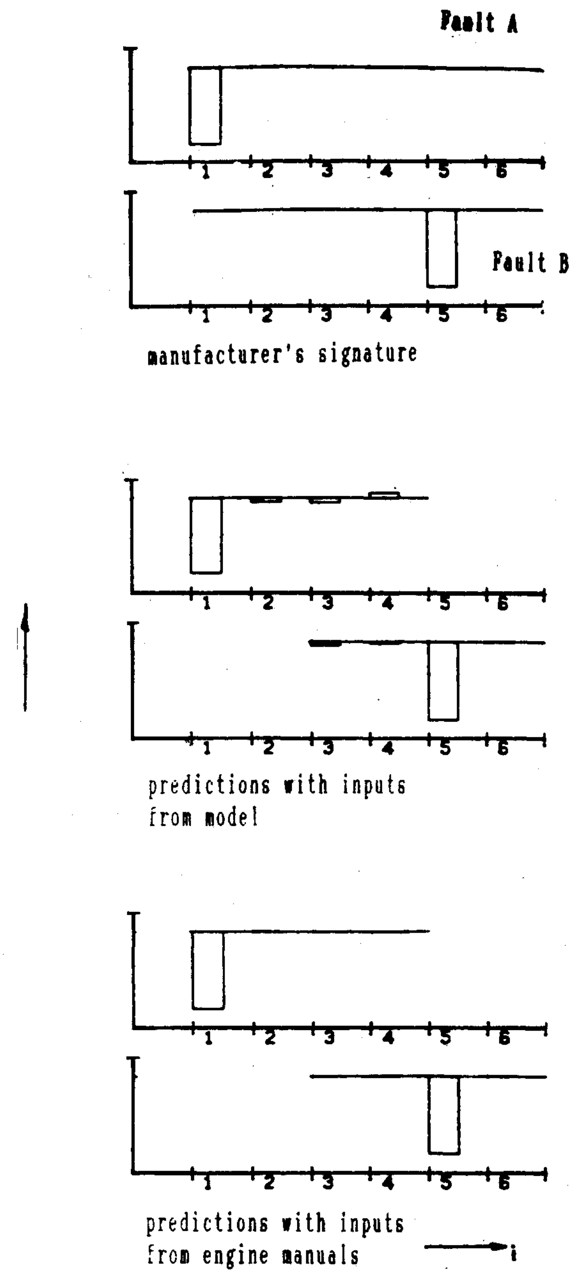


Fig. 7 Comparison of manufacturer's fault signatures and predictions of the present method for four measurements and four estimated deviations.

Finally, in order to directly demonstrate the capabilities of the method, the comparison of fault signatures provided by the manufacturer to the ones predicted are shown in Figs. 7 and 8 for two fault cases. In Fig. 7 a case is presented for which the number of measurements and parameter deviations is four. The agreement is very good. We note, however, that in practice the number of the component parameters is much larger than four. Consequently, when a particular fault must be detected, one has to know a priori the four variables, which have to be predicted. In addition, as one has to select and solve only four of the available equations, zeroing the additional unknowns that exist in them, errors may be introduced in the estimation if the correct set of four variables is not selected. Alternatively, using information provided by measurements at other operating points, one may have the possibility to calculate all the values of the dependent variables. Figure 8 shows results issued by the Discrete Operating Condition Gas Path Analysis, using measurements at three operating points, for this case.

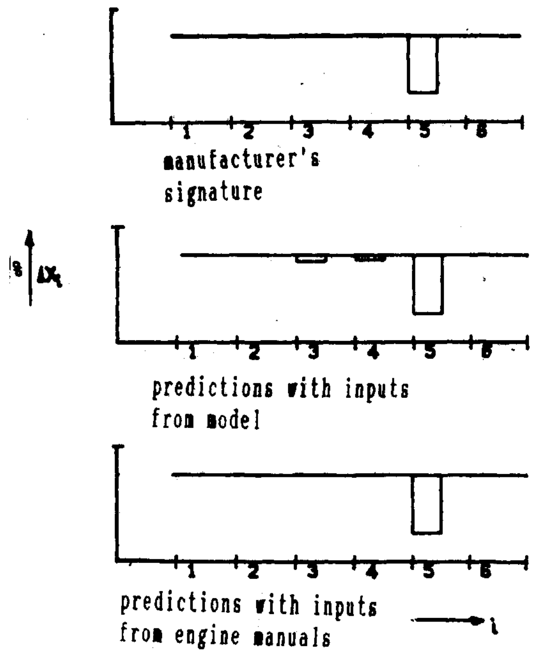


Fig. 8 Comparison of manufacturer's fault signatures and predictions of the present method. Four measurements at three operating points and six estimated deviations.

Conclusions

The present work demonstrates the advantages of using a Gas Path Analysis Technique at Discrete Operating Points together with engine performance models, for fault detection. Already, the proposed GPA method gives the advantage of extracting more information from existing sensors, which may be used for the following:

1) Decreasing the uncertainty of the estimation of parameters, which are used for diagnostic purposes.

2) Performing a diagnosis, when the number of measured quantities is smaller than the number of parameters used for diagnostic purposes.

3) Performing a check on the values of the measured values.

While the GPA method presents the above mentioned advantages, the technique employed along with the customized engine modeling, makes it possible to estimate correctly the values of the ICM elements for the desired operating points, thus avoiding their direct experimental determination.

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