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HEALTH MONITORING OF TURBINE ENGINE GAS PATH COMPONENTS AND MEASUREMENT INSTRUMENTS

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ABSTRACT

A performance simulation program has been used to simulate deteriorated performance of a new augmented turbofan engine developed for fighter aircraft and generate a fault pattern library.

This fault pattern library forms a basis for both understanding degradation trends of engine usage and in developing an engine health monitoring system. An efficient health monitoring method is proposed to identify the engine faults along with measurement uncertainties and faulty instruments, and to reduce false alarms. A pattern matching method is used to discriminate the engine faults by matching the measurement patterns throughout the fault pattern library.

The comparison of this approach to conventional gas path analysis has demonstrated that this approach has comparable ability to monitor engine gas path performance degradation, and provides some capability to handle measurement uncertainties and faults. It also provides a good base for future capability in conjunction with other engine inspection and/or monitoring methods.

INTRODUCTION

The modern gas turbine engine design has benefitted substantially from advances in computer science. This is particularly true for the engine electronic control unit. The versatile engine control unit provides not only the full authority control features but also some of engine health monitoring functions. It may also include build-in health monitoring functions including life management, performance trending data acquisition and electrical control unit fault codes. Within the control unit a build-in test (BIT) capability is also implemented to detect faulty signals and some control component failures. The considerable improvements in computer systems in terms of storage and processor capability allow engine control systems to incorporate fault diagnostic system. By taking the advantage of this technology improvement, it possible to develop a sophisticated engine fault diagnostic system that can tolerate instrumentation error and enhance the accuracy of fault detection.

A fault pattern matching method is introduced in this study. A newly developed module type two-spool turbofan engine is illustrated as a simulation engine for taking advantages of early stage implementation and follows on system verification and maturization. A well-validated computer model is utilised for deteriorated engine performance simulation and fault library generation; a fault diagnostic computer program had been written to include pattern matching, faulty instrumentation screening features.

The success of this system can also be utilised to improve the engine operability and readiness, by setting up a new control mode with the function of directing the control system to accommodate minor faults within the engine condition without losing engine operability and hence improve engine availability.

ENGINE MONITORING SYSTEM

An engine monitoring system(EMS) proposed for this engine is illustrated in fig. 1; it includes data acquisition unit, on-line data reduction & analysis computer (Engine Diagnostic System), data storage & management system(Engine Maintenance Management System) and engine maintenance shops. The EMS data is recorded by engine control computer, then transferred and stored in aircraft data recording & transferring unit (a portable data transferring cartridge), and the ground support computer is used to down-load all data from cartridge. EMS data down-loaded includes three major categories, dictated as:

(1) Performance Trending Data
(2) Life Management Data (life cycle counts)
(3) engine control unit (ECU) Fault Codes

The engine control related faults are detected by ECU built-in test(BIT) circuit and laid down in pre-defined ECU fault codes, which include faulty signals; signal out of limit; engine event flags and some engine component faults. Life Management Data records contain all cycle counting, that is including low cycle fatigue(LCF) counts, HPT Thermal cycle counts and other specified engine operating cycle counts. Performance trending data contains, (1)

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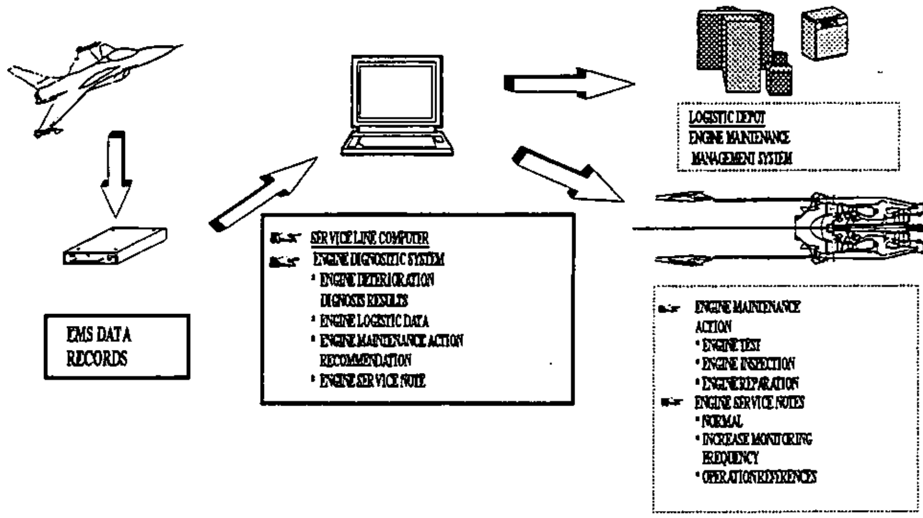

Figure 1 Engine Monitoring System Lay-Out

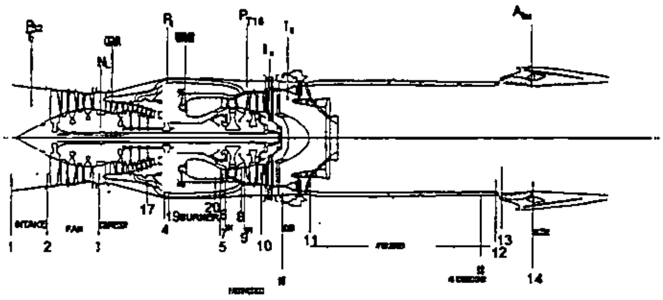

Figure 2 Health Monitoring Instrumentation

Routing data recording, such as take-off recording and steady cruise point recording; (2) Special events recording, that is engine surge, flame out, re-light failure, and others; (3) Engine usage recording, which includes engine running hours, flight hours; (4) Event transient recording.

These data sets are particularly useful for engine diagnostic analysis and play a major role in engine diagnostic system development.

The amount of instrumentation installed on an engine will generally be determined by data acquisition channels available on the aircraft, management cost effectiveness (customer demand), and the engineering requirements. However, the instrumentation is often under-quantity for conventional engine performance diagnostic analysis, such as Gas Path Analysis (Vivian and Singh, 1995). A typical engine performance health monitoring instrumentation is illustrated in Fig. 2. An engine diagnostic system, before it is considered satisfactory from an application viewpoint, need to be able to cope with the limitations of its sensors and manage all available information from the engine monitoring system & ground service check for diagnosing the engine condition. This concept led to the direction of this development.

Engine Diagnostic System

A successful engine diagnostic system should at least possess the following characteristics; effective, reliable, efficient, economical and user friendly. In order to construct an effective engine monitoring system to perform engine trouble shooting and indicate possible maintenance action; all typical engine diagnosis/inspection information should be processed within the engine diagnostic system. The information comes from different health monitoring techniques such as: performance diagnosis, ECU BIT, vibration monitoring, spectrographic oil analysis process (SOAP) and non destructive inspection(NDI). These techniques involve individual specialities but perform interrelated in engine diagnostic system. Performance diagnosis plays the major role for gas path component health monitoring, and ECU BIT is devoted to control & accessory component conditioning; vibration monitoring is used for checking rotating component integrity, bearing support problems, and SOAP for oil lubricated parts and NDI for structure components. For the system to be judged as reliable, it should be able to accurately predict engine faults with minimum of false alarms. This involves minimising the analysis errors and measurement inaccuracies. For efficiency, it should only need minimum effort and time to perform the task, such as automatic data recording, transferring and analysis. An economical system should use standard equipment with minimum set-up and running costs. A user friendly system should provide a non-expert interactive environment and translate engine degradation analysis results to engine maintenance and trouble shooting language.

This paper presents the development of a performance diagnostic method for engine gas path component performance degradation in the presents of measurement uncertainty, including issue of faulty and degraded instrumentation. The objective is to develop a general logic and methodology to perform engine performance diagnosis, which can accommodate any existing engine monitoring instrumentation arrangement, and reduce analysis errors, increase reliability, have multiple faults' delectability, and provide compatible diagnostic information for integration with other engine diagnostic methods.

ENGINE PERFORMANCE DIAGNOSTIC

When an engine consumes its life in service, engine components tend to deteriorate with time because of fouling, erosion, corrosion, etc. This component deterioration can be described by changes of component efficiency and flow capacity or flow area, defined as unmeasurable independent parameters or engine faults. Every individual components degradation will induce overall engine performance deterioration and reveal changes in measurable engine performance parameters, such as fuel flow rate, engine temperature, pressure, rotor speeds and power/thrust output, defined as dependent parameters (Urban, 1972).

In order to identify the engine deterioration, simulation algorithms were used to reproduce the engine deterioration in terms of engine faults respectively, which included performance modelling (Lakshminarasimha and et al, 1994), Implanted Faults Study (Macleod et al, 1992) Transient Fault Diagnosis (Merrington,1989) and Electrostatic Method (Couch, 1978). There were also valuable studies on the development of gas turbine engine performance health monitoring system via processing the inter-relationship of engine independent and dependent parameters, such as compressor fouling study(Aker and Saravanamuttoo, 1989); linear gas path analysis (Urban, 1972); non-linear gas path analysis (Escher and Singh, 1995).

The above mentioned studies had formed a good foundation for engine performance diagnostic system development; where linear gas path analysis drew a base line of quantitative engine performance diagnostic development, and non-linear gas path analysis improved mathematical modeling. They are different from traditional qualitative fault trees and fault matrix method.

Linear Gas Path Analysis

The Urban method of linear gas path analysis is to solve engine component degradation via processing aero-thermodynamic relationship between independent and dependent parameters as described earlier. In order to solve these equations numerically, Urban assumed the engine faults are small such that higher order terms in Taylor series expansion could be ignored. The Taylor series thus linearized allowed the solution of the equations. The mathematical relationship of independent parameters (X) and dependent parameters (Z) can be expressed as:

$$Z = f(X) \qquad (1)$$

Taylor series expansion of this equation yield,

$$Z = Z_0 + \frac{\partial f(X)}{\partial X} \times \Delta X + HOT \qquad (2)$$

by neglecting the higher order terms (HOT), the equation set is linearized,

$$\Delta Z = \frac{\partial f(X)}{\partial X} \times \Delta X \qquad (3)$$

the sets of partial differential equations are known as influence coefficient matrix (as symbolised H). The engine performance diagnostic analysis can now be accomplished by inverting the influence coefficient matrix to solve the independent parameters in terms of dependent matrix,

$$\Delta X = H^{-1} \times \Delta Z \qquad (4)$$

The linear gas path analysis is able to diagnosis small magnitude (less than 1%) multiple faults, but has limited ability in handling more significant faults due to inherent mathematical modeling limitation (the basic assumption). This may be suitable for moderate gas turbine user with daily basis monitoring, such as some airlines. When applying linear gas path analysis for engine performance diagnostics, a compatible number of measurement parameters and monitoring independent parameters are essential (Urban, 1975). This requirement leads to difficulties for many applications, when instrument errors (instrumentation tolerance and usage deterioration) are present.

However this drawback has been well treated and had high degree of success by coupling sensor fault coefficient matrix and incorporating large error recovery logic (Urban and Volponi, 1992). This approach is most comparable to those algorithms with Kalman filter (Luppold and Gallops, 1989) or other statistic estimation algorithm.

Non-Linear Gas Path Analysis

Non-linear gas path analysis introduced Newton-Raphson method to overcome linear gas path analysis technical draw back (Escher and Singh, 1995), and successfully promote the capability in handling more significant faults. However, the instrumentation errors and relative quantity requirement remain a concern.

Some attempts for solving this issue were addressed, such as expert system (Vivian and Singh, 1995) with limitation in solving multiple faults, and Neural Networks (Torella and Lombardo, 1995) for simplified engine faults isolation process. These left a technology gap to be filled in, and the authors present here an alternative method in solving this problem. The pattern matching method is the first attempt in this research task, and the initial results, as discussed in the following sections, are promising.

PERFORMANCE DIAGNOSIS BY PATTERN MATCHING

There are three major tasks for constructing this system: (1) build up engine deterioration fault library, (2) develop pattern matching logic, (3) computerise.

Engine Deterioration Patterns

Steady state pattern was generated by deteriorated performance simulation model, and engine component deterioration is simulated by scaling component maps. Each engine fault signature is denoted by a fault code representing a series of degraded values (∇: Delta) of independent component parameters such as flow & efficiency of fan, compressor and turbines. All the defined fault signatures form the input data bank and are used for deterioration calculation in this study. In this study eight parameters is used for simulating

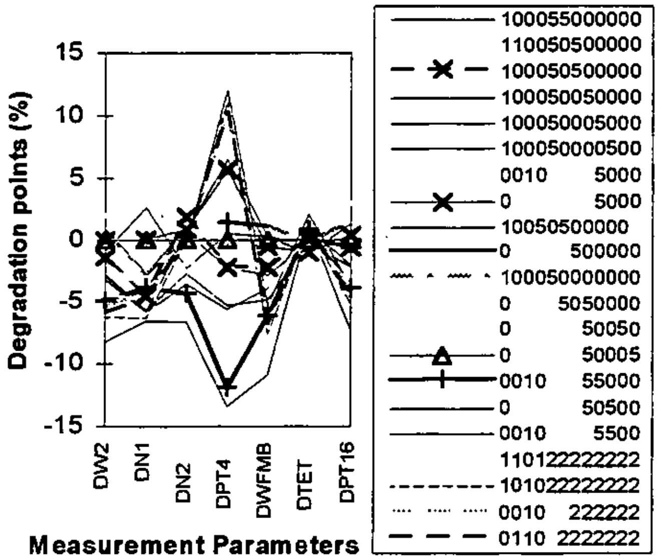

Figure 3 Illustrated Fault Patterns

component fouling, erosion, corrosion, air leaks, contamination, IOD and FOD:

1) Fan air flow (∇W_{FAN}
2) Fan efficiency ($\nabla \eta_{FAN}$)
3) Compressor flow (∇W_{COMP})
4) Compressor efficiency ($\nabla \eta_{COMP}$)
5) HPT nozzle area (∇A_{HPT})
6) HPT efficiency ($\nabla \eta_{HPT}$)
7) LPT nozzle area (∇A_{LPT})
8) LPT efficiency ($\nabla \eta_{LPT}$)

Each fault signature 'Fn' consists of eight delta values of above parameters:

$$Fn = (\nabla W_{FAN} , \nabla \eta_{FAN} , \nabla W_{COMP} , \nabla \eta_{COMP} , \nabla A_{HPT} , \nabla \eta_{HPT} , \nabla A_{LPT} , \nabla \eta_{LPT}) \quad (5)$$

$$\nabla X = \frac{X - X_0}{X_0} \times 100\% \quad (6)$$

where X: deteriorated values
X_0 : base line values
∇X: delta values

Fault signatures are denoted by a set of fault codes consist of twelve digit numbers. The first four digits of fault signature represent sign of mass flow faults ('1' for negative degradation and '0' for positive degradation), and the following eight digits representing the magnitude of faults, as illustrated in the legend box of Fig. 3. All fault signatures have a respective simulation output in terms of measurement parameters called fault patterns, as illustrated in Fig. 3, the parameters in abscissa are:

1) $\nabla W2$: engine inlet air flow
2) ∇N_1 : low spool speed
3) ∇N_2 : high spool speed

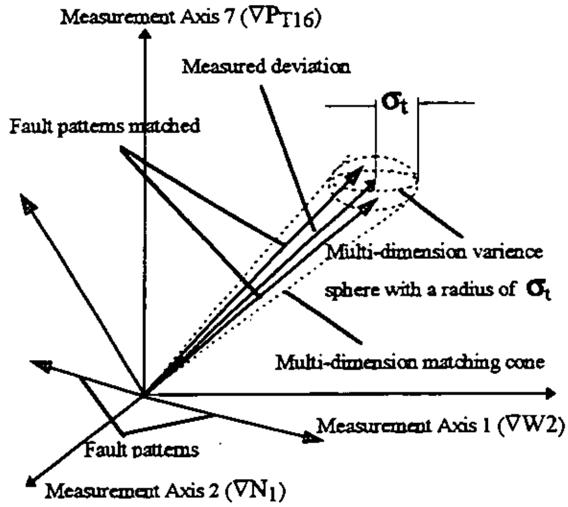

Figure 4 Three Dimensional Measurement Space

4) ∇P_{T4} : compressor outlet total pressure
5) $\nabla WFMB$: main burner fuel flow
6) ∇T_{T8} : turbine outlet temperature
7) ∇P_{T16} : fan bypass duct total pressure

These fault signatures in fault library could be easily transformed into 'measurement space' vectors (Provost and Singh, 1995), and each vector in the multi-dimensional measurement space (in this application it is seven dimensions) representing a fault pattern. The seven deviation values in each fault signature form the components of the corresponding vector, and figure 4 depicts this concept with simplified three dimensions coordinates. Since all fault patterns are related to same baseline condition, all pattern vectors are originated from zero-point of axes.

In practical application the engine simulation program can often be obtained from engine manufacturer (customer deck) to reduce the simulation error by using representing performance maps.

Once the engine configuration confined, the engine pattern library can be generated with the representative performance simulation program, and can be updated in accordance with the engine configuration revisions. The pattern libraries should be coded to respective engine configurations and incorporated into the engine configuration control system. All versions of pattern libraries need to be stored in the engine maintenance management computer of the appropriate logistics system on an accessible level.

Fault Library

The fault library is created by running the performance deterioration simulation program through pre-defined fault range. A general fault library structure is proposed to include sufficient number of faults, for executing a reasonable pattern matching process. The proposed fault library includes two major categories of faults, one for dual faults (for simulating special event faults) and the other for combination faults(for simulating general deterioration faults). The dual faults library includes one or two independent parameters with at least one absolute implanted degradation larger than the upper limit of combination fault library, and less than

Table 1 Patterns Matched Within 1% WFMB Degradation

100040000000	110120102121	110110210020	101 101022
110 303000	110120102110	110110101012	101 101011
101050001000	101120001020	110010101000	101 102022
100040001000	100120000020	110110101120	101 102011
100040002000	100120001020	110110102012	101 102120
11 5040	100120001010	110010102001	111 1201021
11 4040	100120002020	101110002020	101 1201010
1 3040	100120002021	111111202021	101 1202011
100 300002	111121202022	110111200022	11110201010
111020202000	111121201010	110111201022	10110200012
110020200002	110121200011	110111201011	10010202000
110020202011	110121201012	110011202000	11110101021
111120212020	110121202120	111 202011	10110100021
111120211020	110121100020	111 201012	10110102020
110120211022	110121101020	100 201000	10111200020
111120102011	110121102020	101 201122	11120202022
111120101012	111110202012	100 202002	11120201022
110020100000	111110202120	101 211020	10120201010
110020101001	110010200001	111 101022	10120202011
110120101121	110010201002	101 100011	

defined overall maximum degradation value. The combination faults library includes any combination of independent parameters with absolute implanted degradation no more than defined value. The independent parameters used for implanted fault calculation include component air/gas mass flow, pressure and efficiency. In order to simulate compressor/turbine fouling and erosion/corrosion, mass flow degradation involved positive and negative values where efficiency degradation only involved positive values (degraded).

A complete library is generated to reduce the chance of miss-matching in pattern matching process. It is important to check the total number of cases in fault library. The total number of dual fault category can be calculated by using the following parameters and equation:

N_{lib1} : total number of dual fault library
D_h : maximum degradation percentage of dual faults library
D_l : maximum degradation percentage of combination faults library
mp : number of air/gas mass flow parameters
tp : total number of independent parameters for implant faults calculation

$$
\begin{aligned}
N_{lib1} = \; & P_2^{mp} \times 2 \times (D_h - D_l) \times (2 \times D_h) - \\
& C_2^{mp} \times 2 \times (D_h - D_l) \times 2 \times (D_h - D_l) + \\
& P_2^{(tp-mp)} \times (D_h - D_l) \times D_h - \\
& C_2^{(tp-mp)} \times (D_h - D_l) \times (D_h - D_l) + \\
& C_1^{mp} \times C_1^{(tp-mp)} \times 2 \times (D_h - D_l) \times D_h - \\
& C_1^{mp} \times C_1^{(tp-mp)} \times 2 \times (D_h - D_l) \times (D_h - D_l) + \\
& C_1^{mp} \times C_1^{(tp-mp)} \times (2 \times D_h) \times (D_h - D_l) + \\
& C_1^{mp} \times 2 \times (D_h - D_l) + C_1^{(tp-mp)} \times (D_h - D_l) \quad (7)
\end{aligned}
$$

and the total number of combination faults library is:

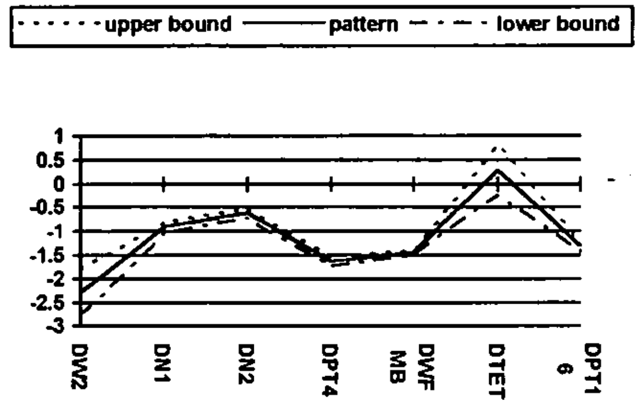

Figure 5 Illustrated Bound Matching

$$N_{lib2} = (2 \times D_l + 1)^{mp} \times (D_l + 1)^{(tp-mp)} \quad (8)$$

where N_{lib2} is total number of combination library, hence total number of fault library N_t is :

$$N_t = N_{lib1} + N_{lib2} \quad (9)$$

In this study we have chosen D_h=5%, D_l=2%, tp=8, mp=4, which give N_{lib1}=1338, N_{lib2}=50625 and N_t=51963. This fault library already includes a fuel burn increase up to 13 % at 30000 ft/.8 mach no. cruise condition. This is much larger than, for example, a commercial GE CF6-50 turbo-fan engine's limit of 2.7% increase in specific fuel consumption during 4000 hours of revenue service (Wulf,1980). In Wulf's report, one percent of fuel consumption means $5.1/flight hours cost saving base on fuel price of $0.60/gallon, for a fleet of ten B747 with average 4000 flight hours a year, the total saving is 0.8 million USD annually, and this could mean a cost effective maintenance issue. But if we monitor only the fuel consumption of the engine in this study, one percent deterioration of fuel consumption can involve 79 fault patterns within general tolerance bound according to our pattern matching analysis. As shown in Table 1, this includes up to 5% of HPT fouling or 3% of CGV fouling and other combination faults. This means without a good engine diagnostics system a proper maintenance planning is often impossible.

Pattern Matching

In the service line (organisational level maintenance), each engine baseline EMS data needs to be recorded when the engine was first installed in the aircraft after new delivery or maintenance turn around, and stored in ground support computer with relative engine label. When the EMS data is down-loaded to ground support computer after each flight, deviation curves will be calculated immediately and automatically, as illustrated in Figure 5. Deviation curves will then be transformed into bounded patterns according to measurement tolerance with respect to individual parameters for first

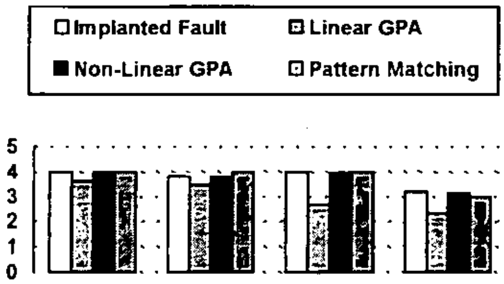

Figure 7 Compressor Mass Flow

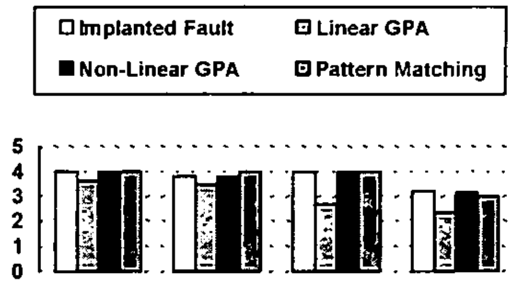

Figure 8 Turbine Mass Flow

step bound matching. These measured deviation values will be used to construct a matching pattern vector in measurement space. Pattern matching will then be performed through minimum displacement matching and maximum similarity factor matching within pattern libraries. When the above pattern matching process completed, it will display at least one of the following messages:

1) Bound matched patterns list;
2) Pattern list within the tolerance RMS bound;
3) Pattern list with minimum matching displacement;
4) Pattern list with maximum similarity factor;
5) Out of limit measurement parameters (faulty instruments);
6) Possible deteriorated instrumentation.

This information can be directed to fault interpretation module and maintenance advice module for displaying the result, which will be included in later tasks. However if there are more than one fault pattern identified from displayed information 1 & 2 given above, then other monitoring/inspection method should be introduced into this system for further screening and/or cross checking. Pattern matching procedure is illustrated in <u>Pattern Matching Flow Chart</u> (Fig. 6 at the end of this paper); two matching function will be used for pattern matching as depicted in chart:

(1) <u>Matching Displacement Factor Calculation</u>: The following equations describe how to perform calculation of matching displacement factor (σ_p) between measurement pattern vector end and fault patterns vector end for 'm' measurement parameters.

$$VM = \sum_{i=1}^{m} (e_i) \nabla XM_i \tag{10}$$

$$VL = \sum_{i=1}^{m} (e_i) \nabla XL_i \tag{11}$$

$$V_p = \sum_{i=1}^{m} (\nabla XM_i - \nabla XL_i)^2 \tag{12}$$

$$\sigma_p = \sqrt{V_p} \tag{13}$$

where ∇XM_i is components of measurement deviation vector, and

∇XL_i is components of fault pattern vector

e_i is unit vector of i-th measurement axis

(2) <u>Similarity Factor Function</u>: Base on Provost's similarity factor calculation, the similarity factor (SF) is equal to dot product of normalised measurement vector (VM) and fault vector (VF), such that

$$SF = \frac{VM}{|VM|} \bullet \frac{VL}{|VL|} \tag{14}$$

The radius of variance sphere (σ_t) is used to take the measurement tolerance (τ_i) into account in pattern matching procedure before minimum displacement matching, in order to accommodate instrumentation tolerance induced error in diagnostic result. Every pattern matched inside the sphere is deemed possible fault patterns and should have equal importance in engine faults. These matched patterns represent a confined engine faults range with known measurement uncertainty bound.

$$V_t = \sum_{i=1}^{m} (\tau_i)^2 \tag{16}$$

$$\sigma_t = \sqrt{V_t} \tag{17}$$

<u>Measurement Parameter Screening</u>

Out-of-limit and degraded instrumentation are screened through fault library absolute bound checking and parameter reduction method. Absolute maximum and minimum deviation value within the fault library are identified and added to a manual input scaling factor to expand the margin in order to include ultimate faults not included in the library. This scaling factor can be adjusted through learning experience for better fault identification. When any measurement deviation value is found to be out of absolute bound the relative instrumentation is identified as inadequate or degraded. The identified parameter is excluded and the system performs the same matching process excluding it and identifies the most possible fault.

Degraded instrumentation is discriminated by parameter reduction method; this process is triggered if none of the fault patterns are matched. The system performs the same pattern matching process but excluding one measurement parameter at a time. For example, if nth parameter being excluded, the vector VM and VL will change to,

$$VM = \sum_{i=1, i \neq n}^{m} (e_i) \nabla XM_i \tag{10}$$

Table 2 Measurement Screening Results

Case	Para.	Degraded point(%)	Screening results
1	PT4	2.0	success
2	PT4	1.5	success
3	PT4	1.0	fail
4	PT4	0.5	fail
5	PT4	20.	Identified bad
6	W2	1.5	success
6	W2	1.0	fail
8	N1	1.5	success
9	N1	1.0	fail
10	N2	1.5	success
11	N2	1.0	fail
12	WFMB	1.5	success
13	WFMB	1.0	fail
14	TT8	1.5	success
15	TT8	1.0	fail
16	PT18	1.5	success

$$VL = \sum_{i=1, i \neq n}^{m} (e_i) \nabla XL_i \qquad (11)$$

and V_t will change to

$$V_t = \sum_{i=1, i \neq n}^{m} (\tau_i)^2 \qquad (16)$$

When the degraded parameter is excluded, the matching result of that vector will have relatively large group of faults than any others vectors including it. After a whole matching turns, the system will come to a conclusion as to which of the degraded readings are being sought. The system will then output the most probable fault with minimum displacement or maximum similarity factor.

RESULTS AND DISCUSSION

Figure 7 & 8 show implanted faults on compressor and turbine components. The chosen fault values of '4','-5', '-4.6', '-4.4',' 3.8', '3.2' simulate significant changes in engine components to demonstrate the system capability. Non-integer faults were used to compare analysis results between different methods. With a given set of monitored measurement readings, the pattern matching method is able to isolate potential component faults and give a quantitative result generally better than linear gas path analysis and comparable with non-linear gas path analysis. Beside the most probable matched patterns, the system also provides all possible fault patterns, whose RMS deltas are within RMS tolerance deviation. A study on instrumentation parameter arrangement with bound pattern matching procedure shows result's curves in Fig. 9. These curves indicate that when monitoring mass flow and efficiency of fan, compressor and both turbines of a two-spool turbo-fan engine, and use instrumentation with typical up to date accuracy level, the most economical instrumentation set contains only 5 monitoring parameters. It also reveals how the accuracy level will influence a diagnostic system performance significantly. For instance, if we choose a set of three monitoring parameters, improve 50% of instrumentation accuracy will improve diagnostic ability by 339% (the possible number of faults within the tolerance bound reduced

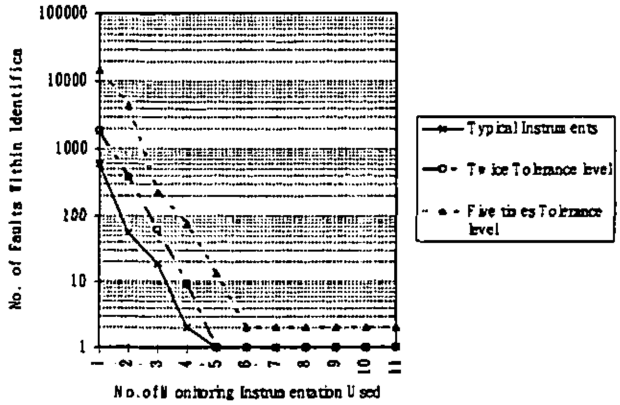

FIGURE 9 Instrument Management Study

from 61 to 18). From this analysis, it demonstrated the pattern matching method has good potential in identifying a suitable instrumentation set.

Table 2 shows some of the results from parameter screening, from the result it can be seen that the system is able to identify instrumentation degradation with minimum sensitivity of 1.5% for all parameters. This system can also identify poor instrumentation readily as depicted in case 5. With all the screening results, the system also identified the implanted fault after excluding degraded parameters.

SUMMARY

In this pattern matching diagnostic system, all the pattern libraries are generated for actual engine configurations and stored in the logistic maintenance management system. The fault libraries can be maintained and revised in a central maintenance management centre and provide the updated representative fault library to every service line (or engine shop), which will reduce on-line system management load.

Modern Engine Monitoring Systems are able to provide many types of data concerning the health of the engine and operating condition. An efficient diagnostic system needs to use all available information for recognising engine faults, providing explanation and maintenance action recommendations. This is the rational for introducing the pattern matching method to form the basis for developing this Integrated Engine Diagnostic System. The main function of this pattern matching algorithm is to provide secure information within confined bounds rather than unique but less certain result for engine health monitoring. From this information and from other monitoring or inspection techniques the result can be further analysed on a surely base and finally identify the cause of engine fault or faults with greater confidence.

This study shows that the pattern matching technique presented in this paper is able to provide reliable results concerning the state of the gas path components in the engine. Further it is able to identify instrument degradation. The technique has the advantage that it is easy to use in line maintenance as it requires no prior knowledge of the user.

Equally, this approach can be readily developed by combination with techniques such as knowledge based systems and Neural Networks.

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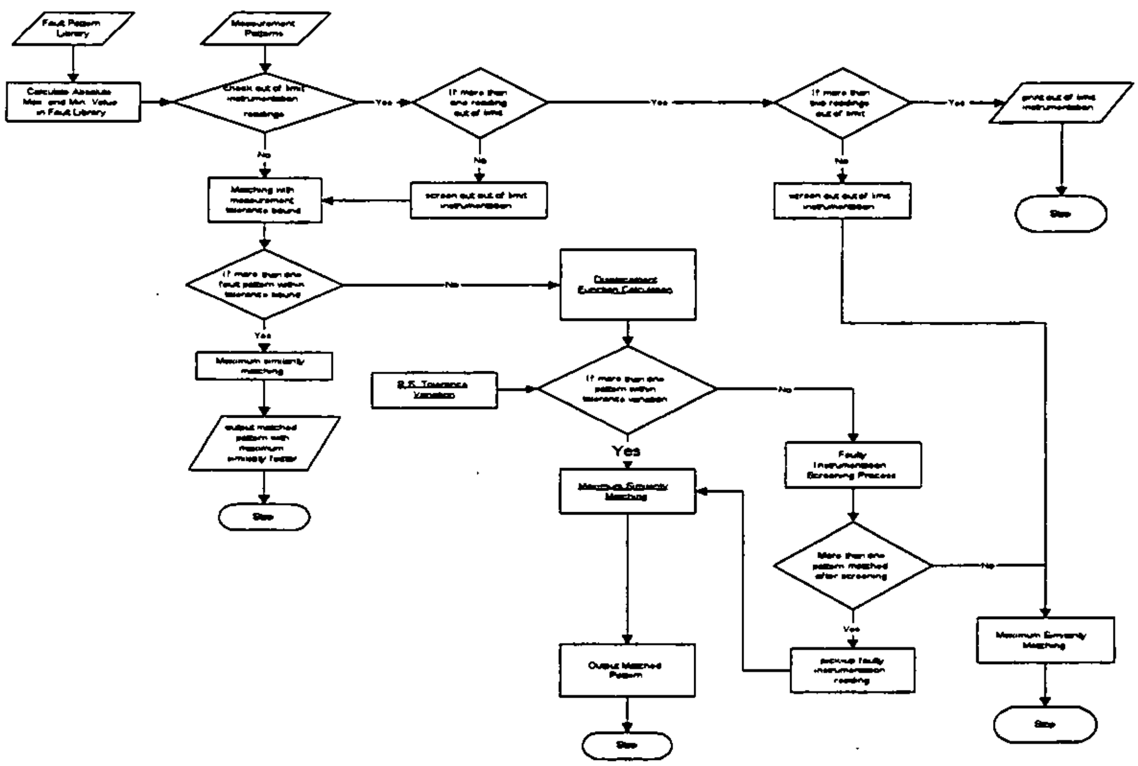

Figure 6 Engine DIagonosis Pattern Matching Flow Chart