Fault Diagnosis in Gas Turbine Engines using Fuzzy Logic*

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Abstract – *This paper describes a fuzzy logic-based method of fault detection and diagnosis in gas turbine engines. The fuzzy logic rule base is derived using heuristics based on designed experiments and flight data. The method is evaluated using model-based residuals and calculated values as inputs. The efficacy of the system is demonstrated using flight data.*

This paper describes how to augment a limited number of input parameters by combining them with the rates of change of the normal input parameters and other derived parameters. This augmented parameter set enables a better estimate of the prediction horizon for diagnosis.

The paper also presents a case study where high-pressure spool deterioration is detected about two months prior to engine failure. Although, the system is demonstrated using the example of high pressure spool deterioration it can be applied to engine failures with similar characteristics.

Keywords: fault detection, diagnosis, fuzzy logic, turbine engine deterioration.

1 Introduction

Accurate turbine engine fault detection and diagnosis (FDD) is vitally important to reducing airline operating costs and improving safety. Incipient fault detection in turbine engines can significantly reduce costs associated with unanticipated schedule changes and delays due to engine failures. Accurate incipient fault detection is necessary for cost-effective preventive maintenance programs.

Turbine engine FDD involves the early detection of both incipient and sudden faults. Detection is followed by diagnosis of a sensor, actuator, or system component fault. Many approaches to FDD are discussed in the literature. Broadly, the two main approaches to FDD are model-based and data-driven [7]. Model-based FDD methods use a physical or empirical model of the system to generate residuals (difference between the model outputs and actual system measurements) [3], [5]. These residuals are passed through a decision logic system to determine a diagnosis. Data-driven methods use historical data from the system to construct quantitative, (neural networks [1], statistical models), or qualitative (trend or rule based) FDD methods.

Many of the approaches discussed in the literature are developed and tested using data generated from models such as in [3] and [5]. These models generally produce data that is well behaved and sampled at regular intervals.

However, in many field applications the data available is neither well behaved nor measured at regular intervals; in fact, engine data is sometimes recorded manually by the pilot. This results in large parameter variations from flight to flight. Further, in many of the older data acquisition systems, a very limited amount of data is recorded per flight, often under a fixed set of operating conditions. The type of noise present in the data from field applications may difficult to accurately capture in a model because it comes from the interaction between many different aircraft systems as well as noise in the measurement systems and differences in climate that affect the engine's behavior.

Under this set of conditions, automated engine monitoring and diagnosis is challenging for several reasons. First, many engine problems are not distinguishable or even visible within the small set of recorded parameters. The standard deviation over the flight-to-flight data points for a normally operating engine may be larger than the distance between the mean of the data associated with the normal condition and the mean of the data associated with the faulty engine condition. Further, having data recorded only under a specific set of operating conditions may result in large data gaps.

* 0-7803-7952-7/03/$17.00 © 2003 IEEE

In this paper, an empirical model of the turbine engine is used to generate residuals of key engine parameters such as the engine speed, exhaust gas temperature, and fuel flow. These parameters are subjected to smoothing techniques and then used to calculate an augmented set of parameters that combines these residuals with the slopes of these residuals and the EGT Margin for the engine.

Automated performance trending and fault isolation is then accomplished by applying expert based fuzzy logic rules to the engine trends based on the residuals, their slopes, and the EGT Margin. Fuzzy logic was chosen because it is a good method to use when there are not clear boundaries between faulty and non-faulty engine behavior [2], [3]. Neural networks have also been applied in the context of turbine engine diagnostics [1]; however, neural networks have a disadvantage in that they are computationally intensive.

The next section of this paper presents some of the details and issues associated with the technical problem of interest. A detailed description of the fuzzy logic approach that is used to solve the problem is presented in Section 3. Section 4 describes a case study representing one of the major engine faults of interest. Included in this case study is the step-by-step development of the diagnostic approach from the input process to the development of the fuzzy logic system and the resulting system output for a faulty engine. Finally, Section 5 provides a summary and conclusions as well as some information about the applicability of the approach to other fault types. Directions for future development of the technique are also discussed.

2 Technical problem

Gas turbine engines are complicated pieces of machinery, so fault diagnosis of these machines is enhanced by a detailed understanding of the equipment. Honeywell as a gas turbine manufacturer has this understanding and is in a good position to lead the way in FDD for their products. A propulsion engine generally contains four modules: a fan module, a gas producing module, a combustor/turbine module, and the accessory gearbox and mechanical components module. The particular types of engine of interest to us in this paper are referred to as twin spool engines. This means that the engines have two shafts, one that operates at low pressure and lower speed (the LP Spool) and one that operates at high pressure and high speed (the HP Spool). The two shafts are generally referred to as the fan shaft and the core shaft respectively.

The primary function of a propulsion engine is to provide thrust to the aircraft, but it may also be required to provide air to airframe systems. This so-called bleed air is air that is taken from the engine core for use in the air conditioning system or for ice removal. The flow of air required for bleed driven systems varies depending on the outside conditions, the passenger load, and the aircraft configuration.

The specific engine of interest for the case study in this paper is a midsized jet engine. This particular series of engine presents unique problems in FDD due to the cost constraints placed on its design and operation.

One of the issues the technique presented in this paper addresses is the limited amount of data recorded over a flight cycle for these engines. Because they tend to operate on smaller planes with less expensive data acquisition systems, data is often recorded only during certain points of interest during the flight cycle. Further, only the parameters critical for studying the performance of the engine core are recorded; with this limited set of flight points and limited number of parameters, many incipient faults are not visible.

One of the major limitations of some FDD systems is that they are only good for engines that have detailed models available or modern data collection systems. With a large amount of available data and modern simulation tools and techniques the problem of detecting and isolation faults is made easier. However, the techniques that work on these engines do not necessarily carry over to older engines that were designed when computer generated models were not available and data acquisition systems had very limited memory.

Another constraint of older engines is that many of the models that exist are empirical in nature and combined with the limited data set available, the models may only be valid under certain operating conditions, such as when the engine is not required to provide bleed air service to other airframe systems. This constraint requires that any FDD system be robust to data gaps.

Finally the lack of automation and computing power associated with older engines led to applications with manual data recording systems or where data storage is limited. This led to manual FDD systems [5] - that is, having trained system experts look at the overall trends of the data. These 'manual' systems are largely based on a single expert with a good intuitive understanding of engine performance. Many of the heuristics developed by these experts are not systematic in nature, (i.e. no numerical bounds are specified) and decisions are made based on general patterns observed over several parameters. Expert systems also tend to be augmented with regular service inspections aimed at prevented any safety critical problems that the experts trending the engine performance may have missed. These methods are costly in terms of both expert training time and the down time associated with scheduled inspections of functioning engines.

Using the residuals of the parameters generated by the model alone is generally sufficient for most FDD applications as is demonstrated in [3], [4] and [5], but this method does not always fully capture faults that develop over time with a reliable prediction horizon. As the experts tend to use the levels of deterioration along with the pattern of the parameters as the engine has deteriorated, using additional parameters that describe the pattern of the data (such as the rate of change of the parameter) more closely mimics the expert system.

3 Fuzzy logic approach

The approach presented in this paper attempts to deal with many of the data-related problems described above, and provides a way to automate the expert heuristics. The approach consists of five steps: 1) using an empirical model of the engine to create residuals of the performance parameters, 2) filtering these residuals to eliminate noise and outliers, 3) computing an augmented parameter set, 4) applying the augmented parameter set to the fuzzy logic system to generate a probability that there is a problem, and 5) interpreting the output. The next section of the paper outlines some of the fundamentals of fuzzy logic.

3.1 Brief description of fuzzy logic

A fuzzy logic system is a nonlinear input-output mapping of a vector of features into a scalar result [3]. These systems are generally regarded as proficient at translating expert system insight into a mathematical formulation. This ability to handle imprecision of input and output variables directly by defining them as fuzzy sets, which can be described using linguistic variables [8], makes fuzzy logic a good method for handling system uncertainty. It is also well suited for use with systems where the inputs are comprised of sets lacking clear crisp boundaries.

A typical Fuzzy logic system consists of a multidimensional input space $V \in R^n$ mapped to a single dimensional output space $W \in R$ using four basic steps: fuzzification of the inputs (creation of membership functions), application of the rules (applying the operator AND or OR and implication from the antecedent to the consequence), an inference engine that aggregates the consequents across the rules, and a defuzzifier.

The basis of fuzzy logic is the concept of a fuzzy set [9], which, in contrast to a traditional set, allows many degrees of membership. The degree of membership to a set is indicated as a number between 0 and 1. This membership function $\mu_A(x)$ includes every number between 0 and 1 and we say that this function maps every element in the universe of discourse X to the interval [0,1] i.e: $\mu_A(x): X \to [0,1]$ [8]. These membership functions can be formed based on intuitive groupings or mathematical methods. Fuzzy sets have similar rules of mathematical operations as traditional sets. For a full description of the mathematics of fuzzy sets see [1], [2], [3] and [9].

Fuzzy rules are used to combine the information in the membership functions and the inference engine then determines how the rules are aggregated. The rules in a fuzzy system are generally relational rules between variables that imply certain outputs. For example, if engine speed is low and fuel consumption is high, then engine performance is poor. The rules can be applied with or without weighting factors.

Defuzzification implies taking the results and resolving the output into a single number. This can be accomplished in a number of ways such as a centroid calculation, bisection, or maximum matching. For a description of these methods see [3].

3.2 Generating residuals

The residuals used in the results presented in this paper were generating using an empirical engine model. This model is valid only at standard temperature and pressure conditions; therefore, all the data had to be normalized before it was applied. The model was developed for two specific flight conditions under specific operating regimes so any data that did not meet the designated criteria was removed.

The model consists of a polynomial in terms of the engine fan speed (N1). It is used to compute the expected values of the core speed (N2), the exhaust gas temperature (EGT), and the fuel flow (WF) given current flight conditions such as the Mach number, outside temperature, and pressure. The expected values are compared to the measured values and the results of this comparison (the residuals) are called ΔN2, ΔEGT and ΔWF respectively. Since these residuals correspond to standard flight speed, temperature and pressure conditions they can be used to compare engine performance on a flight to flight basis.

3.3 Augmenting the parameter set

In order to closely approximate the patterns that experts look for in the residuals the input set was increased by using four calculated values: the slopes of the three residuals and the EGT margin. The slopes of the three residuals (ΔN2, ΔEGT, and ΔWF) are referred to as ΔN2dot, ΔEGTdot, and ΔWFdot respectively. The slopes of the residuals were primarily used to indicate the cases where the increase (or decrease) in the parameter of interest happened at a faster rate. In many of the engine failures that tend to have a substantial time horizon, a sharp increase in the rate of change of the residuals is often a leading indicator of the failure. Using this information coupled with the change in the residual since the engine's install (baseline) performance allows us to be less aggressive with the fault detection thresholds and gives us the ability to generate a better time horizon estimate for the FDD system.

Directly calculating the derivative of the residuals was not possible because the sampling rate of the data was not uniform. Instead a linear fit through the last N samples of the filtered data was used. There is a need to minimize the number of points used to calculate the slopes because the number of points required to generate the first ΔN2dot, ΔEGTdot, and ΔWFdot values directly influences the number of points that it takes to get the first algorithm output. In applications where the fault of interest may be caused by an installation problem or develop quite rapidly it is very desirable to have the online predictions available as soon as possible. Thus, the number N is chosen empirically based on trying to determine the minimum number of points that can be used in the slope calculation to maintain good performance of the fuzzy logic based FDD algorithm.

The EGT Margin is another calculated value used to augment the parameter set. This parameter represents the amount of temperature margin left in the engine. The temperature margin represents the number of degrees between the current operating conditions and the temperature redline for that particular engine model. The engine's redline is the safety limit on temperature for engine operation. If the engine crosses the redline during operation, it must be removed immediately and sent for repair. The calculation for EGT margin uses the current operating conditions and associated temperature along with an empirical model of the engine to estimate the temperature that the engine would attain given extreme atmospheric conditions and the maximum thrust available. This number is then subtracted from the redline temperature to attain the remaining EGT Margin.

The EGT Margin is a good parameter for eliminating any effects caused by engine-to-engine variation because it always indicates the absolute performance of the engine from a temperature perspective. The ΔEGT parameter, on the other hand, is always compared relative to the baseline of each engine's performance, which may vary substantially from engine to engine. It is not, however, completely effective to use this parameter alone as a performance indicator, because an engine doesn't always operate at extreme conditions. Further, the EGT Margin decreases a similar amount for several different types of engine failure modes such as EGT sensor failure, external air leakage, fuel system problems and performance problems associated with both the high speed (pressure) and low speed (pressure) engine shafts. Patterns of deterioration in the other parameters such as residuals and the rate of change of these residuals coupled with EGT Margin are a more complete measure of performance.

3.4 Data processing

Data processing is accomplished using a third order Butterworth filter. The Butterworth filter is a low pass filter with a monotonic amplitude frequency response that is maximally flat at band pass frequencies. Its amplitude frequency response decreases logarithmically with increasing frequency. The Butterworth filter also has minimal phase shift over the filter's band pass when compared to other conventional filters.

A third order filter was chosen to minimize the window of data required to compute the filtered values because the window size directly increases the number of points before the first diagnostic output is generated. The order of the filter may be increased when more aggressive filtering is required due to increased sensor noise.

The low-pass filtering operation is performed on both the residual signals and the slope signals in order to smooth the signals and to decrease the effects of noise in the measurement channels. The slopes are calculated using the smoothed residual signals because this produces a more consistent result.

3.5 The fuzzy logic system

The system flow diagram in Figure 1 shows that the seven inputs to the fuzzy logic system are the smoothed ΔN2, ΔEGT, ΔWF, ΔN2dot, ΔEGTdot and ΔWFdot signals and the unfiltered EGT Margin. Once the input values are calculated, the first X points of data for each parameter after the engine installation is used to obtain an engine-specific mean parameter value for ΔN2, ΔEGT and ΔWF. This mean value (baseline) is then subtracted from all remaining engine data so that a value of zero for each parameter represents the nominal or mean parameter value and any increase (decrease) in the parameter value indicates a positive (negative) number.

All of the input values are mapped into a fuzzy set based on their predefined membership functions. These fuzzy sets are combined using the predefined rules governing the engine behavior during the fault of interest. The Mamdani method is used to compute the system output. Once the probability of the fault is determined using the fuzzy inference system the results are interpreted based on empirically determined fault maps.

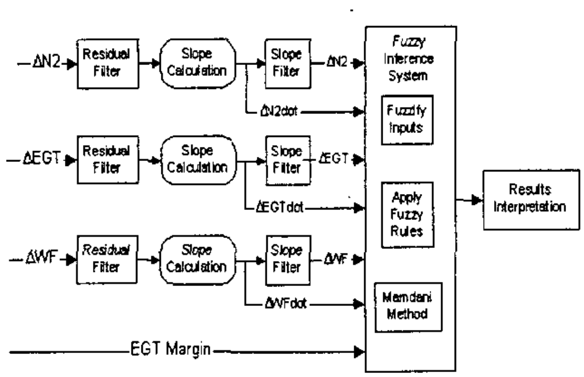

Figure 1 System Block Diagram

The approach to determining the membership functions for each type of failure mode was based on the expert-derived engine heuristics. The heuristics consisted of the rates and directions that each parameter would shift when the engine failed or began to deteriorate and the alert levels for each of the individual parameters. These alert levels were developed assuming that there were single parameter shifts in each direction at a predefined rate. Extensive studies of fault models and flight data from failed engines were used to develop the levels and rates for multiple parameter shifts. The membership functions derived for each input except EGT Margin are symmetric because all of the other alert levels for data are symmetric. Since EGT Margin is an absolute measure rather than a shift from a nominal value it is defined in terms of the levels generally seen during engine operation. The levels and function types for each of the membership functions were determined from engine models and empirical data.

The fuzzy rules we developed were based on the expert heuristics that had been used to manually trend engine behavior. Other rules associated with other engine faults were added to help isolate one fault from another. Finally weighting was applied to these rules so that the strongest data trends would dominate the detection system. A case study in Section 4, showing the development of the fuzzy logic system for HP Spool deterioration illustrates each of these steps.

3.6 Robustness to uncertainty

In this application, both model uncertainties and data uncertainties that can affect the FDD results. Model uncertainty is present because the empirical engine model was developed using a limited amount of engine data that may not cover the full range of engine operation. Uncertainty in engine models is minimized by updating the empirical fits or "maps" with data representing previously unconsidered engine operating conditions. Higher fidelity validated models, such as physics-based models combined with empirical models, can also greatly reduce model uncertainty. Data uncertainty is present due to the nature of the data acquisition system as well as due to the engine sensor characteristics. Data uncertainty is minimized by removing outliers and using a low pass filter to reduce data variability.

4 Case study HP spool inefficiency

In this section we present the development of the fuzzy logic system for HP Spool deterioration. The fuzzy logic results obtained from a specific engine that had experienced HP Spool deterioration is also shown. This case study shows how the system enables us to predict the failure before the engine had to be removed for exceeding temperature safety limits (going over the redline).

All of the signals, with the exception of the EGT margin, are passed through a low-pass filter as described in the data processing section. An example of the data before and after filtering is described in [4].

4.1 The fuzzy inference system

The method is implemented using the *Fuzzy Logic Toolbox* from MATLAB [6]. The membership functions were developed using expert-defined performance limits for safe and effective operation of the engine. For ΔN2 and ΔWF these limits are based on percent speed (N2) and percent fuel flow. For ΔEGT and EGT Margin the limits are based on temperature in degrees Celsius.

The fuzzification functions used for classifying the high, medium and low ranges for all three of the parameters are shown in Figure 2.

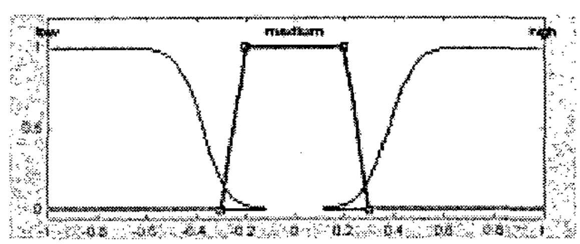

Figure 2. ΔN2 Membership Function Example

The following tables (1-4) describe the parameter values for each of the membership functions.

Table 1. ΔN2 and ΔN2dot Membership Functions

Level	Function	ΔN2	ΔN2dot	Description
Low	sigmoid	-20 -0.375	-1350 -0.003	slope, func. midpoint
Medium	trapezoid	-0.3 -0.2 0.2 0.3	-0.0025 -0.001 0.001 0.0025	min x intercept min flat top max flat top max x intercept
High	sigmoid	20 0.375	1350 0.003	slope func. midpoint

Table 2. ΔEGT and ΔEGTdot membership functions

Level	Function	ΔEGT	ΔEGTdot	Description
Low	sigmoid	-1.25 -20	-50 -0.04	slope, func. midpoint
Medium	trapezoid	-20 -10 10 20	-0.035 -0.015 0.015 0.035	min x intercept min flat top max flat top max x intercept
High	sigmoid	1.25 20	50 0.04	slope func. midpoint

Table 3. ΔWF and ΔWFdot membership functions

Level	Function	ΔWF	ΔWFdot	Description
Low	sigmoid	-6 -0.8	-775 -0.0045	slope, func. midpoint
Medium	trapezoid	-1 -0.5 0.5 1	-0.0015 -0.00105 0.00105 0.0015	min x intercept min flat top max flat top max x intercept
High	sigmoid	6 0.8	775 0.0045	slope func. midpoint

Table 4. EGT Margin membership functions

Level	Function	EGT Margin	Description
Low	sigmoid	-0.75 2.5	slope, func. midpoint
Medium	trapezoid	5 7.5 15 17.5	min x intercept min flat top max flat top max x intercept
High	sigmoid	0.75 20	slope func. midpoint

The basic expert heuristics governing high pressure spool inefficiency are the magnitudes of ΔN2 and ΔN2dot decrease, while ΔEGT, ΔEGTdot, ΔWF and ΔWFdot increase. The main causes of the high pressure spool inefficiency are high pressure compressor, high pressure turbine, or internal air leakage. The root causes of high pressure turbine problems are open tip clearances from blade rubs or blade leading edge erosion. Although there are not enough measured (recorded) parameters to differentiate between these types of problems in an automated fashion, expert examination of the data and fuzzy logic output can map these faults down to a lower level or assign probabilities to a list of root causes.

Based on the heuristics seven rules are applied to the input data. These are:

R1. (ΔN2 = low) & (ΔEGT = high) & (ΔWF = high) & (ΔN2dot = low) & (ΔEGTdot = high) & (ΔWFdot = high) & (EGTMargin = low) => (HPSpool = high)

R2. (ΔN2 = high) & (ΔEGT = high) & (ΔWF = high) & (ΔN2dot = high) & (ΔEGTdot = high) & (ΔWFdot = high) => (HPSpool = low)

R3. (ΔN2 = medium) & (ΔEGT = medium) & (ΔWF = medium) & (ΔN2dot = medium) & (ΔEGTdot = medium) & (ΔWFdot = medium) & (EGTMargin = high) => (HPSpool = low)

R4. (ΔN2 = low) & (ΔEGT = high) & (ΔWF = high) & (ΔN2dot = low) & (ΔEGTdot = high) & (ΔWFdot = medium) & (EGTMargin = low) => (HPSpool = high)

R5. (ΔN2 = low) & (ΔEGT = high) & (ΔWF = high) & (ΔN2dot = low) & (ΔEGTdot = high) & (EGTMargin = low) => (HPSpool = high)

R6. (ΔN2 = low) & (ΔEGT = high) & (ΔWF = high) & (EGTMargin = low) => (HPSpool = high)

R7. (ΔN2 = low) & (ΔEGT = high) & (ΔWF = high) & (ΔN2dot = low) & (ΔEGTdot = high) & (EGTMargin = medium) => (HPSpool = medium)

The rules are implemented using the Mamdani method and the following weighting scheme: 1*R1, 1*R2, 0.5*R3, 1*R4, 1*R5, 1*R6 and 0.5*R7.

Rules R1 and R6 directly implement the expert heuristics, while rule R3 deals with the case of a normally operating engine. Rule R4 deals with the fact that the change in ΔWF lags the response in the other signals. Rule R7 is designed to deal with the fact that the fuel flow measurements tend to have the most noise in the measurement channel and therefore the ΔWFdot calculation is the least reliable. The other rules are designed to deal with engine conditions that may mask either the fault of interest or normal operating conditions.

4.2 Case study results

The results for an engine are shown in Figure 3. In this figure each point represents a flight for which data was recorded and the x-axis is in hours of operation. The time window presented on the x-axis of this figure represents about fifteen months of operation with approximately 1500 flight points. The y-axis is the fuzzy logic FDD output value which roughly corresponds to the likelihood of an engine failure, in this case, the likelihood that there is deterioration in the HP spool.

In Figure 3, the fuzzy system output is a close proxy to the development of the HP spool efficiency that led to engine removal for HP Turbine deterioration. As Figure 3 shows the numerical results of the fuzzy logic system, continue to rise as the failure progresses. Note that at the last data point the engine exceeded temperature limits and had to be removed.

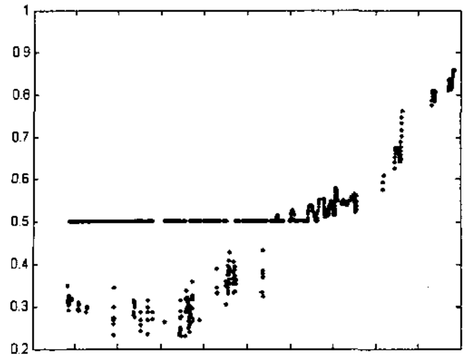

Figure 3: Case Study Results for an Engine

The results interpretation method that is used is based on a threshold of maintaining a level of about 0.75 over M flights to indicate that damage is occurring. The prediction has to hold for M flight samples to further mitigate data outliers and noise. This threshold in combination with the slope of the fuzzy logic FDD system output and the EGT Margin can be further processed to obtain the approximate time-to-failure (a prediction horizon) and the extent of engine deterioration. In the example presented in Figure 3, the fuzzy logic system output indicted that HP spool deterioration began developing at an accelerated rate about two months prior to the failure, which would allow the aircraft operator ample time to schedule testing and removal of the engine.

5 Summary and conclusions

In this paper a method for fault prediction, detection and diagnosis for gas turbine engines was presented. The method was shown produce increasing probabilities of that the fault was present as the fault developed. This enabled the addition of a prediction horizon to the FDD system described in [4]. The method was tested on actual flight data collected in the field on old data systems and was shown to detect problems in the engine even in the presence of data gaps and system noise. A case study demonstrated the prediction of HP Spool deterioration two months prior to an engine exceeding safe operating limits.

The results of the case study show that it is possible to obtain reliable prediction horizon for fault diagnosis with very few parameters and many gaps in the data. This makes the method applicable to older engines that have not traditionally been able to take advantage of FDD due to lack of models, less sensors or lack modern data acquisition and storage systems. By using this method aircraft operators can realize substantial cost savings by proactively scheduling maintenance when a fault begins to develop rather than react to problems by canceling flights, delaying schedules, aborting takeoffs, or taking other costly measures after a fault is discovered. Much of this success is due to Honeywell's understanding of jet engines and the refinement of the performance heuristics that have been developed over the years that Honeywell has been providing customer support for these products.

The technique presented in this paper has also been applied to faults such as bleed band actuator leaks and has shown good success. Work continues on using physics-based models to generate the residuals and robust optimization to generate ΔN2dot, ΔEGTdot and ΔWFdot to see if the system performance improves.

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