Fault Detection and Diagnosis in Turbine Engines using Fuzzy Logic

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Abstract

In this paper, we present a fuzzy logic based method of fault detection and diagnosis in gas turbine engines. The fuzzy logic system rule base is derived using heuristics extracted from designed experiments and flight data representing component performance changes due to field service degradation. The fuzzy logic rule based method incorporates both sensed engine parameters that represent non-deteriorated engine operation and fault conditions related to engine performance such as high pressure turbine, high pressure compressor and combustor deterioration. The fuzzy logic system is evaluated using residuals calculated based on both empirical models as inputs. The efficacy of the fuzzy logic system in detecting and diagnosing engine faults is demonstrated using field test data. We also examine performance robustness in the presence of varying levels of sensor noise and measurement errors.

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 in-flight shutdowns, delays and cancellations, unscheduled engine removals, and take-off aborts. This makes accurate incipient fault detection necessary for cost effective preventive maintenance programs.

Turbine engine FDD involves the early detection of incipient as well as 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 [1]. 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). These residuals are passed through a decision logic system to determine a diagnosis. Data-driven methods use historical data collected from the system to construct quantitative (neural networks, statistical models) or qualitative (trends-based, rule-based) FDD methods.

Turbine engine diagnostics is currently performed by manually trending important engine parameters over time [2]. The trends are examined by engine experts/ maintenance personnel to determine if an engine fault is present.

Engine data is often messy since they are sometimes recorded manually by the pilot; even data collected in an automatic data acquisition system contains noisy data. Noisy data results in large parameter variations on a flight to flight basis. Further, in many of the older data acquisition systems, a very limited amount of data is recorded per flight (one data point per flight is the norm), often under a fixed set of engine operating conditions.

These conditions cause several complications for automated engine monitoring and diagnosis. First, many engine problems are not distinguishable or even visible within the small set of parameters that are recorded. 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. The creation of automated diagnostic systems has been further complicated because experts make decisions based on rules that are not level driven but rather based on patterns observed over several parameters. When looking at this data, experts also filter the outliers and bad data points based on intuition (in a non systematic way).

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 residuals are then subjected to data smoothing techniques, and the smoothened outputs are combined with a fuzzy logic based implementation of system expert heuristics. The data smoothing techniques are applied to address the issues associated with the data variability.

Then automated performance trending and fault isolation is accomplished by applying expert based fuzzy logic rules to the engine trends and the parameter levels. The fuzzy logic method is a good method to use when there are not clear boundaries between faulty and non-faulty engine behavior [3, 4]. Neural networks have also been applied in this context of turbine engine diagnostics [5]. However, neural networks have a disadvantage in that their training times 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 goes through a case study representing one of the major engine faults of interest. This case study includes 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.

Section 5 provides conclusions and a summary. This section also presents some information regarding the approaches applicability to other fault types and directions for future development of this technique.

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 turbine manufacturer, has this understanding and is thus in a good position to lead the way in FDD for their products. A propulsion engine generally contains four main modules: a fan module, a gas producing module, a combustor/turbine module, and the accessory gearbox and mechanical components module. The engines of interest to us in this paper are referred to as twin spool engines. These engines have two shafts: the fan shaft operates at low pressure and lower speed; the core shaft operates at high pressure and high speed.

The propulsion engine's primary function is to provide thrust to the aircraft, but it may also be required to provide air to other 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 these bleed air driven system varies depending on the outside conditions, the passenger load, and the aircraft configuration.

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

One issue associated with these cost constraints that the technique presented 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 only recorded 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.

A major limitation of some FDD systems is that they are only good for engines that have detailed models or modern data collection systems. With a large amount of available data and modern simulation tools and techniques, detecting and isolation faults is made easier. However, the techniques that work on these engines do not necessarily carry over to older engines 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 a limited data set, 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 requires that any FDD system be robust to data gaps.

Finally, the lack of automation and computing power associated with older engines led to many expert-based systems for engine performance monitoring. These systems were largely based on a single expert with a good intuitive understanding of engine performance. Many of the heuristics developed by these experts are non-systematic (no numerical bounds are specified) in nature and tend to be augmented with regular service inspections aimed at preventing 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.

3. Fuzzy logic approach

The approach presented in this paper attempts to deal with many of the data-related problems described above as well as to provide a way to automate the expert heuristics. The approach consists of four steps: the first is using an empirical model of the engine to create residuals of the performance parameters, the second is filtering these residuals to eliminate noise and outliers, the third is to apply the filtered data to the fuzzy logic system to generate a probability that there is a problem, and finally the output must be interpreted. The next section of the paper outlines some of the fundamentals of fuzzy logic and the following sections describe each of the first three steps of the technique in sequence. Methods of interpreting the output are discussed in section 4.3 Case Study Results.

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 being 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 [6], makes fuzzy logic a good method for handling system uncertainty and 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 [7] 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: $\mu_A(x): X \to [0,1]$ [6]. These membership functions can be formed based on intuitive groupings such tall people or good grades. Membership functions can also be defined using statistical or other mathematical methods. Fuzzy sets have similar rules of mathematical operations to traditional sets, for a full description of the mathematics of fuzzy sets, see [3], [4] [5] and [7]. To transform a crisp set into a fuzzy set, the data is fuzzified - that is a function F is applied the crisp set.

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 X is tall and wide, then clothes are of size portly or 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 generated using an empirical engine model. This model is valid only at standard temperature and pressure conditions and 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 equation 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 No., outside temperature, and pressure. The expected values were then compared to the measured values and the results of this comparison, (the residuals) are called ΔN2, ΔEGT and ΔWF respectively. Because all these residuals are calculated based on converting the values to standard flight speed, temperature and pressure conditions, they can be used to compare engine performance on a flight to flight basis.

3.3. 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 and an amplitude frequency response that 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.

The low-pass filtering operation is performed on the residual signals to smooth the signals and to decrease the amount of noise in the signals. The order of the filter may be increased when more aggressive filtering is required due to less accurate sensing.

3.4. The Fuzzy logic system

Figure 1 shows the system flow. As this figure indicates, the three inputs to the fuzzy logic system are the smoothed ΔN2, ΔEGT and ΔWF values. Once the input values were calculated the first n points of data for each parameter after the engine installation were used to get a engine specific mean parameter value. This mean value was subtracted from 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.

These 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 and the Mamdani method [8] 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.

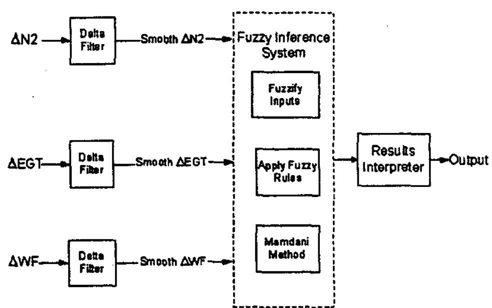

Figure 1. Fuzzy logic system block diagram

The approach to determining the membership functions for each type of failure mode was based on expert derived engine heuristics. These heuristics consisted of the 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. Extensive studies of fault models and flight data from failed engines were used to develop the levels for multiple parameter shifts. The membership functions that were derived for each fault case were symmetric in nature because all of the alert levels for data are symmetric. The levels and function types for each of the membership functions were determined from engine models and empirical data.

The fuzzy rules that were developed were basically the expert heuristics that had been used previously to manually trend engine behavior. Other rules associated with other engine faults were added to aid in isolating 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 showing the development of the fuzzy logic system for HP turbine deterioration will illustrate each of these steps.

3.5. Robustness to uncertainty

In this application, there are 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 and may not cover the entire range of engine operation conditions. Model uncertainty in existing 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 the engine sensor characteristics. Data uncertainty is minimized by removing outliers and by 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 turbine deterioration. The fuzzy logic results obtained from a specific engine that had experienced HP turbine deterioration is also shown. This case shows how the system enables us to predict the failure before the engine had to be removed due to exceeded temperature safety limits.

4.1. Data filtering

The engine residual signals are passed through a low-pass filter as described in the data processing section. Figure 2 shows the unfiltered residual data and Figure 3 shows the residual data after processing with low-pass filters. From Figure 3, it is seen that the data variability is greatly reduced. This greatly improves the performance of the fuzzy logic FDD system.

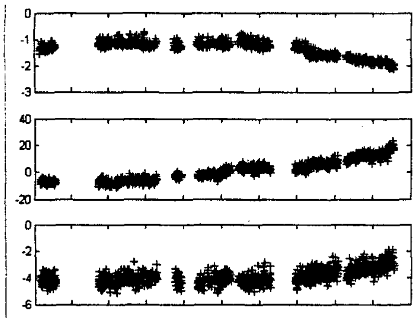

Figure 2. Raw engine data for Engine X

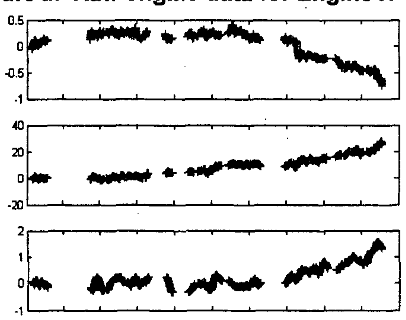

Figure 3. Filtered data for Engine X

4.2. The Fuzzy Inference System

The implementation of the method is accomplished using the Fuzzy logic toolbox from MATLAB [8]. 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.

The fuzzification functions used for classifying the high, medium and low ranges for all three of the parameters are shown in Figure 4. The following tables describe the parameter values for each of these functions.

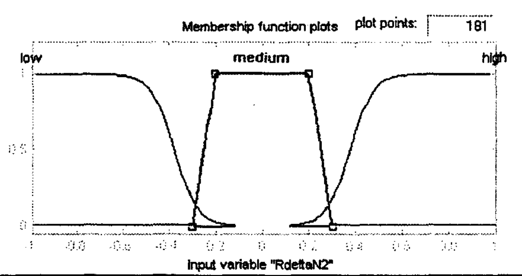

Figure 4. ΔN2 membership function example

Table 1. ΔN2 Membership functions

Level	Function	Values	Description
Low	sigmoid	-20 -0.375	slope, function midpoint
Medium	trapezoidal	-0.3 -0.2 0.2 0.3	min x intercept min flat top max flat top max x intercept
High:	sigmoid	20 0.375	slope function midpoint

Table 2. ΔEGT membership functions

Level	Function	Values	Description
Low	sigmoid	-1.25 -20	slope, function midpoint
Medium	trapezoidal	-20 -10 10 20	min x intercept min flat top max flat top max x intercept
High	sigmoid	1.25 20	slope function midpoint

Table 3. ΔWF membership functions

Level	Function	Values	Description
Low	sigmoid	-6 -0.8	slope, function midpoint
Medium	trapezoidal	-1 -0.5 0.5 1	min x intercept min flat top max flat top max x intercept
High	sigmoid	6 0.8	slope function midpoint

The basic expert heuristics governing high-pressure spool inefficiency are that ΔN2 decreases, while both ΔEGT and ΔWF increase. The main causes of the high-pressure spool inefficiency are high-pressure compressor degradation, high-pressure turbine degradation 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 can map these faults down to a lower level or assign probabilities to a list of root causes.

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

R1. If (ΔN2 == low) & (ΔEGT== high) & (ΔWF == high) => (HPTurbine = high)

R2. If (ΔN2 == high) & (ΔEGT== high) & (ΔWF == high) => (HPTurbine = low)

R3. If (ΔN2 == medium) & (ΔEGT == medium) & (ΔWF == medium) => (HPTurbine = low)

R4. If (ΔN2 == medium) & (ΔEGT == high) & (ΔWF == high) => (HPTurbine = medium)

R5. If (ΔN2 == low) & (ΔEGT == high) & (ΔWF == medium) => (HPTurbine = medium)

The rules are implemented using the Mamdani method and the following weighting scheme:

1*R1, 0.75*R2, 1*R3, 0.5*R4 and 0.5*R5.

The rule R1 directly implements the expert heuristics, while the rule R3 deals with the case of a normally operating engine. The other rules are designed to deal with engine conditions that may mask either the fault or normal operating conditions.

4.3. Case Study Results

The results for a particular engine that had a verified instance of HP deterioration are shown in Figure 5. Here the results clearly show that the output of the fuzzy system gets much higher as the engine deterioration progresses. It should be noted that at the last data point the engine exceeded temperature limits and had to be removed. The fuzzy logic system output showed that the deterioration was progressing about one month in advance.

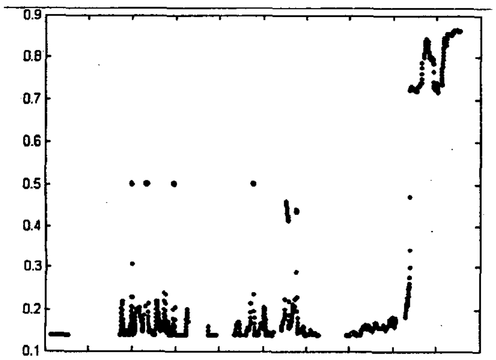

Figure 5. Fuzzy logic FDD system output

In Figure 5, the fuzzy system output is a close proxy to the HP spool efficiency and therefore an excellent measure of the HP turbine deterioration. The fuzzy system output can be processed further to obtain proxies for the time-to-failure and the extent of engine deterioration.

5. Summary and Conclusions

In this paper a method for fault detection and diagnosis for gas turbine engines was presented. This method was tested on actual flight data that was collected on legacy data acquisition systems. The method was shown to detect problems in the engine even in the presence of data gaps and system noise.

The results generated using these methods are very promising as they show that it is possible to reliably diagnose faults with very few parameters and with many gaps in the data. 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. These expert heuristics can be effectively transferred to a fuzzy logic-based FDD method.

This technique has also been applied to abrupt faults such as bleed band rupture and has shown good success. Work continues in the area of changing the input space and using physics based models to generate the residuals to see if the system performance improves.

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