Fault Diagnosis of Gas Turbine Engine LRUs Using the Startup Characteristics

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ABSTRACT

This paper introduces a feature-extraction method to characterize gas turbine engine dynamics. The extracted features are used to develop a fault diagnosis and prognosis method for startup related sub-systems in gas turbine engines - the starter system, the ignition system and the fuel delivery system.

The startup of a gas turbine engine from ignition to idle speed is very critical not only for achieving a fast and efficient startup without incurring stall, but also for health monitoring of many subsystems involved. During startup, an engine goes through a number of phases during which various components become dominant. The proposed approach physically monitors the relevant phases of a startup by detecting distinct changes in engine behavior as it manifests in such critical variables as the core speed and the gas temperature. The startup process includes several known milestones, such as starter-on, light-off, peak gas temperature, and idle. As each of these is achieved, different engine components come into play and the dynamic response of the engine changes. Monitoring engine speed and exhaust gas temperature and their derivatives provides valuable insights into engine behavior.

The approach of the fault diagnosis system is as follows. The engine startup profiles of the core speed (N2) and the gas temperature are obtained and processed into a compact data set by identifying critical-to-characterization instances. The principal component analysis is applied to a number of parameters, and the fault is detected and mapped into three engine component failures which are the starter system failure, the ignition system failure, and the fuel delivery system failure.

In this work, actual engine test data was used to develop and validate the system, and the results are shown for the test on engines that experienced startup related system failures. The developed fault diagnosis system detected the failure successfully in all three component failures.

1. INTRODUCTION

The gas turbine engine is one of the most vital aviation components. While the heart of this propulsion system is the gas producer that converts fuel into mechanical energy, several LRUs (Line Replaceable Units) contribute to the overall health and remaining useful life of the propulsion function. Although some LRUs may not be considered to be engine OEM parts, they nevertheless contribute to the prognostic health of the propulsion system. Consequently, any accurate estimate of propulsion remaining useful life calculation from a CBM (Condition Based Maintenance) perspective must account for all such LRUs (Parthasarathy et al., 2011).

Current LRU fault detection is achieved using built-in-tests (BIT). Unfortunately, these BIT implement simple threshold checks (i.e., hard faults) without taking a systems perspective of the propulsion system. Significant maintenance effort is expended to troubleshoot and isolate in-range (i.e., soft) faults. As a result, when the component fails, it is too late and manifests as an engine shutdown or loss of power control at the propulsion function level. A failed LRU will drive maintenance costs and operational interrupts in two ways: 1) an LRU failure is misdiagnosed as an engine problem and the engine is removed, and 2) the engine must be removed to access certain LRUs.

Most engine fault diagnosis/prognosis is performed using measurement data from engines that are in steady-state conditions. The steady-state data is used for several reasons; most notably, system transients can confuse fault

diagnosis/prognosis methods, giving incorrect results. A more robust approach to developing fault diagnosis/prognosis methods that explicitly accounts for transient data is required (Surender et al., 2005). Furthermore, most turbine engine fault diagnosis/prognosis methods are developed with engine performance models that have been validated only under steady-state conditions or with actual engine data at steady-state conditions. Engine models that accurately represent the system in transient conditions are difficult to develop. Nevertheless, developing fault diagnosis/prognosis methods designed to operate on system data during transient as well as steady-state operation has several important advantages; 1) Certain system faults have a distinct signature during system transient conditions that would not normally be discernible during steady-state conditions. 2) The effect of feedback control action is less dominant during transient conditions than during steady-state conditions. Because feedback control suppresses the effect of sensor and system faults, faults are more evident during transient conditions. 3) Certain engine component incipient faults are manifest only during transient conditions such as startup and shutdown (e.g., starter and igniter system faults) (Uluyol et al., 2006).

Thus, for a vehicle health monitoring system that is comprehensive in its scope, and timely and accurate in its diagnosis, high fidelity engine models and a large amount of high-speed data both in steady-state as well as in transients are needed. However, limited computational resources available on-board, and the limited bandwidth capacity and the high cost of real-time data transmission place serious barriers to fulfilling that need (Kim et al., 2005).

The approach presented in this paper seeks to overcome these barriers by separating the initial feature extraction stage of diagnostics algorithms from the modeling and trending stages. The first stage, which includes the detection of time instances that are critical to diagnosis and control, is performed on board, while the latter stages are performed on a ground station. This paper presents an approach that permits a much greater insight into the engine health than is possible with a couple of snapshots at takeoff and cruise, while keeping the data size much smaller than that of the complete high speed data. The fault diagnosis method for startup related components in turbine engines is developed using continuous time series data. The engine startup data set recorded with high speed sampling rate is analyzed to discover the best conditions for detecting the target component failure. Engine startup profiles of the core speed (N2) and the measured gas temperature (MGT) are then transformed into a compact set by a series of data processing steps. The processing is based on statistical characteristics analysis, and principal component analysis (PCA). The fault is detected and mapped into three engine component failures which are the starter system failure, the ignition system failure, and the fuel delivery system failure.

The remainder of this paper is organized as follows: In Section 2, the functionality of startup related components is described. In Section 3, the engine startup process is described. Section 4 describes the engine startup profile and the critical-to-characterization (CTC) instances. Section 5 presents the developed fault diagnosis/prognosis system with the steps of the algorithm logic. Section 6 shows the results of the developed diagnosis system. The data set used to develop the system is the actual engine data recorded in the test cell. Finally, Section 7 presents the summary and conclusions.

2. ENGINE STARTUP SYSTEM AND COMPONENTS

Gas turbine engines are complicated pieces of machinery, so fault diagnosis of these machines is enhanced by a detailed understanding of the equipment. The engine of interest in this work is a turbo-shaft engine.

The startup system consists of the ignition system, starter motor and the fuel system. The engine ignition system requires an external source of power. The ignition system provides igniters and exciter output circuits, and each igniter and circuit releases sufficient energy for all ground and air starting requirements. The ignition channels are powered by 28 V dc when the starter is energized. It supplies energy for spark at the igniter plugs. Adequate energy is supplied by the ignition system throughout its input voltage operating range to obtain successful engine starts.

For starting on the ground, the automatic start sequence is enabled by the pilot placing the power level angle (PLA) in the IDLE position, and holding the momentary start switch. Given sufficient battery power, the gas producer will begin to accelerate with the ignition enabled. As the gas producer accelerates, the ECU commands introduction of fuel to the engine. Light-off is declared if a rise in MGT is detected based on the MGT rate of change or MGT increase since introduction of fuel, or if Ng is greater than some pre-defined level. There is a start abort if any of the following are detected: excessive MGT, hung start, no light-off, or no Ng rotation.

The fuel system on the turbine engine provides fuel to the engine for proper combustion under all circumstances. The fuel system comprises the FMU (Fuel Metering Unit), fuel pump, high-pressure filter, min-flow valve, and fuel manifold assembly. Fuel metering functions are provided by the FMU. In the installed condition, there is no accessible means for adjusting the FMU. The high-pressure fuel filter is installed upstream of the FMU. It is designed and constructed to minimize the release of contaminants upstream of the metering valve and the fuel manifold.

3. ENGINE STARTUP PROCESS

The key features of the transient startup process are captured and made available as enriched inputs to LRU fault isolation

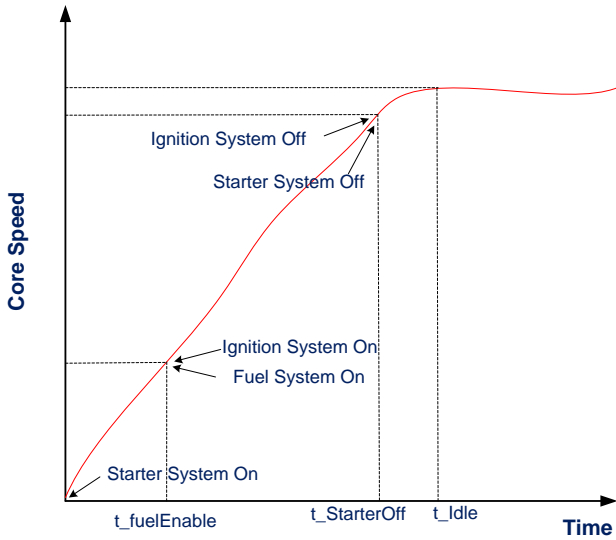algorithm. A typical engine speed plot during startup is shown in Figure 1.

Figure 1. Typical Engine Start Profile

Startup includes several milestones such as starter on, light-off, peak temperature, and idle. As each of these states is achieved, different components come into play, and the dynamic response of the engine changes. The gas producer core speed (NGG) and measured gas temperature (MGT) are two of the most informative measurements for detecting or verifying whether these states are achieved. Monitoring their derivates also provides valuable insights for engine behavior.

In general, the automatic start is performed by latching a combined starter/igniter relay and starter/ignition systems are on. The maximum engine speed gradient occurs when the engine speed has its highest rate of change during startup—usually a few seconds after the starter is switched on. According to the engine control logic, the control system shall deliver regulated fuel flow at the fuel metering unit delivery port when core speed exceeds some pre-defined level of full speed. Light-off occurs when ignition successfully completes and the combustor is able to sustain combustion. The maximum temperature gradient that corresponds to the highest rate of change in MGT follows the light-off several seconds behind during startup. The power section then begins to provide rotational energy to the system. Peak temperature occurs when the engine reaches its highest temperature during startup. At some pre-defined level of engine speed, the starter system and the ignition system are disabled through the ignition/starter relay driver. Finally, the ground idle occurs when the engine reaches its idle speed.

Figure 2 shows the time periods when the function of startup related LRUs is active during the startup process and they will be used to select the proper startup features. For example, the starter system anomaly can be detected and differentiated from the anomalies due to ignition and fuel systems, if the features are selected at 'Fuel Enable'. For the ignition system anomaly detection, the features at 'light-off' and 'peak MGT dot' are more proper, whereas the features at 'peak MGT' and 'idle' are more proper for the fuel system anomaly detection.
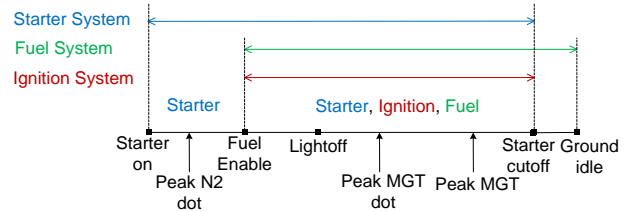

Figure 2. Startup Partition According to LRUs Functional Activity

By storing and analyzing engine sensor data taken during these key conditions of engine startup, the system and method is able to accurately characterize the performance of the engine during startup. This information is the basis for LRU prognostics to determine when faults in the start transient regime are occurring or likely to occur. Furthermore, the approach provides this ability to characterize the engine startup performance using only the sensor data taken during the key conditions.

4. STARTUP PROFILE

In this section, we discuss how the startup can be characterized using a small number of data points rather than equally spaced time series data.

The startup of a gas turbine engine from ignition to idle speed is very critical not only for achieving a fast and efficient startup without incurring stall, but also for health monitoring of many subsystems involved. The state of the art in monitoring engine startup is that engine parameters are sampled at regular frequencies and compared against fixed thresholds on these parameters. Often, the thresholds are set arbitrarily---monitoring parameters at 10%, 20%, 30% engine speed, etc. Sometimes the thresholds are set by experts or based on design specifications. In either case, startup monitoring does not capture the changes in engine response accurately and in a timely manner, since the changes in engine response manifest as an engine achieves certain startup phases, and not necessarily as some arbitrary thresholds are reached.

During startup, an engine goes through a number of phases in which various components become dominant. In the

absence of very detailed and costly engine models, the phases can be determined by monitoring the dynamic response of the engine. Our approach is the combination of monitoring physically relevant phases of a startup and monitoring the engine control schedule. The physically relevant phases can be obtained by detecting distinct changes in engine behavior as it manifests in such critical variables as core speed and exhaust gas temperature. This approach is superior to monitoring predetermined thresholds since the time the data should be captured is determined on the fly (hence, it varies from one flight to another). The engine control schedule can be obtained by the engine control logic. Some of the control logic provides additional insights of the engine operating conditions. For example, the engine control logic schedules the time when the fuel shall start to provide to the engine. This time of instance is very important since the performance of ignition system and fuel delivery system can be evaluated from this point of time. Unless you don't have a very accurate fuel flow measurement sensor (in fact, this is not the case almost always), this information cannot be obtained.

As described in the previous section, startup includes several known milestones, such as light off, peak MGT, and idle. As each of these is achieved, different components come into play and the dynamic response of the engine changes. The engine core speed (N2) and MGT are two of the most informative sensors. Monitoring their derivatives also provides, as we shall see below, valuable insights for engine behavior. Based on the derivatives of N2 and MGT, we can identify very precisely the time instances of light off, peak N2 dot, and peak MGT dot (Uluyol et al., 2005).
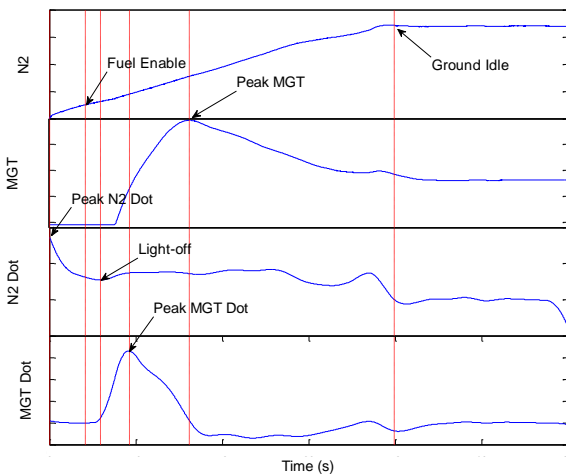

Figure 3. Features Extracted from the Startup Algorithm

When applied to actual startup data, the CTC instances cut across N2 and MGT profiles as well as other engine variables of interest depending on the failure type. An example of indication of CTC instances over the N2 and MGT startup profile plotted with actual data is shown in Figure 3. This figure helps the chronological understanding of the CTC instances occurrence. Notice that the CTC instances are nicely, but not equally, distributed between the start and idle speed. The distance between the lines changes as the startup profile changes. However, the simple patterns that each variable forms retain their shape, thereby allowing an automatic and consistent feature extraction.

5. FAULT DIAGNOSIS SYSTEM

The fault diagnosis system proposed in this work is presented in Figure 4. N2 and MGT, which are the two most important engine performance parameters, are processed at each flight to detect any startup related LRU anomalies.
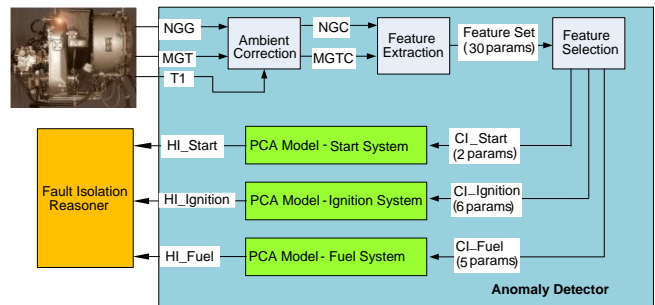

Figure 4. Schematic description of the algorithm

As emphasized earlier, the one of the ideas of developing fault prediction method in this work is based on the data reduction. The N2 and MGT startup profiles are continuous time series data. Considering the engine startup transient time, which typically takes 40-50 seconds, they consist of a large number of samples; the number depends on the sampling rate (for example, 2000-2500 samples with 50 HZ sampling rate, which was used in this work). Rather than analyzing whole continuous profiles having a large number of samples, the processing of a few points that represent the whole profile is much more efficient. In fact, there are two perspectives of data dimensionality reduction: technical perspective and practical perspective. In many problems, reducing the number of input variables can sometimes lead to improved performance for a given data set, even though some information is being discarded. The fixed quantity of data is better able to specify the mapping in the lower dimension space and this more than compensates for the loss of information (Bishop 1995). In the practical perspective, there are several more advantages to condensing the data: 1) It minimizes the cost and space for data collection and storage; 2) Computationally faster data processing makes for timely prognostic decisions; and 3) Not all of the engine data collection system can record continuous high speed data. Thus, a fault diagnosis system based on condensing the data set requires minimal modification of the existing data acquisition system. The

data reduction processing, which reduces the data size from the continuous time series data consisting as many as 2500 samples into 2 - 6 samples, is accomplished in two steps; from the second step to the third step as described below.

The first step in the algorithm covers data extraction from the engine and standardization of the extracted data. Since the startup profiles of N2 and MGT vary depending on the ambient conditions, the abnormal engine startup can result not only from the malfunctioning engine but also from ambient conditions. Correcting engine parameters against the standard condition is necessary to decouple the effect from the varying ambient conditions. The correction of N2 and MGT is done using ambient temperature (T1).

In the second step, we obtain the snapshot data at points that best represent the characteristics of a continuous N2 and MGT startup profile. The six CTC conditions, which are Peak N2 dot, Fuel Enable, Light Off, Peak MGT dot, Peak MGT, and Idle, are selected to represent the startup profile. The snapshot data set of five parameters---Time, N2, MGT, N2 dot, and MGT dot---are obtained at the six CTC conditions, resulting in 30 parameters per startup.

As discussed in Section 3, the time periods when the function of startup related LRUs is active during the startup process are different depending on LRUs, the startup features shall be selected at different CTC instances for each LRU. The selection of proper features are done in the third step, and the resulting output from this step is the down-selected startup features, which is represented by CI (condition indicator) in Figure 4. For the starter system anomaly detection, two CIs are selected at Fuel Enable condition. For the ignition system anomaly detection, six CIs are selected at Light-off and Peak MGT dotcondition. For the fuel delivery system anomaly detection, five CIs are selected at Peak MGT condition.

The fourth step is to detect any anomalies related to starter system, ignition system, and fuel delivery system. The anomaly detection is done based on Principal Components Analysis. The output of this step is the HI (health indicator) indicating existence of any anomalies in the three LRUs. The PCA model establishes correlations between the features. The anomaly detection involves measuring the multivariate distance away from the center of the correlation observed from the training set. If the distance exceeds a given threshold, then an anomaly is flagged.

The anomalies detected in the previous steps indicate faults in the startup process that encompass several components, including the engine. The last step is to isolate the possible root cause of anomalies further to subsystems or components, and to distinguish engine faults that manifest symptoms during the startup process. As shown in Figure 5, the fault isolation reasoner is composed of starter system anomaly reasoner, ignition system anomaly reasoner, and fuel delivery system anomaly reasoner. It also includes the

battery fault isolation logic. The inputs to the fault isolation reasoner are the HIs generated from the anomaly detector, additional measurements of oil temperature and fuel temperature, and the output from a different algorithm detecting fuel system fault. The outputs of the fault isolation reasoner are HIs related to starter motor, battery, igniter, fuel delivery, and engine. The logic of reasoners to isolate the root cause of each LRUs is presented in Section 6.
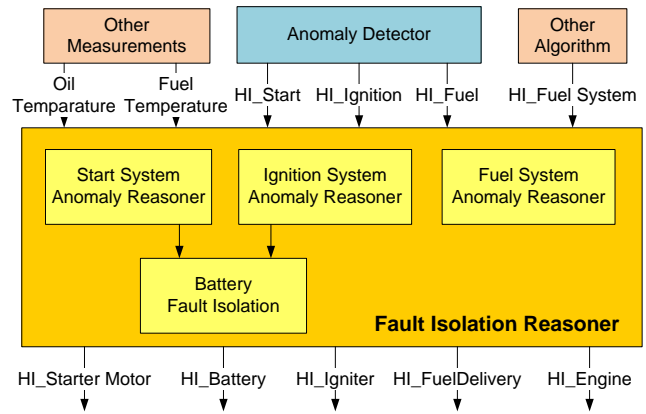

Figure 5. Fault Isolation Reasoner

6. FAULT DIAGNOSIS RESULT

The proposed fault diagnosis system was developed and tested with actual engine data collected from a test cell. The tests were done at the various conditions such as different altitude, Mach no., ambient temperature, oil/fuel temperatures. The startup test includes the initial static start (both cold and hot starts), aborted take-off ground start, and in-flight restart. The sampling rate of this data set is 50 Hz. The extracted parameters are N2, MGT, and T1. The ambient corrected values of N2 and MGT are computed from the empirical correction models, which are functions of T1.

Keeping the size of the data needed for the fault diagnosis much smaller than that of the complete high-speed data is advantageous and much more efficient. The rationale for extracting snapshot data is that a continuous startup profile can be represented by several points without losing its characteristics. Thirty snapshot datum per startup are obtained, each having six CTC conditions: Peak N2 dot, Fuel Enable, Light Off, Peak MGT dot, Peak MGT, and Idle for the five parameters of Time, N2, MGT, N2 dot, and MGT dot where Time, N2, and MGT are measured values and N2 dot and MGT dot are computed values. Table 1 summarizes the 30 parameters showing the CTC conditions in the column level and the engine variables in the row level. In Table 1, the features selected for the starter system anomaly detection are marked in blue and they are the Time

at Fuel Enable, and N2 dot at Fuel Enable. The features selected for the ignition system anomaly detection are marked in green and they are the time interval between Light-off and Fuel Enable, N2 at Light-off, N2 at Peak MGT dot, MGT at Peak MGT dot, N2 dot at Peak MGT dot, and MGT dot at Peak MGT dot. The features selected for the fuel system anomaly detection are marked in yellow and they are time interval between Peak MGT and Light-off, N2 at Peak MGT, MGT at Peak MGT, N2 dot at Peak MGT, and MGT dot at Peak MGT. As shown in Figure 2, the starter system anomaly detection is executed at Fuel Enable condition, the ignition system anomaly detection is executed at Peak MGT dot condition, and the fuel system anomaly detection is executed at Peak MGT condition.

Conditions	Parameters				
	Time	N2	MGT	N2 dot	MGT dot
@ Peak N2dot					
@ Fuel Enable	■			■	
@ Light-off	■	■			
@ Peak MGT dot		■	■	■	■
@ Peak MGT	■	■	■	■	■
@ Idle					

Table 1. Startup Feature Selection (Blue – starter system anomaly detection, Green – igniter system anomaly detection, Yellow – fuel system anomaly detection)

The result of starter system anomaly detection is shown in Figure 6 - Figure 8. Figure 6 shows two startup features selected for the starter system anomaly detection. The upper plot shows the Time at Fuel Enable and the lower plot shows N2 dot at Fuel Enable. The x-axis represents each startup. The normal startup is marked with blue x and the abnormal startup is marked with red dot. Figure 7 shows the PCA model output for starter system anomaly detection. The red horizontal line represents the threshold for the anomaly and blue x represents normal case and red dot represents the abnormal case. From Figure 6, the features themselves are not so distinguishable between the normal and abnormal cases. But as shown in Figure 7, the PCA model generates a clear indication of the anomaly by showing the big variance from the normal correlation among the features. Figure 8 is the N2 startup profile showing differences in the case of typical normal startup (blue curve) and the starter system anomaly (red curve). The two curves are similar to each other except around the Fuel Enable instance; Time at Fuel Enable is much larger in the case of anomaly. This clearly demonstrates that the starter system anomaly shall be detected at Fuel Enable instance. The root cause of the starter system anomaly could be various. According to Figure 6 and Figure 8, the major anomaly signature is the large value of Time to Fuel Enable. The possible root causes of delayed Fuel Enable are the

starter motor fault, the battery fault, the engine drag, and the engine rub. Figure 9 shows the logic to isolate the root cause of starter system anomaly. The ambiguity set is composed of the starter motor fault, the battery fault, the engine drag, and the engine rubs. When the starter system anomaly is triggered, two additional tests are to be done to isolate the root cause. If the oil temperature is too low and below a certain limit, then the probable cause of the delayed Fuel Enable is the engine drag. If the steady state scalar is higher than a certain level, then the Fuel Enable may be delayed due to the engine rubs. If none of those two tests are true, then the probable root causes of starter system anomaly are either the battery deterioration or the starter motor deterioration. The logic to isolate the battery problem is discussed later in this section.
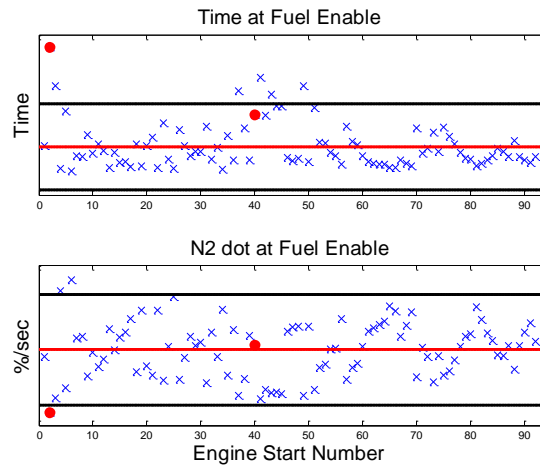

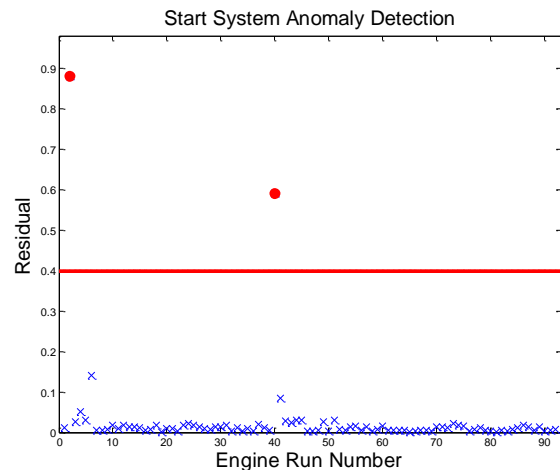Figure 6. Startup Features for Starter System Anomaly Detection

Figure 7. PCA Model Output for Starter System Anomaly Detection
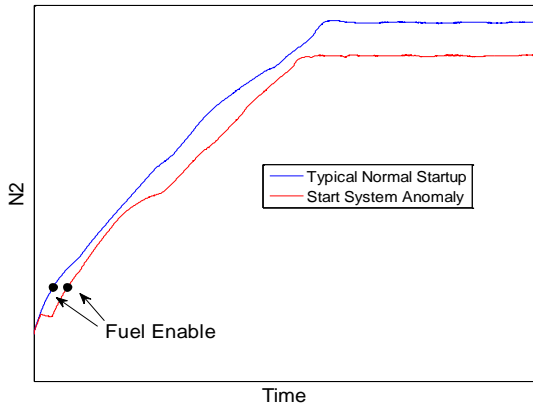
Figure 8. N2 Startup Profile comparing Normal Startup (Blue) and Starter System Anomaly (Red)
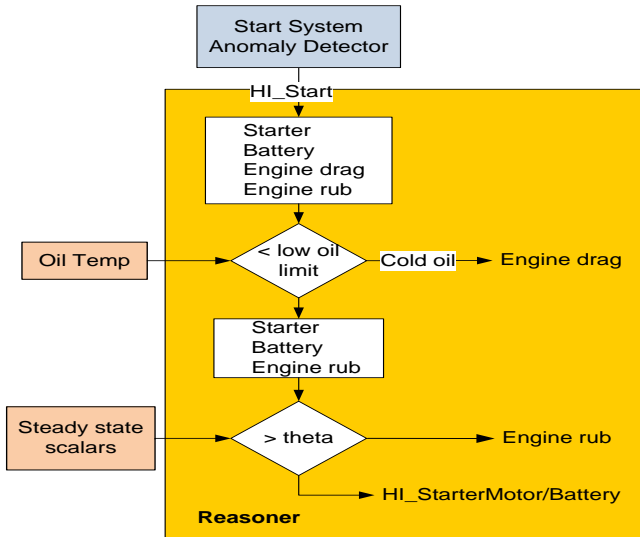

Figure 9. Starter System Anomaly Reasoner

The result of ignition system anomaly detection is shown in Figure 10 - Figure 12. Among six startup features selected for the ignition system anomaly detection, Figure 10 presents the features that show the most distinguishable signatures between the abnormal and normal startups, which are the time intervals between Light-off and Fuel Enable and N2 at Peak MGT dot. Figure 11 shows the PCA model output for ignition system anomaly detection. Figure 12 is the N2 and MGT startup profiles showing differences in the case of typical normal startup (blue curve) and the ignition system anomaly (red curve). The two curves are similar to each other in the early stage of startup but show the big difference around Peak MGT dot instance. This clearly demonstrates that the ignition system anomaly shall be detected at Peak MGT dot instance. The root cause of the ignition system anomaly could be various. According to Figure 10 and Figure 12, the major anomaly signature is the large value of the time interval between Light-off and Fuel

Enable. The possible root causes of delayed Peak MGT dot are the igniter fault, the battery fault, and the fuel/air mixture problem. The fuel/air mixture problem usually occurs at higher altitude resulting in denser fuel in the combustor chamber. Figure 13 shows the logic to isolate the root cause of ignition system anomaly. The ambiguity set is composed of the igniter fault, the battery fault, and the fuel/air mixture problem. There exists another algorithm to diagnose various fuel system faults (Mylaraswamy et al., 2011). This algorithm is based on the performance of control loops by assessing the controller dynamics. This algorithm is called the fuel scout algorithm and it can isolate the fault according to the various fuel system components such as the stepper motor, metering valve, RVDT sensor, fuel manifold sensor, and fuel nozzle. When the ignition system anomaly is triggered, the output of the fuel scout algorithm is referred to confirm if the anomaly is due to the fuel/air mixture problem. If the fuel scout algorithm does not trigger, then the probable root causes of ignition system anomaly are either the battery deterioration or the igniter deterioration. Figure 14 shows the logic to isolate the battery problem, the starter motor problem, and the igniter problem. If the starter system anomaly reasoner concludes that the anomaly is due to either starter motor or battery, and the ignition system anomaly reasoner concludes that the anomaly is due to either igniter or battery, then the probable root cause of both anomalies is the battery, because the starter motor and the igniter are powered by the same battery. If the starter system anomaly reasoner outputs HI of starter motor and battery is true, whereas the ignition system anomaly reasoner outputs HI of igniter and battery is false, then the root cause of the starter system anomaly is the starter motor deterioration. If the starter system anomaly reasoner outputs HI of starter motor and battery is false, whereas the ignition system anomaly reasoner outputs HI of igniter and battery is true, then the root cause of the ignition system anomaly is the igniter deterioration.
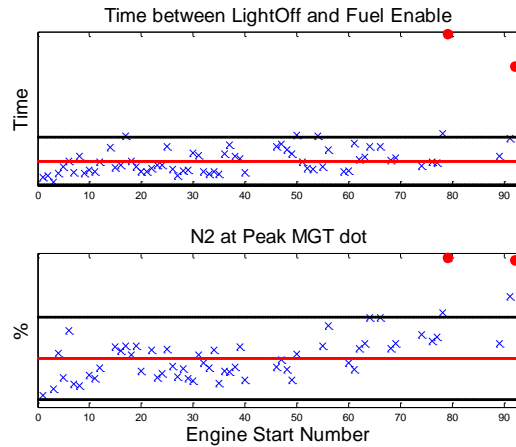

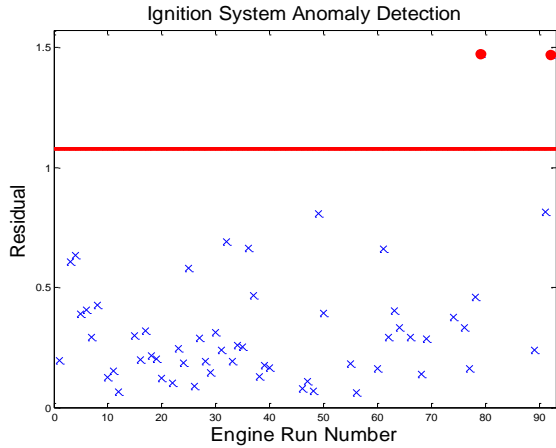Figure 10. Subset of Startup Features for Ignition System Anomaly Detection

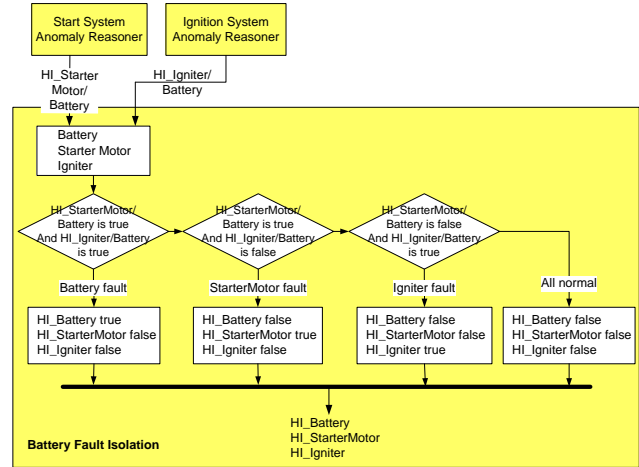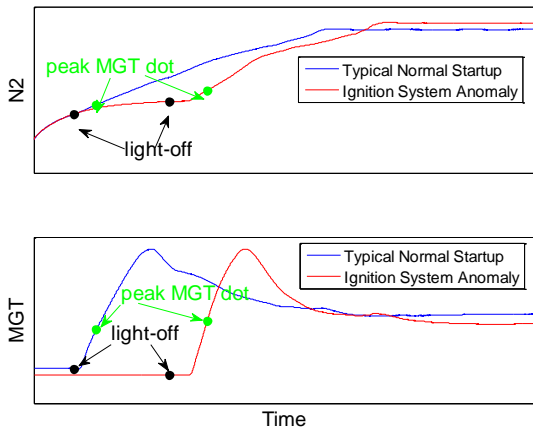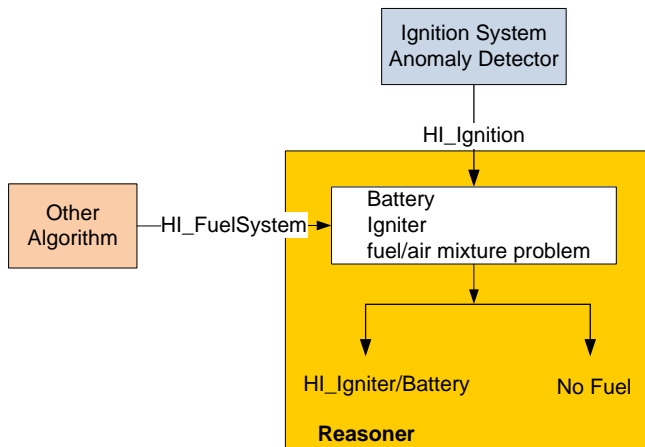Figure 11. PCA Model Output for Ignition System Anomaly Detection

Figure 12. Startup Profiles comparing Normal Startup (Blue) and Ignition System Anomaly (Red)

Figure 13. Ignition System Anomaly Reasoner

Figure 14. Battery Fault Isolation

The result of fuel system anomaly detection is shown in Figure 15 - Figure 17. Among six startup features selected for the fuel system anomaly detection, Figure 15 presents the features that show the most distinguishable signatures between the abnormal and normal startups, which are the time intervals between peak MGT and Light-off and N2 at Peak MGT. Figure 16 shows the PCA model output for fuel system anomaly detection. Figure 17 is the N2 and MGT startup profiles showing differences in the case of typical normal startup (blue curve) and the fuel system anomaly (red curve). The two curves are similar to each other in the early stage of startup but show the big difference around Peak MGT instance. This clearly demonstrates that the fuel system anomaly shall be detected at Peak MGT instance. The root cause of the fuel system anomaly could be various. According to Figure 15 and Figure 17, the major anomaly signature is the large value of the time interval between Peak MGT and Light-off. The possible root causes of delayed Peak MGT are the fuel system deterioration, the engine deterioration, and the low fuel temperature. When the fuel is too cold and the amount of fuel delivered to the combustor chamber is not sufficient enough the secondary fuel nozzle begins to open. The size of secondary fuel nozzle is bigger so the size of the fuel droplet is bigger. Since the fuel is very cold, the colder and bigger fuel sprayed into combustor chamber results in the cool-down and the possible blown-out. Figure 18 shows the logic to isolate the root cause of fuel system anomaly. The ambiguity set is composed of the fuel system deterioration, the engine deterioration, and the low fuel temperature. If the fuel temperature is below a certain limit, then the probable cause of the delayed Peak MGT is the cold fuel. Similarly in the case of ignition system anomaly reasoner, when the fuel system anomaly is triggered, the output of the fuel loop scout algorithm is referred to confirm if the anomaly is due to the fuel system deterioration. If the fuel loop scout algorithm does not trigger, then the probable root cause of fuel system anomaly is the engine deterioration.
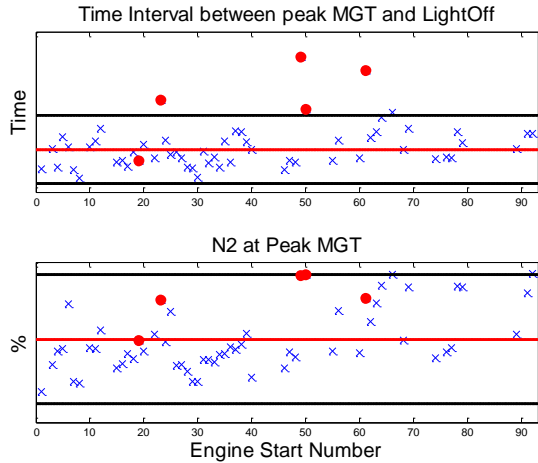
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Figure 15. Subset of Startup Features for Fuel System Anomaly Detection
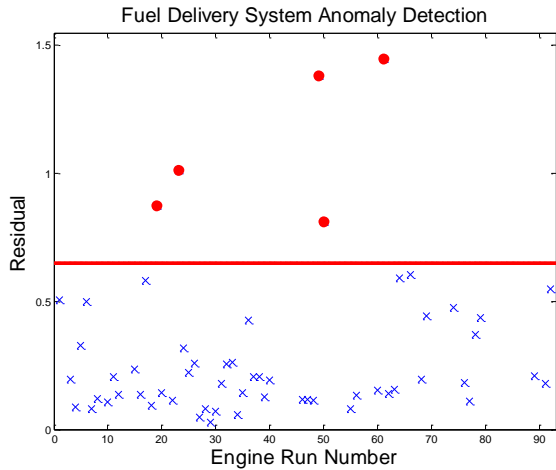

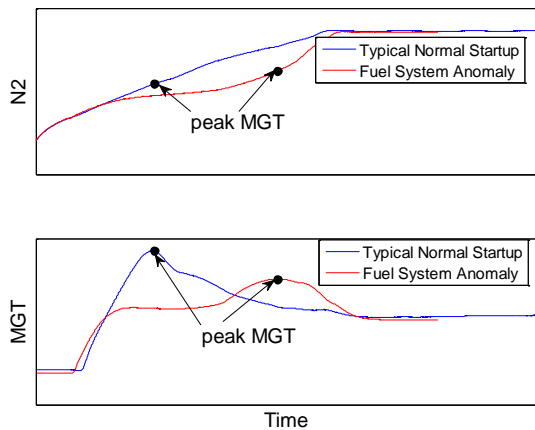Figure 16. PCA Model Output for Fuel System Anomaly Detection

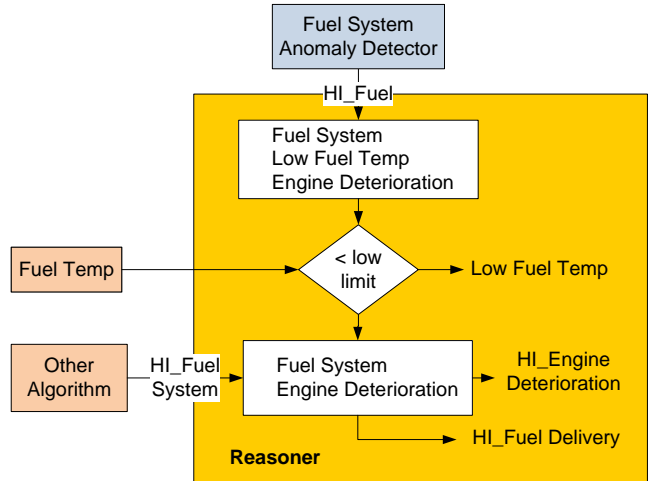Figure 17. Startup Profiles comparing Normal Startup (Blue) and Fuel System Anomaly (Red)

Figure 18. Fuel System Anomaly Reasoner

7. CONCLUSIONS

This paper introduces a method for gas turbine LRU anomaly detection during the engine startup. The approach seeks to strike a balance between the need for a large amount of high-speed data for accurately characterizing the engine condition not only at steady-state but also at transients, and the limited computational resources available on-board and the difficulties associated with storing and transmitting data. Extracting features based on actual engine dynamics and the engine control logic can be done with very minimal computational resources that are already available on most aircraft.

The time that snapshot data is taken is as important as the engine variable that is captured in the snapshot. We have shown that the conditions of Fuel Enable is more useful for the starter system anomaly detection, the Peak MGT dot condition is more useful for the ignition system anomaly detection, and the Peak MGT condition is more useful for the fuel system anomaly detection. The logic to isolate the anomaly of each LRU is also presented.

The approach has been applied on actual engine data collected in test cell. The measurements of interest are the N2 and MGT during engine startup. The developed system detects the anomalies related to the starter system, ignition system and fuel system. The main contributions of this paper are;

- This paper identifies the CTC conditions by the combination of the engine control logic and the engine dynamics.
- This paper provides the method to condense the data required to characterize engine dynamics from several hundred seconds of high speed data to about two dozen data points per startup, which has tremendous implications in engine health monitoring. Implementing

- the approach on-board allows real-time data transfer and makes timely prognostics possible.
- This paper is focused on the different stages of the engine startup process, which enables to cover multiple LRUs which are critically associated to the engine startup. This paper identifies the specific time intervals when the function of a certain LRU is dominant, and the fault detection of that particular LRU is done during the identified time intervals.
- Identifies three different time intervals when the fault detection of three LRUs are done, the three LRUs include start system, ignition system and fuel system.
- Identifies three sets of fault features that exhibit the symptoms of three LRUs most effectively.
- There exist a number of causes that show the anomaly in the fault features. This is called the ambiguity set. This paper identifies the ambiguity set of each three LRUs and isolates the root cause of each anomaly.

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